Individuals, Firms, and Market Dynamics – Four Essays in Applied Microeconomics

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Introduction

Applied microeconomics studies how individual agents –consumers, firms, and managers– make decisions and how those decisions shape market outcomes. Understanding these dynamics is critical to addressing today's economic challenges, from consumer protection in the digital age to anti-competitive behavior by firms. This thesis, "**Individuals, Firms, and Market Dynamics – Four Essays in Applied Microeconomics**," explores these topics through several empirical studies, each examining different aspects of individual and firm behavior within diverse market contexts. Collectively, the chapters contribute to our understanding of how individual behavior and firm strategies affect market dynamics and provide valuable implications.

Chaper 1 of this thesis, "*Do Consumers Care? Collusion, Inattention, and the Power of Information*", investigates consumer behavior in response to collusion. The impact of price changes on consumer behavior is a critical aspect of today's economy, affecting both producers and consumers. While economic theory suggests that price increases typically lead to reduced demand as consumers seek more affordable alternatives (Samuelson 1983), real-world behavior often deviates from this prediction (Thaler 1994; Gabaix 2019). Despite prices being crucial determinants in purchasing decisions (Alba et al. 1999; Monroe 1973), numerous studies indicate that consumers possess limited knowledge about prices and tend to overestimate them (Engel et al. 1973; Evanschitzky et al. 2004; Flemming 1972). This behavior is particularly evident in grocery stores (Gabor and Granger 1961, where routine shopping leads consumers to overlook potential savings from switching to substitutes Goldman 1977), indicating inattention.

Firms can exploit consumers' inattention to price changes, especially in markets with significant market power. This power is maximized during collusion, as firms aim for a monopoly position and raise prices without fear of consumer backlash. Thus, cartels can lead to higher prices and reduced consumer welfare (Levenstein and Suslow 2006). While the detrimental effects of cartels on consumers are recognized, there is a limited understanding of consumer behavior in these contexts for two main reasons. First, cartel studies tend to focus on firm behavior, often overlooking consumer responses. Second, consumers are typically unaware of cartel activity due to asymmetric information, making it difficult to analyze their behavior in response to such activity.

This chapter examines how consumers react to price changes resulting from competitive misconduct, taking into account the influence of additional information under the constraint of inattention. In doing so, I address two main questions: How do consumers respond to small price changes, and how does this response change with additional information? In this chapter, I argue that inattentive consumers may not change their behavior in response to price changes but that providing relevant information may shape their responses.

In this chapter, I use cartels to examine consumer behavior under price changes independent of demand. By focusing on US manufacturing cases, particularly consumer goods, the analysis aims to answer the question of how consumers react to the existence of cartels and the resulting price change during the collusion period and after the cartel's breakup. In the next step, I use media reports as consumers' primary source of information to analyze the influence of information exposure. Thus, I examine how consumer behavior changes when information asymmetries between colluding firms and consumers are eliminated. I use three main datasets: NielsenIQ Homescan data on consumer purchasing behavior, information on cartels from the Department of Justice (DoJ) and the Federal Trade Commission (FTC), and media reports from Nexis Uni.

I use a difference-in-differences (DiD) estimator and find that consumers react to cartels by reducing demand. However, consumers only react in the post-cartel period, suggesting that they were not attentive to the price change during the cartel. Adding news to the equation shows that news articles significantly reduce consumer demand in the post-cartel period compared to the pre-cartel period. In the heterogeneity analysis, I show that not all consumers are equally inattentive. While higher-income consumers tend to be inattentive during the cartel periods but attentive to the news in both periods, lower-income consumers are attentive to price changes and news. Furthermore, I use sentiment analysis to show that the degree of negativity in the news influences consumer behavior: More negative news has a stronger impact on consumer behavior than less negative news.

This chapter contributes to understanding consumer behavior by addressing the interaction between price changes and consumer inattention. It bridges the gap in the literature by examining how consumer behavior changes in response to competitive misconduct and information exposure under the constraint of inattention (e.g., Hirshleifer and Teoh 2003). The results of this chapter shed light on the relationship between consumers' price perceptions (e.g., Monroe 1973; Flemming 1972; Engel et al. 1973) and their behavior (e.g., Lancaster 1966; Gabaix 2019), highlighting the role of consumer characteristics. In addition, this chapter contributes to the literature on collusion (e.g., Donsimoni et al. 1986; Harrington 2006) by examining how consumers respond to cartel behavior and information exposure. Ultimately, the results contribute to understanding how consumers behave due to price dynamics and additional information.

Chapter 2, "*Do Managerial Incentives Facilitate Anti-Competitive Behavior? Evidence from Collusion*", examines the role of managerial incentives in anticompetitive behavior. Whether managerial incentives facilitate collusion is of particular interest as it is the top management who decides on the firm's strategy (Antón et al. 2023; Harrington and Chang 2009). Managers, acting as agents of the principal owner, often have interests that diverge from the goal of maximizing firm value (Holmström 1999; Jensen and Murphy 1990). To mitigate this agency problem, compensation schemes are designed to align management incentives with firm performance (Jensen 1986; Narayanan 1985). However, this alignment may encourage anti-competitive behavior such as collusion, raising questions about the effect of specific compensation structures on such behavior. Therefore, I explore the relationship between managerial incentives and collusion in this chapter.

I use a rich dataset that combines information on cartels, managers, and firms to examine whether and how managerial compensation schemes might affect the formation and stability of collusive agreements. I combine data sources from John Connor's Private International Cartel database (Connor 2020), the Department of Justice (DoJ), the Federal Trade Commission (FTC) websites, Compustat, and ExecuComp.

This dataset includes cartel and firm information and provides insights into executive compensation schemes. The empirical analysis shows that a higher proportion of long-term compensation in managers' total compensation is correlated with increased incentives to collude. This suggests that managers with higher long-term incentives are more likely to initiate or participate in collusive agreements. Furthermore, I consider overconfidence and risk-taking incentives as factors influencing cartel decisions. Managers with higher overconfidence and risk-taking incentives show stronger incentives to collude. These findings have implications for corporate governance and competition authorities. Although owners may not intend it, they create incentives for their managers to engage in anticompetitive behavior. Aligning managers' incentives with profit maximization thus requires a balanced approach. However, competition authorities may be well advised to consider managerial incentives when conducting market investigations and screening for cartels.

This chapter contributes to several strands of the literature. The impact of managerial compensation schemes on collusion is an area that has received limited empirical attention. This chapter builds on theoretical discussions of cartel formation and stability (e.g., determinants Harrington 2006; Donsimoni et al. 1986) by introducing novel empirical evidence related to managerial incentives (e.g., Spagnolo 2000; Spagnolo 2005). Moreover, this chapter bridges the gap between studies of executive compensation (Cornett et al. 2008; Jensen and Murphy 1990; Murphy 1985; Ntim et al. 2015) and firm behavior (e.g., Makri et al. 2006) by linking compensation structures to the willingness to collude. This analysis highlights the complex interplay between managerial incentives and anticompetitive behavior and argues for a review of compensation mechanisms to mitigate the incentives for collusion.

Chapter 3, "*The Impact of Consumer Protection in the Digital Age: Evidence from the European Union*", examines the impact of the European Union's (EU) Unfair Commercial Practices Directive (UCPD) on consumer trust and behavior. The EU online shopping landscape is characterized by a significant gap between domestic and cross-border transactions. Despite the potential of digital technologies to reduce barriers, only a small share of consumers engage in cross-border online business-to-consumer (B2C) trade (Eurostat 2018). This is mainly due to persistent negative distance and border effects, reinforced by language differences, cultural nuances, and trust challenges (Gomez-Herrera et al. 2014; Cowgill and Dorobantu 2012; Blum and Goldfarb 2006; McCallum 1995).

E-commerce contributes to economic growth and trade expansion by reducing information costs and distance constraints. However, as the market expands, sellers face increased competition. The European Commission has pursued harmonization efforts, supported by consumer protection and data security standards, to promote a "Digital Single Market" (European Commission 2015) by reducing key differences between the online and offline worlds within Europe (Craswell 1982; Pitofsky 1977). The EU's Single Market policy aims to remove barriers to cross-border trade, and the Unfair Commercial Practices Directive (UCPD) was enacted to regulate unfair commercial practices within the EU, improving consumer protection and increasing consumer trust. As consumer protection became more important, the European Commission introduced the "New Deal for Consumers" directive in 2018 to address the challenges of e-commerce. The importance of e-commerce has also attracted global attention, as evidenced by initiatives taken by the World Trade Organization in 2017.

This chapter analyzes the impact of the UCPD on consumer trust and shopping behavior in the EU. It examines consumers' attitudes towards retailers in their home country, trust in public authorities, and cross-border shopping behavior. Using data from the Eurobarometer survey and Civic Consulting, the chapter employs a multiple difference-in-difference (DiD) approach to show that the UCPD significantly affects consumer trust and cross-border shopping. The UCPD increases consumers' trust in retailers and services in their own country and their trust in public authorities. It also has a positive effect on online purchases from other EU countries.

The chapter contributes to several strands of literature. It examines the impact of the UCPD on consumer behavior and trust, providing empirical insights into the effectiveness of the regulatory framework. While existing studies have examined trust in the digital age (e.g., Culnan and Armstrong 1999; Doney and Cannon 1997; Gefen and Straub 2004; Hoffman et al. 1999; Jarvenpaa et al. 2000; Lee and Turban 2001; Lim et al. 2006; McKnight and Choudhury 2006; Palvia 2009; Teo and Liu 2007; Wright et al. 2009), this chapter provides a comprehensive analysis of the role of the UCPD in shaping consumer trust and behavior. The analysis also contributes to legal literature by adding empirical evidence of the effectiveness of the UCPD's impact on consumer trust and behavior (e.g., Collins 2005; Collins 2010; Gomez 2006; Schulte-Nölke 2007; Velentzas et al. 2012; Wright et al. 2009). In the broader economic literature on policy evaluation, the chapter follows the trend of analyzing causal treatments using methods such as the difference-in-difference estimator (e.g., Abadie and Cattaneo 2018). It contributes to the field of evidence-based policy analysis by examining whether the UCPD is successful in achieving its intended goal of increasing consumer trust and cross-border trade.

Finally, **Chapter 4**, "*Reaching for Society: The Commercialization Effects of NASA Technology Transfer*", examines the impact of technology transfer on the societal benefits of federally funded research. The United States has experienced a substantial increase in annual federal research and development (R&D) expenditures, growing from approximately $61 billion to $128 billion between 1990 and 2010 (Sargent 2022). This substantial allocation, which represents a significant proportion of U.S. GDP, has sparked debate about the effectiveness and societal benefits of government-funded research (Fleming et al. 2019; Lach et al. 2021; Myers and Lanahan 2022; Nelson 1981). This research serves critical societal functions and provides the foundation for subsequent innovations with far-reaching welfare implications. Nevertheless, debates persist about the effectiveness of publicly funded research, especially by government agencies such as NASA, because the realization of benefits is often below the socially desired level (Bezdek and Wendling 1992; Fleming et al. 2019; Lach et al. 2021).

This chapter explores the link between the commercialization of government-funded research through licensing and its impact on the innovation behavior of third parties. This issue is central to ongoing debates about whether patenting and licensing are effective tools for promoting follow-on innovation (Drivas et al. 2017; Gallini and Winter 1985; Heller and Eisenberg 1998; Nagler et al. 2022; Williams 2017). The question arises because of the mixed effects of licensing on subsequent research. On the one hand, licensing could indicate the commercial value of an invention and raise awareness, while on the other hand, it could serve to exclude other inventors from the market. Although there is evidence of positive spillovers from licensed academic research, evidence of government-funded research, which is critical to societal welfare, remains scarce. This chapter, however, analyzes the relationship between technology commercialization, particularly through licensing, and subsequent innovation.

In the 1980s, the U.S. enacted a series of policies to promote government-funded research, such as the Bayh-Dole Act and the Stevenson-Wydler Technology Innovation Act. The latter also led to the enactment of Technology Transfer Programs (TTPs), which laid the groundwork for the transfer of technology from public institutions such as NASA to private industry, for example, through licensing. This chapter assesses the impact of exclusive licensing of government-funded research on subsequent innovation. The sample for the analysis in this chapter comes from information on NASA patents. Combined information from the TTP website, the NASA Technical Report Server, and PATSTAT provides a complete picture of NASA's patent portfolio. In addition, Federal Register announcements are used to distinguish between patents announced for availability and exclusive licensing.

First, the chapter examines NASA's patent portfolio and finds that exclusively licensed technologies are more novel, based on basic research, and part of larger patent families. The analysis then examines how the commercialization and commercializability of NASA-invented technologies influence follow-on innovation. While there is no significant difference in follow-on innovation patterns between licensed and non-licensed technologies, there is a pronounced increase in follow-on innovation for exclusively licensed technologies. This pattern is further supported by a conditional difference-in-differences approach, reinforcing the notion that commercialization, particularly through exclusive licensing, is positively correlated with follow-on innovation.

In conclusion, this chapter contributes to several strands of literature by shedding light on the complex relationship between technology commercialization and follow-on innovation in government-funded inventions. It is consistent with existing evidence on the economic effects of government-funded research (e.g., Fleming et al. 2019; Lach et al. 2021; Myers and Lanahan 2022), innovation policy (e.g., Edler and Fagerberg 2017; Mazzucato and Semieniuk 2017), and licensing (Arora and Fosfuri 2003; Arora et al. 2013; Arora and Gambardella 2010; Palermo et al. 2019). Importantly, it emphasizes that exclusive licensing of government inventions can yield substantial societal benefits, underscoring the need to improve licensing programs to optimize the benefits of government-funded research. This perspective also adds a unique dimension to the debate about technology markets and the impact of licensing on further research.

The findings from these chapters have significant **policy implications**, particularly in the areas of consumer protection, corporate governance, and innovation. First, the findings in Chapter 1 highlight the need for improved consumer awareness and information dissemination mechanisms to ensure that consumers can respond effectively to price changes and competitive misconduct. Policymakers should consider implementing stricter transparency requirements for firms and encouraging media coverage of anti-competitive behavior, allowing consumers to make informed decisions. Chapter 2 suggests that corporate governance reforms should address the structure of managers' incentives. For instance, long-term performance measures can be incorporated to discourage anti-competitive behavior while promoting ethical business practices. Additionally, it might be worthwhile for competition authorities to consider managerial incentives when screening for anti-competitive behavior. Chapter 3 highlights the effectiveness of the EU's Unfair Commercial Practices Directive in promoting consumer trust and facilitating cross-border purchases. This suggests that similar international regulatory frameworks could benefit all participating regions: Consumers in regions with lower levels of protection tend to increase trust and cross-border shopping. This additionally benefits other regions as consumption increases and competition is fostered. Aiming for similar regulatory frameworks can thus enhance consumer trust and global e-commerce growth. Finally, Chapter 4 demonstrates the positive impact of exclusive licensing on follow-on innovation and highlights the importance of robust technology transfer programs, such as NASA's Technology Transfer Program. Policymakers may focus on improving these programs to maximize the societal benefits of government-funded research, ensure that innovations reach the marketplace, and stimulate further technological advances. These policy implications aim to create a more transparent, competitive, and innovative economic environment that benefits both consumers and businesses.

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1

Do Consumers Care? Collusion, Inattention, and the Power of Information[1]

[1]Researcher's own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

1.1 Introduction

What shapes consumers' reactions to price changes? Price changes frequently occur in today's economy and can significantly impact both producers and consumers. While standard economic theory predicts that price increases lead to reduced demand as consumers seek more affordable alternatives (e.g., Samuelson 1983), real-world behavior often diverges from this expectation (e.g., Thaler 1994; Gabaix 2019). Although prices are a determining variable of the choice to buy or not to buy a product (e.g., Alba et al. 1999; Monroe 1973), strong evidence indicates that consumers often lack precise knowledge of prices and tend to overestimate them (e.g., Engel et al. 1973; Evanschitzky et al. 2004; Flemming 1972). This seems to be particularly evident in routine grocery shopping, where consumers often operate on autopilot (e.g., Gabor and Granger 1961, Goldman 1977). Consequently, consumers persist in purchasing despite rising prices, overlooking potential savings from switching to substitutes.

For firms, it can be highly advantageous when consumers do not pay close attention to price changes, particularly in markets where firms have market power or engage in anti-competitive behavior. When consumers lack attention to price changes, firms can collectively raise prices with minimal risk of consumer backlash. Thus, the inability of consumers to pay detailed attention to price changes can provide firms with greater pricing power and enable anti-competitive behavior. This includes, for instance, collusive activities such as cartels, that might be facilitated (e.g., Levenstein and Suslow 2006), leading to higher prices and ultimately reduced consumer welfare (e.g., Baumol 1964). Despite the well-documented negative effects of cartels, research on consumer reactions to collusive price increases is limited. Existing studies tend to focus on firm behavior, including those within and outside the cartel and those affected by the cartel's actions (e.g., Asch and Seneca 1976; Bajari and Ye 2003), rather than how consumers respond to these price changes. Thus, there is a considerable gap in our understanding of consumers' reactions to collusion.

This paper aims to fill this gap. Consequently, I examine in detail how consumers react to price changes resulting from competitive misconduct. Additionally, I analyze how these reactions are influenced when additional information reducing information asymmetry regarding collusive practices within a market. To address this, I focus on two main research questions: (1) How do consumers react to small price changes resulting from collusive behavior? (2) What is the consumer response when additional information is provided?

In the first step of this analysis, I examine consumers' reactions to price changes driven by the supply side, specifically focusing on cartel activities. The primary aim of this part of the analysis is to investigate the impact of reduced market competition, resulting in higher prices, on consumer behavior and the incentives to change consumption patterns. Cartels, known to cause higher prices, allow for analyzing consumer behavior in response to price changes not directly caused by supply or demand shocks. To analyze consumer behavior, I use consumer-level NielsenIQ Homescan Data from Booth's Kilts Center for Marketing. This dataset provides detailed information on when and where consumers purchased products and at what prices. I examine several price-fixing cartel cases[2] in the U.S. manufacturing industry, focusing on consumer goods. To do so, I use information on cartels and their breakdowns. I obtained this data from the Department of Justice's (DOJ) website, which includes details on specific cartels and the involved firms, including the nature of the violations and the timeline of the cartel agreement. This information is gathered through web scraping and text mining from three key documents released by the DOJ's Antitrust Division: the information document, plea agreement, and final judgment.[3] This part of the analysis seeks to answer two key questions: (i) Do consumers react to small price changes induced by cartel agreements?, and (ii) how do consumers respond to potential price changes during different periods, including the collusion period and after the cartel's breakdown? By addressing these questions, I aim to determine whether collusive agreements and

[2]The data used for this analysis identifies whether a cartel has been detected. For detected cartels, I define price increases during the cartel period as cartel-induced price changes. Note that there may be other undiscovered cartels in the data that I cannot capture. Therefore, I classify products of uncovered cartels as cartelized and all others as non-cartelized products.

[3]In cases involving international cartels where the DOJ was not the primary competition authority, I also collect relevant documents from other authorities, such as the Competition Bureau Canada, using the same methodology.

subsequent cartel breakdowns influence product pricing in the market and, thereby, demand without consumers being aware of the underlying cause.

The second part of the analysis focuses on additional information and its effect on consumer behavior. Once a cartel breaks down and competition authorities publish investigation reports, the information becomes accessible to the general public. Media coverage, including press releases and news reports, further disseminates this information. Two important pieces of information are revealed at this stage. First, prices were increased in the past, and consumers may or may not have noticed this. Second, the cause for the price increase is revealed, thereby educating consumers about the reason for the price increase. This exposure provides an opportunity to gain deeper insights into consumer behavior and to investigate whether inattention and information asymmetry explain the initial responses to price increases. Media reports such as newspapers, providing details about the investigation, competition authority findings, and DOJ cases, are thus utilized as the primary information source for analyzing information exposure. I collect these reports using the Nexis Uni database (hereafter Nexis) and extract relevant information through text mining. Consequently, I use media reports on detected cartels to examine how consumer behavior changes when the information asymmetry between colluding firms and consumers is resolved. This may result in various consumer reactions, which are discussed. This part of the analysis aims to answer the questions: Do consumers react to information exposure regarding a past price increase, and if so, how?

I investigate the causal link between competitive misconduct and consumer behavior, particularly under the potential constraint of inattention. To do this, I use collusion events and their breakdowns as shocks to competition, analyzing their effects on demand.[4] I employ difference-in-differences (DiD) approaches, with the control group consisting of firms operating in the same market but not participating in the cartel. These firms serve as a baseline for assessing the minimum effects on consumer

[4]From a consumer's perspective, a cartel represents a market shock, though it may not be entirely exogenous. However, a cartel breakdown can be considered an exogenous shock to the industry, as colluding firms are often unaware of the antitrust authority's investigation.

behavior.

There are three main results from the analysis. First, there is an indication that consumers are largely inattentive to price changes in the short term. Thus, the findings show that consumers react to collusion events by reducing their demand for the cartelized product, but this reaction occurs only in the long run. In contrast, news reports have an immediate impact, prompting consumers to significantly lower their demand during the post-cartel period. Two scenarios illustrate the changes in consumer behavior: On the one hand, consumers may not initially notice a price change but, once aware, adjust their demand in a delayed reaction, indicating inattention to minor price variations. On the other hand, consumers may notice the price increase but either not care or attribute it to a valid reason. If subsequent information reveals that this reason is invalid, consumers may react by changing their demand, possibly feeling betrayed. In both scenarios, consumer behavior is shaped by inattention to specific product information. Although distinguishing between these two reasons is challenging, underlying consumer characteristics that drive such behavior are discussed in the heterogeneity analysis.

Second, further analysis reveals differences in behavior among consumer groups. Consumers who respond only to price increases but not to the underlying reasons might have other characteristics that explain this difference. Low- and high-income consumers react significantly differently to price increases. Although the true reason for a price increase is hidden, low-income consumers choose not to purchase the product while high-income consumers do not show a pronounced reaction to price increases. This behavior suggests that low-income consumers are attentive to price increases, which seems logical as they face stricter budget constraints than high-income consumers. The distinguished reactions of low- and high-income consumers align further with the theory of rational inattention, which suggests that consumers allocate their attention based on the perceived importance and relevance of the information at hand (e.g., Gabaix 2019). However, when looking at consumers' reaction to news reports, both low- and high-income consumers change their behavior and reduce their demand. Thus, although low-income consumers have already lowered their demand with a cartel in place, they show another negative reaction when the information about the price increase is revealed. Additionally, high-income consumers, who do not face strict budget constraints, will reduce their demand in response to the information of a cartel and price increase in the past. On the one hand, this could be as high-income consumers become attentive to the price increases in the past and thus show a delayed reaction as they are, in principle, also price sensitive. On the other hand, although high-income consumers can, in principle, afford the higher prices, they feel betrayed by the cartel firms. Thus, they lower their demand to show dissatisfaction with the firm's strategy. Both reasoning align with the results for low-income consumers as they might also become (even) more attentive to prices or feel betrayed by the firm, leading to lower demand for cartelized products. Furthermore, consumers who only react to price increases in the first place and not to the underlying reason might be considered as behaving in a typically *rational* manner. I do not find, however, strong support for this in my analysis, as all consumer groups react to news reports revealing the reason for a price increase.

The third result of my analysis is related to the news reports. A sentiment analysis of the content of news reports reveals that the negativity of news reports influences consumer reactions: the more negative the article, the stronger the demand response. Additionally, I distinguish between news reports that explicitly state the names of the cartel firms and news reports that only name the broader market that is affected by the cartel. This analysis reveals that the effect on demand is even more pronounced, and consumers purchase fewer products affected by the cartel.

This paper contributes to several strands in the literature. First, this study contributes to the broader field of consumer behavior (e.g., Lancaster 1966; Gabaix 2019). While empirical research on consumer behavior dates back to Stigler (1954)[5] the understanding of how consumers respond to price changes, especially under conditions of inattention, remains underexplored. Various models have been developed to an-

[5]An introduction of the early advances in demand research can be found in Brown and Deaton (1972).

alyze consumer behavior (e.g., Nevo 2011) empirically. This paper focuses on how the availability of additional information influences consumers' awareness of price changes. This aligns with the literature on consumer inattention, which has predominantly focused on investor behavior (e.g., Hirshleifer and Teoh 2003; Karlsson et al. 2009; Philippas et al. 2019) due to the accessibility of financial data. However, the dynamics in financial markets differ significantly from those in consumer markets, such as supermarkets, where both the customer base and the incentives to stay informed are distinct. This paper addresses a gap in the literature on inattention by examining consumer behavior in everyday contexts.

This paper also contributes to the literature on consumers' perception of prices and their corresponding behaviors (e.g., Monroe 1973; Flemming 1972; Engel et al. 1973). My findings show that price perception is correlated with consumer characteristics, such as income and household composition, thereby showing a distributional difference in the perception of prices. While predominantly high-income consumers are inattentive to prices, low-income consumers notice these adjustments and modify their behavior accordingly. This nuanced understanding of price perception adds depth to the literature on consumer pricing responses.

The paper further contributes to the literature on collusion and cartel behavior. While the literature on price-fixing cartels is extensive, covering theoretical models (e.g., Bos and Harrington 2010; Donsimoni et al. 1986; Schmalensee 1987) and experimental studies (e.g., Fischer and Normann 2019; Hinloopen and Soetevent 2008), empirical analyses, particularly those that consider consumer reactions, are less common and often determinant-driven or industry-specific (e.g., Harrington 2006b; Levenstein and Suslow 2006; Giebel and Rösner 2023). This study fills a gap by examining how consumers respond to collusion, particularly in the periods during and after a cartel's breakdown. By doing so, it highlights consumer behavior in response to market power abuses. This is an area that has received little attention in the literature.

Finally, this paper contributes to the literature on the impact of media coverage on behavior. Previous studies have shown that media coverage can influence the actions of firms (e.g., Baloria and Heese 2018; Bednar et al. 2013; Dyck et al. 2008) and public institutions (e.g., Gao et al. 2020). Media effects have also been studied in finance (e.g., Barber and Odean 2007; Engelberg and Parsons 2011; Fang and Peress 2009), policy (e.g., Aker et al. 2017; Chiang and Knight 2011; DellaVigna and Kaplan 2007; Miller et al. 1979), and macroeconomics (e.g., Carroll 2003; Lamla and Lein 2014; Lamla and Maag 2012). However, beyond the context of advertising (e.g., Nelson 1981), the influence of newspapers on consumers' day-to-day purchasing decisions remains underexplored. This paper demonstrates that news reports can significantly affect consumer behavior, showing that the tone and content of media coverage can foster consumer reactions, thereby contributing new insights to the literature on media influence.

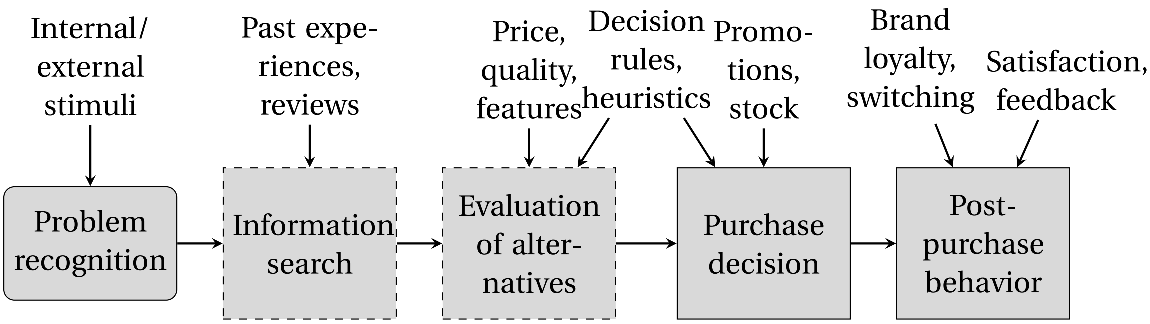
The paper is organized as follows: Section 1.2 discusses how inattention, collusive behavior and media coverage influence the consumer behavior. Section 1.4 details the data and identification strategy. The results of the baseline and sensitivity tests are discussed in Section 1.5. In Section 1.6, I discuss and present the result of a heterogeneity analysis focusing on different consumer groups and news sources. Finally, the paper concludes with Section 1.7.

1.2 Theoretical framework

1.2.1 Inattention in consumer's decision-making process

Understanding consumer decision-making is essential for analyzing how consumers respond to price changes, particularly in markets influenced by collusion. The classic consumer decision process involves five stages: problem recognition, information search, evaluation of alternatives, purchase decision, and post-purchase behavior (e.g., Engel et al. 1990). However, the assumption that consumers follow this process perfectly, as often depicted in models of rational decision-making (e.g., Smith 1776), overlooks the cognitive limitations humans face. Thus, unlike the assumption of perfect rationality—where consumers are presumed to have unlimited cognitive resources and access to all relevant information (e.g., Smith 1776)—the human brain has a finite capacity for handling and processing information (e.g., Miller 1956). When faced with these constraints, consumers tend to become inattentive, leading them to deviate from rational decision-making. This inattention can allow firms to raise prices without facing significant consumer response, as small price increases may go unnoticed until external information draws attention those price increases. Figure 1.1 outlines the consumer decision-making process, highlighting how inattention affects key stages, particularly during the information search and evaluation phases, where consumers are most vulnerable to missing critical market signals.

Figure 1.1: Consumer decision-making process



Note: This figure is primarily based on the Engel-Blackwell-Miniard (EBM) model by Engel et al. (1990). It provides an overview of the key phases and factors involved in a typical consumer decision-making process. The process begins with problem recognition, followed by information search and evaluating alternatives, leading to the purchase decision. The final stage is post-purchase behavior, which can be influenced by satisfaction, brand loyalty, or switching behavior. Each stage of the process is guided by various factors that influence consumer decisions. While this model outlines the typical decision-making process, it is important to note that it serves as a general guideline. In reality, consumers may face inattention and rely on heuristics or simplified decision rules to navigate the process. The solid lines in the figure represent stages that occur in every decision, while the dashed lines indicate stages that may be reduced or skipped when consumers encounter cognitive limitations.

Inattention in the consumer decision-making process gives rise to two main concepts: bounded rationality (Simon 1997) and rational inattention (Sims 2010).[6] While both bounded rationality and rational inattention address deviations from perfect rationality, they differ in key aspects. Bounded rationality emphasizes individuals' overall cognitive limitations to *process* information (Simon 1997). In contrast, rational inattention focuses on how consumers strategically *allocate* their limited attention, prioritizing the most relevant information based on a cost-benefit analysis (Sims 2010). Consumers choose to focus their limited attention on other decisions that have greater

[6]A detailed description and discussion of both concepts can be found in Appendix 1.A.

perceived importance (e.g., Gabaix 2019). Bounded rationality often leads to systematic biases, while rational inattention leads to strategic ignorance, where consumers intentionally ignore certain information to manage cognitive load. Thus, bounded rationality affects all stages of the consumer decision process, from problem recognition to post-purchase behavior, more uniformly. In contrast, rational inattention primarily affects the information search and evaluation stages, where attention allocation is most critical.[7]

Consequently, inattention leads consumers to simplify decisions by using heuristics[8] and focusing on a subset of attributes, especially when faced with complex choices or information overload (e.g., Kahneman and Tversky 1979; Wang et al. 2018). This tendency can lead to systematic biases. For instance, consumers may stick with default options, rely on easily accessible information rather than making thorough comparisons, or pay close attention to the prices of a few essentials while overlooking changes in the prices of less frequently purchased items.[9] This selective attention can lead consumers to overlook important details, such as hidden fees or long-term costs.

Both concepts of inattention—bounded rationality and rational inattention—can help explain why consumers might overlook small price changes or additional product details. Bounded rationality suggests that consumers simplify their decisions by focusing on a limited set of attributes, which may not include price. Rational inattention, on the other hand, suggests that consumers may intentionally choose to ignore certain details, such as small price changes because the effort to consider them outweighs the perceived benefit. However, when price changes are more noticeable, they may trigger immediate consumer responses, such as switching to alternative products or reducing consumption. Thus, the degree of inattention plays a crucial role in determining consumers' response to price changes (e.g., Gabaix 2019).

[7] In Appendix 1.B, I discuss the consumer decision process in detail and analyze how each stage is influenced by bounded rationality and rational inattention.

[8] A more detailed discussion of the most relevant behavioral biases and their consequences can be found in Appendix 1.C.

[9] For instance, the average number of objects an individual can hold in working memory is about seven. This concept can be applied to memorizing prices as well. Thus, consumers might be able to remember the prices of seven products, while on the other hand, the average number of purchased items per shopping trip largely exceeds this (e.g., Namin and Dehdashti 2019).

As a result, when consumers are inattentive, they may not notice small but frequent price increases (e.g., Grubb 2015, Civelli et al. 2018, Maćkowiak et al. 2023), leading to higher overall spending without significant behavioral adjustments. These purchases are often made under constraints, such as limited shopping time, with choices influenced by factors such as store displays. Over time, many purchase decisions become so routinized that consumers almost automatically make them, often not realizing what they have bought until the items are already in their shopping carts.

1.2.2 Firm's exploitation of consumers' inattention

Consumers being inattentive can be advantageous for firms, as they might exploit consumer inattention, whether intentionally or unintentionally, through various strategies. Inattention leads to information asymmetries, where one party has more or better information than the other in a transaction (e.g., Akerlof 1970; Ellison 2006). Some degree of information asymmetry between consumers and firms is unavoidable. Typically, this involves scenarios where sellers have more knowledge about a product than buyers, such as production processes, recipes, or supply chains. These could not be fully transparent due to the high costs associated with revealing them, such as losing a competitive advantage. However, if consumers are unaware of relevant product information, this can become problematic since it significantly affects consumers' ability to make informed decisions.

If firms do not intend to exploit information asymmetries between themselves and consumers, they can use signaling to address those asymmetries. Signaling involves actions taken by the informed party to convey critical information to the uninformed party (e.g., Spence 1973). This strategy is particularly effective when firms recognize the potential for unintentional exploitation due to consumer inattention and seek to bridge the information gap. For instance, labels on products can attract consumer attention and signal quality, helping to clarify information that might otherwise go unnoticed. Another approach to mitigating information asymmetry involves actions taken by the uninformed party to obtain additional information from the informed party, a process known as screening. In this scenario, the uninformed party actively seeks out more information in recognition of its initial knowledge deficit. For instance, health insurers often require medical examinations to assess an individual's risk level, thereby compensating for the underlying information asymmetry. Similarly, consumers can use screening as a tool to reduce the effects of asymmetric information caused by inattention (e.g., Rothschild and Stiglitz 1978). However, this strategy is typically used when the purchase decision is considered important enough to justify extensive problem-solving rather than routine or unimportant decisions.

Firms often take advantage of consumers' limited cognitive capacity by employing strategies that create or reinforce information asymmetries. A common strategy is using complex pricing structures that make it difficult for consumers to compare prices. For example, tiered pricing or bundling of services can obscure the true cost of a product or service, leading to sub-optimal consumer decisions (e.g., Gabaix and Laibson 2006; Ellison 2005). Another common strategy is to emphasize low upfront costs while hiding higher long-term fees or charges, which is a strategy often seen in industries such as telecommunications and insurance. This practice is characterized by "drip pricing", in which additional costs are gradually disclosed throughout the purchase process (e.g., Greenleaf et al. 2016; Kalaycı and Potters 2011). In addition, firms may design products with salient features that attract consumers' attention, thereby shifting the focus away from less favorable attributes of the product. For instance, a smartphone might be marketed primarily for its high-resolution camera while downplaying less appealing aspects such as short battery life or limited durability (e.g., Bordalo et al. 2013). These strategies can be used by firms individually or, even more concerningly, in a coordinated manner, resulting in anti-competitive conduct.

The potential for firms to collectively exploit consumer inattention raises concerns about market fairness and competitive practices. When firms within an industry engage in similar deceptive strategies through tacit collusion or explicit agreements, they can collectively reduce competition, leading to higher prices and reduced consumer welfare. This convergence of strategies blurs the distinction between competitive behavior and anti-competitive practices, potentially contributing to the formation of cartels.

Cartels are typically defined as formal agreements between competing firms to manipulate market conditions for their mutual benefit.[10] The secretive nature of cartels means that consumers, other competitors, and regulators usually remain unaware of their existence. The economic rationale for the formation of cartels is based on the desire to maximize profits through reduced competition. Cartel members can avoid undercutting each other by coordinating prices and presenting a united front against competitive pressures (e.g., Porter 1983). This strategic pricing ensures that all cartel members benefit from higher prices without the risk of losing market share due to price competition (e.g., Genesove and Mullin 1998). Such behavior typically results in a reduction of market supply (e.g., Landes 1983), which drives up prices and allows cartel members to secure profits greater than those achievable in a competitive market (e.g., Posner 1976). Thus, colluding firms can set higher prices, restrict output, and create barriers to entry for other competitors (e.g., Stiglitz 1989). The stability of cartels often depends on the ability to monitor and enforce compliance among members, as cheating by undercutting agreed-upon prices can undermine the cartel's objectives (e.g., Levine and Pesendorfer 1995; Harrington 2006a). Thus, cartels often involve a small number of firms that dominate a market, making coordinating and enforcing collusion easier (e.g., Levenstein and Suslow 2006; Stigler 1964).

1.2.3 The relationship between collusion, prices and consumer awareness

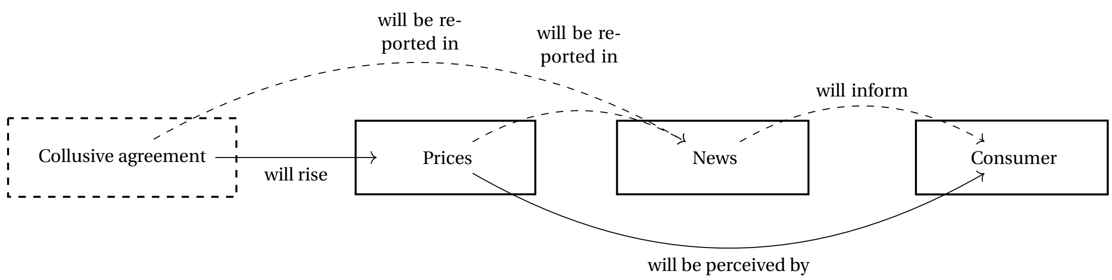
When firms enter into collusive agreements, they typically raise prices.[11] However, because these agreements are kept secret, consumers remain unaware of the under-

[10] There are important distinctions between explicit and tacit collusion. Explicit collusion involves formal, often secret, agreements between firms to coordinate actions such as price-fixing or market allocation. These agreements are intentionally designed to manipulate market conditions. Tacit collusion, on the other hand, occurs without formal agreements; firms implicitly understand that by engaging in certain practices, such as price leadership or signaling, they can achieve results similar to those of explicit collusion. Although tacit collusion is more difficult to detect and prove, it can still lead to reduced competition and higher prices. Because tacit collusion lacks formal agreements and hard evidence, it is generally not prohibited by law (e.g., Kovacic et al. 2007; Vives 1999).

[11] In price-fixing agreements, the prices are directly increased, while in agreements restricting the output, the price increase is a more indirect but often unavoidable consequence.

lying cause of the price changes. While prices are theoretically visible to consumers in stores, limited attention often prevents them from noticing small, marginal price increases, particularly during routine activities such as grocery shopping. This creates an information asymmetry that benefits the firms. The media plays a significant role in overcoming this asymmetry by reporting collusion and related price increases, enabling consumers to make more informed purchasing decisions. This relationship between collusion, price increases, and consumer awareness is illustrated in Figure 1.2 and will be discussed in more detail in the following.

Figure 1.2: Illustration of the effects of collusion on prices and media taking into account consumers' limited cognitive capacities



Note: This figure illustrates the underlying mechanisms analyzed in this paper. Information that is, in principle, visible to consumers is shown in solid lines, and information that is hidden to consumers is shown in dashed lines. While collusion is at first secretly agreed between the firms, it will become visible to the consumers when the media informs them about the agreement and the increased prices. Prices are generally visible to the consumers. However, their increase is often overlooked due to consumers' limited attention.

Because cartels operate in secret, consumers' primary indicator of collusion is often price increases. However, collusion can lead to price stability at artificially high levels. By collectively agreeing to maintain prices above the competitive equilibrium, cartel members reduce the incentive for individual firms to lower prices, relying instead on the mutual agreement to maintain higher profits (e.g., Stigler 1964; Posner 1976). This price-fixing behavior minimizes the risk of price wars and ensures consistent revenue streams for cartel members. Unfortunately, this comes at the expense of consumers, who are subjected to higher prices and limited choices. Consumers may adjust their expectations and budgeting behavior when they observe stable prices over time, potentially becoming less vigilant in price comparisons and more accustomed to the inflated prices set by the cartel (e.g., Porter 1983; Harrington 2006a). This adaptation may decrease price sensitivity and a reduced likelihood of seeking alternatives, further entrenching the cartel's market power and making it more difficult for new entrants to disrupt the market (e.g., Vives 1999).

In contrast, price flexibility in competitive markets leads to frequent price changes in response to fluctuations in supply and demand. This dynamic pricing reflects true market conditions, promotes economic efficiency, and benefits consumers through lower prices and greater choice (e.g., Maskin and Tirole 1988). In competitive environments, firms must continually adjust prices to attract and retain customers, fostering a more responsive and consumer-friendly pricing landscape (e.g., Varian 1992).

When firms collude, the relative rigidity of prices, coupled with the limited cognitive capacity of consumers, prevents them from recognizing that they are paying too much for cartelized products. Consumers may end up purchasing goods or services at inflated prices due to inattention, lack of information, and the rigidity of cartelized prices (e.g., Gabaix and Laibson 2006; Ellison 2005). Although signaling and screening are effective strategies for overcoming information asymmetries, they require action by either the informed or the uninformed party. In the context of cartel behavior, especially in food markets, neither party is motivated to use these strategies. Firms have no incentive to signal their secret agreements or price increases to consumers, while consumers, limited by their cognitive capacities, often fail to recognize that they are being exploited (e.g., Akerlof 1970; Stiglitz 1989).

A key method of reducing information asymmetries is through external sources of information, particularly news reports. The media acts as a critical intermediary, disseminating information to consumers and thereby bridging the knowledge gap between firms and the public, thereby reducing information asymmetries (e.g., Jin and Leslie 2003; Dranove and Jin 2010). The quality and depth of news reporting can vary widely, from superficial coverage to in-depth investigations that reveal hidden or obscure information to the public. For instance, investigative journalism plays an important role in exposing collusive practices or deceptive marketing strategies, which can inform consumers about unfair market behaviors and practices (e.g., Hamilton 2016; Stiglitz 2000). By increasing market transparency, investigative journalism empowers consumers to make more informed decisions, potentially leading them to avoid exploitative firms and seek out more trusted alternatives (e.g., Besley and Prat 2006; Oberholzer-Gee and Strumpf 2007). This shift in consumer behavior can have a profound impact on market dynamics, forcing companies to reconsider deceptive practices in favor of greater transparency. Moreover, the impact of investigative reporting goes beyond consumer awareness. It has been shown to trigger regulatory responses and influence public policy, further enhancing consumer protection (Dyck et al. 2008; Puglisi and Snyder Jr 2015). This regulatory response can deter companies from engaging in anti-competitive behavior, as the risk of exposure and subsequent legal or financial consequences becomes a significant deterrent (Prat and Strömberg 2013; Gentzkow and Shapiro 2006).

As limited attention is not restricted to specific types of information, it can also extend to media coverage. Thus, consumers may be inattentive to media coverage, which can prevent them from changing their behavior in response to coverage of corporate misconduct. Since consumers lack the capacity to absorb all publicly available information, the way information is coded and presented becomes increasingly important (e.g., Mullainathan and Shleifer 2005). When news reports highlight issues such as price-fixing, product recalls, or unethical business practices, they can capture consumer attention and trigger immediate responses (e.g., Barber and Odean 2007), such as boycotts or shifts in brand loyalty (e.g., Larcinese et al. 2011; Bushee et al. 2010). For instance, the Volkswagen diesel scandal had a significant impact on consumer behavior and sales, largely due to extensive media coverage and resulting shifts in public sentiment (e.g., An et al. 2018; Bachmann et al. 2023; Jong and van der Linde 2022). Although consumers do not actively seek out or track information, such as price developments (e.g., Ellison and Ellison 2009; Sims 2010), media headlines can capture their attention (e.g., Gentzkow and Shapiro 2010). This underscores the media's important role in shaping public opinion, as consumers rely on accessible sources to update their information sets (e.g., DellaVigna and Gentzkow 2010; Eisensee and Strömberg 2007). Therefore, news reporting can play a significant role in mitigating the effects of information asymmetry in cartel cases by disseminating relevant information about market conditions, prices, and firm behavior, even when consumers are subject to inattention. In addition, the media helps interpret complex economic information and contributes to the process of making such information understandable to the general public (e.g., Tuchman 1978; Hamilton 2004). In this way, the media bridges the gap between the availability of information and consumer awareness and plays a critical role in holding firms accountable for anti-competitive practices (e.g., Zingales 2017).

1.2.4 Expectations about consumer's response to price changes and information

From the discussion, it becomes evident that consumers' inattention to small price changes in routine activities such as grocery shopping is particularly detrimental when firms exploit it through collusive arrangements. Small price increases, especially when they are subtle and spread across different products, tend to go unnoticed by consumers, allowing firms to benefit from information asymmetry without immediate backlash. This behavior is consistent with the concept of rational inattention, where consumers, constrained by cognitive resources, focus on more pressing or relevant information (e.g., Sims 2010). Additionally, bounded rationality further explains this phenomenon, as cognitive limitations lead consumers to rely on heuristics, making them prone to systematic biases (e.g., Gabaix 2014; Simon 1997). Consequently, in such scenarios, although prices are visible, without external intervention, the public may remain largely unaware of the overpricing resulting from collusion.

However, media coverage can dramatically shift this situation. When news outlets expose price increases resulting from collusion, they effectively draw consumers' attention to the fact that they have been overpaying in the past. This disclosure can trigger strong emotional responses, such as feelings of betrayal or injustice, significantly influencing consumer behavior. For instance, consumers may decide to boycott the companies involved, switch to alternative brands, or even demand compensation (e.g., Bushee et al. 2010; DellaVigna and Pollet 2009; Hendel et al. 2017). The intensity of the behavioral change is often enhanced when the media highlights the perceived severity of the overpricing, thereby reinforcing the emotional response. (e.g., Kahneman and Tversky 1979; Tetlock 2007).

Nevertheless, media coverage of collusive practices typically depends on the actions of competition authorities. Regulators play a key role in uncovering illegal collusion by providing the basic information that media outlets later disseminate to the public (e.g., Buccirossi et al. 2013). The extent and impact of consumer response also depend on the depth and intensity of media coverage. Limited coverage can result in low consumer awareness and minimal behavior change. Conversely, widespread and intense media coverage can significantly increase public awareness (e.g., Dranove et al. 2003). This wide coverage also creates additional pressure on firms, as the resulting negative publicity can damage the reputation and consumer trust (e.g., Fombrun and Shanley 1990). Thus, effective cooperation between and within competition authorities and the media is essential to ensure that collusive practices are widely reported. Therefore, the interaction between competition authorities and the media ensures that anti-competitive practices are not only detected but also brought to the general public's attention, thereby enabling informed consumer reactions.

1.3 Institutional framework

There is a general awareness that collusion harms consumers as cartel firms can exploit consumers without them being aware of it. Collusion distorts market conditions, leading to inefficiencies and fewer incentives to innovate (e.g., Vives 2008), and consumers face higher prices and fewer choices, resulting in reduced consumer welfare (e.g., Baumol 1964). Thus, antitrust enforcement mechanisms exist to constantly monitor markets, investigate potential collusion between firms, and impose fines. It is important to demonstrate the negative impact of cartels on consumer welfare and overall economic efficiency in order to demonstrate the relevance of antitrust enforcement to society.[12]

[12] However, it is worth asking whether antitrust enforcement is sufficient to fully address the harms caused by collusive behavior. The damage to consumer welfare and overall economic efficiency may be greater than what current enforcement mechanisms can address.

Collusion is a global phenomenon that restricts competition, deters new entry, and inflates prices. As a result, competition or antitrust authorities are present in almost all countries worldwide, and colluding is prohibited almost everywhere. The Sherman Antitrust Act, passed by Congress in 1890, has a long history of prohibiting cartels in the US. The laws prohibit horizontal price agreements, making price fixing or price inflating agreements between direct competitors *per se* illegal. It is essential to note that the prohibition of cartels is rooted in the goal of protecting consumers from harm. While antitrust enforcement is in place to prevent collusion, questions remain about the extent of consumer and welfare damages caused by cartels and whether the current enforcement mechanisms are enough to address these harms. Therefore, examining the antitrust policies and enforcement in greater detail is necessary to understand their implications for consumer welfare and market outcomes.

One of the primary challenges is the difficulty in detecting and proving collusion, as cartels operate secretly and engage in subtle forms of anti-competitive behavior that are hard to identify. Antitrust authorities employ various methods to detect and prosecute cartel activity. One of the most effective tools is the leniency program, which offers immunity or reduced fines to the first cartel member to confess and provide evidence. This approach has proven successful in uncovering many cartels and encouraging other members to come forward. Additionally, antitrust authorities may conduct unannounced "dawn raids" to gather evidence, including seizing documents and electronic devices. [13]

In the US, the Antitrust Division of the Department of Justice and the Bureau of Competition of the Federal Trade Commission (FTC) jointly deal with collusion, while the Department of Justice mainly enforces criminal conduct.[14] While there has been

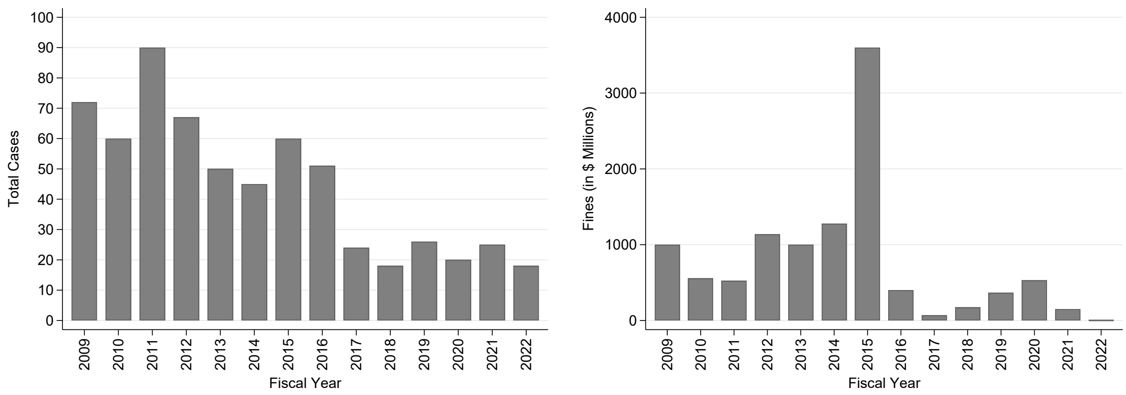
[13]Despite the efforts of antitrust authorities to detect and prosecute cartel activity, their effectiveness has several limitations. For instance, coordinating enforcement across different jurisdictions can be complicated, particularly if countries have different legal systems or levels of resources. Another limitation is that even when cartels are uncovered and prosecuted, firms may engage in other forms of anti-competitive behavior that are harder to detect or punish, such as tacit collusion or strategic product design.

[14]The two most influential systems of competition regulation are, as stated, the United States antitrust law and European Union competition law. As the data used in this study is from the US, I will mainly focus on describing antitrust enforcement in the US.

a noticeable decrease in the number of criminal antitrust cases and fines imposed by the Antitrust Division since 2015, the reasons for this trend are not entirely clear. Some possible explanations include changes in enforcement priorities or companies becoming more savvy in avoiding detection. According to the Department of Justice, the number of charged corporations decreased from 66 in the fiscal year 2015 to 18 in 2022 (see Figure 1.3, panel (a)), and fines decreased from a high of about 3.6 billion dollars in 2015 to roughly 2 million dollars in 2022 (see Figure 1.3, panel (b)) (Department of Justice 2023). It is worth noting, however, that 2015 was a year with exceptionally high criminal fines and penalties due in part to five major banks being fined for conspiring to manipulate prices of US dollars and euros. In that year, they had to pay a total of 2.5 billion dollars, with three of the conspirators being fined the highest corporate fines due to a Sherman Act violation from the Department of Justice ever (Citicorp with $925M, Barclays PLC with $650M, and JPMorgan Chase & Co. with $550M). Although the trend in Figure 1.3 might suggest that there is a decline in investigations and leniency applications, this is, in fact, not the case. There are still pending grand jury investigations and the number of leniency applications is not lower than historical averages (Department of Justice 2023).

Figure 1.3: Total criminal case filed and fines imposed by the DoJ between 2009 – 2022

(a) Total criminal cases (b) Total fines and penalties



Note: This figure shows the total criminal cases files and fines imposed by the Department of Justice between 2009 – 2022. Panel (a) shows the total criminal cases the Department of Justice filed. Note that the declining trend in the last years can be attributed to pending grand jury investigations and not to a decreasing number of leniency applications. Panel (b) shows the total fines and penalties the Department of Justice imposes. Note that 2015 was a year with exceptionally high criminal fines and penalties due to a cartel between five major banks. Lower cases and total fines and penalties in the last years can also be attributed to pending grant jury investigations and not necessarily a general decline in cases and fines.

1.4 Data and empirical strategy

1.4.1 Data

Consumer data. The data used in this study comes from three different sources. Firstly, NielsenIQ Homescan Data from Booth's Kilts Center for Marketing is used to provide consumer-level data between 2004-2019[15]. This data allows for the precise identification of the product purchased by each individual, including the price and retailer. The NielsenIQ Consumer Panel Data has already been used for research in various contexts[16].

Cartel cases. Secondly, information on cartels and their breakdowns is required. To obtain cartel information, I leverage three documents for each case released by the De-

[15]In principle, more years after 2019 are available, but due to the Corona crisis, corresponding lockdowns and other measures that influenced consumer behavior, I only analyze data until and including 2019.

[16]For instance, previous studies have investigated consumer behavior related to (mental) health (e.g., He and Lusk 2021; Meckel and Shapiro 2021; Oster 2018), taxes (Bollinger and Sexton 2023; Cawley et al. 2019; Cotropia and Rozema 2018; Kifer 2015; Lozano-Rojas and Carlin 2020; Parker and Souleles 2019) and brands (Bronnenberg and Dubé 2017; Grasby et al. 2019; Koschmann and Sheth 2016).

partment of Justice's antitrust division: an information document, a plea agreement, and a final judgment. These documents offer comprehensive information about the colluding firms, the nature of the violation (such as price fixing or bid rigging), and the timing and extent of the collusion. Both text mining techniques and hand collection of data are used to extract and analyze this information, which is available on the Department of Justice website. As the consumer data is the baseline dataset, I study consumption cartels that started and ended within the time frame of the NielsenIQ data set (2004-2019). During this time, I identified seven major cases in which firms engaged in price-fixing for an extended period in the consumption industry. These cases cover a range of markets (referred to as case 1-7, respectively). It is worth noting that while some cartels are formed in the manufacturing sector, the impact of these cartels ultimately affects the final consumer if every intermediary passes on the cartelized price.[17] For this reason, I analyze both types of cartels in this study. Table 1.D1 gives an overview of the cartels analyzed in this dataset. Due to anonymity reasons, the names of firms or brands involved in the cartels are not disclosed. Instead, the respective cartels are referred to as cases 1-7.

News articles. Third, for the information exposure event, I leverage a comprehensive dataset of news articles obtained from Nexis, covering the period from 2004 to 2019[18]. Nexis is a search engine covering international sources and information in full text on news. The dataset includes a wide range of news articles, encompassing general news articles, business news, market reports, and industry-specific coverage. I applied a set of carefully selected keywords[19] to identify relevant articles related to collusive firm behavior. These keywords were chosen to capture information exposure regarding price fixing, cartel cases, and related firms. Additionally, the dataset was cleaned of duplicates and standardized for consistent text formats. Table 1.E1 gives an overview

[17] This is true for all analyzed cases as I found consumer damage reports in the respective case documents of the DoJ and FTC.

[18] From the descriptive statistics in Table 1.E1 - 1.E8 it becomes evident that I collected the news reports until July 2023. The reason for collecting more news is to append the analyses successively with more consumer data.

[19] The specific keywords used to collect the data on news articles can be found in Appendix 1.E.

of the amount collected news articles using the keyword “price fixing”[20] and the corresponding case[21]. Appendix 1.E shows a news document as an example.[22] Table 1.E2 - 1.E8 shows the amount of collected news articles referring to the keywords “price fixing” and the firms that have been known to be part of the cartel. Besides the headlines[23] and the main text of the news articles, and due to matching and controlling, I also extracted additional information such as the publication date and the source.

1.4.2 Identification strategy

Measuring competition in empirical studies presents two key challenges: First, traditional measures like concentration ratios (C3, C5) or the Herfindahl-Hirschman Index (HHI)[24] often fail to fully capture the level of market competition (e.g., Bos et al. 2017). Second, competition is inherently endogenous and may correlate with unobserved factors that also influence the outcome of interest. This study uses collusion as a proxy for anti-competition, leveraging cartel formations and breakups as exogenous shocks. While cartel formation reduces competition by design, cartel breakups lead to an unexpected and abrupt return to competitive behavior, addressing endogeneity concerns.[25]

Following the framework in Section 1.2, it is possible to illustrate a typical timing of events taking into account the collusive behavior of firms, the investigation of the

[20]Note that I chose to use the keyword “price fixing” referring to a cartel or collusion as it is more common to describe the behavior of firms to fix prices than naming it a cartel in news articles targeting the broader public. Additionally, the term “cartel’ is often used in other contexts, such as a drug cartel, especially in news articles. The search is not limited to the exact term “price fixing” but also searches for “fixing price” or in a context like “the price has been fixed”.

[21]Note that using the corresponding case name leads to imprecise results as the case name is also related to other situations than the respective collusion case. For instance, it might be that the case has been mentioned in an article about another case or in the context of other firm behavior. However, it is worthwhile to study the behavior of consumers after reading the case name in these situations while not referring to a specific firm.

[22]Note that this news article is just an example and not related to any of the analyzed cartel cases in this paper.

[23]For an overview of the news articles’ headlines see Table 1.E10.

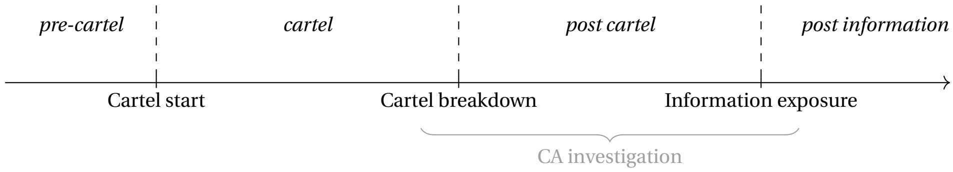
[24]The sum of the market share of the three largest firms, C3, the sum of the market shares of the five largest firms, C5 or the Herfindahl-Hirschmann index (HHI).

[25]A cartel breakup is unexpected to the colluding firms. The investigation by the competition authority has to be silent. This is the case for some of the analyzed cartel cases, where the DoJ collected evidence silently, making the investigation invisible to the colluding parties. In other cases, cartel breakup due to the leniency application of one of the parties, which is also treated to be exogenous as no other than the applicant knew in advance about the forthcoming breakup. In these cases, I can account for the applicants.

competition authority, and the event of media coverage (information exposure). In the first period, it is assumed that all firms compete in a market where no cartel is prevalent (yet). This period is referred to as *pre-cartel* and is based on the CA's definition before the cartel was evident.[26] As soon as a cartel has been formed with the event 'cartel start', the period is called *cartel.* When the cartel breaks down for some reason, the *post-cartel* period starts. I refer to the period *post information* if there has been information exposure in the form of media coverage (i.e., news reports) about the cartel. The CA investigates before or at the event of the cartel breakdown. The exact time varies with the type of breakdown. If a cartel breaks down due to the investigation of the CA, likely, the CA has already been investigating before the breakdown to collect evidence. If the cartel breaks down due to leniency application, the breakdown and the start of the CA investigation can also fall together. Additionally, the length of an investigation by the CA can vary. Sometimes, the authorities investigate only before releasing a press note, and the investigation stops then. In other cases, the investigation will continue after the information exposure, either because the CA has released information before or the information has leaked to the press. This timing is illustrated in Figure 1.4, which shows the potential overlap between cartel behavior, CA investigations, and media coverage.

[26]The CA defines the cartel start based on the evidence which certainly documents the existence of a cartel. In principle, it is, therefore, possible that the cartel started earlier, and the CA simply did not find evidence of it. The pre-cartel period should, therefore, be treated with caution and will be interpreted correspondingly.

Figure 1.4: Illustration of cartel behavior, information, and the competition authority



Note: This figure illustrates the underlying timing and periods relevant to the empirical strategy. Important to note is that the figure just illustrates exemplary underlying timing, especially concerning the competition authority's investigation. The CA will probably investigate right before or as soon as the cartel breaks down, depending on how the cartel terminates (e.g., caused by the investigation or due to leniency application). It is assumed that they will reveal information about their investigation to the greater public as soon as the investigation is ended or at least as soon as the evidence for a cartel agreement is convincing. Revealing the information about a cartel agreement to the greater public is meant by information exposure. In all cases, there is more than one information exposure event, as different newspapers tend to report about a case at different times and whenever there is new information, e.g., about the agreement or the involved parties.

To identify the causal effects of collusion and information exposure on consumer demand, the empirical approach in this paper follows a two-step procedure. In the first step, I estimate the actual demand change due to the collusive agreement considering the respective consumer behavior. The second step is the analysis of the information exposure and the change in consumer behavior.[27] I utilize the discussed consumer-level data to investigate the demand changes caused by collusion and information exposure. To study the causal relationship, I use a difference-in-difference (DiD) approach and compare the consumption of cartelized products to non-cartelized products within the respective periods. As a baseline, I use products of a cartelized industry (treatment group) and compare them to products of firms in the same market that was not part of the cartel (control group). This allows for a comparison of changes in demand across the pre-cartel, cartel, and post-cartel periods.

Additionally, non-cartel firms in the same market may engage in tacit collusion by increasing their prices in response to the cartel's price increase. However, their prices remain lower than those of cartel members. This phenomenon, known as the umbrella effect, introduces another layer of complexity to the analysis. In such cases, I compare cartel prices (p_{C}) with the prices of tacit colluders (p_{U}) rather than the competitive

[27]The assumption underlying this choice is that the price fixing cartels analyzed in this study increased the price. This is incorporated in the design of the empirical study explained in this section.

price (p_{N}).[28] Consequently, the measured effect may be only the minimum bar of the total effect and the sizes have to be interpreted carefully.

Collusion and information as a natural experiment. In the first step, I implement a simple difference-in-difference estimation equation to analyze a cartelized product's price and demand.

$$y_{ijt} = \beta_0 + \beta_1(Cartel_{jt} \times During_t) + \beta_2(Cartel_{jt} \times Post_t) + \gamma_i + \tau_t + \delta_j + u_{ijt} \tag{1.1}$$

where the outcome of interest y_{ijt} captures the quantity of product j purchased by consumer i at time t. The dependent variable y_{ijt} is regressed on an interaction term between the treatment $Cartel_{jt}$ and a time dummy $During_{jt}$ (or later $Post_t$). The variable $Cartel_{jt}$ captures a cartel of product j while $During_{jt}$ indicates the time when the cartelization happened. Therefore, $Post_t$ marks the post period after the cartel of product j broke down. Product (δ_j) and household (γ_i) fixed effects are included so that constant product and household characteristics are canceled out, and only changing characteristics play a role in determining the demand for that specific product. In addition, time-fixed effects are added by τ_t.

A similar approach is also used for the analysis of the impact of information exposure on the demand for cartelized products:

$$\begin{aligned} y_{ijt} = \beta_0 &+ \beta_1(Cartel_{jt} \times During_t \times News\ report_{jt}) \\ &+ \beta_2(Cartel_{jt} \times During_t \times No\ news\ report_{jt}) \\ &+ \beta_3(Cartel_{jt} \times Post_t \times News\ report_{jt}) \\ &+ \beta_4(Cartel_{jt} \times Post_t \times No\ news\ report_{jt}) \\ &+ \gamma_i + \tau_t + \delta_j + u_{ijt} \end{aligned} \tag{1.2}$$

whereby the outcome of interest, y_{ijt}, is the demand for product j purchased by consumer i at time t. This demand is regressed on an interaction between the $Cartel_{jt}$ and time $During_{jt}$ (later $Post_t$) indicator, multiplied by the News treatment $News\ report_{jt}$.

[28] Textbook prices hold: $p_{\mathrm{C}} > p_{\mathrm{U}} > p_{\mathrm{N}}$.

The variable *News report*$_{jt}$ indicates whether a news report about product j at time t has taken place. However, I am also including the interaction between cartel and time with *No news report*$_{jt}$ indicating that no news report has been published about product j at time t. This ensures the comparison group consists of no cartelized products. The remaining variables and fixed effects remain the same as in Equation 1.1.

1.5 Results

1.5.1 Descriptives

I present descriptive statistics from the consumer panel, the cartel database, and the news articles. Table 1.1 shows the descriptive statistics. From these, it becomes evident that about 22.8 percent of the observations are from cartelized products. Of the 16,693,634 products in the sample, about 13,4 percent are cartelized products observed during the cartel period. Additionally, about 9.3 percent of the sample are cartelized products during the cartel period where at least one news article has been published about the cartelized product. In contrast, cartelized products during the cartel where no news has been published make up 4.1 percent of the overall sample. A similar picture emerges for the cartelized products in the post-cartel period: about 8 percent of all products in the dataset are cartelized products in the post-cartel period. While 5.8 percent are cartelized products in the post-period where at least one news article has been published, I observe that 2.2 percent of all products are cartelized in the post-cartel period, and no news article has been published. For log(Price), it can be observed that the price is, in general, lower for products that are cartelized than for products that are not cartelized. In contrast, the quantity is higher for cartelized products than for products that are not. This might have diverse reasons. First, products are different; thus, comparing cartelized products with non-cartelized products might lead to false conclusions. Second, these means do not differ between the pre-, during, and post-cartel periods and thus might lead to misleading conclusions. Lastly, it has to be emphasized that these are just descriptive statistics, and no causal analysis underscores these results.

Additionally, the descriptive statistics show household characteristics. These are important to analyze possible differences between consumer groups. For instance, the household income is a categorial variable showing that the average household in the sample is 20, meaning that the average household has an annual income between \$45,000 and \$59,999. To gain a deeper understanding of the households' income, I calculated the median nationwide, which showed the median income lies between \$50,000 and \$59,99, thus potentially higher than the average income. However, it seems plausible that there are regional differences. Thus, I use the median income based on the scantrack market (defined by NielsenIQ). Moreover, the age and presence of children are reported, which is also a categorical variable indicating whether there are children under 18 in the household and their corresponding ages. Based on this, I indicated with the variable "Child" whether the household has at least one child under 18 in the household or not. Lastly, the categorical variable "Marital status" indicates whether the household is married, widowed, divorced, or single. In all household characteristics, there are significant differences between the cartelized and non-cartelized products purchased.

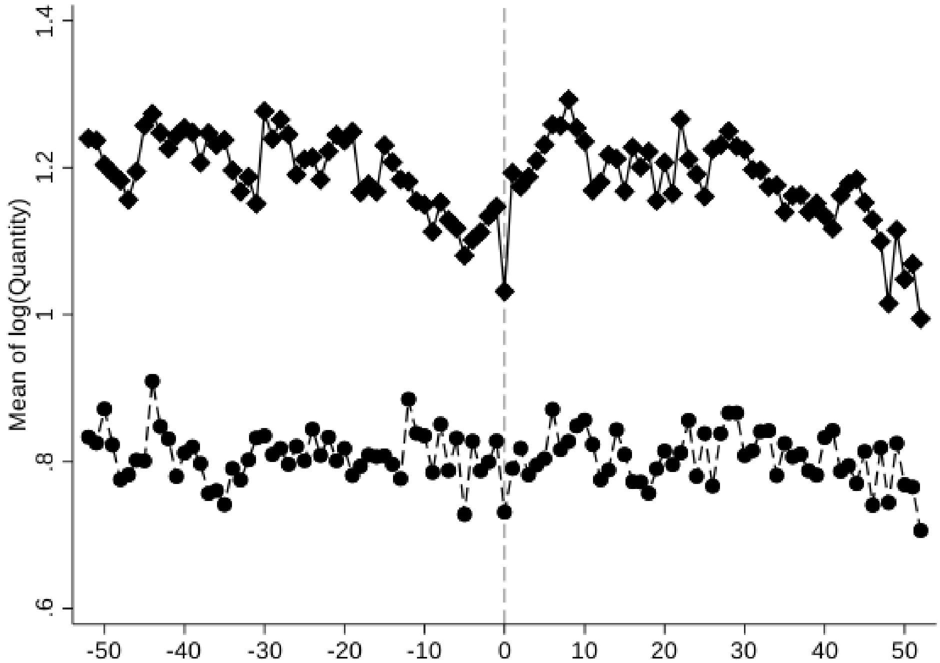
Table 1.1: Descriptive statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All observations		No cartel		Cartel		Difference	
	Mean	SD	Mean	SD	Mean	SD	(5)-(3)	p-value
Cartels, periods, news								
Cartel	0.228	0.420						
Cartel cases	0.812	1.640						
Cartel × During	0.134	0.341						
Cartel × Post	0.080	0.271						
Cartel × During × News	0.093	0.291						
Cartel × During × No news	0.041	0.198						
Cartel × Post × News	0.058	0.233						
Cartel × Post × No news	0.022	0.147						
Products								
log(Price)	0.818	0.870	0.839	0.879	0.747	0.835	-0.091***	(0.000)
log(Quantity)	0.776	0.915	0.654	0.818	1.189	1.088	0.535***	(0.000)
Households								
Household income	20.028	6.210	20.043	6.212	19.977	6.203	-0.062***	(0.000)
Median income (nation-wide)	0.492	0.500	0.493	0.500	0.489	0.500	-0.004***	(0.000)
Median income (scantrack)	20.718	1.707	20.725	1.711	20.692	1.692	-0.033***	(0.000)
Age & presence of children	7.488	2.666	7.468	2.682	7.555	2.611	0.087***	(0.000)
Child	0.265	0.441	0.268	0.443	0.255	0.436	-0.013***	(0.000)
Marital status	1.687	1.087	1.680	1.083	1.708	1.100	0.028***	(0.000)
Observations	16,693,634		12,882,267		3,811,367		18,456,136	

Note: This table shows descriptive statistics of the sample used in the baseline model described in Section 1.4.2. Variable means are shown in columns (2), (4), and (6). The corresponding standard deviations (SD) are displayed in columns (3), (5), and (7). The mean differences between firms in a cartel and those that are not are shown in column (8). The p-values for a test on the equality of means are shown in column (9). Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1%.

Figure 1.5 shows the main variable of interest, quantity, over time, centered around zero, the cartel start. The graph shows that the quantity for both cartelized and non-cartelized products is similar before a cartel. However, there is a difference in the long run after its beginning. While the non-cartelized products are demanded the same amount as before, the demand for the cartelized products decreases about 30 weeks after the cartel start.

Figure 1.5: Mean of log(Quantity) over time for cartelized and non-cartelized products



Note: This figure shows the mean of weekly log(Quantity) over time for cartelized and non-cartelized products one year before and after a cartel.

Consequently, consumer responses to price changes can be categorized into short-term and long-term responses, each influenced by factors such as awareness of collusion, media coverage, and behavioral biases. Short-term reactions typically occur immediately after a price change and are potentially driven by an initial sense of shock or surprise. For instance, a sudden price increase may cause consumers to reduce consumption or switch to alternative products temporarily. However, 1.5 indicates this is not true. Instead, one explanation could be that consumers face limited attention and, thus, they might not react to those price increases. These immediate reactions are usually based on the limited information available at the time and the consumer's ability to process it quickly.

In contrast, long-term behavioral adjustments develop over time, influenced by factors such as habit persistence, memory, and the gradual dissemination of information. When media coverage reveals collusive behavior, it may take time for consumers to fully understand the implications and react accordingly. This delay is often due to the cognitive process of gathering and interpreting information from multiple sources, including media reports, personal experience, and social networks. Over time, as consumers gain a complete understanding of the price changes and their underlying causes, they may make more significant adjustments to their purchasing behavior, as pricing can act as a catalyst for deeper consideration and reevaluation of their consumption choices (e.g., Wathieu and Bertini 2007). Thus, memory and past experience play a significant role in shaping these long-term reactions. Consumers' memories of past instances of collusion or price fixing can influence future purchasing decisions. For instance, when consumers recall past instances of price fixing, they may become more alarmed and cautious in their consumption choices, reflecting a deeper understanding of market dynamics and a more strategic approach to consumption. In the descriptive results of 1.5, it may be the case that consumers learn that prices have changed over the 30-week period. However, since I do not distinguish between different periods, it could also be the case that the cartels broke down after an average of more than 30 weeks and that consumers react to the information published by the media rather than the prices itself.

Consumers might also react in the short term if they notice the price increase. Thus, in the short run, consumers may reduce their consumption immediately after a price increase, only to purchase as before shortly after that. In the long run, however, they may permanently switch to other brands or product categories if they perceive the price changes as persistent or unfair. This shift often reflects a learned response to repeated price changes, where consumers adapt to anticipate and respond to market conditions over time (e.g., Tversky and Kahneman 1974; Kahneman 2011).

If consumers would not change their behavior at all, they tend to stick with established habits (e.g., Samuelson and Zeckhauser 1988) despite changes in the market dynamics. In the context of collusion, the discussed behavioral biases can slow down the adjustment process (e.g., Gilovich et al. 2002), allowing firms to maintain higher prices for an extended period. This can be overcome through repeated exposure to information and consistent media coverage, which gradually shifts consumer behavior toward more informed and rational decisions.

1.5.2 The impact of collusion on consumer behavior

All results are generally presented in the following way: The tables consist of four main columns. The first column shows the results for the respective outcome when considering all periods, namely pre-, during, and post-cartel for cases 1-7. Column 2 - 4 differentiate between the observed cartel subgroups in the respective periods. This means column 2 shows the result for cartels observed in the dataset in all three periods. Column 3 shows the respective results for cartel cases observed in the periods pre-and during the cartel, while column 4 shows the outcomes when the cartel case is observed only in the during and post-periods.

Table 1.2 represents the results for consumer behavior, consequently showing the results from equation 1.1 with the outcome log(Quantity). From the table, it becomes evident that a cartel generally has a negative impact on demand. In other words, consumers react to a cartel by reducing their purchase of cartelized products. Columns 1 and 2 show similar results: There is a statistically significant and negative effect compared to the pre-cartel period. In other words, compared to the time before the cartel, consumers purchase less cartelized products in the cartel and post-period. Utilizing the subgroups of cases in columns 3 and 4 supports these results.

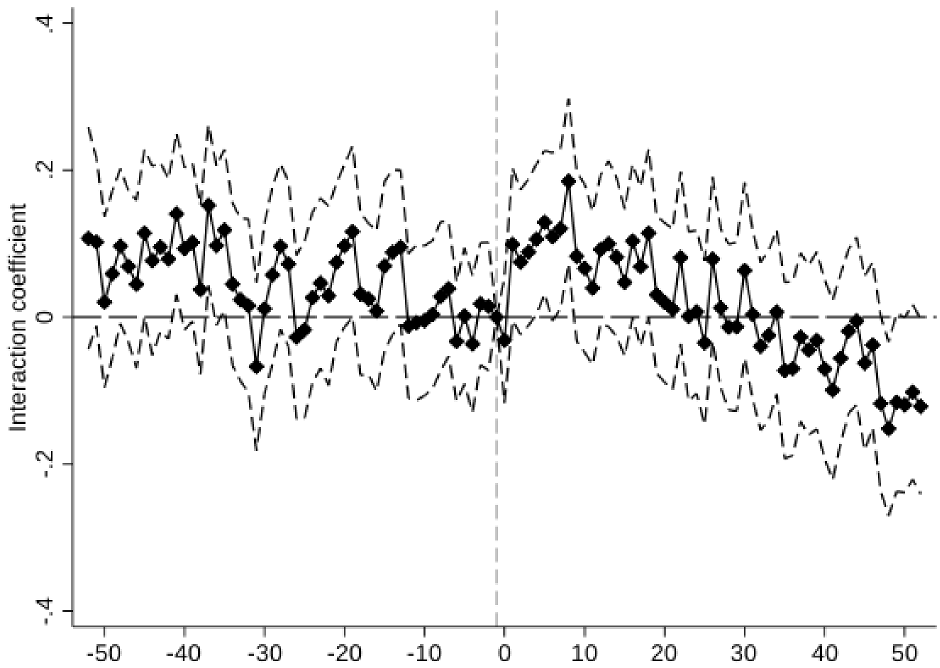
Table 1.2: Collusion and consumer behavior

	(1)	(2)	(3)	(4)
	All cases	Subgroup of cases		
Periods	*All*	*All*	*Pre, During*	*During, Post*
Cartel × During	-0.012	-0.049*	-0.148***	
	(0.026)	(0.026)	(0.054)	
Cartel × Post	-0.086***	-0.095**		-0.014
	(0.029)	(0.042)		(0.027)
Constant	0.785***	0.683***	0.637***	0.778***
	(0.005)	(0.001)	(0.002)	(0.004)
Consumer FE	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
During vs post	0.000	0.153		
R-square	0.506	0.478	0.459	0.530
Observations	18,436,238	14,796,223	5,558,692	10,372,923

Note: This table shows the estimation results of the difference-in-difference approach specified in equation 1.1 in Section 1.4.2. The primary outcome variable is 'log(Quantity)' - the logarithm of the quantity. In column (1), all cartel cases are included in the estimation. Columns (2) - (4), however, only use the subgroups of the cartels that are available in the respective time period, i.e., in column (2), the cases that are observed in all periods are used, in column (3), only the cases that are observed in the pre- and cartel-period are included in the estimations, and, finally, in column (4) cartel cases are used that are observed only in the cartel and post-cartel period. The variables of interest are 'Cartel × During' and Cartel × Post. The variable to measure the change in demand for cartelized products compared to non-cartelized products in the period between the start and the end of a cartel is 'Cartel × During'. The variable 'Cartel × Post' measures the change in demand for cartelized products after the end of a cartel compared to the pre-cartel time period and the non-cartelized products. Each regression includes a set of consumer, product and time fixed effects. Standard errors clustered at the UPC level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

Figure 1.6 shows the quantity one year before and after cartels started on a weekly average. In the pre-cartel period, there are barely any significant differences between the cartel and non-cartelized products, especially in the weeks shortly before the cartels started. However, looking at the later weeks of the cartel period, a declining trend is visible. Consumers' reaction to a cartel seems rather late as quantity differences are only significant nearly three quarters after the cartel start. This is, however, in line with Figure 1.5 and explains why the demand effect is rather small. In sum, this evidence indicates that the common trend assumption holds.

Figure 1.6: Log(Quantity) over time in an event study approach



Note: This figure shows the weekly log(Quantity) differences between the cartel and non-cartelized products one year before and after the cartel.

1.5.3 The impact of news articles on consumer behavior

Consumers generally have no information about the cause of a price increase. They may rely on public information, such as media coverage, as a source of information. When the competition authority publishes a press release, newspapers and other institutions can access information about the conduct. This additional information can mitigate the information asymmetries between firms and consumers.

News articles can significantly impact consumer behavior (e.g., Goh et al. 2011) by, for instance, prompting them to seek out alternative products or services or by causing them to boycott a company altogether. For example, if an investigative news article uncovers evidence of price increases among several products in a market, consumers may become more sensitive to price changes and seek out substitutes. Thus, information in newspapers has the power to shape consumers' decisions. Due to the mitigated information asymmetries, it seems plausible that consumers change their demand after a news report uncovers information about price changes. Especially inattentive consumers who did not realize that prices changed in the first place should realize that there has been a price increase in the past and react accordingly.

News articles can also raise awareness about unethical business practices or other market issues that may interest consumers, such as product safety concerns or environmental impacts. This increased awareness may lead to consumers avoiding products or services from that company in favor of a competitor they perceive to be more ethical. Thus, I expect another group of consumers to react by decreasing their demand: Consumers who realized the price increase initially but attributed it to a 'valid' reason. That could be, for example, inflation, higher wages, and higher production costs in general. These consumers realize that the price increased for another reason and feel betrayed; consequently, they might refuse to buy the product anymore, as a sort of unorganized boycott.

Table 1.3 shows the result when analyzing news articles and consumer behavior. The results in column 1 show that consumers do not react to news published during the cartel period compared to the pre-cartel period. However, looking at the post-cartel period in comparison to the pre-cartel period, the results clearly show that consumers reduce their demand after a news article has been published. The same seems to be true for the post-cartel period and cartels where no news has been published. However, this effect cannot be reinforced when considering the specific cartel cases (column 2). Interestingly, in column (3), the results indicate that consumers reduce their demand if a news article has been published during the cartel period compared to the pre-cartel period. This might indicate that consumers become more attentive during the cartel period if a news article has been published compared to the pre-cartel period.

Table 1.3: News and consumer behavior

	(1)	(2)	(3)	(4)
	All cases	Subgroup of cases		
Periods	*All*	*All*	*Pre, During*	*During, Post*
Cartel × During × News	-0.013	-0.057**	-0.156***	
	(0.026)	(0.025)	(0.054)	
Cartel × During × No news	-0.008	-0.029	-0.128**	
	(0.026)	(0.027)	(0.054)	
Cartel × Post × News	-0.094***	-0.107***		-0.023
	(0.029)	(0.041)		(0.027)
Cartel × Post × No news	-0.066**	-0.063		0.009
	(0.029)	(0.042)		(0.027)
Constant	0.785***	0.683***	0.637***	0.778***
	(0.005)	(0.001)	(0.002)	(0.004)
Consumer FE	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
During: News vs no news	0.003	0.000	0.000	
Post: News vs no news	0.000	0.000		0.000
R-square	0.506	0.478	0.459	0.530
Observations	18,436,238	14,796,223	5,558,692	10,372,923

Note: This table shows the estimation results of the difference-in-difference approach specified in equation 1.2 in Section 1.4.2. The primary outcome variable is 'log(Quantity)' - the logarithm of the quantity. In column (1), all cartel cases are included in the estimation. Columns (2) - (4), however, only use the subgroups of the cartels that are available in the respective time period, i.e., in column (2), the cases that are observed in all periods are used, in column (3), only the cases that are observed in the pre- and cartel-period are included in the estimations, and, finally, in column (4) cartel cases are used that are observed only in the cartel and post-cartel period. The variables of interest are 'Cartel × During × News', 'Cartel × During × No News', 'Cartel × Post × News', 'Cartel × Post × No news'. The variable to measure the change in demand for cartelized products that had at least one news article published compared to non-cartelized products in the period between the start and the end of a cartel is 'Cartel × During × News'. Accordingly, 'Cartel × During × No news' captured the change in demand of cartelized products where no news articles have been published in the period between the start and the end of a cartel. The variable 'Cartel × Post × News' measures the change in demand for cartelized products after the end of a cartel with at least one news published compared to the pre-cartel time period and the non-cartelized products. Additionally, the change in demand of non-cartelized products with no news articles published compared to in the period after the cartel end is captured by 'Cartel × Post × No news'. Each regression includes a set of consumer, product and time fixed effects. Standard errors clustered at the UPC level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

1.6 Heterogeneity

The diversity in consumers' preferences, constraints, and abilities to respond to market signals, often driven by factors such as income, household size, and composition, directly influence the effectiveness of market interventions and policy measures. This becomes particularly evident in contexts like collusion, where price-fixing can have uneven effects across consumer groups. Consumers with differing financial capabilities and information access experience these market disruptions differently. By acknowledging the diverse ways in which different consumer groups respond to market changes, policymakers and firms can better design interventions to promote competition and protect vulnerable populations. Demographic factors like income and household composition are key determinants of how consumers engage with price changes, making it essential to consider these factors when studying market dynamics (e.g., Bertrand et al. 2004; Chetty et al. 2009). Therefore, failure to account for these differences risks creating policies that disproportionately benefit some groups while leaving others vulnerable. Consequently, understanding consumer heterogeneity is crucial for accurately analyzing consumer behavior in response to price changes and information exposure.

1.6.1 Analyzing consumers groups based on income

Income plays a fundamental role in shaping how consumers react to price changes and information regarding market misconduct. Lower-income households are typically more sensitive to price changes due to budget constraints, which force them to prioritize essential spending. As a result, they exhibit a higher price elasticity of demand, reacting quickly to price increases by reducing consumption or switching to cheaper alternatives (e.g., Chetty et al. 2009). In contrast, higher-income consumers tend to have more financial flexibility, allowing them to absorb price increases without significantly altering their consumption patterns. This financial buffer enables them to be less price-sensitive and more inattentive to smaller price changes.

The disparity between income groups is particularly pronounced in markets for essential goods, such as food and utilities, where small price increases can lead to severe consumption adjustments for lower-income households. Conversely, higher-income households may not exhibit immediate reactions to price changes for non-essential or luxury goods due to their discretionary income and ability to absorb higher costs (e.g., Gabaix 2019).

Access to information also differs significantly across income groups. Higher-income consumers often have access to more information sources and the educational background to process complex economic data more effectively, allowing them to respond faster to news about collusion or market misconduct. In contrast, lower-income consumers may rely on fewer, less detailed information sources, which can delay their reactions to market changes and increase their vulnerability to the negative effects of collusion (e.g., Bertrand et al. 2004). This information asymmetry is a critical driver of income-based heterogeneity in consumer behavior. This underscored the relevance for effective competition policy enabling fair prices for *all* consumers.

Table 1.4 consumer behavior in response to collusion, with a focus on income heterogeneity. Rather than using national income benchmarks, I calculated the median income within specific regions (Scantrack markets defined by NielsenIQ) to provide a more accurate analysis of income effects. [29] Interestingly, while consumers with both above-median and below-median incomes respond to cartel behavior, below-median-income consumers exhibit stronger reactions. Specifically, these consumers show a greater reduction in demand for cartelized products in the post-cartel period compared to the pre-cartel period (columns 1 and 2). They also exhibit significant reactions during the cartel compared to both pre- and post-cartel periods (columns 2 and 3).

In contrast, the above-median-income consumers did not show strong reactions across these periods. Two possible explanations arise: First, higher-income consumers may not be as sensitive to small price changes, suggesting a lower price elasticity of

[29] As income varies strongly with the region, using the median income within the US does not seem plausible. Thus, within each region, I differentiated between households with an income above or below the median income in their region.

demand. Alternatively, higher-income consumers may be more inattentive to price changes, as they can afford to be less vigilant. These findings are in line with literature on income-based differences in price sensitivity, such as Chetty et al. (2009), which shows that lower-income households are more sensitive to sales tax changes, indicating greater attention to prices.

Table 1.5 provides further evidence of heterogeneity in response to news articles. Consumers from both income groups respond to news about price-fixing, reducing demand in the post-cartel period compared to the pre-cartel period. The result for both groups considering pre- and during-cartel periods supports this result as they both react in response to news articles. This suggests that news articles help reduce information asymmetries between firms and consumers, consistent with findings in DellaVigna and Pollet (2009), which shows that media coverage influences financial markets through increased awareness of firm behavior.

However, below-median-income consumers react more strongly to negative news about collusion in the post-cartel period. This supports the hypothesis that lower-income households are more sensitive to information that could affect their budgets, while higher-income households may be more insulated from such concerns.

Table 1.4: Consumer behavior and income

	(1)	(2)	(3)	(4)
	All cases	Subgroup of cases		
Periods	*All*	*All*	*Pre, During*	*During, Post*
Panel A: Income above median income in scantrack region				
Cartel × During	-0.004	-0.030	-0.106	
	(0.024)	(0.024)	(0.068)	
Cartel × Post	-0.087***	-0.085**		0.001
	(0.027)	(0.036)		(0.057)
Constant	0.776***	0.678***	0.633***	0.764***
	(0.005)	(0.001)	(0.004)	(0.008)
Consumer FE	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
During vs post	0.000	0.057		
R-square	0.513	0.489	0.475	0.537
Observations	8,201,229	6,601,240	2,294,524	4,817,998
Panel B: Income below median income in scantrack region				
Cartel × During	-0.024	-0.069**	-0.197***	
	(0.030)	(0.030)	(0.042)	
Cartel × Post	-0.090***	-0.109**		-0.041
	(0.033)	(0.050)		(0.025)
Constant	0.796***	0.689***	0.641***	0.796***
	(0.006)	(0.001)	(0.002)	(0.004)
Consumer FE	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
During vs post	0.003	0.290		
R-square	0.506	0.474	0.456	0.531
Observations	8,474,379	6,780,078	2,718,875	4,572,466

Note: This table shows the estimation results of the difference-in-difference approach specified in equation 1.1 in Section 1.4.2. The primary outcome variable is 'log(Quantity)' - the logarithm of the quantity. In column (1), all cartel cases are included in the estimation. Columns (2) - (4), however, only use the subgroups of the cartels that are available in the respective time period, i.e., in column (2), the cases that are observed in all periods are used, in column (3), only the cases that are observed in the pre- and cartel-period are included in the estimations, and, finally, in column (4) cartel cases are used that are observed only in the cartel and post-cartel period. The variables of interest are 'Cartel × During' and Cartel × Post. The variable to measure the change in demand for cartelized products compared to non-cartelized products in the period between the start and the end of a cartel is 'Cartel × During'. The variable 'Cartel × Post' measures the change in demand for cartelized products after the end of a cartel compared to the pre-cartel time period and the non-cartelized products. Each regression includes a set of consumer, product and time fixed effects. Standard errors clustered at the UPC level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

Table 1.5: Consumer behavior, news and income

	(1) All cases	(2)	(3) Subgroup of cases	(4)
Periods	*All*	*All*	*Pre, During*	*During, Post*
Panel A: Income above median income in scantrack region				
Cartel × During × News	-0.007	-0.038	-0.115*	
	(0.024)	(0.023)	(0.068)	
Cartel × During × No news	0.004	-0.010	-0.083	
	(0.024)	(0.025)	(0.068)	
Cartel × Post × News	-0.095***	-0.098***		-0.010
	(0.027)	(0.035)		(0.057)
Cartel × Post × No news	-0.065**	-0.054		0.023
	(0.027)	(0.037)		(0.057)
Constant	0.776***	0.678***	0.633***	0.764***
	(0.005)	(0.001)	(0.004)	(0.008)
During: News vs no news	0.000	0.000	0.000	
Post: News vs no news	0.000	0.000		0.000
R-square	0.513	0.489	0.475	0.537
Observations	8,201,229	6,601,240	2,294,524	4,817,998
Panel B: Income below median income in scantrack region				
Cartel × During × News	-0.024	-0.075**	-0.203***	
	(0.030)	(0.030)	(0.042)	
Cartel × During × No news	-0.024	-0.052	-0.182***	
	(0.030)	(0.032)	(0.043)	
Cartel × Post × News	-0.097***	-0.120**		-0.050**
	(0.033)	(0.050)		(0.025)
Cartel × Post × No news	-0.072**	-0.079		-0.019
	(0.033)	(0.051)		(0.025)
Constant	0.796***	0.689***	0.641***	0.796***
	(0.006)	(0.001)	(0.002)	(0.004)
During: News vs no news	0.771	0.029	0.004	
Post: News vs no news	0.000	0.000		0.000
R-square	0.506	0.474	0.456	0.531
Observations	8,474,379	6,780,078	2,718,875	4,572,466

Note: Standard errors clustered at the UPC level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.This table shows the estimation results of the difference-in-difference approach specified in equation 1.2 in Section 1.4.2. The primary outcome variable is 'log(Quantity)' - the logarithm of the quantity. In column (1), all cartel cases are included in the estimation. Columns (2) - (4), however, only use the subgroups of the cartels that are available in the respective time period, i.e., in column (2), the cases that are observed in all periods are used, in column (3), only the cases that are observed in the pre- and cartel-period are included in the estimations, and, finally, in column (4) cartel cases are used that are observed only in the cartel and post-cartel period. The variables of interest are 'Cartel × During × News', 'Cartel × During × No News', 'Cartel × Post × News', 'Cartel × Post × No news'. The variable to measure the change in demand for cartelized products that had at least one news article published compared to non-cartelized products in the period between the start and the end of a cartel is 'Cartel × During × News'. Accordingly, 'Cartel × During × No news' captured the change in demand of cartelized products where no news articles have been published in the period between the start and the end of a cartel. The variable 'Cartel × Post × News' measures the change in demand for cartelized products after the end of a cartel with at least one news published compared to the pre-cartel time period and the non-cartelized products. Additionally, the change in demand of non-cartelized products with no news articles published compared to in the period after the cartel end is captured by 'Cartel × Post × No news'. Each regression includes a set of consumer, product and time fixed effects. Standard errors clustered at the UPC level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

1.6.2 Heterogeneity based on household composition

In addition to income, household size and composition also play a significant role in determining how consumers react to price changes and market disruptions. Larger households, especially those with children, tend to engage in more price-seeking behavior, driven by the need to meet higher consumption demands on a potentially constrained budget (e.g., Gauri et al. 2008). Households with young children are particularly sensitive to price increases in essential goods, as their consumption needs are higher and more inflexible.

Household composition affects not only the price sensitivity of consumers but also their attention to market signals. Larger households may be more motivated to track price changes or seek discounts, as even small price adjustments can have a magnified impact on their overall budget (e.g., Lichtenstein et al. 1993). In contrast, smaller households or those without children may be less reactive to price changes, as their consumption patterns are more flexible and less driven by immediate needs.

Moreover, household composition influences how consumers prioritize spending across different categories. For instance, families with children are more likely to reduce spending on discretionary items when faced with higher prices for essential goods (e.g., Aguiar and Hurst 2007; Griffith et al. 2009), whereas households without children may have more flexibility in managing their budgets. These differences highlight the importance of considering household composition when analyzing the distributional impacts of collusion and information exposure.

Consequently, in the next step, I distinguish between consumers who have a child (or children) below 18 years and those who do not have a child or whose child is above 18. The results for consumer behavior in response to collusion are presented in Table 1.6. Contrary to the expectation that households with young children might be more sensitive to price changes, the results do not indicate significant differences between households with children and those without. Both groups show sensitivity to cartel behavior in the during- and post-cartel periods compared to the pre-cartel period.

However, the results show that both consumer groups are sensitive to cartels during and post-cartel periods, compared to the pre-and during periods. Although the individual effects differ slightly, it is difficult to state that a consumer group lowers their demand on average more than the other group. Interestingly, households with children show a larger reduction in demand in the post-cartel period compared to the pre-cartel period, while households without children (or with older children) exhibit stronger reactions during the cartel period compared to other time frames. These findings suggest that both household types react to price changes and collusion, albeit with slightly different timing. This outcome aligns with literature on household sensitivity to market changes. For instance, Gauri et al. (2008) suggests that larger households, especially those with children, tend to engage in more price-seeking behavior. This could explain the stronger demand reduction post-cartel among households with children, as they may be more focused on managing expenses over time.

A similar picture arises when considering news articles and consumer behavior in Table 1.7. Both household groups reduce demand in the post-cartel period when exposed to news articles. This suggests that media reports successfully inform both groups, leading to a reduction in demand for cartelized products. Both household groups also show a demand reduction when news is published during the cartel period compared to other periods. While the timing of the responses varies slightly, the overall trend is that media exposure effectively reduces information asymmetry for all households, regardless of their composition. This finding is consistent with the results of Gentzkow and Shapiro (2006), highlighting how media coverage shapes consumer attitudes and influences economic behavior across household groups.

The previous analysis confirms that consumer heterogeneity—whether based on income or household composition—plays a significant role in shaping demand responses to both price-fixing and media reports. Lower-income consumers are more sensitive to price changes, while media reports effectively reduce information asymmetries across income groups and household types. These results underscore the importance of considering demographic factors in understanding market behavior and developing policies to protect consumers from the harms of collusion.

Table 1.6: Consumer behavior and children in the household

	(1)	(2)	(3)	(4)
	All cases	Subgroup of cases		
Periods	*All*	*All*	*Pre, During*	*During, Post*
Panel A: Child(s) below the age of 18				
Cartel × During	-0.024	-0.074**	-0.087**	
	(0.028)	(0.032)	(0.039)	
Cartel × Post	-0.089***	-0.095**		0.113
	(0.032)	(0.044)		(0.092)
Constant	0.785***	0.681***	0.644***	0.758***
	(0.006)	(0.001)	(0.001)	(0.012)
Consumer FE	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
During vs post	0.008	0.503		
R-square	0.518	0.491	0.476	0.545
Observations	4,888,874	3,925,834	1,630,149	2,569,255
Panel B: No child or child above the age of 18				
Cartel × During	-0.005	-0.042*	-0.170***	
	(0.026)	(0.025)	(0.062)	
Cartel × Post	-0.083***	-0.093**		-0.037
	(0.029)	(0.041)		(0.036)
Constant	0.785***	0.684***	0.635***	0.784***
	(0.005)	(0.001)	(0.003)	(0.005)
Consumer FE	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
During vs post	0.000	0.124		
R-square	0.506	0.478	0.459	0.530
Observations	13,521,264	10,845,311	3,915,278	7,784,836

Note: This table shows the estimation results of the difference-in-difference approach specified in equation 1.1 in Section 1.4.2. The primary outcome variable is 'log(Quantity)' - the logarithm of the quantity. In column (1), all cartel cases are included in the estimation. Columns (2) - (4), however, only use the subgroups of the cartels that are available in the respective time period, i.e., in column (2), the cases that are observed in all periods are used, in column (3), only the cases that are observed in the pre- and cartel-period are included in the estimations, and, finally, in column (4) cartel cases are used that are observed only in the cartel and post-cartel period. The variables of interest are 'Cartel × During' and Cartel × Post. The variable to measure the change in demand for cartelized products compared to non-cartelized products in the period between the start and the end of a cartel is 'Cartel × During'. The variable 'Cartel × Post' measures the change in demand for cartelized products after the end of a cartel compared to the pre-cartel time period and the non-cartelized products. Each regression includes a set of consumer, product and time fixed effects. Standard errors clustered at the UPC level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

Table 1.7: Consumer behavior, news, and children in the household

	(1)	(2)	(3)	(4)
	All cases	Subgroup of cases		
Periods	*All*	*All*	*Pre, During*	*During, Post*
Panel A: Child(s) below the age of 18				
Cartel × During × News	-0.025	-0.083***	-0.096**	
	(0.028)	(0.032)	(0.039)	
Cartel × During × No news	-0.021	-0.051	-0.062	
	(0.028)	(0.035)	(0.040)	
Cartel × Post × News	-0.097***	-0.110**		0.104
	(0.032)	(0.043)		(0.093)
Cartel × Post × No news	-0.068**	-0.060		0.136
	(0.032)	(0.046)		(0.093)
Constant	0.785***	0.684***	0.635***	0.784***
	(0.005)	(0.001)	(0.003)	(0.005)
During: News vs no news	0.140	0.006	0.000	
Post: News vs no news	0.000	0.000		0.000
R-square	0.518	0.491	0.476	0.545
Observations	4,888,874	3,925,834	1,630,149	2,569,255
Panel B: No child or child above the age of 18				
Cartel × During × News	-0.007	-0.049**	-0.178***	
	(0.026)	(0.025)	(0.062)	
Cartel × During × No news	-0.001	-0.023	-0.152**	
	(0.026)	(0.026)	(0.062)	
Cartel × Post × News	-0.090***	-0.104**		-0.046
	(0.029)	(0.041)		(0.036)
Cartel × Post × No news	-0.063**	-0.062		-0.014
	(0.029)	(0.042)		(0.036)
Constant	0.785***	0.684***	0.635***	0.784***
	(0.005)	(0.001)	(0.003)	(0.005)
During: News vs no news	0.002	0.001	0.000	
Post: News vs no news	0.000	0.000		0.000
R-square	0.506	0.478	0.459	0.530
Observations	13,521,264	10,845,311	3,915,278	7,784,836

Note: This table shows the estimation results of the difference-in-difference approach specified in equation 1.2 in Section 1.4.2. The primary outcome variable is 'log(Quantity)' - the logarithm of the quantity. In column (1), all cartel cases are included in the estimation. Columns (2) - (4), however, only use the subgroups of the cartels that are available in the respective time period, i.e., in column (2), the cases that are observed in all periods are used, in column (3), only the cases that are observed in the pre- and cartel-period are included in the estimations, and, finally, in column (4) cartel cases are used that are observed only in the cartel and post-cartel period. The variables of interest are 'Cartel × During × News', 'Cartel × During × No News', 'Cartel × Post × News', 'Cartel × Post × No news'. The variable to measure the change in demand for cartelized products that had at least one news article published compared to non-cartelized products in the period between the start and the end of a cartel is 'Cartel × During × News'. Accordingly, 'Cartel × During × No news' captured the change in demand of cartelized products where no news articles have been published in the period between the start and the end of a cartel. The variable 'Cartel × Post × News' measures the change in demand for cartelized products after the end of a cartel with at least one news published compared to the pre-cartel time period and the non-cartelized products. Additionally, the change in demand of non-cartelized products with no news articles published compared to in the period after the cartel end is captured by 'Cartel × Post × No news'. Each regression includes a set of consumer, product and time fixed effects. Standard errors clustered at the UPC level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

1.6.3 Sentiment of news, firm-specific news, and consumer behavior

The role of media bias and framing effects is critical in shaping consumer responses, as discussed in Section 1.2. The media may present information in a way that emphasizes certain aspects over others, influencing public perceptions and behavior (e.g., Clemente and Gabbioneta 2017). For example, sensationalized reporting can exaggerate risks and lead to overreactions, while underreporting important issues can lead to complacency. How news is framed- whether it focuses on negative aspects, such as scandals, or positive aspects, such as innovation- can significantly alter consumer attitudes and actions.

Sentiment analysis—the process of quantifying the emotional tone of news—plays a significant role in shaping consumer perceptions and behavior. Whether positive or negative, the sentiment conveyed in news stories can influence how consumers view the economy, their financial well-being, and their subsequent spending decisions. Positive sentiment tends to foster consumer confidence, leading to increased spending and investment. Conversely, negative sentiment tends to reduce consumer confidence, leading to more cautious financial behavior and reduced spending.

A large strand in the mostly psychological literature links sentiment with consumer behavior, showing that emotional and psychological factors can drive economic decisions (e.g., Shiller 2017; Kahneman and Tversky 1984). Sentiment acts as a key driver of consumer behavior, influencing decisions beyond traditional economic factors. When sentiment is positive, consumers are more likely to take risks and spend more (e.g., Lemmon and Portniaguina 2006; Baker and Wurgler 2007). In contrast, negative sentiment typically leads to risk aversion and reduced spending (e.g., De Bondt and Thaler 1985; Akerlof and Shiller 2010). In addition, changes in sentiment can predict household spending behavior, with negative sentiment often leading to preventive savings and reduced consumption (e.g., Carroll et al. 1994; Barsky and Sims 2012).

This paper focuses specifically on media sentiment, which refers to the tone and emotional content of news reports. While media sentiment differs from consumer sentiment (which reflects individuals' personal financial outlook), the two are closely related. Media sentiment, particularly negative coverage of firm behavior, can shape consumer sentiment by influencing public perceptions of firms and the economy at large. When newspapers report on price-fixing or collusion, negative sentiment may prompt consumers to reduce their demand for products associated with the related firms.

Negative news coverage, particularly when tied to unethical practices like collusion, tends to heighten consumers' risk aversion. This aligns with findings from Baker and Wurgler (2007), who demonstrate how negative sentiment in financial markets drives investors to avoid risky assets. This pattern can also be observed in consumer markets where negative media reports lead to more conservative spending. Similarly, Akerlof and Shiller (2010) argue that negative narratives in the media can trigger "animal spirits" leading consumers to pull back from the market and reduce expenditures. Although this paper analyzes media coverage sentiment, its impact on consumer behavior is significant because negative sentiment associated with collusion can indirectly damage trust and increase risk perceptions, thereby reducing demand for the firms involved.

Sentiment analysis methodology.[30] To investigate how sentiment in news articles affects consumer behavior, I employ a text-mining approach using a natural language processing (NLP) technique called BERT (Bidirectional Encoder Representations from Transformers) to assess the sentiment of news articles collected from Nexis. BERT is a deep learning model developed by Google that has demonstrated success in a wide range of NLP tasks, including sentiment analysis (e.g., Nemes and Kiss 2021). Unlike traditional models, BERT is bidirectional, meaning it considers the context of each word based on the surrounding words, which allows it to capture complex linguistic patterns.

[30] Empirical sentiment analysis methods include quantitative and qualitative approaches. Text mining techniques analyze large volumes of text data to identify patterns and measure sentiment. For instance, NLP algorithms can assess the tone of news articles to determine the prevailing sentiment, as is done in this paper. However, qualitative techniques, such as surveys, capture direct feedback from consumers about their attitudes and expectations, providing insights into how sentiment may shape behavior.

For the purpose of my analysis, I utilized two versions of BERT: DistilBERT[31] and RoBERTa[32]. It is important to note that while BERT and DistilBERT are powerful tools for sentiment analysis, they are not without limitations. The accuracy of the sentiment analysis heavily depends on the quality and relevance of the training data. Additionally, contextual nuances and sarcasm in the text can challenge the model's interpretation. Analyzing business news, this seems rather not a problem in this dataset. However, to overcome potential limitations, strengthen the analysis, and ensures robust results, I use both models, DistilBERT and RoBERTa.

The sentiment analysis involved tokenizing each news article into smaller units (tokens), which were then processed by the models, DistilBRT or RoBERTa, to generate sentiment scores. Each article was categorized based on its negativity score, where 0 represents no negativity, and 1 represents complete negativity.[33] Given the length of many news articles, they were broken into smaller chunks for analysis, and a mean negativity score was calculated for each article.

As Fedyk (2024) highlights, the placement of news within a newspaper (e.g., front page vs. back pages) can influence how much attention consumers pay to it. While the exact placement of articles cannot be determined in this analysis, I address attention limitations by distinguishing between the sentiment of headlines and main text. Some consumers may only read headlines, while others engage with the full article. Thus, the analysis compares cases where the sentiment in headlines matches the main text to cases where they differ, offering insights into how differences in sentiment shape consumer behavior.

Descriptive results. Figure 1.F1 shows the distribution of the articles' degree of

[31] DistilBERT is a more lightweight and efficient version of the original BERT model, making it well-suited for large-scale sentiment analysis tasks. DistilBERT achieves this efficiency using a distillation technique that compresses the larger BERT model while retaining much of its predictive power. (Sanh et al. 2020)

[32] RoBERTa has undergone more extensive training than its predecessors, including exposure to a larger and more diverse dataset. This results in a heightened ability to understand nuanced sentiment expressions, idiomatic language, and contextual cues. Similarly, RoBERTa excels at providing detailed and refined sentiment analysis due to its comprehensive training, enabling it to uncover subtle sentiment variations that BERT and DistilBERT might overlook. (Liu et al. 2019)

[33] After the tokens are fed into the models, the output of the model provided a numerical representation of the sentiment of each article, reflecting whether the overall tone was positive, negative, or neutral. This sentiment score was then used to categorize the news articles based on their negativity.

negativity sentiment scores, differentiated by the headlines and the main texts' sentiment scores. Additionally, the scores are shown for each analyzed case separately. In general, the mean negativity degree is about 30%. There are significant differences between the degrees of negativity in the headline and the main text. In general, the headlines seem to be more negative than the main text. This seems plausible as headlines are usually formulated strikingly, and especially in online news, shall incentivize clicking on the news website (in the extreme case, this is called click-baiting). While most cases have a similar pattern, Case 5 shows notable differences compared to the others. The small number of news articles could drive this result. Additionally, Figure 1.F3 shows the degree of negativity for all cases when searching for specific, topic-related words within the headline and the main text. Interestingly, the degree varies with the respective word. Words that can also be used in a more general context, such as "agree" or "fix", have a lower degree of negativity than words that already have a negative sentiment per se, like "conspiracy" or "price fix". There are also differences between headlines and the main text's degree of negativity. For instance, the words "fix" and "price" in the main text are classified as less negative than when used in the headline. These distributions show that headline and main text degrees of negativity differ significantly for specific words. While the headlines' distribution is in some cases characterized by a few high spikes between 20 and 70%, the main text distribution is much more spread out. However, these patterns also represent low observation numbers for the headlines.

The influence of the negativity degree in news articles on consumer behavior. In the next step, I analyze whether the degree of negativity influences consumer behavior. The question is whether more negative news shapes consumer behavior differently than less negative news. To answer this, I utilize the score of the negativity degree as a continuous measure in Equation 1.2. The results for this exercise are shown in Table 1.8. From the results, it becomes evident that the degree of negativity indeed impacts consumer behavior. The results suggest that the higher the negative degree of a news article, the more consumers reduce their demand. This effect is especially pronounced in the post- and during cartel period compared to the pre-cartel period. Additionally, compared to the during-cartel period, the effect is also significant and negative in the post-cartel period. These results also underscore the baseline news result.

This finding is consistent with prior research, which shows that negative sentiment tends to foster behavioral responses in economic contexts (e.g., Loughran and McDonald 2011; Tetlock 2007). In particular, the strong negative tone of media coverage can act as a catalyst for consumer behavior, causing consumers to reduce their demand for cartelized products, similar to how sentiment affects investor behavior (e.g., Pang et al. 2008).

Table 1.8: Negativity degree of news and consumer behavior

	(1)	(2)	(3)	(4)
	All cases	Subgroup of cases		
Periods	*All*	*All*	*Pre, During*	*During, Post*
Cartel × During × News	0.063**	-0.065	0.011	
	(0.026)	(0.046)	(0.017)	
Cartel × During × No news	0.025***	0.006	0.031***	
	(0.009)	(0.016)	(0.007)	
Cartel × Post × News	-0.155***	-0.205***		-0.018**
	(0.038)	(0.078)		(0.007)
Cartel × Post× No news	-0.019*	-0.018		0.028***
	(0.012)	(0.026)		(0.003)
Constant	0.777***	0.681***	0.630***	0.776***
	(0.001)	(0.000)	(0.000)	(0.000)
Consumer FE	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
During: News vs no news	0.030	0.027	0.152	
Post: News vs no news	0.000	0.000		0.000
R-square	0.506	0.478	0.459	0.530
Observations	18,436,238	14,796,223	5,558,692	10,372,923

Note: This table shows the estimation results of the difference-in-difference approach specified in equation 1.2 in Section 1.4.2. The primary outcome variable is 'log(Quantity)' - the logarithm of the quantity. In column (1), all cartel cases are included in the estimation. Columns (2) - (4), however, only use the subgroups of the cartels that are available in the respective time period, i.e., in column (2), the cases that are observed in all periods are used, in column (3), only the cases that are observed in the pre- and cartel-period are included in the estimations, and, finally, in column (4) cartel cases are used that are observed only in the cartel and post-cartel period. The variables of interest are 'Cartel × During × News', 'Cartel × During × No News', 'Cartel × Post × News', 'Cartel × Post × No news'. The variable to measure the change in demand for cartelized products that had at least one news article published compared to non-cartelized products in the period between the start and the end of a cartel is 'Cartel × During × News'. Accordingly, 'Cartel × During × No news' captured the change in demand of cartelized products where no news articles have been published in the period between the start and the end of a cartel. The variable 'Cartel × Post × News' measures the change in demand for cartelized products after the end of a cartel with at least one news published compared to the pre-cartel time period and the non-cartelized products. Additionally, the change in demand of non-cartelized products with no news articles published compared to in the period after the cartel end is captured by 'Cartel × Post × No news'. Each regression includes a set of consumer, product and time fixed effects. Standard errors clustered at the UPC level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

Firm-specific news and consumer behavior. Besides the negativity degree, I can also distinguish between news generally reported about a cartel, a specific cartel, and a specific firm[34] (concerning collusion). The results in Table 1.9 show that if the news reported about a specific firm related to collusion[35], consumers react by reducing their demand. This finding is consistent with research by Bushee et al. (2010) and An et al. (2018), who demonstrate that firm-specific negative news, especially when linked to misconduct, has a significant impact on consumer behavior.

This significant and negative effect is visible in the post-cartel period compared to the pre-cartel period (columns 1 and 2) and in the during period compared to the post-cartel period. This aligns with Hendel et al. (2017), who show that consumers often engage in activism or reduce demand when unethical pricing practices are exposed in the media. Moreover, Fombrun and Shanley (1990) suggest that firm-specific mentions in the media damage a firm's reputation, leading to consumer distrust and a subsequent reduction in demand.

A large negative effect is also visible in the during-period compared to the post-cartel period. This highlights how firm-specific news about collusion has a much stronger impact on consumer behavior than general cartel-related news, in line with the findings of Jin and Leslie (2003), who demonstrate that consumers are more responsive to specific firm-level information.

[34] The news observations collected for this analysis are reported in Table 1.E2 - 1.E8.

[35] "Related to collusion" means that the firm has been mentioned in the same article with the keyword "price-fixing". Thus, while it can be that the article reports about a price-fixing case of that firm, it might also only relate the firm to the word "price-fixing".

Table 1.9: Firm-specific news and consumer behavior

	(1)	(2)	(3)	(4)
	All cases	Subgroup of cases		
Periods	*All*	*All*	*Pre, During*	*During, Post*
Cartel × During × News	-0.032	-0.119***	-0.262***	
	(0.028)	(0.033)	(0.094)	
Cartel × During × No news	-0.009	-0.064**	-0.216**	
	(0.028)	(0.031)	(0.094)	
Cartel × Post × News	-0.101***	-0.150***		-0.094**
	(0.030)	(0.042)		(0.040)
Cartel × Post × No news	-0.062**	-0.075*		-0.047
	(0.030)	(0.043)		(0.039)
Constant	0.784***	0.684***	0.635***	0.794***
	(0.006)	(0.001)	(0.003)	(0.006)
Consumer FE	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
During: News vs no news	0.000	0.000	0.000	
Post: News vs no news	0.000	0.000		0.000
R-square	0.511	0.482	0.461	0.539
Observations	6,294,649	5,060,304	2,134,550	3,268,351

Note: This table shows the estimation results of the difference-in-difference approach specified in equation 1.2 in Section 1.4.2. The primary outcome variable is 'log(Quantity)' - the logarithm of the quantity. In column (1), all cartel cases are included in the estimation. Columns (2) - (4), however, only use the subgroups of the cartels that are available in the respective time period, i.e., in column (2), the cases that are observed in all periods are used, in column (3), only the cases that are observed in the pre- and cartel-period are included in the estimations, and, finally, in column (4) cartel cases are used that are observed only in the cartel and post-cartel period. The variables of interest are 'Cartel × During × News', 'Cartel × During × No News', 'Cartel × Post × News', 'Cartel × Post × No news'. The variable to measure the change in demand for cartelized products that had at least one news article published compared to non-cartelized products in the period between the start and the end of a cartel is 'Cartel × During × News'. Accordingly, 'Cartel × During × No news' captured the change in demand of cartelized products where no news articles have been published in the period between the start and the end of a cartel. The variable 'Cartel × Post × News' measures the change in demand for cartelized products after the end of a cartel with at least one news published compared to the pre-cartel time period and the non-cartelized products. Additionally, the change in demand of non-cartelized products with no news articles published compared to in the period after the cartel end is captured by 'Cartel × Post × No news'. Each regression includes a set of consumer, product and time fixed effects. Standard errors clustered at the UPC level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

1.7 Conclusion

This paper analyzes consumer behavior, specifically in response to collusion under the constraint of inattention. Although rational assumptions about consumers have a long-standing history, their real-world evidence is limited. In contrast, consumers are often inattentive due to cognitive limitations and suffer from information asymmetries. While this seems plausible for complex and expensive decisions, it has been shown that consumers often are unaware of the prices they encounter daily, for instance, in a supermarket (e.g., Evanschitzky et al. 2004). Thus, consumers seem inattentive to prices and their changes. However, additional information in the form of a media report can attract consumers' attention by prominently reporting price changes and collusive behavior.

In the first step, I analyze whether consumers change their purchasing behavior in response to a small price change. To measure small price changes that are not driven by demand or supply shocks, I utilize cartel agreements between firms that coordinate on price-fixing in different markets. Besides being exogenous from a consumer's perspective, analyzing cartel cases brings another advantage. As consumers are unaware of the reason for the price increase, it is possible to distinguish consumer response from other effects usually related to consumer behavior and prices. After a cartel breakdown has been reported in the media, consumers will realize there has been a price increase in the past (if inattentive before) and learn the reason for those price increases.

The baseline results show that consumers react to cartels by reducing the demand. However, consumers only react in the post-cartel period, indicating that they have not been attentive to price changes during the cartel. Adding news to the equation sheds light on this, as news in the post-cartel period significantly reduced consumers' demand compared to the pre-cartel period. In the heterogeneity analysis, I show that not all consumers are similarly inattentive. While higher-income consumers tend to be inattentive in the cartel periods but attentive to the news in both periods, lower-income consumers are attentive to price changes and news. Moreover, with the sentiment analysis, I show that the degree of negativity and the specific mention of the cartel firms also influence consumer behavior: More negative news has a stronger impact on consumers' behavior than less negative news. Additionally, the specific mention of cartelized firms rather than only writing about the affected market also strengthens the negative impact on the demand of the cartelized products.

With my analysis, I show that consumer heterogeneity can have significant impacts on market outcomes and welfare. One key area where consumer types can differ is their price sensitivity and responsiveness to changes in market conditions. For instance, low-income consumers are more likely to stop buying a product in response to price increases, while those with a higher income may be more likely to stick with their current choices. This aligns with the rational inattention theory, where consumers allocate their attention and prioritize information important to them over other attributes. Lower-income consumers face budget constraints. Thus, they allocate their attention to prices to stay within their budget. At the same time, higher-income consumers have more flexibility and choose not to spend their attention on price monitoring in grocery products. If firms producing essential products cartelize and increase prices coordinately, this may come at the expense of consumers who value prices more highly, i.e., low-income consumers. However, firms able to address the preferences of certain consumer types may capture a larger market share and generate greater profits without collusive agreements, potentially leading to higher levels of investment and innovation.

Furthermore, my analysis of consumer behavior in response to cartel-induced price changes provides insight into the effectiveness of antitrust policies aimed at detecting and preventing collusion. As discussed in Section 1.3, violations of the cartel prohibition can yield high fines. However, given that consumers are at least partly inattentive, it has to be re-evaluated whether the fines are high enough to cover the consumer's harm. The consequences of inattentive behavior can be significant for consumers and producers. For consumers, this consumption behavior can lead to overpaying for products, resulting in a lower standard of living. For producers, this consumer behavior can lead to higher profits, as producers with market power can raise prices without fear of losing customers to competitors, thereby increasing concerns about rising markups and market power (e.g., De Loecker et al. 2020). However, this can also lead to losing trust among consumers, who may feel they have been taken advantage of as soon as such strategies become visible.

Additionally, the findings of this paper have significant implications for competition policy, particularly regarding how authorities can mitigate the adverse effects of collusion on consumers. Three key areas stand out for policy intervention: improving consumer awareness, targeting to vulnerable groups in their communication, and leveraging media coverage to foster the reach of antitrust enforcement actions. First, improving transparency around cartel activities is essential to addressing the information asymmetry that benefits firms engaged in collusion. Consumers, particularly in essential goods markets, often remain unaware of price-fixing until the media expose it. To counteract this, competition authorities such as the DOJ and FTC should prioritize the timely dissemination information about ongoing investigations or confirmed cartel activities. Public announcements could be made more accessible through social media and consumer-facing platforms and apps, ensuring consumers are informed before price increases severely impact their welfare (e.g., Liu and Serfes 2013).

Second, since my analysis shows that low-income consumers are disproportionately affected by cartel-driven price increases, particularly in markets with inelastic demand, competition authorities should design policies that target vulnerable consumer groups. Collaboration with consumer protection agencies could help ensure that information is delivered through channels that are more accessible to these consumers, such as community centers, local newspapers, and public service announcements. By providing clear and actionable information, these efforts can help vulnerable households make more informed purchasing decisions.

Third, the role of news and media in reducing information asymmetry and influencing consumer behavior is significant. By disseminating crucial information and shaping public perceptions, the media can drive more informed and proactive consumer actions, ultimately contributing to more transparent and fair market dynamics.

The effectiveness of the media in this role depends on their ability to provide credible, unbiased, and timely information to the public. This highlights the need for greater engagement between competition authorities and media outlets. Ensuring that media coverage is timely, thorough, and easily understandable would help reduce the lag between the exposure of cartel activity and changes in consumer behavior. Media coverage also multiplies, raising public awareness beyond direct consumers of the affected products (e.g., Zingales 2017).

Finally, behavioral insights should be integrated into the design of consumer protection policies. Public authorities can encourage consumers to pay more attention to price changes by using nudges to guide consumer behavior in the desired direction without limiting choice. (e.g., Thaler and Sunstein 2008). For instance, competition authorities could encourage retailers to display price histories or include “price change alerts” to help consumers notice patterns that might indicate collusive behavior.

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Appendix

1.A Detailed discussion of bounded rationality and rational inattention

The key insight from applying the EBM model to this context is that rational inattention and bounded rationality often prevent consumers from going through the full decision-making process. When firms engage in collusion, consumers may fail to recognize price increases, conduct limited information searches, and make suboptimal purchasing decisions. It is only when external information—such as media reports or competition authority findings—breaks through their inattention that they adjust their behavior. This dynamic plays a central role in understanding how consumers respond to cartel-induced price increases and why these responses are often delayed.

The first concept, bounded rationality, as described by Simon (1997), recognizes the constraints that real-world conditions impose on decision-making. Thus, consumers are limited in their ability to *process* information, make decisions, and optimize outcomes (Gabaix 2019), ultimately affecting their economic decisions. These constraints can begin with consumers failing to recognize their needs due to cognitive limitations or lack of awareness. Even when a problem is recognized, the perception of that problem is shaped by the information available to them. Due to time constraints, limited cognitive capacity, and restricted access to information, consumers often cannot process all available information. Instead, they use heuristics (as discussed in Appendix 1.C) or the rules of thumb to gather sufficient information and evaluate different options to make a decision. For instance, they may rely on past experience, brand reputation, or recommendations without exhaustive comparison of alternatives.

Thus, consumers seek satisfactory behavior where an option meets acceptable criteria rather than optimizing for maximum utility. This approach, a direct result of bounded rationality, acknowledges that optimizing would require more information and cognitive resources than consumers possess (e.g., Thaler 1985). After purchase, consumers' satisfaction and subsequent actions (such as repeat purchases or word-ofmouth recommendations) are influenced by their initial expectations and the limited evaluation they conduct. Cognitive dissonance and post-purchase rationalization can occur as consumers justify their choices. Thus, bounded rationality introduces systematic biases in decision-making, such as overconfidence, anchoring, and availability heuristics, affecting how consumers forecast future utility and make choices.

In the second key concept, consumers are aware of their cognitive limitations and *allocate* their limited attention and cognitive resources optimally based on the costs and benefits of acquiring and processing information (Sims 2003). Rational inattention[36] acknowledges that gathering and processing information is costly in terms of time and mental effort, leading consumers to make thoughtful choices about what information to pay attention to and what to ignore. This involves a cost-benefit analysis, where consumers weigh the benefits of gathering more information against the cognitive costs. As a result, they make efficient decisions given their limited cognitive resources, but not necessarily optimal from a utility-maximization perspective. During the information search stage, consumers decide how much effort to invest in gathering information based on its perceived importance, strategically distributing their attention to more significant decisions while making other decisions with minimal effort. This distinction can be referred to as limited versus extensive problem-solving (Howard and Sheth 1969). Both can be described as extremes on a spectrum, involving varying degrees of information search and deliberation. Extensive problem-solving involves carefully considering all available information, whereas limited problem-solving relies on habitual decision-making. When making limited problem-solving consumers often perceive alternative products as fundamentally similar, overlooking less obvious factors due to the cognitive costs associated with considering every detail. The opposite is true for decisions involving extensive problem solving. In addition, consumers selectively process information that they believe will have the greatest impact on their utility. This selective processing can lead to biases and gaps in their knowledge that affect their ability to truly maximize utility. They

[36] See, for instance, Maćkowiak et al. (2023) for a recent literature review on rational inattention.

may limit their search to easily accessible information or sources they consider most reliable, ignoring potentially useful but less accessible data. In evaluating alternatives, rational inattentive consumers often use heuristics to simplify the process, focusing their attention on the most relevant attributes and options. Consumers perceive alternative products as essentially similar and overlook less obvious factors or alternatives due to the cognitive cost associated with considering every possible detail.

The actual purchase decision is influenced by the information consumers have paid attention to. Since they have selectively chosen and processed information, their decisions are based on an incomplete set of data. Therefore, consumers make decisions based on limited information, aiming for an acceptable level of utility under these constraints rather than the maximum possible utility because the cost of acquiring and processing additional information outweighs the expected benefit. Like bounded rationality, rational inattention leads to satisficing behavior. After the purchase, consumers continue to allocate their attention selectively. They may focus on aspects of the product that confirm their choice while ignoring negative information to reduce cognitive dissonance. The limited information they have attended to shapes their post-purchase evaluations and future behavior.

1.B Stages of the consumer decision process that are affected by inattention

The consumer decision-making process typically begins when a consumer identifies a need or problem that requires a solution. This need can be triggered by internal stimuli (e.g., running out of a product) or external stimuli (e.g., seeing an advertisement). Especially social factors in external stimuli seem to be a determining factor in today's economy as recommendations from friends, family, or social networks can drive demand for popular or prestigious products, a phenomenon increasingly relevant due to social media and influencers (e.g., Appel et al. 2020; Dubé et al. 2010; Shareef et al. 2020). Once a need is recognized, consumers may seek information through internal searches (e.g., recalling past experiences) or external searches (e.g., consulting friends, reading reviews, or using search engines like Google). Consumers may fail to recognize price changes despite internal and external search opportunities. Rational inattention explains why consumers, particularly in low-stakes environments like grocery shopping, may not notice small, incremental price increases (e.g., Gabaix 2019). Instead of actively monitoring prices, consumers tend to focus on more immediate concerns, like convenience, or rely on habitual purchasing behavior (e.g., Grubb 2015). Additionally, information asymmetry (Akerlof 1970) complicates the recognition of price changes. Firms engaging in collusion hide the reasons behind price increases, making it difficult for consumers to detect the 'true' source of their rising costs. Without clear signals, consumers may not search for additional information or alternatives, allowing firms to continue benefiting from elevated prices (Stiglitz 2000).

In the next stage, "Evaluation of alternatives", consumers assess different products or brands based on attributes like price and quality. They assess how these attributes align with the desired characteristics or outcomes they hope to achieve. This also includes, for instance, price sensitivity, the degree to which price changes impact consumer choices and are influenced by factors such as income, necessity, and the availability of substitutes (e.g., Tellis 1988). Moreover, higher quality often justifies higher prices, impacting consumer decisions and loyalty (e.g., Zeithaml 1988).

However, when attention is limited, consumers rely heavily on heuristics or mental shortcuts, which may prevent them from thoroughly comparing prices (e.g., Kahneman and Tversky 1979). As Grubb (2015) shows, when prices are not salient or highlighted to consumers, they may completely overlook price changes, which allows firms to increase prices without prompting an immediate demand shift. In this context, consumers might continue purchasing cartelized products because they fail to notice or evaluate the alternatives available to them. For instance, loyal consumers may stick to their preferred brands, even if those brands are part of a cartel, as they rely on brand reputation or convenience over price evaluation (e.g., Chaudhuri and Holbrook 2001). This behavior aligns with the concept of bounded rationality, where consumers simplify their decision-making process to minimize cognitive effort, even at the expense of optimal decision-making (e.g., Thaler 1985).

After evaluating alternatives, consumers proceed to the actual purchase decision. Product availability and ease of purchase, such as online versus in-store options, can significantly influence decisions at this stage (e.g., Campo et al. 2003). For instance, stockouts or limited availability can drive consumers to competitors (e.g., Anderson et al. 2006). Additionally, individual preferences, influenced by cultural, social, and personal factors, shape purchasing decisions (e.g., Assael 2004). Typically, the evaluation of alternatives and the purchase decision are guided by utility maximization, where individuals aim to make choices that enhance their well-being based on their judgments. However, successful utility maximization requires accurate forecasting of how different outcomes will be experienced. If these forecasts are systematically biased, choices may consistently fail to maximize utility (e.g., Kahneman and Thaler 2006).

The final phase of the consumer decision-making process is "Post-purchase behavior", which includes the consumer's experience with the product and the likelihood of repeat purchases. Consumers often adjust their purchasing behavior based on value for money, but the price elasticity of demand can vary significantly across different products and consumer segments (e.g., Ter Hofstede et al. 1999). Satisfaction or dissatisfaction with the product can lead to brand loyalty or switching behavior, influencing future decision-making. Consumers' reflections on whether their decision provided value for money shapes future purchasing patterns. However, even if consumers are dissatisfied with rising prices, their responses may be delayed due to a lack of clear information. The extent and quality of information available to consumers affect decision-making. Well-informed consumers will likely make better choices, while information asymmetry can lead to suboptimal decisions (e.g., Stiglitz 2000). When media reports or competition authorities expose cartel behavior, this external information can trigger an adjustment in consumer behavior, but often after a lag (e.g., DellaVigna and Gentzkow 2010). Thus, for some consumers, news exposure serves as a shock that corrects their previous inattention or reliance on heuristics. Consumers may react immediately or over time, depending on the news's salience and income sensitivity (Chetty et al. 2009). This delayed adjustment underscores the role of bounded rationality, where consumers continue to act on outdated or incomplete information until new, salient information forces a behavioral shift.

1.C Detailed discussion of behavioral biases and heuristics influencing consumer decision-making

This section discusses the most relevant cognitive biases and heuristics affecting consumer decision-making and market pricing. It provides insight into how these biases can distort consumer behavior, often benefiting firms involved in collusive activities. Understanding these biases is crucial for firms and regulators to design more effective pricing strategies and policies that safeguard consumer welfare.

One of the most well-documented biases in consumer behavior is loss aversion, which refers to the phenomenon where losses loom larger than gains in a consumer's decision-making process. According to Tversky and Kahneman (1991)), consumers tend to experience the pain of losing something more intensely than the pleasure of gaining an equivalent amount. In the context of pricing, loss aversion suggests that consumers may be more sensitive to price increases than to price decreases, leading them to respond strongly to perceived losses in purchasing power.

For instance, when prices increase due to collusion, consumers may quickly shift to alternative suppliers, even if the price increase is marginal. This effect can be especially strong when consumers feel a sense of loyalty or attachment to their current supplier. Samuelson and Zeckhauser (1988) further argues that loss aversion may be compounded by the fear of future regret, where consumers worry that sticking with their current supplier might lead to higher future costs. This motivates them to switch suppliers sooner than they otherwise would.

Confirmation bias is the tendency of consumers to seek out information that supports their preexisting beliefs and to discount or ignore information that contradicts those beliefs (e.g., Fisher and Statman 2000; Nickerson 1998). In the case of collusion, confirmation bias may cause consumers to either overestimate or underestimate the likelihood of price-fixing. For example, if a consumer believes a particular firm has engaged in unethical practices, they are more likely to interpret price increases from that firm as evidence of collusion, even when legitimate market forces are at play. This bias can also work in the opposite direction: if a consumer holds a favorable view of a firm, they may ignore news reports or evidence suggesting price-fixing behavior. Confirmation bias becomes problematic when it causes consumers to act on incomplete or biased information, leading them to make suboptimal purchasing decisions.

Anchoring refers to the cognitive bias where individuals rely heavily on the first piece of information they encounter—often referred to as the “anchor”—when making subsequent decisions (Tversky and Kahneman 1974). In consumer markets, the initial price a consumer sees for a product or service can serve as an anchor, influencing how they perceive subsequent price changes. Even if future prices deviate from the competitive level, consumers may fail to recognize this because their reference point is anchored to the initial price. In markets with collusion, this bias can be exploited by firms that slowly increase prices over time. Having anchored their expectations to the original price, consumers may perceive subsequent price increases as reasonable, even when those prices exceed competitive levels. This makes it easier for cartels to raise prices incrementally without triggering significant consumer backlash.

The availability heuristic occurs when individuals base their judgments on information that is most readily available to them rather than seeking out comprehensive or balanced information (e.g., Tversky and Kahneman 1973). In the context of consumer behavior, this bias means that consumers may rely on recent or salient information—such as news reports of shortages or market disruptions—when evaluating price changes. For instance, if consumers recently encountered news suggesting a shortage of a particular product, they may accept higher prices for that product without questioning whether the price increase is due to collusion. The availability heuristic can thus prevent consumers from fully processing or investigating the reasons behind price increases, especially when the information at hand seems plausible or urgent.

Another common bias that affects consumer decision-making is status quo bias, which refers to the tendency of individuals to prefer the current state of affairs and resist changes (e.g., Samuelson and Zeckhauser 1988). In pricing, this means that consumers may be reluctant to switch suppliers, even when faced with rising prices, simply because they prefer to maintain the status quo. This bias is often linked to inertia, where consumers find it easier to stick with their existing choices rather than explore alternatives. In the context of collusion, status quo bias can be particularly problematic because it may allow firms to maintain higher prices without losing customers. Consumers' preference for stability may outweigh their concerns about price increases, especially if switching suppliers requires effort or if alternative options are perceived as less convenient.

Present bias refers to the tendency of individuals to prioritize immediate benefits over long-term gains (eg., Laibson 1997). In consumer markets, present bias can lead individuals to make purchasing decisions that prioritize short-term convenience or satisfaction, even at the expense of long-term financial well-being. For instance, consumers may choose to continue purchasing from a supplier despite price increases simply because it is the most immediate and convenient option. This bias can also explain why consumers fail to invest time in comparing prices across suppliers, as the immediate effort required is perceived as not worth the future savings. As a result, collusive price increases may go unchallenged in the short term, allowing firms to profit from consumers' focus on the present.

The presence of these cognitive biases and heuristics has significant implications for how consumers respond to price changes, particularly in markets where collusion occurs. Firms can exploit these biases to maintain higher prices, as consumers may be slow to react or may misinterpret the reasons behind price increases. Moreover, these biases suggest that consumers do not always act rationally or in their best interest, emphasizing the importance of policy interventions that account for these behavioral tendencies. Regulators and policymakers should consider these biases when designing interventions aimed at improving market transparency and helping consumers make more informed decisions. For example, making price comparison tools easily accessible or highlighting price changes prominently could help mitigate the effects of anchoring and status quo bias.

1.D Cartel cases

Table 1.D1: Cartels

Cartel	Years	Firms(#)
Case 1	1999 – 2011	8
Case 2	2012–2019	11 (6)
Case 3	2002 – 2008	6
Case 4	2002 – 2008	23
Case 5	2000 – 2008	7
Case 6	08/2005 - 04/2008	6
Case 7	2010 – 2013	<5

Note: This table gives an overview of the studies cartels and their characteristics. Column "Date" gives information on the date the cartel started and broke down based on investigations by the DoJ. In case 2, only parts of the cartel firms could be identified due to document anonymization by the DoJ. Due to anonymity reasons, the actual number of cartel firms are not disclosed in cases with less than five cartel participants.

1.E Additional information: news search and documents

Nexis search terms for cartel-focused news coverage:

- All cases (Table 1.E1)
  - (price fixing AND (case 1 OR case 2 OR case 3 OR case 4 OR case 5 OR case 6 OR case 7)
- Case 1 (Table 1.E2)
  - (price fixing AND (case1-firm A us OR case1-firm B OR case1-firm C OR case1-firm D OR case1-firm E OR case1-firm F OR case1-firmG OR case1-firm H))
- Case 2 (Table 1.E3)
  - (price fixing AND (case2-firm A OR case2-firm B OR case2-firm C OR case2-firm D OR (case2-firm E AND case 2) OR case2-firm F))
- Case 3 (Table 1.E4)
  - (price fixing AND case 3 AND (case3-firm A OR case3-firm B OR case3-firm C OR case3-firm D OR case3-firm E))
- Case 4 (Table 1.E5)
  - (price fixing AND case 4 AND (case4-firm A OR case4-firm B OR case4-firm C OR case4-firm D OR case4-firm E OR case4-firm F OR case4-firm G OR case4-firm H OR case4-firm I OR case4-firm J OR (case4-firm K AND case 4) OR case4-firm L OR case4-firm M))
- Case 5 (Table 1.E6)
  - (price fixing AND case 5 AND (case5-firm A OR case5-firm B OR case5-firm C OR case5-firm D OR (case5-firm E AND case 5) OR case5-firm F OR case5-firm G))
- Case 6 (Table 1.E7)
  - (price fixing AND case 6 AND (case6-firm A OR case6-firm B OR case6-firm C OR case6-firm D OR case6-firm E OR case6-firm F OR (case6-firm G AND case6) OR (case6-firm H AND case6) OR (case6-firm I AND case6) OR case6-firm J))
- Case 7 (Table 1.E8)
  - (price fixing AND case7-firms)

Table 1.E1: News documents searching for a general category

Keywords	Results(#)
price fixing	1,333,931
+Case 1	202
+Case 2	8,059
+Case 3	5,903
+Case 4	5,996
+Case 5	56
+Case 6	1,799
+Case 7	1,394

Note: This table gives an overview of the analyzed news articles searching for the general category of a market that has been cartelized. The keyword search leading to the results of this table did not contain any firm names. Thus, this table does not summarize the tables in which a specific category is analyzed (Tables 1.E2 - 1.E8). The column Results(#) represents all news articles found for the respective search term (combination) and is limited to English news published in North America between January 1st, 2004, and July 28, 2023.

Table 1.E2: News documents of specific firms, case 1

Keywords	Results(#)
price fixing	
+case1-firm A	515
+case1-firm B	51
+case1-firm C	<10
+case1-firm D	<10
+case1-firm E	<10
+case1-firm F	<10
+case1-firm G	<10
+case1-firm H	26

Note: This table gives an overview of the analyzed news articles in the respective category. Note that some firms that were part of this cartel have not been mentioned in the news. The column Results(#) represents all news articles found for the respective search term (combination) and is limited to English news published in North America between January 1st, 2004, and July 28, 2023. Due to anonymity, the actual number of news documents relating to the firms is not disclosed if the number is below ten.

Table 1.E3: News documents of specific firms, case 2

Keywords	Results(#)
price fixing	
+case2-firm A	215
+case2-firm B	329
+case2-firm C	340
+case2-firm D	259
+case2-firm E(*)	1,379
+case2-firm F	818

Note: This table gives an overview of the analyzed news articles in the respective category. For some firms(*), the search had to be further specialized by adding the word of the category to the keywords (e.g., "price fixing" + "case2-firm X" + "case 2"). The column Results(#) represents all news articles found for the respective search term (combination) and is limited to English news published in North America between January 1st, 2004, and July 28, 2023.

Table 1.E4: News documents of specific firms, case 3

Keywords	Results(#)
price fixing	
+ case3-firm A	820
+ case3-firm B	759
+ case3-firm C	1,088
+ case3-firm D	558
+ case3-firm E	189

Note: This table gives an overview of the analyzed news articles in the respective category. The column Results(#) represents all news articles found for the respective search term (combination) and is limited to English news published in North America between January 1st, 2004, and July 28, 2023.

Table 1.E5: News documents of specific firms, case 4

Keywords	Results(#)
price fixing	
+case4-firm A	12
+case4-firm B	68
+case4-firm C	260
+case4-firm D	75
+case4-firm E	373
+case4-firm F	18
+case4-firm G	23
+case4-firm H	<10
+case4-firm I	<10
+case4-firm J	17
+case4-firm K(*)	30
+case4-firm L	<10
+case4-firm M	<10

Note: This table gives an overview of the analyzed news articles in the respective category. Note that some firms that were part of this cartel have not been mentioned in the news at all. For some firms(*), the search had to be further specialized by adding the word of the category to the keywords (e.g., "price fixing" + "case4-firm X" + "case 4"). The column Results(#) represents all news articles found for the respective search term (combination) and is limited to English news published in North America between January 1st, 2004, and July 28, 2023. Due to anonymity, the actual number of news documents relating to the firms is not disclosed if the number is below ten.

Table 1.E6: News documents of specific firms, case 5

Keywords	Results(#)
price fixing	
+case5-firm A	33
+case5-firm B	40
+case5-firm C	19
+case5-firm D	<10
+case5-firm E(*)	<10
+case5-firm F	<10
+case5-firm G	<10

Note: This table gives an overview of the analyzed news articles in the respective category. For some firms(*), the search had to be further specialized by adding the word of the category to the keywords (e.g., "price fixing" + "case5-firm X" + "case 5"). The column Results(#) represents all news articles found for the respective search term (combination) and is limited to English news published in North America between January 1st, 2004, and July 28, 2023. Due to anonymity, the actual number of news documents relating to the firms is not disclosed if the number is below ten.

Table 1.E7: News documents of specific firms, case 6

Keywords	Results(#)
price fixing	
+case6-firm A	21
+case6-firm B	160
+case6-firm C	<10
+case6-firm D	<10
+case6-firm E	17
+case6-firm F	28
+case6-firm G(*)	132
+case6-firm H(*)	113
+case6-firm I(*)	11
+case6-firm J	95

Note: This table gives an overview of the analyzed news articles in the respective category. For some firms(*), the search had to be further specialized by adding the word of the category to the keywords (e.g., "price fixing" + "case6-firm X" + "case 6"). The column Results(#) represents all news articles found for the respective search term (combination) and is limited to English news published in North America between January 1st, 2004, and July 28, 2023. Due to anonymity, the actual number of news documents relating to the firms is not disclosed if the number is below ten.

Table 1.E8: News documents of specific firms, case 7

Keywords	Results(#)
price fixing	
+ case7-firms	1,403

Note: This table gives an overview of the analyzed news articles in the respective category. The column Results(#) represents all news articles found for the respective search term (combination) and is limited to English news published in North America between January 1st, 2004, and July 28, 2023. Note that the cartel was formed between less than five firms. Due to anonymity reasons, the actual number of cartel firms and the news documents are not disclosed.

Table 1.E9: News documents containing specific words

Word	Headline	Main text
abuse	98	6,125
agree	585	56,73
antitrust	2,068	13,807
cartel	746	8,206
collu*	350	6,539
conspiracy	550	9,702
fix	7,241	56,473
fix price	49	7,885
illegal	143	12,615
investigat*	844	29,570
manipulat*	208	7,245
negative	78	19,562
price	14,520	190,555
price fix	2,423	22,894
violat*	144	9,642

Note: This table gives an overview of the analyzed news articles searching within each news article for specific words. Some words (*) have been searched to capture different forms of the word, e.g., "collu" captures "collude", "colluded", and "collusion".

Table 1.E10: Headline examples of the analyzed news articles (anonymized)

Markets
Antitrust litigation action in the market for product
Are prices in market tipping consumers scale of justice?
Justice Department looks into possible price fixing
Firms
Collusion inquiry targets product companies
Firms were fixing prices
Firm guilty of price fixing
Firms accused of price fixing
Firms seek probe of high profits as US product price skyrocket
Price fixing case begins
Firm agrees to settle antitrust claim
New documents boost price fixing case
Firm to assist US authorities in price fixing inquiry
Firm not charged in product price fixing
US court rejects price-fixing class action appeal
Fines
Firm settles case over price-fixing for $ XX Mio
Firm to pay $ XX Mio in price-fixing case
Firm hit with price-fixing fine
Firm fined $ XX Mio, admits price-fixing
Firm admits fixing prices, face $ XX Mio fine
Damage claims
Firm sues three case firms for price fixing
Firm sues over price fixing by product companies
If you or your firm purchased products from firm your rights could be affected
Firm settles with additional retailers over price-fixing
More lawsuits allege product price fixing
Firm files lawsuit in alleged price-fixing
Managers / (former) CEOs / Individuals
Person pleads guilty to price fixing scheme
Person accused for price fixing
Person ordered to pay $ XX Mio fine in price-fixing case
Former CEO gets jail time
Former owner and CEO sentenced to prison for price fixing
Ex-CEO found guilty
CEO sentenced to prison for price-fixing
Former exec pleas guilty for price-fixing
Ex CEO convicted in price-fixing conspiracy
Antitrust alert: CEO indicted for price-fixing

Note: This table gives an overview of different headlines of the analyzed news articles. All headlines are anonymized, meaning "Firm" or "Person" refer to a real firm or individual, and "$ XX Mio" stands for the amount of fine. In some cases, more anonymization was needed so that the exact headline differs from the presented headline. Further, note that these headlines are only a fraction of the used news articles and only serve as examples.

Figure 1.E1: Example of a news document

Report: Illegal Price-Fixing Conspiracies are Widespread in U.S. Economy

PR Newswire

April 18, 2023 Tuesday 8:00 AM EST

Length: 457 words

Dateline: WASHINGTON, April 18, 2023

Body

PR Newswire

A new report from the research group Good Jobs First finds that large companies operating in the U.S. have since 2000 paid $96 billion in fines and settlements to resolve allegations of covert ***price-fixing*** in violation of antitrust laws.

Illegal ***pricing*** conspiracies have occurred in many industries, affecting the cost of products ranging from grocery items to electronics. In industries such as financial services and pharmaceuticals, almost every major corporation (or a subsidiary) has been a defendant.

These are the key findings ofConspiring Against Competition, a report from the Corporate Research Project of Good Jobs First, a non-profit center focused on corporate accountability. The report, available at goodjobsfirst.org, draws on data collected from government agencies and court records for inclusion in the Violation Tracker database.

"Large corporations which are supposed to be competing with one another are often secretly conspiring to set ***prices***," said Philip Mattera, research director of Good Jobs First and author of the report. "In doing so, they cause economic harm to consumers and contribute to inflation."

Of the more than 2,000 cases in which companies made payments to resolve civil and criminal ***price-fixing*** allegations 357 were brought by the Justice Department and other federal agencies ($26 billion in penalties); 269 cases were brought by state attorneys general ($15 billion); and 1,407 were private class-action lawsuits ($55 billion).

Over one-third of the $96 billion in penalties was paid by financial services companies, mainly to resolve allegations they rigged interest-rate benchmarks. The second most penalized industry, at $11 billion, is pharmaceuticals, due largely to conspiracies to block the introduction of lower-cost generic alternatives.

Along with conspiracies to raise ***prices***, the report reviews litigation involving schemes to depress wage rates. These include cases in which companies entered into agreements not to hire people working for each other. These no-poach agreements inhibit worker mobility and depress pay levels.

Despite the substantial sums corporations pay in penalties, ***price-fixing*** scandals continue to emerge on a regular basis, and numerous corporations have been named in repeated cases.

"Higher penalties could reduce recidivism," Mattera said. "But putting a real dent in ***price-fixing*** will require aggressive steps to deal with the structural reality that makes it more likely to occur: excessive market concentration."

Contact: Philip Mattera (202-725-7906) orpmattera@goodjobsfirst.org

View original content:https://www.prnewswire.com/news-releases/report-illegal-***price-fixing***-conspiracies-are-widespread-in-us-economy-301799891.html

SOURCE Good Jobs First

Classification

Language: ENGLISH

Publication-Type: Newswire

Subject: ***PRICE FIXING*** (95%); NEGATIVE BUSINESS NEWS (92%); ANTITRUST & TRADE LAW (90%); ASSOCIATIONS & ORGANIZATIONS (90%); BUSINESS TORTS (90%); CONSPIRACY (90%); ECONOMIC CONDITIONS (90%); ECONOMY & ECONOMIC INDICATORS (90%); FINES & PENALTIES (90%); NEGATIVE MISC NEWS (90%); PRESS RELEASES (90%); ***PRICES*** (90%); RESTRAINT OF TRADE (90%); SUITS & CLAIMS (90%); CORPORATE WRONGDOING (89%); LITIGATION (89%); NEGATIVE NEWS (89%); AGREEMENTS (78%); CONSUMERS (78%); GENERIC DRUGS (78%); GENERIC PRODUCTS (78%); LAW ENFORCEMENT (78%); NEGATIVE PRODUCT NEWS (78%); RESEARCH & DEVELOPMENT (78%); WAGES & SALARIES (78%); ATTORNEYS GENERAL (77%); CRIME, LAW ENFORCEMENT & CORRECTIONS (77%); INFLATION (77%); ***PRICE*** CHANGES (77%); ***PRICE*** INCREASES (77%); GOVERNMENT & PUBLIC ADMINISTRATION (73%); NONPROFIT ORGANIZATIONS (73%); SCANDALS (72%); JUSTICE DEPARTMENTS (70%); LAW COURTS & TRIBUNALS (69%); RECIDIVISM RATES (66%); INTEREST RATES (63%); GOODJOBS-report (%); SVY Surveys, polls & research studies (%); LAW Legal Issues (%)

Company: Good Jobs First

Organization: US DEPARTMENT OF JUSTICE (55%)

Industry: ***PRICE FIXING*** (95%); BANKING & FINANCE (78%); GENERIC DRUGS (78%); GENERIC PRODUCTS (78%); PHARMACEUTICALS & BIOTECHNOLOGY (78%); ATTORNEYS GENERAL (77%); ***PRICE*** CHANGES (77%); ***PRICE*** INCREASES (77%); INTEREST RATES (63%); CPR Computer; Electronics Products (%)

Geographic: DISTRICT OF COLUMBIA, USA (79%); UNITED STATES (93%); District of Columbia

Load-Date: April 18, 2023

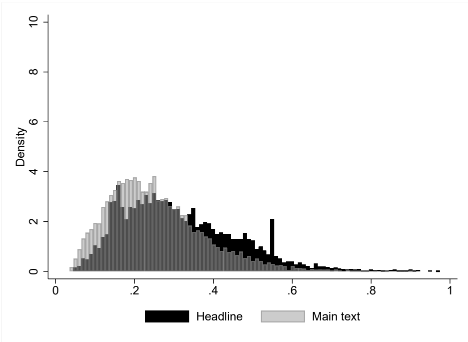
End of Document

Note: This document is an example of the analyzed news articles and shows the different extracted information and categories. Note that this example is not related to the cases in this paper. The keyword search was limited to: “price fixing” in North America. *Source:* Mattera (2023) via Nexis.
In the sentiment analysis described in Section 1.6.3, the headline of this document has a degree of negativity of 50% while the main text (i.e., all text after “Body” and before“Classification”) scored 31.4%.

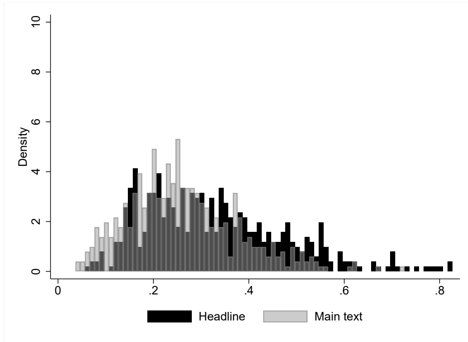
1.F Additional information: News degree of negativity

Figure 1.F1: Degree of negativity for all cases and each case separately

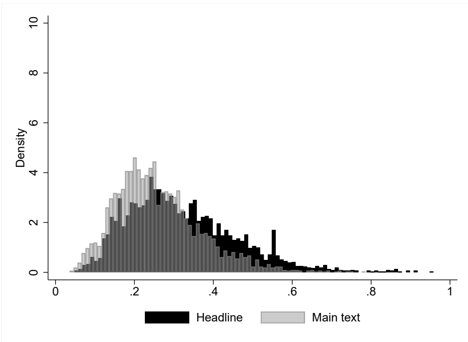
(a) All cases



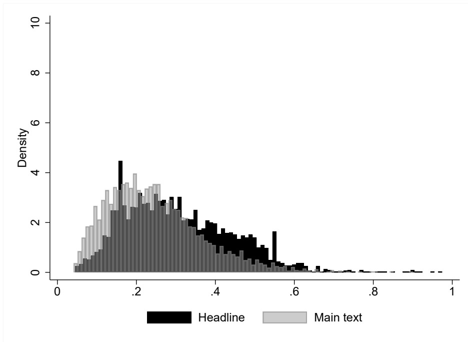
(b) Case 1



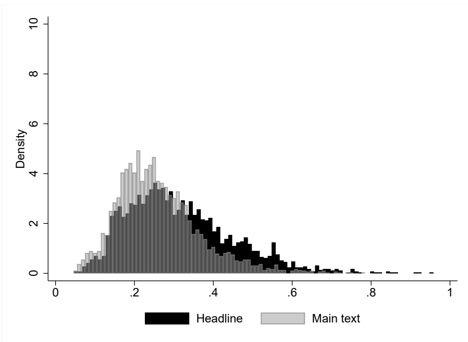
(c) Case 2



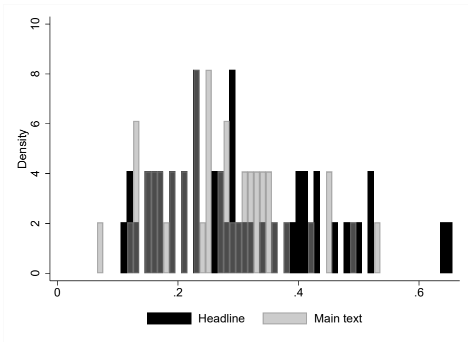
(d) Case 3



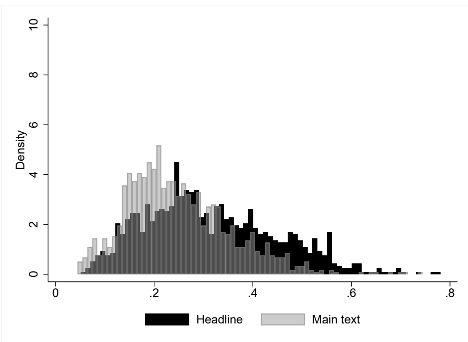
(e) Case 4



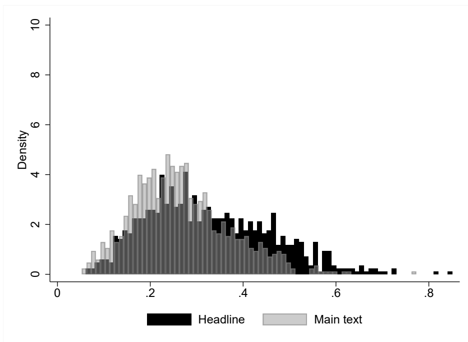
(f) Case 5



(g) Case 6

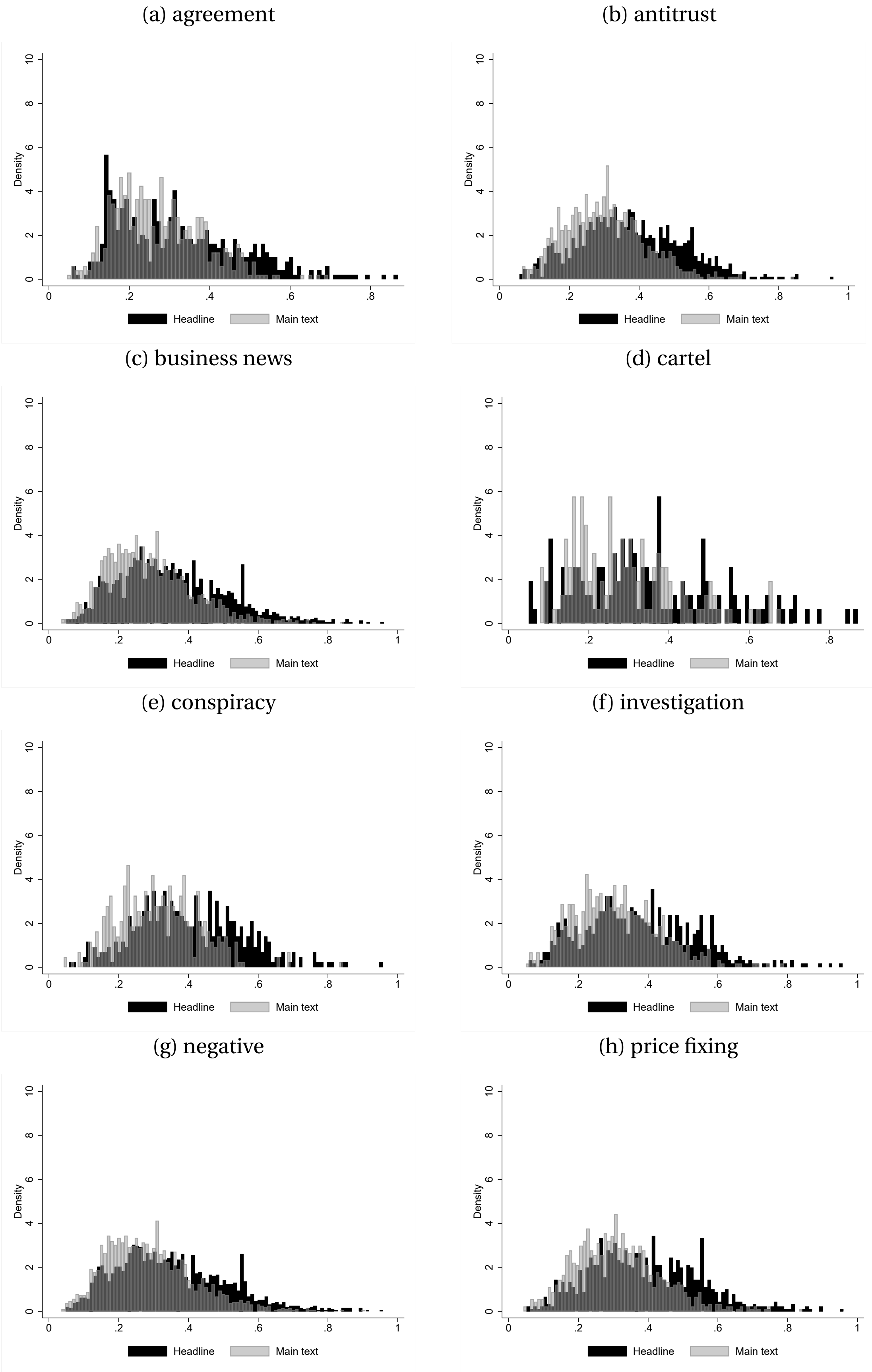


(h) Case 7



Note: This figure shows the mean sentiment scores for all cases (a) and each case separately (b) - (h). The degree of negativity is retrieved by the sentiment analysis with DistilBERT and RoBERTa as described in Section 1.6.3 and lies between 0 and 1: 0 - no negativity, 1 - 100% negativity.

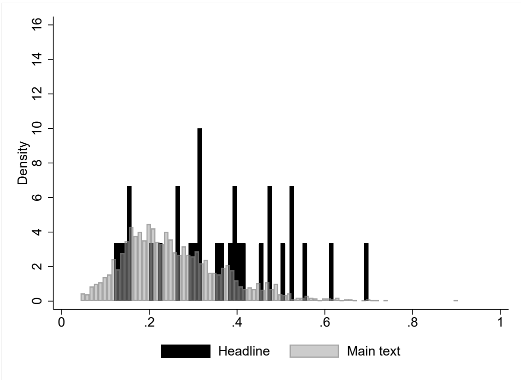
Figure 1.F2: Degree of negativity for news documents categorized in subjects



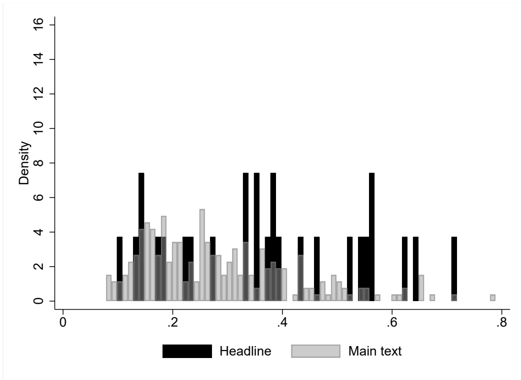
Note: This figure shows the distribution of the negativity degree for all news articles differentiated by subjects generated by Nexis. The sentiment analysis with DistilBERT and RoBERTa retrieved the degree of negativity as described in Section 1.6.3 and lies between 0 and 1: 0 - no negativity, 1 - 100% negativity.

Figure 1.F3: Degree of negativity for news documents containing specific words

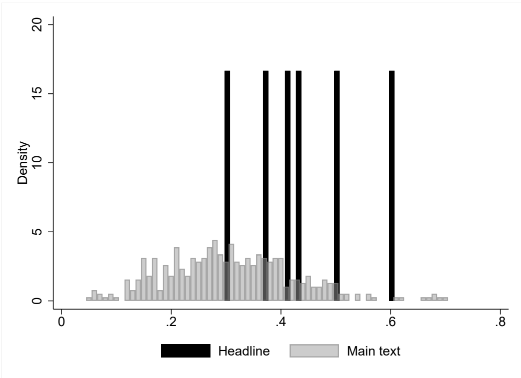
(a) agree



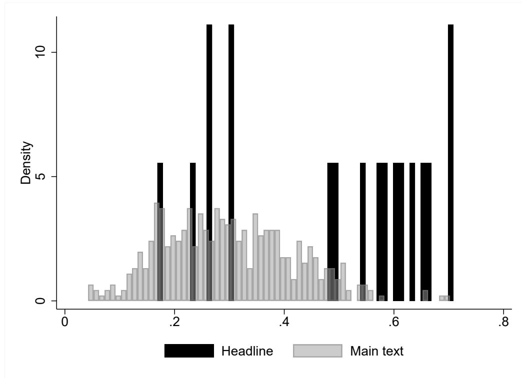
(b) cartel



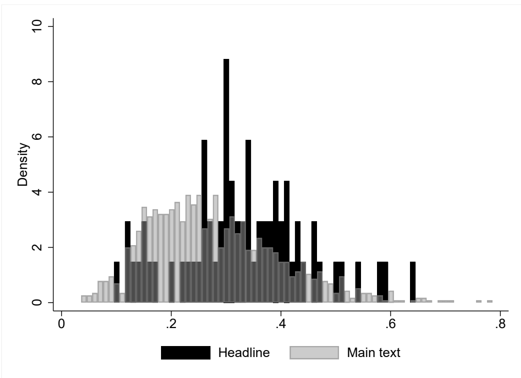
(c) collu*



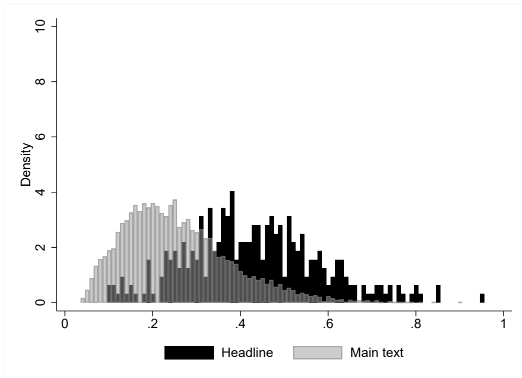
(d) conspiracy



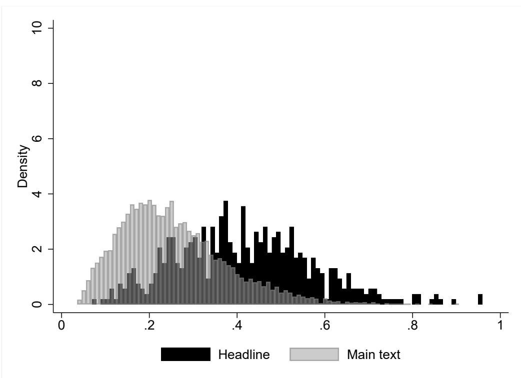
(e) investigat*



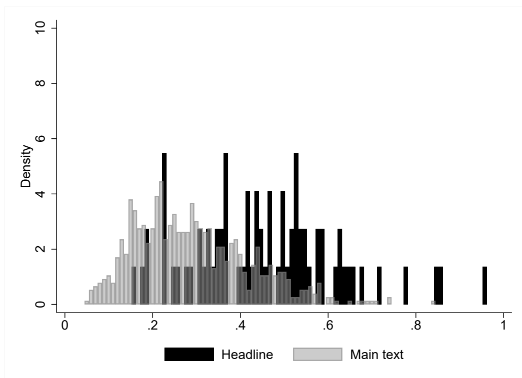
(f) fix



(g) price



(h) price fix



Note: This figure shows the distribution of the negativity degree for all news articles while searching for specific words within the headline and the main text. Table 1.E9 gives an overview of the amount of articles found with the respective word. However, some words are not represented in this Figure due to small observation sizes. The degree of negativity is retrieved by the sentiment analysis with DistilBERT and RoBERTa as described in Section 1.6.3 and lies between 0 and 1: 0 - no negativity, 1 - 100% negativity.

2

Do Managerial Incentives Facilitate Anti-Competitive Behaviour? Evidence from Collusion

with Marek Giebel

2.1 Introduction

Do managerial incentives facilitate collusion? This question is of particular interest as the competitive strategy of the firm is decided by the top management (Antón et al. 2023; Harrington and Chang 2009). Following the common narrative of the structure of the firm, managers are installed to act as agents on behalf of the principal owner. While the latter wants to maximize the firm value, the manager is motivated to maximize her own utility (Holmström 1999; Jensen and Murphy 1990). Specific management remuneration schemes are put into place to reduce agency problems resulting from diverging interests and asymmetric information. These are usually designed to link management pay and company performance (Jensen 1986; Narayanan 1985). This relationship does not constitute a problem per se as it largely shapes managers' incentives to improve the company's results. While this is beneficial from a private point of view, the means to achieve this goal could be detrimental from a social welfare perspective. Consequently, whether specific management remuneration schemes lead to increased incentives for anti-competitive behavior such as collusion remains questionable.

Anti-competitive behavior in the context of management remuneration and firm performance might allow the manager to receive her reward independent of the success of her efforts. Thus it might act as insurance against uncertainties and possible outside influences. To analyze anti-competitive behavior, our analysis focuses exclusively on collusion, which has mainly two reasons. First, a collusive agreement, especially in the form of a hard-core cartel, is the most extreme expression of competition violations (Competition Bureau 2018).[37] Another second reason is that the intent of strategic corporate behavior is always anti-competitive in the case of explicit collusion. Consequently, we investigate how the structure of the management remuneration scheme affects the formation of a collusive agreement and its stability.

To investigate the incentives of managers to engage in collusive agreements, we

[37] In a collusive agreement, competitors act as a monopoly to suspend competition in a market. If not all firms enter the collusive agreement, a goal is usually to drive remaining competitors out of the market. It might be the case that the remaining competitors do not play any significant role in the market such that the cartel can effectively act as a monopoly, although not all firms in a market are part of the collusive agreement.

combine three different data sets. First, we exploit information on collusive firm agreements obtained from two sources. On the one hand, a part of the data stems from John Connor's Private International Cartel database (Connor 2020). This rich data set offers detailed insights into the collusive agreements, participants, and legal results. Second, we combine this data with ExecuComp, which includes detailed information about managers and their remuneration schemes. This allows us to track the managers responsible for the firm action and strategy at a specific time. Moreover, we are able to observe the managers' remuneration schemes. Thus, the fixed and variable parts of payment, but also the short- and long-term shares of total remuneration. Third, for firm information, we utilize the Compustat database. This allows us to control for firm-specific factors in the empirical analysis. Taken together, we assemble a rich dataset including information on the manager, the firms, and the cartels.

The empirical analysis shows that a higher long-term share in managers' total compensation leads to larger incentives for collusion. Thus, executives with higher long-term incentives are more likely to start or be part of a collusive agreement. For the probability of terminating a collusive agreement, we do not find a significant effect of the executives' incentive structure. The results are robust to a broad range of sensitivity tests, including alternative choices regarding the applied empirical models, used instrumental variables, and definitions of the outcome and incentive variables.

Second, we show that these results do not remarkably differ when distinguishing between the position of the executives. Since incentive schemes for CEOs and other top managers differ, we construct the share of long-term remuneration in total remuneration for several groups of executives: all executives, all other executives without CEOs, only CEOs, only CFOs, and only COOs. In the next step, we subsequently apply these variables similarly to the main analysis. We find that the previously described effect – a higher share of long-term remuneration leads to increased incentives for collusion – holds for all types of executives. Although this is the case, effect sizes differ slightly. Particularly for non-CEOs and CFOs, we find a higher impact of long-term remuneration on the probability of being part of a collusive agreement.

In the third step, we consider two major factors that play a huge role in firm decision-making: the equity share in the compensation package and risk-taking incentives. Since it could be assumed that a higher degree of equity compensation makes collusive agreements more likely, we first distinguish the long-term incentives variable in the equity and non-equity share of the remuneration. In addition, we calculate the delta and vega values of management compensation (e.g., Coles et al. 2006). While delta reflects the pay-performance sensitivity, vega determines the wealth to stock sensitivity (Coles et al. 2006). Similar to the baseline estimates, the probability of being part of or starting a collusive agreement increases with the value of all three measures. This implies that higher equity compensation and risk-taking incentives are indeed related to incentives to engage in collusion.

The results of our analysis have important implications for corporate governance and for competition authorities. The owner of the firm has to rethink the corporate governance mechanism. On the one hand, she is willing to motivate managers to act in the firm's best interest. That can be done by aligning firm profits to managers' remuneration schemes as is often already the case. On the other hand, we provide evidence that this alignment will increase incentives for becoming part of and stabilize already existing cartels. An owner might not be interested in the anti-competitive behavior of her firm and, additionally, she is not willing to take the risk of being detected. Thus, the owner needs to apply a more balanced approach to align the interest of the firm and managers to reduce the incentives for anti-competitive behavior. Another aspect could be that owners are not averse to collusion, for example, because of their interest in achieving higher firm profits. In this case, they might use specific incentive mechanisms to motivate collusion - unintentionally or intentionally. This leads to direct implications for competition authorities. It might be worth considering management remuneration when detecting cartels. In that respect, a disclosure policy might be the first step toward more transparency. We also show that individual and manager factors are important to be considered for detecting collusion.

Besides these important implications, our study contributes to the literature in several ways. In general, we contribute to the strand in the literature that determines and analyzes anti-competitive, and especially collusive, behavior. In this context, determinants of cartel formation and stability are widely discussed in theoretical (e.g., Bos and Harrington 2010; Donsimoni et al. 1986; Schmalensee 1987), empirical (e.g., Harrington 2006; Levenstein and Suslow 2006) and experimental (e.g., Fischer and Normann 2019; Hinloopen and Soetevent 2008) works (e.g., Asker and Nocke 2021).[38] Although these studies consider firm characteristics, the incentives of those who lead the firm - the manager - remain largely underinvestigated with only a few recent studies (e.g., Bloomfield et al. 2023; González et al. 2019; Ha et al. 2024). González et al. (2019) shows that managers of convicted cartels benefit from cartel participation in terms of higher compensation and job security. While Bloomfield et al. (2023) analyzes the association between cartel membership and usage of relative performance evaluation, Ha et al. (2024) shows that lower antitrust enforcement increased the sensitivity of executive pay to the performance of rivals. Thus, our paper adds to these works by providing novel empirical evidence for the impact of management remuneration schemes on collusion. Especially the empirical results lead to novel evidence for an additional determinant of collusion. Second, we contribute to the theoretical literature, which investigates the impact of managers on firm collusion (e.g., Buccirossi and Spagnolo 2006; Paha 2017; Raith 2003; Siegert 2014; Sonnenfeld and Lawrence 1978; Spagnolo 2000; Spagnolo 2005; Thépot 2019). We add novel empirical evidence for the various theoretical predictions made in this strand of literature.

Additionally, we add to the literature on executive compensation (e.g., Murphy 1999). More specifically, this paper is related to studies analyzing the relationship between executive compensation and corporate performance (e.g., Cornett et al. 2008; Jensen and Murphy 1990; Murphy 1985; Ntim et al. 2015), the effects of incentive-based compensation on firm behavior (e.g., Makri et al. 2006), the design of effective compensation contracts (e.g., Edmans and Gabaix 2016; Edmans et al. 2017), compensation schemes and managerial behavior (e.g., Jensen and Meckling 1976; Jensen

[38] See Asker and Nocke (2021) for a recent and extensive review of the literature concerning the determinants of collusion.

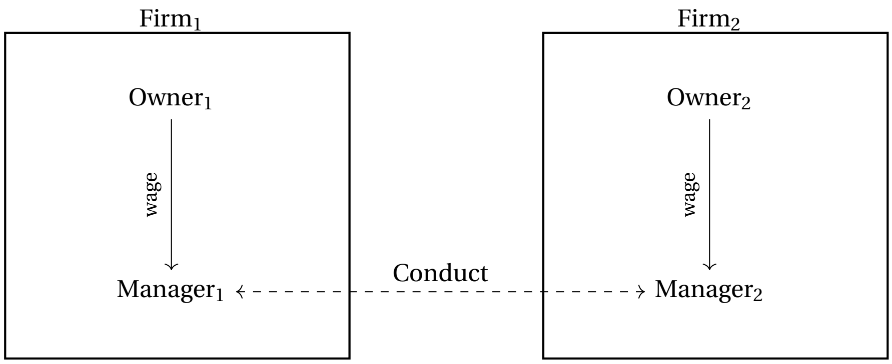
1986), the relation of executive compensation and product market competition (e.g., Raith 2003), and the impact of managerial short-termism (e.g., Bolton et al. 2006; Han 2012; Varas 2018). We do so by connecting management compensation with a firm outcome, namely collusion. Thus, our results provide evidence that the structure of executive compensation affects the firm strategy. More specifically, we show that a higher degree of long-term incentives is correlated with collusive behavior.

The remainder of the paper proceeds as follows. Section 2.2 covers theoretical predictions. Section 2.3 includes a description of the data and our strategy. Following these, the results of the empirical analysis and robustness tests are described in Section 2.4. The penultimate Section 2.5 covers heterogeneity tests related to management position and risk-taking. Section 2.6 concludes.

2.2 Management remuneration and collusion

The formation and stability of collusive agreements depend on factors from outside and inside of firms (Levenstein and Suslow 2006). The decision to participate, however, comes from top management (Harrington and Chang 2009). Thus, when it comes to cartel formation, it is important to consider the firm structure (e.g., Harrington 1989, Spagnolo 2000, Spagnolo 2005, and Thépot 2019). In that respect, it could be assumed that a firm is owned by a principal (owner) and run by an agent (manager). This multidimensional system of principals and agents is illustrated for the case of a duopoly in Figure 2.1. While the owner sets general goals for the firm, the manager is expected to implement and execute the strategies to fulfill the firm's goals. She is responsible for the implementation and realization of the firm's profits and, therefore, is able to influence output and pricing. This constellation may lead to a principal-agent problem due to asymmetric information (e.g., Alexander and Cohen 1999; Fama 1980; Holmström 1982; Wagner-von Papp 2016). Although the owner is interested in maximizing firm value, the manager might not follow this direction and act following its own objectives. The owner is not aware of how the profits are generated as well as how the firm's goals are reached. In consequence, the owner imposes a remuneration scheme to reduce the misalignment in incentives so that the manager maximizes firm profits (e.g., Jensen and Meckling 1976; Jensen 1986; Narayanan 1985). In the following, we describe how the structure of the compensation could lead to conduct between the managers of firms.

Figure 2.1: Multidimensional principal-agent system



Note: This figure illustrates the multidimensional principal-agent system that is in place when having at least two owners and two managers.

The structure of executive compensation packages varies (Edmans and Gabaix 2016; Edmans et al. 2017), and the most common components are salary, annual bonus, payouts from long-term incentive plans, restricted option grants, and restricted stock grants. Thereby, contracts usually consist of a mixture of these components, whereby they could be distinguished into fixed (e.g., salary) and variable (e.g., bonus or equity pay) parts, whereby the latter could be distinguished into short-term (e.g., bonus) and long-term (e.g., option grants) components. Interestingly, the composition of compensation packages changed over time and nowadays consists of a larger degree of stock and option-based compensation (about 55 percent in 2014) compared to 30 years ago (Edmans et al. 2017). Thereby, with about 80 percent, the largest share of compensation is comprised of variable components (Edmans et al. 2017).

It is widely acknowledged that executive compensation and firm performance are related (e.g., Cornett et al. 2008; Jensen and Murphy 1990; Murphy 1985; Ntim et al. 2015). It is particularly that increase in performance-based equity pay that led to an increase in the share of long-term pay of the executives. Since it is largely bound to the performance of the firm, it aims to align managerial behavior with the long-term goal of firm value increase. However, other long-term performance pay measures, such as bonuses, are also aimed at increasing firm performance. Given that the remuneration of the manager is related to the firm success, as outlined above, the incentives for collusive behavior result from several factors (e.g., Harrington 1989, Raith 2003, Siegert 2014, Spagnolo 2000, Spagnolo 2005, Thépot 2019). First, from the uncertainty regarding the success of managerial efforts. Thereby, a collusive agreement would increase firm profits and thereby secure the manager's reward independent of the success of the effort. Second, collusive incentives might stem from outside factors that affect the firm's share price. Thereby, collusion would insure against possible outside influences from competitors. Factors such as intense competition would decrease firm profits and, as a result, manager's wages. These effects could be argued to be heterogeneous according to the structure of the executive's compensation package.[39]

To determine how the latter affects collusion incentives, we provide the sketch of a stylized theoretical framework following works like Harrington (1989), Spagnolo (2000), Spagnolo (2005) and Thépot (2019) in Appendix 2.A. Thereby, we find in line with this literature that a higher emphasis on long-term remuneration decreases the threshold that enables a collusive agreement to a strong degree. On the one hand, the weight of a long-run loss from deviation increases with a higher emphasis on long-term remuneration. On the other hand, a higher degree of long-term remuneration leads to lower incentives for deviation as less value is placed on short-term gains. This aligns with the finding in Spagnolo (2000) that higher stock-oriented compensation (long-term incentives) increases the incentives for collusion as it reduces the short-run gains from deviation. Moreover, this is also consistent with the finding that financial incentives matter significantly for an executive's performance, as efforts are rewarded ex-post (Edmans et al. 2023). Thus, we can conclude that collusion is easier to sustain with a higher emphasis on long-term profits.

[39]It has to be noted that besides the components of contracts, their length might be related to the competitive behavior of firms (e.g., Bolton et al. 2006; Varas 2018). In that respect, managerial short-termism could be also related to anti-competitive behavior (e.g., Han 2012).

2.3 Data and empirical strategy

2.3.1 Data

To analyze the relationship between managerial incentives and collusion, we combine firm data with information about executive compensation and collusive actions. First, we use firm balance sheet information from the Compustat firm database as the core. These comprise, among others, cash flow and income statements. This allows for adding and controlling information about the related companies. Second, we combine this data source with ExecuComp. It covers information on firm executives and their remuneration in the U.S. for the years between 1992 and 2020 from companies included in the Standard and Poor's 500 (S&P 500) index. This comprises details about the structure of the executives' remuneration scheme that includes components like salary, bonus, and options.

Third, we add information about the collusive actions of firms. These are obtained from two different sources: First, we use cartels within the United States from John Connor's data on Private International Cartels (PIC) (Connor 2020). This includes private international price-fixing agreements detected between 1990 and 2019 that are employed by the US Department of Justice (DoJ) or other jurisdictions. Thus, the database includes cartels operating on a global or national scale without any restriction related to geography or industry. We complement parts of this data with background information on the specific cases that are provided online by the DoJ and the Federal Trade Commission (FTC). The combined data sources on cartels contain rich information on the cartels themselves. This includes, among others, the start and end dates of the collusive agreements, the involved firms, and which manager was the firm's executive at that time. Due to the availability of the different data sets, our sample is restricted to the years 1992 to 2014.

Combining all three mentioned data sources allows us to investigate the impact of management remuneration on collusion. It has to be noted that collusion is an illegal activity so its detection is not an easy task which increases the demand for more sophisticated methods (e.g., Aryal et al. 2022; Harrington and Imhof 2022; Hyytinen et al. 2018; Silveira et al. 2023). In this paper, we use information on detected illegal cartels. This leaves room for potential bias that could affect the results as detected illegal cartels are a biased subset of all illegal cartels (e.g., Harrington and Wei 2017). Thus, information like the cartel start and end must be treated cautiously as they are likely imprecise (e.g., Harrington and Wei 2017). However, due to the nature of hidden illegal activities, this issue hardly be avoided when working with data covering illegal cartels (e.g., Bos et al. 2018; Harrington and Wei 2017). This problem could be particularly severe when executive compensation is correlated with the detection of cartels. Since we cannot formally test for the bias, our variable construction presented in 2.3.2 and the empirical strategy discussed in Section 2.3.3 are intended to reduce biases as far as possible. Additionally, we provide a variety of robustness tests in Section 2.4.2 that among others cover the composition of colluding and (most likely) non-colluding firms.

2.3.2 Variables

Collusive behavior of firms. To analyze the impact of different incentive schemes on collusion, we construct three different outcome variables for the collusive behavior of firms. The first indicator variable 'Cartel' reflects the situation when a firm is part of a collusive agreement. Thus, this variable takes value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collusion period. For all firms that are not part of a collusive agreement, this variable also takes the value zero. We augment this general cartel variable with two additional measures. The second variable 'Cartel start' reflects the start of a collusive agreement as indicated in the case information. Thus, this variable takes value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement has started. According to the present case information, we assign the value zero for the focal firm for the points in time when they were not part of a cartel. Third, we generate the variable 'Cartel termination', which is constructed to indicate the ending of a collusive period. We restrict this indicator exclusively to firms that were part of a cartel during the sample period.

Thus, the variable takes unit value if the last period of a detected collusive agreement is reached. It takes the value zero for the cartel periods before the last for firms that were part of a collusive agreement. Accordingly, no value is assigned for firms that were never part of a collusive agreement at any point in time in our dataset.

Managers' incentives. Next, we construct variables to investigate the impact of the remuneration scheme of the firm's top management on the incentives for collusion. As our main focus is whether higher weighted shares of long-term compensation facilitate collusion, our main variable of interest is the share of long-term incentives within the total compensation of a manager. Total compensation includes the following components: salary, bonus, other annual compensation, restricted stock grants, long-term incentive plan (LTIP) payouts, and all other compensation and value of option grants. Any compensation paid out annually is defined as short-term. This includes salary, bonus, and other annual compensation. That leaves restricted stock grants, LTIP payouts, all other compensation, and the value of option grants as long-term incentives. Thus, we utilize the variable 'Long-term incentives' which reflects the share of long-term remuneration (e.g., stock grants, long-term incentive plan payouts, and equity) of the executive's total pay. Due to the possible difference in the incentive mechanism for CEO and non-CEO executives, we construct this variable in our baseline estimation in three different ways. First, we generate it for all executives, including the CEOs and non-CEOs. Second, we construct the variable only utilizing the information of the CEOs' remuneration schemes in our data. Third, we generate the variable by using only the information available for the non-CEO executives of a specific firm in our database.[40]

Control variables. To control for various firm-specific factors, we additionally utilize several firm-level variables. First, we control for the size of the firm by including the variable 'Sales' which is measured as the firm's sales over total assets. We also include a variable to account for the profit situation of the firm. To capture the profitability

[40] In Section 2.5.1, we analyze the heterogeneity within managers' positions further. Thus, we construct the before-mentioned 'Long-term incentives' variable additionally and in a similar way separately for CFOs and COOs.

relative to the company's total assets, we include the variable 'Return on assets'. Respectively, we construct this variable as net income (or loss) value over total assets. Finally, we account for the dividend payments of the firms, which are also considered part of the firm's net worth. Thus, we add the variable 'Dividends' which is the value of common and preferred dividends over total assets. Next, we account for the available financial means' impact on cash balances and cash flow. Thus, we capture the impact of cash holdings readily available for the firm by incorporating the variable 'Cash' in our analysis. This variable is generated as the value of cash and short-term investments over the firm's total assets. Moreover, we control the available cash flow by utilizing the variable 'Cash flow', which is the sum of income before extraordinary items and depreciation and amortization over firm assets. Another important factor with respect to the facilitation and stability of collusion is the capital structure of firms (e.g., Ferrés et al. 2021). Thus, we include two additional variables to account for the impact of capital intensity and leverage on collusion. First, we use the variable 'Capital intensity', which is the value of capital expenditures over total firm assets. Second, we also control for the leverage situation of the firm. Thus, the variable 'Leverage' is constructed as the sum of the firms' long-term debt and debt in current liabilities divided by the stockholder's equity. Last, we also include two additional variables to account for the impact which might come from the CEO itself. It is quite likely that the CEO's personal characteristics affect the decision-making process concerning collusion. Thus, we first consider the impact of the CEO's age. For this purpose, we utilize the variable 'log(CEO age)' which incorporates the current CEO's age in logarithm. In addition to this variable, we also account for the experience of the CEO by including her tenure. Thus, the variable 'log(CEO tenure)' is constructed as the logarithm of CEO tenure. To prevent the impact of large outliers, all variables are winsorized at the lower and upper 1%.

Descriptive statistics are shown in Table 2.1. From these, it becomes evident that about 3.5 percent of the observations are from firms that are actually part of a collusive agreement in a particular year. Moreover, 0.5 percent of the firms are starting a collusive agreement in the sample period. The remainder of firm-year observations is from firms that are not part of a detected collusive agreement in any year.[41] For the cartel firms, we have 863 firm-year observations. About 14 percent of these are part of the termination period. The following is observed for the variables that measure the impact of management remuneration on collusion. Taking all executives, the average share of long-term incentives of total remuneration is about 55 percent, which is similar to the CEO-only share. Finally, when considering only the non-CEO information of the executives, the mean of the long-term incentives share amounts to about 52 percent. Thus, from this, we can deduce that the share of long-term incentives is larger for non-CEOs than for CEOs. This aligns with the assumption that CEOs and non-CEOs have different incentive mechanisms. When comparing colluding and non-colluding observations, we find that the latter has about a 9 percent lower share of long-term incentives and achieves significantly lower total earnings (columns 8 and 9 in Table 2.1). Similar figures are observed when looking at the CEO and non-CEO means separately. Furthermore, we observe that collusion is correlated with a higher CEO age and lower CEO tenure. Concerning the firm variables, we find that there is a positive association between collusive firms and the financial positions of the firm in terms of return on assets, cash flow, dividends, and leverage.

[41] It has to be noted that these firms could be part of a not detected illegal collusive agreement as discussed in Section 2.3.1. To account for potential biases, we present robustness tests in Section 2.4.2 in which we tease out the least likely cartel participants among these firms.

Table 2.1: Descriptive Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All observations			No collusion		Collusion		Difference	
	Count	Mean	SD	Mean	SD	Mean	SD	(6)-(4)	p-value
Collusive behavior									
Cartel	24,361	0.035	0.185						
Cartel start	23,527	0.005	0.072						
Cartel end	863	0.140	0.347						
Incentives									
All executives									
Total remuneration	24,097	2443.777	3440.563	2321.017	3103.026	5756.742	7754.294	3442.120***	(0.000)
Long-term incentives	24,097	0.549	0.224	0.546	0.224	0.630	0.195	0.088***	(0.000)
CEO									
Total remuneration	24,097	5113.206	9864.045	4871.059	8679.135	11648.100	25430.318	6792.372***	(0.000)
Long-term incentives	24,097	0.554	0.272	0.551	0.272	0.635	0.243	0.088***	(0.000)
log(Delta)	22,160	4.473	1.439	4.431	1.419	5.567	1.519	1.136***	(0.000)
log(Vega)	22,484	3.049	1.510	3.004	1.490	4.235	1.534	1.231***	(0.000)
Non-CEO									
Total remuneration	24,097	1819.831	2539.225	1721.772	2198.051	4466.154	6546.054	2748.746***	(0.000)
Long-term incentives	24,097	0.515	0.222	0.512	0.222	0.595	0.203	0.082***	(0.000)
Firm controls									
Cash	24,361	0.140	0.168	0.141	0.169	0.113	0.118	-0.029***	(0.000)
Sales	24,361	0.989	0.731	0.993	0.737	0.882	0.532	-0.111***	(0.000)
Capital intensity	24,361	0.052	0.052	0.052	0.053	0.050	0.044	-0.002	(0.286)
Return on assets	24,361	0.036	0.103	0.035	0.104	0.053	0.072	0.018***	(0.000)
Cash flow	24,361	0.036	0.100	0.036	0.101	0.054	0.068	0.018***	(0.000)
Dividends	24,361	0.013	0.020	0.013	0.019	0.017	0.020	0.004***	(0.000)
Leverage	24,361	0.854	1.858	0.842	1.828	1.175	2.536	0.333***	(0.000)
Manager controls									
log(CEO age)	24,361	4.008	0.128	4.007	0.129	4.034	0.105	0.027***	(0.000)
log(CEO tenure)	24,361	1.736	0.872	1.741	0.872	1.584	0.865	-0.157***	(0.000)

Note: This table shows descriptive statistics of the sample used in the baseline model described in Section 2.3.3. Variable means are shown in columns (2), (4), and (6). The corresponding standard deviations (SD) are displayed in columns (3), (5), and (7). The mean differences between firms in a collusive agreement and those that are not are shown in column (8). The p-values for a test on the equality of means are shown in column (9). All variables are calculated as described in Section 2.3.2. The variables 'Total remuneration' and 'Long-term incentives' are calculated utilizing the information of all executives (all executives), only CEOs (CEO), or only the non-CEO executives (Non-CEO). Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1%.

2.3.3 Empirical strategy

Baseline estimation. To analyze the effect of management incentive schemes on collusion, our baseline regression equation looks as follows:

$$\text{Collusion}_{fjmt} = \beta_0 + \beta_1 \text{Incentives}_{fjmt-1} + \beta_k \text{X}_{k,fjt-1} + \beta_l \text{C}_{l,jmt-1} + \delta_j + \phi_t + u_{fjmt}, \quad (2.1)$$

where the indices f, j, m, and t refer to firms, industries, managers, and time, respectively. On the left-hand side, Collusion_{ft} compromises the different outcome variables that reflect the cartel behavior (i.e., 'Cartel', 'Cartel start', 'Cartel termination' as described in Section 2.3.2) of the firm. The main variable of interest is '$\text{Incentives}_{fmt-1}$', which compromises the measurement of the managerial incentive schemes. This is computed as the one-year-lagged share of long-term remuneration to the total remuneration of the manager as outlined in Section 2.3.2.Using the one-year-lagged long-term incentives to determine how last year's incentives impact the collusive behavior of the current year at least partially reduces the bias stemming from the possibility that the executive compensation is affected by the collusive agreement. In addition, this reflects the manager's long-term considerations. As the executive board consists of the CEO and the non-CEO members, we construct the measure for all executives. Additionally, we add several one-period lagged variables to control for firm-specific determinants (X_{fjt-1}) on the one hand, and executive-specific characteristics (C_{jmt-1}) on the other hand, as outlined in Section 2.3.2. Furthermore, we include industry (δ_j) and time (ϕ_t) fixed effects to account for possible industry and year-specific influences. Moreover, we apply standard errors that are clustered at the firm level. Due to varying firm sizes, standard errors may be inconsistent otherwise (Bertrand et al. 2004).

An estimation as described in equation (2.1) might provide a picture of the relationship between managerial incentives on the collusive behavior of firms, but it has to be noted that the estimates are likely biased due to endogeneity issues. There are various reasons for this assumption. First, it is quite likely that contracts determining the long-term incentive shares are not randomly assigned to the managers but are rather the result of self-selection. This is rooted in the fact that the specific contract depends on the characteristics of the manager as it is negotiated before and even continuously during their employment relationship with the owner. In a similar line of reasoning, the second source of bias to the estimated effects is unobservable firm or individual characteristics. If these drive the sorting of managers into specific firms and contracts, the presented estimates would differ remarkably from the true effects. Third, reverse causality could be considered another potential source of endogeneity. Since firms that are part of a cartel have, on average, higher profits, managers might choose these firms and their compensation schemes on purpose. Thus, firms that are more likely to enter collusive agreements would influence the choice of a long-term incentive scheme and not vice versa. If this conjunction is true, the estimates presented above would reflect the reverse effect rather than the intended one.

Shift-share instruments. To account for these selection biases, we exploit an instrumental variable approach based on shift-share instruments (Bartik 1991; Flabbi et al. 2019).[42] By doing so, we account for potential endogeneity induced by time-varying firm-level shocks. A significant change to unobservable characteristics, such as 'corporate culture' may lead to more long-term incentivized executives but also indirectly affect collusive outcomes. It is not possible to account for such an unobservable change by adding proxy variables or firm-fixed effects. With a shift-share instrument, however, it is possible to tackle this kind of endogeneity (Goldsmith-Pinkham et al. 2020). To apply this methodological approach, we utilize information about the long-term incentives at the beginning of the observation period. These are measured at the firm level, and the growth in long-term incentive share is measured at the regional and two-digit SIC industry level. The regional industry trend should be correlated with the incentive measure of firms in the region and industry in a given year (e.g., Benson et al. 2020; Kini and Williams 2012). However, it should not be correlated with time-varying firm-level heterogeneity that may endogenously affect collusive outcomes and long-term incentives in a specific firm.

[42]We provide the results using alternative instruments and from robustness tests concerning the instrument construction in Section 2.4.2.

We construct an instrument for long-term incentives as follows: We assume that the base year value is exogenous when conditioning on the other control variables, which include firm fixed effects. The base year varies and equals the first year of each firm in our dataset. For each firm f, we then compute the average value of the share of long-term incentives by year, region, and two-digit SIC code over all firms with the exclusion of the focal firm f. We denote this average by $\bar{g}^{r(f)}_{t,-f}$, where $r(f)$ is the geographical regional location of firm f. It is necessary to exclude firm f from that average. Otherwise, an endogenous factor might be affecting one firm's long-term incentives contaminating the average. In the next step, we compute the yearly growth rates of these averages by region relative to the base year. These growth rates are denoted as $\Upsilon^{r(f)}_{t,f} = \frac{\bar{g}^{r(f)}_{t,-f}}{g^{r}_{\text{baseyear},-f}}$. The instrument $\tilde{g}_{t,f}$ is constructed by multiplying these growth rates $\Upsilon^{r(f)}_{t,f}$ with the base year value of the share of long-term incentives ($g_{\text{baseyear},f}$):

$$\tilde{g}_{t,f} = g_{\text{baseyear},f} \times \Upsilon^{r(f)}_{t,f}. \tag{2.2}$$

Using this instrument finally allows us to perform the following two-stage least squares estimation:

$$\text{Incentives}_{fjmt-1} = \gamma_0 + \gamma_1 \tilde{g}_{t-1,f} + \gamma_k X_{k,fjt-1} + \gamma_l C_{l,jmt-1} + \delta_j + \phi_t + u_{fjmt}, \tag{2.3}$$

$$\text{Collusion}_{fjmt} = \beta_0 + \beta_1 \widehat{\text{Incentives}}_{fjmt-1} + \beta_k X_{k,ft-1} + \beta_l C_{l,jmt-1} + \delta_j + \phi_t + u_{fjmt}. \tag{2.4}$$

The parameter of interest β_1 informs us about the impact of the share of long-term incentives in the manager's total compensation on collusion.

2.4 Results

2.4.1 Baseline results

In this section, we present the results of our empirical analysis. As outlined in Section 2.3.3, our baseline results are based on two different estimation strategies. That is, on the one hand, a simple OLS regression and, on the other hand, an instrumental variable approach with shift-share instruments. As stated earlier in Section 2.3.2, we analyze three different outcomes reflecting specific collusive behaviors ('Cartel', 'Cartel start', and 'Cartel end'). The results of the first-stage regression of the IV approach are shown in Appendix 2.B, Table 2.B1. To remain valid, the instrument has to be relevant and exogenous. While arguments for the validity of both characteristics are provided above, the relevance of the instrument can be directly tested. This is done by inspecting the Kleibergen-Paap first-stage F-statistics of the excluded instruments in the first stage. They indicate that the instrument is highly relevant with first-stage F-statistics beyond the critical value of 10 for the 'Cartel' and 'Cartel start' variables. Although the coefficient is highly significant in the first stage of 'Cartel end', the F-statistic is slightly lower than 10. This implies that the instrument is rather weak for this particular sample and that we treat the results with caution. In the next step, we analyze the results from OLS regressions and the valid IV estimates shown in Table 2.2 for each outcome separately. While panel A shows the estimation results without firm and CEO controls described in Section 2.3.2, panel B reports the results with both categories of control variables.

Being part of a cartel agreement. The first outcome variable 'Cartel' is an indicator that turns one if firm f was involved in cartel activity in year t and zero otherwise. To put it differently, that means this indicator is zero if a firm is currently not or never was part of a cartel. The respective results can be found in Table 2.2, columns (1) and (2). For our main variable of interest, the share of long-term incentives of the managers' remuneration scheme, we find a positive and highly significant effect in panels A and B for the OLS and IV results in columns (1) and (2), respectively. This implies that a higher share of long-term incentives is associated with a higher probability of collusive activity of the respective firm. A 10 percent increase in long-term incentive shares leads to an increase in the probability of being part of a collusive agreement by about 3.3 percent (panel B, column (2)). Under the assumption of the validity of our IV approach, the difference between both estimates implies that OLS underestimates the effect to a large degree.

Starting a cartel agreement. Next, we investigate the impact of long-term incentives on the probability of starting a collusive agreement ('Cartel start'). For this purpose, the dependent variable takes value one if the firm is engaged in the start of a collusive agreement. The value zero is assigned for all firms that are not starting a collusive agreement or, otherwise, are not part of a cartel. Thus, the coefficient of the variable 'Long-term incentives' reflects the impact of the long-term incentives on the probability of starting a collusive agreement. From the results in Table 2.2, column (3), OLS, and (4), IV, it becomes evident that, again, the probability increases with a stronger degree of long-term incentives in the managers' remuneration scheme. In terms of its size, the coefficient in panel B, column (4) implies that a 10 percent increase in long-term incentive shares leads to an increase in the probability of being part of a collusive agreement by about 0.4 percent. Compared to the IV estimates, we again find that the OLS estimates seem to underestimate the effect to a large degree.

Terminating a cartel agreement. In the last step, we investigate the probability that an existing collusive agreement has ended ('Cartel end') conditional on the share of long-term incentives in the remuneration scheme of the manager. Thus, we estimate equation (2.4) for the sample for firms that were part of a collusive agreement. The corresponding outcome variable takes the value one if the collusive agreement is terminated and zero else. From the results in Table 2.2, column (5), OLS, and (6), IV, it becomes clear that there is no significant influence of the long-term incentives on the probability of terminating a collusive agreement. As stated, the results have to be interpreted with caution as the OLS estimates might be biased due to endogeneity, as the instrument might not be relevant, which is indicated by the Kleibergen-Paap first-stage F-statistics. However, the results might indicate that managerial incentives measured through remuneration schemes are probably not the main driver of cartel breakdowns.

In general, it can be acknowledged that our empirical results support the theoretical predictions, independently of whether we perform the empirical analysis by an OLS estimation or an IV approach with shift-share instruments.[43] Despite this, the IV

[43]Since it remains debatable how to set up shift-share instruments to obtain the best-unbiased estimates (e.g., Broxterman and Larson 2020, Goldsmith-Pinkham et al. 2020), we also performed tests

results are for all three outcomes larger than the OLS results but still very similar. Thus, higher long-term incentives increase the probability of being part of a cartel and starting a cartel.

Table 2.2: Baseline results using OLS and shift-share instruments

	(1)	(2)	(3)	(4)	(5)	(6)
	Cartel		Cartel start		Cartel end	
	OLS	IV	OLS	IV	OLS	IV
Panel A: Without firm and CEO control variables						
Incentives	0.068***	0.390***	0.009***	0.049***	0.008	0.426
	(0.012)	(0.093)	(0.003)	(0.017)	(0.070)	(0.538)
Panel B: With firm and CEO control variables						
Incentives	0.065***	0.330***	0.009***	0.041**	0.007	0.787
	(0.011)	(0.087)	(0.003)	(0.016)	(0.071)	(0.622)
FE Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,076	24,076	23,267	23,267	836	836

Note: This table shows the estimation results of a linear regression model of equation (2.1) and an IV approach by estimating equations (2.3) and (2.4). The coefficients for the IV estimates are obtained by instrumenting the long-term remuneration share on the firm level by shift-share instruments as described in Section 2.3.3. The measure of interest 'Incentives' is calculated as the share of long-term remuneration parts over total compensation. The first outcome is an indicator 'Cartel' that takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collision period (columns (1) and (2)). The outcome in columns (3) and (4) is an indicator 'Cartel start' that takes the value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement started. For columns (5) and (6), the outcome is an indicator 'Cartel end' that takes the value one for a firm that is part of a collusive agreement at the point in time when the last period of a collusive agreement is reached. The specification in panel A includes only industry and year fixed effects. In panel B, firm and manager controls are applied as described in Section 2.3.3. The firm controls include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets as well as leverage. CEO controls include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

2.4.2 Robustness and sensitivity tests

Accounting for the binary nature of the outcome variables. It might be argued that the results rely on the choice of a limited probability model. To test for this issue, we account for the nature of our dichotomous outcome variables. We first estimate a sim-

with a fixed base year (i.e., 1992) that lead to comparable results of a drastically smaller sample. Similar results for the IV estimation are also achieved when using the one-digit SIC industry level. Moreover, results differ not to a large degree if the regional level is obtained by using ZIP codes or a state-level classification.

ple probit model to rule out a strong model dependency of our results. The results in Appendix 2.C, Table 2.C1, panel A are similar to the baseline estimates, which indicates our findings' validity. Additionally, we face a very low number of collusive events compared to the non-colluding firms in our sample. That is why we apply a complementary log-log model in an additional test. For small values of events, the complementary log-log transformation is close to the logit model and thus suitable for our purpose. The corresponding results using this estimation approach are shown in Appendix 2.C, Table 2.C1, panel B. They are, however, similar to the baseline estimates for the results concerning being part of a cartel and starting it (columns 1 to 4). It has to be noted that for the binary instrumental variable regressions, the probability of ending a cartel agreement becomes positive as well (column 6).

Definition of the outcome variables. It might be argued that the results are biased due to the nature of the outcome variable. As discussed in Section 2.3.1, using detected cartels leaves out all undetected collusive actions. To account for this potential source of bias, we tear down the group of non-collusive observations to those least likely to engage in a collusive agreement. To determine the firms and firm years that are least likely part of a collusive agreement, we estimate a probit equation with the cartel participant indicator as the dependent variable and employ the set of control variables described in Section 2.3.2. However, we leave out the long-term incentive variable to avoid a potential bias. We subsequently calculate the propensity that a firm is part of a collusive agreement and discard firms with at most a 5 percent likelihood during the observation period. This leaves us with a final sample of firms that have been part of a collusive agreement and those that have a propensity of less than five percent according to the observable characteristics. Secondly, we discard every observation that has a less than 5 percent likelihood of being a cartel participant at any time during the observation period. Last, we discard firm years with a less than 5 percent likelihood of being cartel observations during the sample period. Re-estimating the baseline results with these modifications to the outcome variable still leads to similar effects (Appendix 2.C, Table 2.C2).

Definition of the incentive variable. Another important point is the definition of the incentive variable. We stress the results of our analysis by changing the management variables in different ways. First, we test whether the results hold when we apply the share of long-term over total remuneration at the same point in time the cartel took place. The results are shown in Appendix 2.C, Table 2.C4 and are similar to the baseline estimates. Moreover, as bonuses are often paid if a specific goal is achieved, it might encourage managers to achieve long-term goals or follow a long-term strategy for multiple years, although it is paid only annually. Thus, we re-estimate the results by excluding bonuses from the definition of short-term incentives and, in an additional test, include them in long-term incentives. The results of these exercises are shown in Appendix 2.C, Table 2.C6, panels A and B. It becomes evident that they are very similar to the findings presented in the baseline estimation, indicating that bonuses are not driving the results. Next, it is possible to argue that the variable parts of managerial compensation are more important to spur firm profit-maximizing behavior of the manager than the fixed parts. We re-calculate the long-term incentives as shares from the variable total compensation to account for this. The results applying this change to the incentive variable are reported in Appendix 2.C, Table 2.C6, panel C and look fairly similar to the baseline results. In a further test for the reliance of the results on the definition of the long-term share, we construct three indicator variables. These take the value one if the share of long-term incentives is larger than the lower quartile, median, or third quartile of all observations. All three estimation results shown in Appendix 2.C, Table 2.C8, panels A to C are in line with the results of our baseline estimation.

Alternative instruments. As outlined in the baseline estimation strategy in Section 2.3, we use Bartik instruments to account for the possible endogeneity in our empirical setup. We extend these considerations by applying an additional instrument related to the corporate tax rate following the literature (e.g., Armstrong and Vashishtha 2012; Core and Guay 1999). The idea is that a higher marginal tax rate makes option-based compensation more costly (e.g., Core and Guay 1999; Hall and Liebman 2000). This is related to the expected higher value of deferred compensation due to future tax deductions compared to instantaneous tax deductions from cash compensation (Core and Guay 1999). To proxy for the marginal tax rate, we follow Armstrong and Vashishtha 2012 and apply an indicator variable that takes value one if the firm had a tax loss carried forward in the last three years and zero else. The results when using this additional instrument in accordance with works like Armstrong and Vashishtha (2012) are shown in Appendix 2.C, Table 2.C10. First, the Sargan-Hansen test on overidentifying restrictions implies that the null hypothesis that the instruments are valid could not be rejected. This further underlines the validity of our approach. Second, it becomes evident that the second-stage estimation results remain similar to those presented earlier.

In our baseline setup, we are left with another problem. As discussed in the literature, the incentive scheme is endogenous as a manager will negotiate with a firm about compensation before joining the firm. Therefore, it might be difficult to distinguish whether the compensation scheme influences a collusive outcome or whether the collusive strategy impacts the negotiation about the compensation scheme. Thus, we implement additional tests to address the endogeneity problem besides the presented instruments. For this purpose, we include further lags of the incentive variable as instruments. The fourth and fifth lags are assumed to be suitable as we are dealing with long-term incentives since they allow us to reduce the problem of reverse causality. The results for each lag and applying them jointly are presented in Appendix 2.C, Table 2.C12, panels A to C. The results remain comparable when applying every single instrument but also when both are used simultaneously.

Matching estimator. Next, we apply a matching approach to find comparable twins among the firms with high and low long-term remuneration schemes. This allows for comparing the remuneration scheme of these pairs, which are as equal as possible regarding observable characteristics. To approach this, we first estimate a probit equation to determine the probability that a firm's remuneration scheme is, on average, above the sample median (Table 2.C14, Appendix 2.C). The predicted probabilities are used to calculate inverse probability weights to re-weight the baseline regressions accordingly (e.g., Imbens and Wooldridge 2009). If the matching approach is successful, the differences between the two groups should vanish. As the results in Table 2.C15 in Appendix 2.C indicate, this is the case. Thus, we use the calculated weights and re-estimate our baseline estimates. The corresponding results in Appendix 2.C, Table 2.C16 imply that the significant differences in the incentive mechanisms between these two types of firms persist even after matching observable characteristics. Thus, the results remain comparable to the baseline estimates.

2.5 Heterogeneity within managers

2.5.1 Manager's position and incentives for collusion

In the baseline analysis in Section 2.4, we calculated the relationship between long-term incentives in managerial compensation schemes and the collusive behavior of firms as an average effect of all top executives in our dataset. However, it could be assumed that executives in different positions have varying incentives. There is convincing evidence that not all different manager positions face the same incentive schemes through their remuneration packages (e.g., Kim et al. 2011). The differences between the positions also become evident from the descriptive statistics in Table 2.1, showing that the share of long-term incentives is generally higher in executives other than the CEO. While non-CEOs have on average a share of long-term incentives of 52%, CEOs only have a long-term incentive share of 22%. Thus, we test for heterogeneous effects between the different executive positions. In our dataset, we can further distinguish between all executives, all non-CEO executives, CEOs, CFOs, and COOs. These different executive positions are associated with different responsibilities. The influence of the CFO on the price-setting strategies is rather small compared to the CEO. The CFO, however, is responsible for negotiations with suppliers and vendors and, thus, may also be able to influence price decisions at least indirectly. Consequently, it seems to be easier for a CEO to influence the decision for a collusive agreement. She can then either implement the strategy on her own or assign the middle management to implement her strategy (with or without them knowing of the collusive agreement). Thus, it only seems to be natural to account for different positions when analyzing the managerial incentives for collusion.

The results presented for the different sub-samples in Table 2.3 show a clear picture.[44] Panel A shows the baseline effects for comparison reasons, which can also be found in Table 2.2. All estimates in panels B – E are positive although the IV estimates are higher for all panels. Similar to the aggregated effects, we find significant effects for panel B (All executives without CEOs), panel C (CEOs), and panel D (CFOs) when it comes to the probability of being part of a cartel ('Cartel') as well as to start a collusive agreement ('Cartel start'). However, we still do not find any significant effect on the probability of ending a cartel agreement ('Cartel end'). It also has to be noted that the effects for the CFOs-only panel are higher for the cartel start indicator than for any other panel. This indicates that firms in which higher shares of long-term incentives compensate a CFO are more likely to start a collusive agreement. Although the same is true for the samples of CEOs only and all executives, the size of the effects differ remarkably. Thus, these results reinforce the notion that having higher long-term incentives drives the incentives for all executives to engage in collusive agreements, however, for CFOs in particular. This might be rooted in the fact that CFOs are better able to influence the pricing strategy of the firm and, ultimately, collusion.

[44]The corresponding first stage results are shown in Appendix 2.B, Table 2.B2.

Table 2.3: OLS and IV results for different managers' positions in the firm

	(1)	(2)	(3)	(4)	(5)	(6)
	Cartel		Cartel start		Cartel end	
	OLS	IV	OLS	IV	OLS	IV
Panel A: All executives (*Basline results from Table 2.2*)						
Incentives	0.065***	0.330***	0.009***	0.041**	0.007	0.787
	(0.011)	(0.087)	(0.003)	(0.016)	(0.071)	(0.622)
Observations	24,076	24,076	23,267	23,267	836	836
Panel B: All executives without CEOs						
Incentives	0.063***	0.354***	0.009***	0.046**	0.032	0.880
	(0.011)	(0.094)	(0.003)	(0.018)	(0.063)	(0.737)
Observations	23,817	23,817	23,015	23,015	829	829
Panel C: CEOs						
Incentives	0.043***	0.295***	0.005**	0.036***	0.020	1.116
	(0.009)	(0.076)	(0.002)	(0.014)	(0.056)	(1.153)
Observations	24,076	24,076	23,268	23,268	835	835
Panel D: CFOs						
Incentives	0.036***	0.323***	0.005**	0.052***	-0.052	0.254
	(0.010)	(0.094)	(0.002)	(0.020)	(0.074)	(0.590)
Observations	15,364	15,364	14,954	14,954	420	420
Panel E: COOs						
Incentives	0.036***	0.429**	0.003	0.023	0.026	3.790
	(0.013)	(0.178)	(0.004)	(0.034)	(0.092)	(2.824)
Observations	7,261	7,261	7,054	7,054	222	222
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
CEO controls	Yes	Yes	Yes	Yes	Yes	Yes
FE Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE Year	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the estimation results of a linear regression model of equation (2.1) and an IV approach by estimating equations (2.3) and (2.4) for different executive positions. The coefficients of the IV estimates are obtained by instrumenting the long-term remuneration share on the firm level by shift-share instruments as described in Section 2.3.3. The measure of interest 'Incentives' is calculated as the share of long-term remuneration parts over total compensation. The first outcome is an indicator 'Cartel' that takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collision period (columns (1) and (2)). The outcome in columns (3) and (4) is an indicator 'Cartel start' that takes the value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement started. For columns (5) and (6), the outcome is an indicator 'Cartel termination' that takes the value one for a firm that is part of a collusive agreement at the point in time when the last period of a collusive agreement is reached. Controls are applied as described in Section 2.3.3. The firm controls include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets, and leverage. CEO controls include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

2.5.2 Components of executive compensation packages

Next, we are interested in the heterogeneity of the managers concerning the components of their compensation package and risk-taking incentives. For this purpose, we exploit various measures that are related to overconfidence and risk-taking behavior.

Equity and non-equity share of long-term incentives. We first test for the composition of executive compensation by distinguishing the long-term incentives variable in the equity and non-equity share of the remuneration. It could be assumed that a higher degree of equity compensation makes collusive agreements more likely. This is mainly related to the theoretical finding that stock-oriented compensation can incentivize a long-term behavior like collusion as it reduces the manager's short-run gain from deviation (e.g., Spagnolo 2000). Thus, we create two new variables that cover the related information. The first variable consists of the non-equity compensation part (e.g., long-term incentive plan-related payments) of the manager's long-term pay, scaled by the total remuneration. The second variable is constructed using the equity share of the managers' compensation package. This includes restricted stock granted and options granted. We add these two elements for the respective variable and scale them by the total remuneration. The results of applying these two variables are presented in Table 2.4, panels A and B.[45] While they look fairly similar to the baseline results for the equity share of the remuneration package, the effects are rather weak for the non-equity part. Thus, this leaves us with the conclusion that the relation between long-term incentives and collusion is mainly attributed to the share of equity compensation, which aligns with the theoretical finding in Spagnolo (2000).

Equity compensation and risk-taking incentives. Second, we extend the previous considerations and analyze the impact of the managers' compensation packages concerning risk-taking incentives. Usually, managerial risk-taking is defined as the top managers' choice of strategies with an uncertain outcome (e.g., Bowman 1980, Hoskisson et al. 2017, Palmer and Wiseman 1999). These strategies relate, for instance, to R&D spending, acquisitions, and divestitures as well as competitive actions. A col-

[45]The corresponding first stage results are shown in Appendix 2.B, Table 2.B3.

lusive agreement, such as e.g., a price-fixing agreement, is usually a risky decision as it is related to uncertainties regarding stability, firm fines, individual sanctions, and reputation. These risk-taking actions can be incentivized by the compensation schemes of the managers (e.g. Chava and Purnanandam 2010; Windram 2005). To analyze the relationship between risk-taking incentives and collusive outcomes, we rely on two different sensitivity measures 'Delta' and 'Vega' that are commonly applied in the literature (e.g., Core and Guay 2002; Fahlenbrach and Stulz 2011; Guay 1999; Liu and Mauer 2011). The measure 'Delta' is a proxy for pay-performance sensitivity and provides a broad measure for how well top executive incentives are aligned with shareholder interests (e.g., Fahlenbrach and Stulz 2011). It can also be interpreted as an indirect measure of risk-taking incentives. The effect of delta on collusion could be either positive or negative. On the one hand, a higher delta implies that the compensation scheme is more aligned with the shareholder interest (Liu and Mauer 2011). From here, it is possible to conclude that the more these are in line, the more shareholders are also interested in a collusive agreement if the manager has incentives for collusion. On the other hand, it could also be the case that high pay-performance sensitivity in the executive's compensation package incentivizes her to adopt less risky corporate policies (Liu and Mauer 2011). Moreover, a higher delta could be associated with a lower long-term orientation (e.g., O'Connor et al. 2013; Coles et al. 2006). This would make a collusive agreement less likely. Next, 'Vega', provides an explicit measure of the pay-for-risk sensitivity of executive compensation (e.g., Liu and Mauer 2011). Moreover, higher vega values could be associated with a stronger long-term orientation (e.g., Ellul et al. 2023; O'Connor et al. 2013; Coles et al. 2006). Using vega, we directly measure risk-taking incentives from the change in option holdings to changes in stock return volatility. Since option values increase with firm risk, even risk-averse executives may be more willing to take riskier actions like collusive agreements.

The results for applying 'Delta' and 'Vega' as measures for risk-taking are shown in Table 2.4, panels B and C. First, the OLS estimates for 'Delta' in panel B support the hypothesis that risk-taking and being part of a collusive agreement and starting one are associated with each other. However, there are no statistically significant effects for the IV estimates when it comes to starting a collusive agreement. The effects of terminating a cartel are not statistically relevant in either case (columns (5) and (6)). The results when applying 'Vega' as a proxy for managerial risk-taking are shown in Table 2.4, panel C. Our results align with the hypothesis stated above. We find positive and highly statistically significant effects for all models. This indicates that a larger vega value, or more precisely, more risk-taking incentives from option grants, is associated with a higher probability of being part of a cartel or starting one.

Overconfidence. Next, we consider the effect of managerial overconfidence, which is a behavioral bias of managers that usually refers to the underestimation of failure (e.g., Malmendier and Tate 2015). In that regard, it has been shown that overconfident managers tend to underestimate risk, which is discussed in various contexts like acquisitions (e.g., Malmendier and Tate 2008), innovation (e.g., Galasso and Simcoe 2011), and corporate investment (e.g., Malmendier and Tate 2005). In the context of collusion, we first expect that overconfident managers would underestimate the likelihood that the other firm would deviate. Moreover, second, they would underestimate the likelihood of being detected by the competition authority. Both situations would lead to managers which are more likely to engage in a collusive agreement as they underestimate the corresponding risks. Thus, overly confident managers tend to form and stabilize collusive agreements compared to less overconfident managers. In other words, overconfidence in managers leads to a higher probability of engaging and starting a collusive agreement. To determine the impact of CEO overconfidence on collusion, we follow the literature and classify a manager as overconfident if she held vested options until the year of expiration (Malmendier and Tate 2005; Malmendier and Tate 2015). We define the variable 'Longholder' accordingly. The results for the relationship between overconfidence and collusive behavior can be found in Table 2.4, panel A. From these, it becomes evident that there is a positive association between overconfidence and collusive behavior. However, it has to be noted that these relationships are not statistically different from zero if we instrument the respective variables.

Table 2.4: Results for taking into account risk-taking incentives within the compensation of CEOs

	(1)	(2)	(3)	(4)	(5)	(6)
	Cartel		Cartel start		Cartel end	
	OLS	IV	OLS	IV	OLS	IV
Panel A: Only equity part of long-term remuneration						
Incentives	0.053***	0.370***	0.009***	0.048**	0.009	0.382
	(0.012)	(0.095)	(0.003)	(0.019)	(0.068)	(0.288)
Observations	23,910	23,910	22,874	22,874	809	809
Panel B: Only long-term incentive plan part of long-term remuneration						
Incentives	0.037*	3.967**	-0.002	0.454**	-0.004	-1.164
	(0.022)	(1.884)	(0.006)	(0.230)	(0.117)	(1.086)
Observations	23,912	23,912	22,859	22,859	835	835
Panel C: CEO delta						
ln(CEO *Delta*)	0.021***	0.032**	0.004***	0.009	-0.003	0.118
	(0.004)	(0.015)	(0.001)	(0.005)	(0.013)	(0.106)
Observations	18,648	18,648	18,010	18,010	665	665
Panel D: CEO vega						
ln(CEO *Vega*)	0.015***	0.052***	0.002***	0.008**	0.018	0.123
	(0.003)	(0.015)	(0.001)	(0.003)	(0.013)	(0.092)
Observations	18,648	18,648	18,027	18,027	645	645
Panel E: CEO overconfidence						
Longholder	0.046***	0.033	0.008***	0.001	-0.024	-0.025
	(0.012)	(0.038)	(0.003)	(0.006)	(0.030)	(0.110)
Observations	9,460	9,460	8,992	8,992	499 499	
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
CEO controls	Yes	Yes	Yes	Yes	Yes	Yes
FE Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE Year	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the estimation results of the complementary log-log model of equation (2.1) and an IV approach by estimating equations (2.3) and (2.4). The coefficients display the marginal effects at the mean of all other explanatory variables. The measures of interest 'CEO *Delta*' and 'CEO *Vega*' are both lagged by one period. The table reflects two different analyses for each outcome: First, we analyze the main variable of interest 'CEO *Delta*', and second we include the other variable of interest 'CEO *Vega*'. The outcomes of each regression are three different indicators. 'Cartel' takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collusion period. 'Cartel formation' takes the value one only in the first period of a collusive agreement, zero for all periods a firm was not part of a cartel and missing otherwise. 'Cartel breakdown' indicates the very last period of a collusive agreement, zero for all cartel periods before within the collusion time and missing otherwise. Controls are applied as described in Section 2.3.3. The firm controls include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets as well as leverage. CEO controls include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

2.6 Conclusion

We investigate how incentive schemes of managers affect the anti-competitive behavior of firms. As a measure of anti-competitive behavior, we use detected cartel agreements. A benefit is that these are clear and quantifiable expressions of the anti-competitive behavior of firms. However, on the shortcoming side, it has to be noted that this sample of detected illegal activities might be biased as illegal activities are intended to remain hidden. While most studies analyzing collusive outcomes of firms focus on firm determinants, the top management is responsible for decisions like price-setting schemes and thus collusive behavior. As incentives for manager and owner differ, complex compensation schemes are implemented to incentivize the manager to act in the firm's best interest. This is mainly done by emphasizing long-term incentives within the remuneration schemes of the managers. In this way, a manager is incentivized to maximize a firm's long-term profits rather than short-term gains. In this study, we propose the hypothesis that managers with more weight on long-term incentives will be more likely to engage in anti-competitive behavior.

For our empirical test, we combine three main data sources: Compustat, ExecuComp, and John Connor's Database on Private International Cartels. Our robust empirical results imply that managers with stronger long-term incentives have a higher probability of (i) being part of a cartel and (ii) forming a cartel. In our analysis, we do not find (iii) any effect on the probability of ending a cartel, which indicates that these incentives are not the main driver of cartel termination. Taken together, we find strong evidence that top management remuneration schemes effectively enhance collusive behavior. This is not only found on an aggregate level but also in different manager positions, like CEOs and CFOs.

From the results of our analysis, different implications can be drawn. First, our findings are important for corporate governance. Long-term incentives allow owners to align the firm's interest to achieve high firm values with the manager's. The manager, however, might be incentivized to influence the size of her payment through illegal activities stemming from anti-competitive behavior like cartel agreements. This behavior might be beneficial from a private profit perspective but might yield negative effects from a social welfare perspective. While the latter might not be part of the maximization problem of the owner or manager, negative effects could even arise on the private level. Thus, the firm and its value could be affected negatively, for instance, by the detection by the competition authority (e.g., Bos et al. 2019).

A more alarming line of reasoning would be that the owner wants her manager to maximize firm profits regardless if this might involve illegal activities. In this case, long-term incentives seem to be an appropriate tool for facilitating unlawful behavior, like collusion, which can lead to significant consumer welfare losses. This, however, leads to direct implications of our results for competition authorities as top managers' remuneration schemes might also indicate collusive behavior. This is in line with studies that find that the existence of relative performance evaluation in CEO pay plans is highly correlated with collusive behavior (e.g., Bloomfield et al. 2023). Consequently, it might be worthwhile to consider the management remuneration schemes as another indicator in detecting cartels besides firm and market characteristics. The latter consideration might even be extended to other anti-competitive behaviors, such as abuse of a dominant position.

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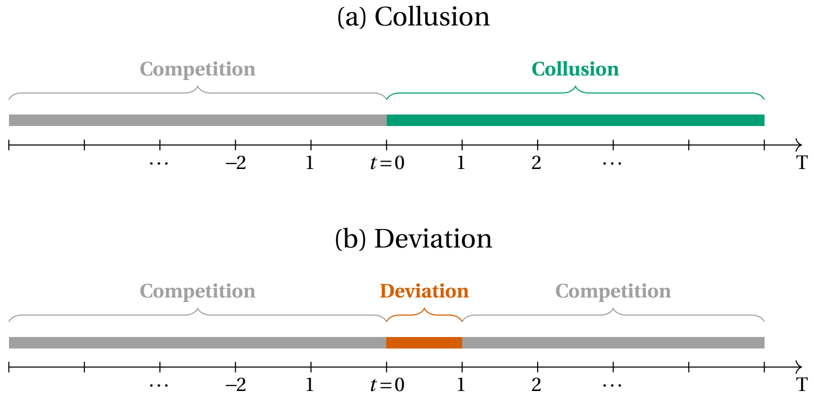
Appendix

2.A Stylized model

Our stylized statistic theoretical framework for investigating incentives for collusion follows studies like Harrington (1989), Spagnolo (2000), Spagnolo (2005), and Thépot (2019). It is based on the following simplified setting: We assume two symmetric firms are engaged in an infinitely repeated Bertrand competition. For the purpose of this framework, we define the profits π^N, π^C, and π^D as the firm profits in a symmetric duopoly (π^N), in the collusive equilibrium (π^C) and in the case of deviation (π^D) of the firm. The ranking of the value of these firm profits is assumed to be as follows $\pi^D > \pi^C > \pi^N$.

Figure 2.A1 shows the general timing of the firm strategies. A firm can choose between the following three actions: compete, collude, or deviate. In a competition setting, the firm will play competition and thus gain π^N in all past and future periods. Once the firm decides in favor of a collusive outcome, she will play collusion for all future periods, gaining profits π^C. This strategy is displayed in panel (a). When choosing deviation, the firm chooses to deviate from the agreement on a certain price with the other colluding firm. Panel (b) in Figure 2.A1 shows the timing if a firm directly chooses to deviate from a collusive agreement. It is also possible to model this case by first playing the collusive outcome for a couple of periods and then letting one firm deviate. Assuming risk-neutral and profit-maximizing agents, there is, however, no reason for the manager to suddenly deviate. Thus, she would either deviate in the first period or never. We assume in any case that if a firm deviates, the other firm(s) will punish her with a grim trigger strategy so that afterward, all firms gain the competitive outcome.

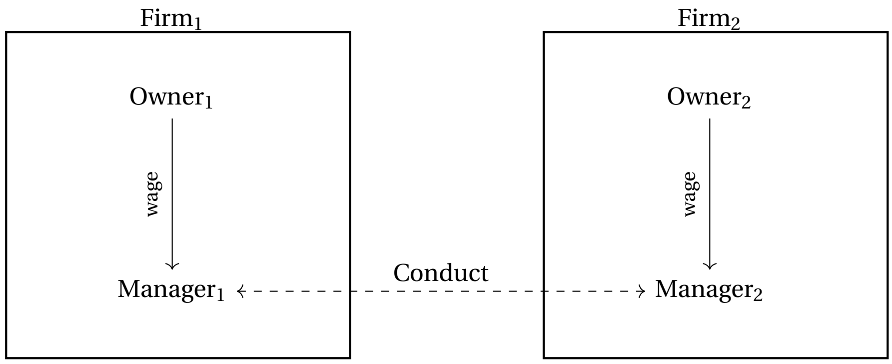
Figure 2.A1: General timing



Note: This figure illustrates the timing in our model. Panel (a) shows the timing for a collusive agreement at time t. We assume that once played collusion, firms stick to that strategy. Panel (b) illustrates the timing for the deviating strategy. As soon as one firm deviates from a collusive agreement, the other firm punishes by playing a grim trigger strategy. Thus, we assume that once deviated, the firms play Nash equilibrium, i.e. competition, from then on. Panel (b) could also be illustrated in a way that firms firstly play competition for a couple of rounds and only after these, a firm will deviate. This does not change our results. In both scenarios, we assume an infinite horizon in the past as well as in the future.

When it comes to cartel formation, it is important to consider the firm structure. Each firm is owned by a principal (owner) and run by an agent (manager). While the owner set general goals for the firm, the manager is expected to implement and execute the strategies to fulfill the firm's goals. She is responsible for the implementation and realization of the firm's profits and therefore able to influence output and pricing. This constellation may lead to a principal-agent problem due to asymmetric information: The owner is not aware of how the profits are generated as well as how the firm's goals are reached. Thus, the manager may generate profits due to conduct between her and managers of other firms. This multidimensional system of principals and agents is illustrated for the case of a duopoly in Figure 2.A2.

Figure 2.A2: Multidimensional principal-agent system



Note: This figure illustrates the multidimensional principal-agent system that is in place when having at least two owners and two managers.

For the remainder of the theoretical framework, we assume both managers and owners act rationally. Additionally and for the sake of simplicity, we assume them to be risk neutral and to maximize their expected payoff. The owner imposes a remuneration scheme of the following form to provide the manager incentives to maximize firm profits. The manager's wage w is composed of the weighted sum of a short-term and long-term part, which both are dependent on the firm's outcome π_i. The respective weight $\tau \in (0,1)$ reflects the reliance on the firm's short-term profits. Accordingly, $(1-\tau)$ determines the weight of long-term profits. Thus, the manager's wage w is the sum of the weighted wage parts from short-term profits (w_s) and long-term profits (w_l):

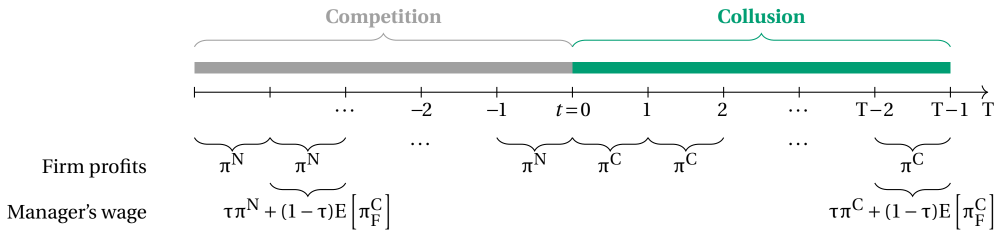
$$w = \underbrace{(\tau) \times \pi_s}_{w_s} + \underbrace{(1-\tau) \times \pi_l}_{w_l}, \tag{2.1}$$

where π_s denotes the payoffs of the firm in period t. The term π_l represents the future profit expected by the manager. This expectation depends on the firm's profits in future periods. The manager's valuation for any action A can be described as the sum of all wages she is gaining when playing action A, thus:

$$V^A = w_t^A + \delta w_{t+1}^A + \delta^2 w_{t+2}^A + \delta^3 w_{t+3}^A + \cdots. \tag{2.2}$$

Valuation of collusion. In the first step, we determine the manager's gains from collusion. Before turning to the analytical solution, an illustration of the gains for the manager is given in Figure 2.A3. It shows a timeline including the firm's profits on which the manager bases her consideration according to her wage. In the pre-collusion period ($t < 0$), the manager's wage consideration consists of a share of the short-term firm profits π^{N} and the expected future profits $\pi_{l} = \mathrm{E}\left[\pi_{F}^{C}\right]$, achieved in the long run. In the first period after the collusive agreement was put into place ($t = 1$), the manager gains the collusive profits π^{C} in the short-term and $\mathrm{E}\left[\pi_{F}^{C}\right]$ as long-run profits. While the elements of the first period and before are the same, the manager gains collusive profits in period $t = 1$ and all following.

Figure 2.A3: Manager's wage for collusion dependent on firm profits



Note: This figure illustrates the manager's considerations depending on the firm's profits in a collusive setting. We define the profits π^{N}, π^{C}, and π^{D} as the firm profit in a symmetric duopoly (π^{N}), in the collusive equilibrium (π^{C}) and in the case of deviation of the firm while the other firm sticks to the collusive price (π^{D}). The ranking of the value of these firm profits is assumed to be as follows $\pi^{D} > \pi^{C} > \pi^{N}$.

Taking these considerations into account, it is possible to depict the incentives for collusion of the individual manager, dependent on the weight of the manager's wage on short-term profits τ. Thus, we turn to the determination of incentives for managers to engage in collusion conditional on their emphasis on short- and long-term profits. The manager's valuation for collusion can be described as the sum of all wages she is gaining when playing collusion, thus:

$$V^{C} = w_{t}^{C} + \delta w_{t+1}^{C} + \delta^{2} w_{t+2}^{C} + \delta^{3} w_{t+3}^{C} + \cdots . \tag{2.3}$$

Accordingly, we replace w^{C} with the weighted wage from equation (2.1), so that

$w^{C} = \tau\pi^{C} + (1-\tau)\mathrm{E}\left[\pi_{F}^{C}\right]$. After rearranging, the manager's valuation of a collusive agreement is depicted as follows:

$$V^{C} = \sum_{t=0}^{T} \delta^{t} \left(\tau\pi^{C} + (1-\tau)\mathrm{E}\left[\pi_{F}^{C}\right]\right), \tag{2.4}$$

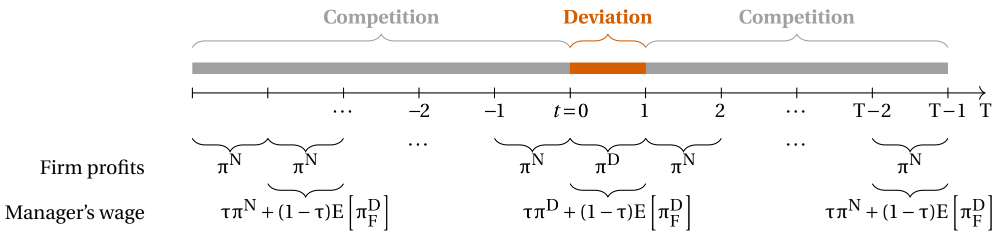
where $\tau\pi^{C} + (1-\tau)\mathrm{E}\left[\pi_{F}^{C}\right]$ illustrates the manager's gain from collusion in the first period and all following $T-1$ periods. It consists of the weighted short-term benefit $\tau\pi^{C}$ and the weighted long-term profits from previous periods $(1-\tau)\mathrm{E}\left[\pi_{F}^{C}\right]$.

Valuation of deviation. For the case of deviating[46] from the collusive agreement, the profits from the perspective of the manager are depicted in Figure 2.A4. Again, the figure shows managers' considerations in dependence on firm profits. The expected future profits before the collusive agreement might take place are expressed by $\mathrm{E}\left[\pi_{F}^{D}\right]$. When deviating, the profit in the first period is now denoted by π^{D}. Thus, these profits represent the case of deviating, while the other firm sticks to the collusive outcome in the first period. In this period, the manager gains a share of the long-term profits $\mathrm{E}\left[\pi_{F}^{D}\right]$ and the short-term profits π^{D}.

Moreover, the figure shows the situation in the period $T-1$ after the deviation took place. We assume a grim trigger strategy of the non-deviating firm. That means, once deviated, the other firm will punish the deviating firm by playing the competition outcome in the first period after deviation and for every following period. In this period, the firm's profits are equal to π^{N} due to the punishment of the deviation. Consequently, the manager earns a share of the short-term gains π^{N} and the long-term firm profits $\mathrm{E}\left[\pi_{F}^{D}\right]$.

[46]The general timing of deviation is given in Figure 2.A1, panel (b) in Appendix 2.A.

Figure 2.A4: Manager's considerations for deviation



Note: This figure illustrates the manager's considerations depending on the firm's profits in a deviation setting. We define the profits π^N, π^C, and π^D as the firm profit in a symmetric duopoly (π^N), in the collusive equilibrium (π^C) and in the case of deviation of the firm while the other firm sticks to the collusive price (π^D). The ranking of the value of these firm profits is assumed to be as follows $\pi^D > \pi^C > \pi^N$.

Taking these profit situations into account, the valuation of deviation from the collusive agreement by the manager is depicted by the following equation:

$$V^D = \tau\pi^D + (1-\tau)\,E\left[\pi_F^D\right] + \sum_{t=1}^{T} \delta^t \left(\tau\pi^N + (1-\tau)E\left[\pi_F^D\right]\right), \tag{2.5}$$

where we observe, again, two parts of the valuation of deviation by the manager. However, different from equation (2.4), in equation (2.5), the manager now gains short-term earnings $\tau\pi^D$ in the first period when she is deviating from the collusive agreement. As shown above, this short-term evaluation for deviating is larger than the short-term profits from collusion. From her remuneration scheme, the manager also earns the weighted future deviation profits $E\left[\pi_F^D\right]$ in the first deviation period. The second difference appears when looking at the future payoffs. Thus, the manager only earns short-term profits $\tau\pi^N$ in future periods. The weighted long-term profits are depicted as $(1-\tau)E\left[\pi_F^D\right]$.

Incentives for collusion. To determine the incentives to engage in a collusive agreement, we compare the valuation of collusion to the valuation of deviation. By determining the critical discount factor δ, it is possible to find the threshold level where collusion will be facilitated. Moreover, we determine the role of the parameter τ, which represents the manager's reliance on short-term profits. To achieve a stable collusive agreement the following relation has to hold:

$$V^C > V^D. \tag{2.6}$$

It implies that the manager has a larger value from collusion than from deviating from the agreement. Otherwise, a manager would deviate from a collusive agreement, and, thus, collusion is not stable. Inserting equations (2.4) and (2.5) in equation (2.6) and rearranging the terms to δ leads to

$$\delta > \frac{\tau(\pi^D - \pi^C) + (1-\tau)(E\left[\pi_F^D\right] - E\left[\pi_F^C\right])}{\tau(\pi^D - \pi^N)} \equiv \bar{\delta}, \tag{2.7}$$

which defines the discount factor $\bar{\delta}$ at which collusion is facilitated. Equation (2.7) clearly implies that this discount factor depends on the parameter τ. In addition, it does not only depend on the short-term but also long-term profits ($E\left[\pi_F^C\right]$ and $E\left[\pi_F^D\right]$) the manager earns. Thus, we determine whether the incentives for collusion depend on our parameter of interest, the dependency on long-term profits (τ). Using the generalized critical discount factor determined in equation (2.7), it could be shown that it increases with a higher emphasis on the short-term components of the remuneration package (i.e., $\frac{\partial \bar{\delta}}{\partial \tau} > 0$). This makes collusion less likely. Moreover, this result aligns with the finding in Spagnolo (2000) that higher stock-oriented compensation (long-term incentives) increases the incentives for collusion as it reduces the short-run gains from deviation. Thus, we can conclude that collusion is easier to sustain for a higher emphasis on long-term profits (lower values of τ).

2.B Additional tables

First-stage regression results

Table 2.B1: First-stage regression results using shift-share instruments - baseline results

	(1) Cartel	(2) Cartel start	(3) Cartel end
Panel A: Without firm and CEO control variables			
Shift-share IV	0.399***	0.394***	0.225**
	(0.027)	(0.028)	(0.096)
First-stage F-statistic	215.450	197.506	5.509
Observations	24,319	23,485	863
Panel B: With firm and CEO control variables			
Shift-share IV	0.412***	0.409***	0.206**
	(0.027)	(0.028)	(0.095)
First-stage F-statistic	234.247	218.054	4.729
Observations	24,319	23,485	863
Firm controls	Yes	Yes	Yes
CEO controls	Yes	Yes	Yes
FE Industry	Yes	Yes	Yes
FE Year	Yes	Yes	Yes

Note: This table shows the estimation results of a linear regression model. The coefficients display the first-stage results of the instrumental variable approach as described in Section 2.3.3. The endogenous variable of interest 'Long-term incentives' is calculated as the share of long-term remuneration parts over total compensation. The outcome is an indicator 'Cartel' that takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collusion period (column (1)). The outcome in column (2) is an indicator 'Cartel start' that takes the value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement started. For column (3), the outcome is an indicator 'Cartel end' that takes the value one for a firm that is part of a collusive agreement at the point in time when the last period of a collusive agreement is reached. Controls are applied as described in Section 2.3.3. The firm controls in panel B include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets as well as leverage. CEO controls in panel B include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 2.B2: First-stage regression results using shift-share instruments - manager position

	(1) Cartel	(2) Cartel start	(3) Cartel end
Panel A: All executives			
Shift-share IV	0.412***	0.409***	0.206**
	(0.027)	(0.028)	(0.095)
First-stage F-statistic	234.247	218.054	4.729
Observations	24,319	23,485	863
Panel B: Non-CEOs only			
Shift-share IV	0.386***	0.381***	0.193*
	(0.026)	(0.027)	(0.097)
First-stage F-statistic	215.365	199.331	3.916
Observations	24,057	23,225	861
Panel C: CEOs only			
Shift-share IV	0.468***	0.471***	0.135
	(0.030)	(0.030)	(0.109)
First-stage F-statistic	249.807	241.061	1.527
Observations	24,319	23,485	863
Panel D: CFOs only			
Shift-share IV	0.366***	0.361***	0.322***
	(0.030)	(0.031)	(0.109)
First-stage F-statistic	149.319	139.930	8.757
Observations	15,519	15,094	434
Panel E: COOs only			
Shift-share IV	0.355***	0.353***	0.206
	(0.039)	(0.041)	(0.175)
First-stage F-statistic	81.205	74.206	1.393
Observations	7,334	7,122	227
Firm controls	Yes	Yes	Yes
CEO controls	Yes	Yes	Yes
FE Industry	Yes	Yes	Yes
FE Year	Yes	Yes	Yes

Note: This table shows the estimation results of a linear regression model. The coefficients display the first-stage results of the instrumental variable approach as described in Section 2.3.3. The endogenous variable of interest 'Long-term incentives' is calculated as the share of long-term remuneration parts over total compensation. The outcome is an indicator 'Cartel' that takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collusion period (column (1)). The outcome in column (2) is an indicator 'Cartel start' that takes the value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement started. For column (3), the outcome is an indicator 'Cartel end' that takes the value one for a firm that is part of a collusive agreement at the point in time when the last period of a collusive agreement is reached. Controls are applied as described in Section 2.3.3. The firm controls include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets as well as leverage. CEO controls include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 2.B3: First-stage regression results using shift-share instruments - equity compensation and risk-taking

	(1) Cartel	(2) Cartel start	(3) Cartel end
Panel A: Only equity part of long-term remuneration			
Shift-share IV	0.362***	0.357***	0.355***
	(0.025)	(0.026)	(0.085)
First-stage F-statistic	201.453	184.218	17.611
Observations	23,433	22,643	809
Panel B: Only long-term incentive plan part of long-term remuneration			
Shift-share IV	0.039***	0.042***	-0.109*
	(0.013)	(0.013)	(0.055)
First-stage F-statistic	9.668	10.792	3.909
Observations	23,436	22,633	835
Panel C: CEO Delta			
Shift-share IV	0.001***	0.001***	0.001**
	(0.000)	(0.000)	(0.000)
First-stage F-statistic	245.873	229.544	5.474
Observations	18,836	18,167	698
Panel D: CEO Vega			
Shift-share IV	0.010***	0.010***	0.004**
	(0.001)	(0.001)	(0.002)
First-stage F-statistic	254.745	265.457	5.289
Observations	18,836	18,167	698
Firm controls	Yes	Yes	Yes
CEO controls	Yes	Yes	Yes
FE Industry	Yes	Yes	Yes
FE Year	Yes	Yes	Yes

Note: This table shows the estimation results of a linear regression model. The coefficients display the first-stage results of the instrumental variable approach as described in Section 2.3.3. The endogenous variable of interest 'Long-term incentives' is calculated as the share of long-term remuneration parts over total compensation. The outcome is an indicator 'Cartel' that takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collusion period (column (1)). The outcome in column (2) is an indicator 'Cartel start' that takes the value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement started. For column (3), the outcome is an indicator 'Cartel end' that takes the value one for a firm that is part of a collusive agreement at the point in time when the last period of a collusive agreement is reached. Controls are applied as described in Section 2.3.3. The firm controls include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets as well as leverage. CEO controls include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

2.C Results of robustness and sensitivity tests

Accounting for the binary nature of the outcome variables

Table 2.C1: Applying estimation methodologies to account for binary dependent variables

	(1)	(2)	(3)	(4)	(5)	(6)
	Cartel		Cartel start		Cartel end	
	Binary	Binary IV	Binary	Binary IV	Binary	Binary IV
Panel A: Probit						
Incentives	0.057***	0.223***	0.009***	0.028***	-0.046	0.455**
	(0.010)	(0.023)	(0.002)	(0.008)	(0.065)	(0.216)
Observations	24,649	24,649	21,544	21,544	869	869
Panel B: Complementary log-log						
Incentives	0.050***	0.185***	0.008***	0.025***	-0.040	0.337*
	(0.009)	(0.020)	(0.002)	(0.007)	(0.053)	(0.174)
Observations	24,649	24,649	21,544	21,544	869	869
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
CEO controls	Yes	Yes	Yes	Yes	Yes	Yes
FE Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE Year	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the estimation results of a non-linear regression model of equation (2.1) and an IV approach by estimating equations (2.3) and (2.4). The coefficients for the IV estimates are obtained by instrumenting the long-term remuneration share on the firm level by shift-share instruments as described in Section 2.3.3. The measure of interest 'Incentives' is calculated as the share of long-term remuneration parts over total compensation. The first outcome is an indicator 'Cartel' that takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collusion period (columns (1) and (2)). The outcome in columns (3) and (4) is an indicator 'Cartel start' that takes the value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement started. For columns (5) and (6), the outcome is an indicator 'Cartel end' that takes the value one for a firm that is part of a collusive agreement at the point in time when the last period of a collusive agreement is reached. Controls are applied as described in Section 2.3.3. The firm controls include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets as well as leverage. CEO controls include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Definition of the outcome variables

Table 2.C2: Including non-cartel observations that are least likely to collude

	(1)	(2)	(3)	(4)
	Cartel		Cartel start	
	OLS	IV	OLS	IV
Panel A: At least one period with a less than 5 percent probability colluding				
Incentives	0.067***	0.325***	0.009***	0.041**
	(0.011)	(0.086)	(0.003)	(0.017)
Observations	23,579	23,579	22,770	22,770
Panel B: Maximum is 5 percent probability colluding over time				
Incentives	0.108***	0.620***	0.018***	0.103***
	(0.017)	(0.137)	(0.005)	(0.034)
Observations	12,701	12,701	11,892	11,892
Panel C: Periods with a less than 5 percent probability colluding				
Incentives	0.078***	0.381***	0.012***	0.053**
	(0.013)	(0.097)	(0.003)	(0.021)
Observations	19,126	19,126	18,317	18,317
Firm controls	Yes	Yes	Yes	Yes
CEO controls	Yes	Yes	Yes	Yes
FE Industry	Yes	Yes	Yes	Yes
FE Year	Yes	Yes	Yes	Yes

Note: This table shows the estimation results of a non-linear regression model of equation (2.1) and an IV approach by estimating equations (2.3) and (2.4). The coefficients for the IV estimates are obtained by instrumenting the long-term remuneration share on the firm level by shift-share instruments as described in Section 2.3.3. The measure of interest 'Incentives' is calculated as the share of long-term remuneration parts over total compensation. The first outcome is an indicator 'Cartel' that takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collusion period (columns (1) and (2)). The outcome in columns (3) and (4) is an indicator 'Cartel start' that takes the value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement started. Controls are applied as described in Section 2.3.3. The firm controls include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets as well as leverage. CEO controls include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 2.C3: First-stage regression results handling the outcome variable

	(1) Cartel	(2) Cartel start
Panel A: At least one period with a less than 5 percent probability colluding		
Shift-share IV	0.414***	0.411***
	(0.027)	(0.028)
First-stage F-statistic	231.830	215.059
Observations	23,819	22,985
Panel B: Maximum is 5 percent probability colluding over time		
Shift-share IV	0.421***	0.412***
	(0.039)	(0.041)
First-stage F-statistic	119.207	99.181
Observations	12,851	12,017
Panel C: Periods with a less than 5 percent probability colluding		
Shift-share IV	0.401***	0.395***
	(0.030)	(0.031)
First-stage F-statistic	182.441	165.062
Observations	19,331	18,497
Firm controls	Yes	Yes
CEO controls	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes

Note: This table shows the estimation results of a linear regression model. The coefficients display the first-stage results of the instrumental variable approach as described in Section 2.3.3. The endogenous variable of interest 'Long-term incentives' is calculated as the share of long-term remuneration parts over total compensation. The outcome is an indicator 'Cartel' that takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collusion period (column (1)). The outcome in column (2) is an indicator 'Cartel start' that takes the value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement started. Controls are applied as described in Section 2.3.3. The firm controls include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets as well as leverage. CEO controls include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Definition of the incentive variable

Table 2.C4: Regression results using the share of long-term remuneration of the present year

	(1)	(2)	(3)	(4)	(5)	(6)
	Cartel		Cartel start		Cartel end	
	OLS	IV	OLS	IV	OLS	IV
Incentives	0.056***	0.206***	0.007***	0.029**	0.061	0.656
	(0.010)	(0.073)	(0.002)	(0.013)	(0.060)	(0.610)
Observations	23,930	23,930	23,139	23,139	805	805
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
CEO controls	Yes	Yes	Yes	Yes	Yes	Yes
FE Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE Year	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the estimation results of a linear regression model of equation (2.1) and an IV approach by estimating equations (2.3) and (2.4). The coefficients for the IV estimates are obtained by instrumenting the long-term remuneration share on the firm level by shift-share instruments as described in Section 2.3.3. The measure of interest 'Incentives' is calculated as the share of long-term remuneration parts over total compensation. The first outcome is an indicator 'Cartel' that takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collusion period (columns (1) and (2)). The outcome in columns (3) and (4) is an indicator 'Cartel start' that takes the value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement started. For columns (5) and (6), the outcome is an indicator 'Cartel end' that takes the value one for a firm that is part of a collusive agreement at the point in time when the last period of a collusive agreement is reached. Controls are applied as described in Section 2.3.3. The firm controls include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets as well as leverage. CEO controls include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 2.C5: First-stage regression results using the share of long-term remuneration of the present year

	(1) Cartel	(2) Cartel start	(3) Cartel end
Incentives	0.382***	0.382***	0.134
	(0.026)	(0.027)	(0.096)
First-stage F-statistic	216.746	204.805	1.924
Observations	23,920	23,090	856
Firm controls	Yes	Yes	Yes
CEO controls	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes

Note: This table shows the estimation results of a linear regression model. The coefficients display the first-stage results of the instrumental variable approach as described in Section 2.3.3. The endogenous variable of interest 'Long-term incentives' is calculated as the share of long-term remuneration parts over total compensation. The outcome is an indicator 'Cartel' that takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collusion period (column (1)). The outcome in column (2) is an indicator 'Cartel start' that takes the value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement started. For column (3), the outcome is an indicator 'Cartel end' that takes the value one for a firm that is part of a collusive agreement at the point in time when the last period of a collusive agreement is reached. Controls are applied as described in Section 2.3.3. The firm controls include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets as well as leverage. CEO controls include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 2.C6: Regression results handling the incentives variable

	(1)	(2)	(3)	(4)	(5)	(6)
	Cartel		Cartel start		Cartel end	
	OLS	IV	OLS	IV	OLS	IV
Panel A: Excluding bonus from short-term remuneration						
Incentives	0.078***	0.321***	0.012***	0.038**	0.014	0.950
	(0.012)	(0.084)	(0.003)	(0.015)	(0.075)	(0.755)
Observations	24,076	24,076	23,272	23,272	830	830
Panel B: Including bonus in long-term remuneration						
Incentives	0.089***	0.375***	0.012***	0.044**	0.008	1.208
	(0.014)	(0.098)	(0.003)	(0.017)	(0.094)	(1.167)
Observations	24,076	24,076	23,278	23,278	824	824
Panel C: Scaling long-term remuneration by variable remuneration						
Incentives	0.026***	0.717***	0.003	0.092**	0.041	1.680
	(0.008)	(0.203)	(0.002)	(0.036)	(0.068)	(1.663)
Observations	24,045	24,045	23,221	23,221	852	852
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
CEO controls	Yes	Yes	Yes	Yes	Yes	Yes
FE Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE Year	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the estimation results of a linear regression model of equation (2.1) and an IV approach by estimating equations (2.3) and (2.4). The coefficients for the IV estimates are obtained by instrumenting the long-term remuneration share on the firm level by shift-share instruments as described in Section 2.3.3. The measure of interest 'Incentives' is calculated as the share of long-term remuneration parts over total compensation. The first outcome is an indicator 'Cartel' that takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collusion period (columns (1) and (2)). The outcome in columns (3) and (4) is an indicator 'Cartel start' that takes the value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement started. For columns (5) and (6), the outcome is an indicator 'Cartel end' that takes the value one for a firm that is part of a collusive agreement at the point in time when the last period of a collusive agreement is reached. Controls are applied as described in Section 2.3.3. The firm controls include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets as well as leverage. CEO controls include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 2.C7: First-stage regression results handling the incentives variable

	(1) Cartel	(2) Cartel start	(3) Cartel end
Panel A: Excluding bonus from short-term remuneration			
Shift-share IV	0.423***	0.420***	0.179*
	(0.027)	(0.028)	(0.094)
First-stage F-statistic	247.308	232.787	3.666
Observations	24,319	23,485	863
Panel B: Including bonus in long-term remuneration			
Shift-share IV	0.361***	0.359***	0.128
	(0.023)	(0.024)	(0.082)
First-stage F-statistic	236.066	223.913	2.423
Observations	24,319	23,485	863
Panel C: Scaling long-term remuneration by variable remuneration			
Shift-share IV	0.191***	0.190***	0.102
	(0.024)	(0.025)	(0.089)
First-stage F-statistic	64.363	60.010	1.303
Observations	24,287	23,453	863
Firm controls	Yes	Yes	Yes
CEO controls	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes

Note: This table shows the estimation results of a linear regression model. The coefficients display the first-stage results of the instrumental variable approach as described in Section 2.3.3. The endogenous variable of interest 'Long-term incentives' is calculated as the share of long-term remuneration parts over total compensation. The outcome is an indicator 'Cartel' that takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collusion period (column (1)). The outcome in column (2) is an indicator 'Cartel start' that takes the value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement started. For column (3), the outcome is an indicator 'Cartel end' that takes the value one for a firm that is part of a collusive agreement at the point in time when the last period of a collusive agreement is reached. Controls are applied as described in Section 2.3.3. The firm controls include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets as well as leverage. CEO controls include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 2.C8: Regression results applying dummy variables for long-term incentives

	(1)	(2)	(3)	(4)	(5)	(6)
	Cartel		Cartel start		Cartel end	
	OLS	IV	OLS	IV	OLS	IV
Panel A: Long-term incentive share not in the lower quartile of the distribution						
Incentives	0.026***	0.270***	0.004***	0.033**	-0.018	0.406
	(0.004)	(0.073)	(0.001)	(0.013)	(0.031)	(0.314)
Panel B: Above median long-term incentive share						
Incentives	0.023***	0.174***	0.002**	0.022**	-0.023	0.426
	(0.005)	(0.046)	(0.001)	(0.009)	(0.024)	(0.380)
Panel C: Long-term incentive share in the upper quartile of the distribution						
Incentives	0.019***	0.202***	0.003**	0.025**	-0.025	1.911
	(0.006)	(0.056)	(0.001)	(0.010)	(0.031)	(6.069)
Observations	24,649	24,236	23,804	23,417	870	844
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
CEO controls	Yes	Yes	Yes	Yes	Yes	Yes
FE Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE Year	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the estimation results of a linear regression model of equation (2.1) and an IV approach by estimating equations (2.3) and (2.4). The coefficients for the IV estimates are obtained by instrumenting the long-term remuneration share on the firm level by shift-share instruments as described in Section 2.3.3. The measure of interest 'Incentives' is calculated as the share of long-term remuneration parts over total compensation. The first outcome is an indicator 'Cartel' that takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collusion period (columns (1) and (2)). The outcome in columns (3) and (4) is an indicator 'Cartel start' that takes the value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement started. For columns (5) and (6), the outcome is an indicator 'Cartel end' that takes the value one for a firm that is part of a collusive agreement at the point in time when the last period of a collusive agreement is reached. Controls are applied as described in Section 2.3.3. The firm controls include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets, and leverage. CEO controls include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 2.C9: First-stage regression results for the dummy variable specifications

	(1) Cartel	(2) Cartel start	(3) Cartel end
Panel A: Long-term incentive share not in the lower quartile of the distribution			
Shift-share IV	0.507***	0.513***	0.330*
	(0.039)	(0.040)	(0.196)
First-stage F-statistic	165.688	160.878	2.848
Observations	24,483	23,638	872
Panel B: Above median long-term incentive share			
Shift-share IV	0.787***	0.778***	0.342
	(0.052)	(0.053)	(0.240)
First-stage F-statistic	231.263	214.213	2.024
Observations	24,483	23,638	872
Panel C: Long-term incentive share in the upper quartile of the distribution			
Shift-share IV	0.684***	0.683***	0.128
	(0.057)	(0.058)	(0.238)
First-stage F-statistic	145.041	139.688	0.288
Observations	24,483	23,638	872
Firm controls	Yes	Yes	Yes
CEO controls	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes

Note: This table shows the estimation results of a linear regression model. The coefficients display the first-stage results of the instrumental variable approach as described in Section 2.3.3. The endogenous variable of interest 'Long-term incentives' is calculated as the share of long-term remuneration parts over total compensation. The outcome is an indicator 'Cartel' that takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collusion period (column (1)). The outcome in column (2) is an indicator 'Cartel start' that takes the value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement started. For column (3), the outcome is an indicator 'Cartel end' that takes the value one for a firm that is part of a collusive agreement at the point in time when the last period of a collusive agreement is reached. Controls are applied as described in Section 2.3.3. The firm controls include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets as well as leverage. CEO controls include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Alternative instruments

Table 2.C10: Marginal tax rate as additional instrument

	(1)	(2)	(3)	(4)	(5)	(6)
	Cartel		Cartel start		Cartel end	
	OLS	IV	OLS	IV	OLS	IV
Incentives	0.074***	0.352***	0.008**	0.045**	-0.061	0.660
	(0.014)	(0.105)	(0.003)	(0.021)	(0.078)	(0.480)
Hansen J statistic (p-value)		0.731		0.755		0.348
Observations	15,986	15,986	15,446	15,446	569	569
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
CEO controls	Yes	Yes	Yes	Yes	Yes	Yes
FE Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE Year	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the estimation results of a linear regression model of equation (2.1) and an IV approach by estimating equations (2.3) and (2.4). The coefficients for the IV estimates are obtained by instrumenting the long-term remuneration share on the firm level by shift-share instruments as described in Section 2.3.3 and the marginal tax rate instrument as described in Section 2.4.2. The measure of interest 'Incentives' is calculated as the share of long-term remuneration parts over total compensation. The first outcome is an indicator 'Cartel' that takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collusion period (columns (1) and (2)). The outcome in columns (3) and (4) is an indicator 'Cartel start' that takes the value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement started. For columns (5) and (6), the outcome is an indicator 'Cartel end' that takes the value one for a firm that is part of a collusive agreement at the point in time when the last period of a collusive agreement is reached. Controls are applied as described in Section 2.3.3. The firm controls include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets as well as leverage. CEO controls include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 2.C11: First-stage regression results for the marginal tax rate as additional instrument

	(1) Cartel	(2) Cartel start	(3) Cartel end
Incentives	0.344***	0.334***	0.261***
	(0.031)	(0.032)	(0.099)
Tax-loss carryforward	0.039***	0.039***	0.018
	(0.007)	(0.007)	(0.031)
First-stage F-statistic	88.944	82.874	3.496
Observations	16,147	15,593	583
Firm controls	Yes	Yes	Yes
CEO controls	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes

Note: This table shows the estimation results of a linear regression model. The coefficients display the first-stage results of the instrumental variable approach as described in Section 2.4.2. The endogenous variable of interest 'Long-term incentives' is calculated as the share of long-term remuneration parts over total compensation. The instrument 'Tax-loss carryforward' takes value one if the firm reported a tax loss carryforward in any of the three years preceding the year used to calculate the long term incentive share. The outcome is an indicator 'Cartel' that takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collusion period (column (1)). The outcome in column (2) is an indicator 'Cartel start' that takes the value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement started. For column (3), the outcome is an indicator 'Cartel end' that takes the value one for a firm that is part of a collusive agreement at the point in time when the last period of a collusive agreement is reached. Controls are applied as described in Section 2.3.3. The firm controls include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets as well as leverage. CEO controls include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 2.C12: Lagged instruments

	(1)	(2)	(3)	(4)	(5)	(6)
	Cartel		Cartel start		Cartel end	
	OLS	IV	OLS	IV	OLS	IV
Panel A: Fourth lag as instrument						
Incentives	0.088***	0.213***	0.018***	0.040***	0.087	-0.030
	(0.020)	(0.046)	(0.004)	(0.011)	(0.111)	(0.296)
Observations	10,340	10,340	9,858	9,858	487	487
Panel B: Fifth lag as instrument						
Incentives	0.083***	0.254***	0.015***	0.052***	0.105	0.727***
	(0.024)	(0.060)	(0.006)	(0.014)	(0.111)	(0.264)
Observations	7,923	7,923	7,524	7,524	397	397
Panel C: Fourth and fifth lags as instruments						
Incentives	0.091**	0.291***	0.014**	0.037**	0.029	0.361
	(0.036)	(0.085)	(0.007)	(0.018)	(0.155)	(0.387)
Observations	4,252	4,252	4,008	4,008	229	229
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
CEO controls	Yes	Yes	Yes	Yes	Yes	Yes
FE Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE Year	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the estimation results of a linear regression model of equation (2.1) and an IV approach by estimating equations (2.3) and (2.4). The coefficients for the IV estimates are obtained by instrumenting the long-term remuneration share on the firm level by lagged instruments as described in Section 2.4.2. The measure of interest 'Incentives' is calculated as the share of long-term remuneration parts over total compensation. The first outcome is an indicator 'Cartel' that takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collusion period (columns (1) and (2)). The outcome in columns (3) and (4) is an indicator 'Cartel start' that takes the value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement started. For columns (5) and (6), the outcome is an indicator 'Cartel end' that takes the value one for a firm that is part of a collusive agreement at the point in time when the last period of a collusive agreement is reached. Controls are applied as described in Section 2.3.3. The firm controls include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets as well as leverage. CEO controls include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 2.C13: First-stage regression results for the lagged instruments specifications

	(1) Cartel	(2) Cartel start	(3) Cartel end
Panel A: Fourth lag as instrument			
Incentives$_{t-4}$	0.439***	0.438***	0.381***
	(0.014)	(0.014)	(0.072)
First-stage F-statistic	1028.247	979.302	30.934
Observations	10,444	9,945	503
Panel B: Fifth lag as instrument			
Incentives$_{t-5}$	0.378***	0.376***	0.367***
	(0.015)	(0.015)	(0.071)
First-stage F-statistic	621.464	590.621	28.992
Observations	7,982	7,568	411
Panel C: Fourth and fifth lags as instruments			
Incentives$_{t-4}$	0.284***	0.285***	0.204*
	(0.020)	(0.020)	(0.114)
Incentives$_{t-5}$	0.200***	0.200***	0.191**
	(0.017)	(0.017)	(0.093)
First-stage F-statistic	213.429	199.004	9.089
Hansen J-statistic	3.388	0.304	1.033
(p-value)	0.066	0.581	0.309
Observations	4,274	4,024	233
Firm controls	Yes	Yes	Yes
CEO controls	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes

Note: This table shows the estimation results of a linear regression model. The coefficients display the first-stage results of the instrumental variable approach as described in Section 2.4.2. The endogenous variable of interest 'Long-term incentives' is calculated as the share of long-term remuneration parts over total compensation. The outcome is an indicator 'Cartel' that takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collusion period (column (1)). The outcome in column (2) is an indicator 'Cartel start' that takes the value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement started. For column (3), the outcome is an indicator 'Cartel end' that takes the value one for a firm that is part of a collusive agreement at the point in time when the last period of a collusive agreement is reached. Controls are applied as described in Section 2.3.3. The firm controls include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets as well as leverage. CEO controls include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Matching estimator

Table 2.C14: Probit estimation to obtain the inverse probability weights

	(1)	(2)	(3)
	Dependent variable: High incentives		
	Cartel	Cartel start	Cartel end
Cash	0.186***	0.196***	-0.163
	(0.023)	(0.023)	(0.194)
Sales	-0.088***	-0.084***	-0.122**
	(0.006)	(0.006)	(0.055)
Capital intensity	0.384***	0.414***	0.245
	(0.076)	(0.077)	(0.574)
Return on assets	0.121	0.129	2.747
	(0.164)	(0.165)	(1.707)
Cash flow	0.436**	0.405**	-2.095
	(0.170)	(0.171)	(1.721)
Dividends	-0.787***	-0.909***	1.118
	(0.189)	(0.192)	(1.223)
Leverage	0.007***	0.007***	-0.017**
	(0.002)	(0.002)	(0.009)
log(CEO age)	-0.120***	-0.147***	0.055
	(0.029)	(0.029)	(0.193)
log(CEO tenure)	-0.019***	-0.018***	-0.058**
	(0.004)	(0.004)	(0.024)
Observations	24,319	23,485	860
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes

Note: Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 2.C15: Mean comparison after matching

	(1)	(2)	(3)	(4)
	Mean		Difference	
	High incentives	Low incentives	(1)-(2)	p-value
Panel A: Cartel sample				
Cash	0.145	0.147	-0.001	0.573
Sales	0.994	0.990	0.004	0.708
Capital intensity	0.051	0.051	-0.000	0.691
Return on assets	0.032	0.035	-0.003	0.148
Cash flow	0.032	0.035	-0.002	0.159
Dividends	0.012	0.013	-0.000	0.860
Leverage	0.852	0.845	0.007	0.797
log(CEO age)	4.006	4.005	0.000	0.954
log(CEO tenure)	1.735	1.738	-0.003	0.804
Panel B: Cartel start sample				
Cash	0.146	0.148	-0.002	0.491
Lsaleat	0.998	0.994	0.004	0.751
Capital intensity	0.051	0.052	-0.000	0.719
Return on assets	0.032	0.034	-0.002	0.183
Cash flow	0.032	0.034	-0.002	0.196
Dividends	0.012	0.012	-0.000	0.960
Leverage	0.841	0.831	0.009	0.736
log(CEO age)	4.005	4.004	0.000	0.831
log(CEO tenure)	1.740	1.743	-0.002	0.871
Panel C: Cartel end sample				
Cash	0.117	0.125	-0.008	0.523
Lsaleat	0.918	0.888	0.030	0.491
Capital intensity	0.050	0.049	0.001	0.766
Return on assets	0.051	0.058	-0.007	0.421
Cash flow	0.051	0.058	-0.007	0.408
Dividends	0.016	0.018	-0.002	0.407
Leverage	1.084	1.153	-0.069	0.723
log(CEO age)	4.035	4.031	0.004	0.674
log(CEO tenure)	1.553	1.567	-0.014	0.837

Note: This table shows the differences in mean values between the groups of firms with high-incentive and low-incentive managers. High incentives are defined as having an above-median share of long-term incentives in the remuneration package. The difference and corresponding p-value are displayed in columns (3) and (4).

Table 2.C16: Matching estimator

	(1)	(2)	(3)	(4)	(5)	(6)
	Cartel		Cartel start		Cartel end	
	OLS	IV	OLS	IV	OLS	IV
Incentives	0.058***	0.305***	0.007***	0.039***	0.024	0.916
	(0.010)	(0.083)	(0.002)	(0.015)	(0.071)	(0.720)
Observations	24,076	24,076	23,267	23,267	830	830
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
CEO controls	Yes	Yes	Yes	Yes	Yes	Yes
FE Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE Year	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the estimation results of a linear regression model of equation (2.1) and an IV approach by estimating equations (2.3) and (2.4). The coefficients for the IV estimates are obtained by instrumenting the long-term remuneration share on the firm level by shift-share instruments as described in Section 2.3.3. The measure of interest 'Incentives' is calculated as the share of long-term remuneration parts over total compensation. The first outcome is an indicator 'Cartel' that takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collusion period (columns (1) and (2)). The outcome in columns (3) and (4) is an indicator 'Cartel start' that takes the value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement started. For columns (5) and (6), the outcome is an indicator 'Cartel end' that takes the value one for a firm that is part of a collusive agreement at the point in time when the last period of a collusive agreement is reached. Controls are applied as described in Section 2.3.3. The firm controls include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets as well as leverage. CEO controls include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 2.C17: First-stage regression results for the matched sample

	(1) Cartel	(2) Cartel start	(3) Cartel end
Incentives	0.451***	0.447***	0.224*
	(0.032)	(0.033)	(0.113)
First-stage F-statistic	200.508	185.410	3.915
Observations	24,318	23,484	857
Firm controls	Yes	Yes	Yes
CEO controls	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes

Note: This table shows the estimation results of a linear regression model. The coefficients display the first-stage results of the instrumental variable approach as described in Section 2.3.3. The endogenous variable of interest 'Long-term incentives' is calculated as the share of long-term remuneration parts over total compensation. The outcome is an indicator 'Cartel' that takes the value one if the firm is part of a collusive agreement at time t and zero in any period before and after the collusion period (column (1)). The outcome in column (2) is an indicator 'Cartel start' that takes the value one for a firm that is part of a collusive agreement at the point in time when the collusive agreement started. For column (3), the outcome is an indicator 'Cartel end' that takes the value one for a firm that is part of a collusive agreement at the point in time when the last period of a collusive agreement is reached. Controls are applied as described in Section 2.3.3. The firm controls include the lagged variables for cash scaled by assets, sales scaled by assets, capital intensity scaled by assets, return on assets, cash flow scaled by assets, dividend payments scaled by assets as well as leverage. CEO controls include the logarithm of age and tenure. Moreover, each regression includes a set of industry and year-fixed effects. Standard errors clustered at the firm level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

3

Consumer Protection in the Digital Age: Evidence from the European Union[47]

with Justus Haucap and Ulrich Heimeshoff

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3.1 Introduction

In 2017, more than half of the 560 million consumers in the European Union shopped online, but only 13 percent of them shopped cross-border (Eurostat 2018). Although digital technologies have the potential to reduce information costs, negative distance and border effects still exist in online business-to-consumer (B2C) cross-border trade (Gomez-Herrera et al. 2014; Cowgill and Dorobantu 2012; Blum and Goldfarb 2006; McCallum 1995). As e-commerce is a global phenomenon, it is connected with several issues such as language barriers, cultural differences or trust frictions (Gomez-Herrera et al. 2014; Cowgill and Dorobantu 2012; Blum and Goldfarb 2006; McCallum 1995). To support the development of an integrated European market - a digital single market - the European Commission has long engaged in extensive harmonization exercises. Moreover, consumer authorities argue for international standards regarding consumer protection and data security (Craswell 1982; Pitofsky 1977).

Consumer protection has gained more prominence in recent years. Many recent developments demonstrate the high relevance of consumer protection and regulation of e-commerce in the European Union. In 2018, the European Commission published a draft for a new guideline called "New Deal for Consumer" (European Commission 2018).[48] The increasing focus on e-commerce is not confined to European activities but also illustrated by initiatives of the World Trade Organization for a public-private dialogue on e-commerce in 2017 (World Trade Organization 2017).

E-commerce has a significant impact on economic growth and trade (see e.g., Terzi 2011). As information costs are reduced and distance becomes less important, markets expand in size and competition intensifies. While consumers unambiguously benefit from market expansion and more intensive competition, effects on sellers are more ambiguous: Although they benefit from markets expansions (e.g., Grandon and Pearson 2004), as they can reach out to more potential customers, they also face more in-

[48] The key goal is to strengthen consumer protection by building on existing consumer policy framework concerning unfair business-to-consumer commercial practices. The commission proposed modern rules to fit the fast-changing markets and business practices which are part of the today's digital markets. Amongst others, public and private damage claims as well as fines from national consumer protection authorities are part of this new deal.

tensive competition.

The EU single market policy seeks to eliminate barriers to cross-border flows of goods, services, capital and labor between the EU member states. E-commerce contributes to this and thus plays an important role in EU policy. However, a general European standard in terms of consumer protection has been missing for a long time. To boost consumer confidence and to make it easier to trade across borders, the European Parliament and the European Council passed the Unfair Commercial Practice Directive (UCPD) as Directive 2005/29/EC (Council of European Union 2005). It regulates unfair business practices in the European Union, as part of European consumer law, based on the principle of *minimum* harmonization. In order to remove internal market barriers and to increase legal certainty for both consumers and businesses, the UCPD was passed by the European Parliament and the European Council in 2005 and enacted into national law by member states from 2007 on. The aim was a European minimum standard for consumer protection at a specific level. Consumers' uncertainty about different consumer protection standards was seen as a significant barrier to online cross-border shopping by final consumers. Hence, EU-wide protection of consumer rights is a key pillar in the EU's consumer agenda.

Our paper now analyzes the UCPD's effects on consumer trust and shopping behavior within the EU. More specifically, in terms of consumer attitudes we analyze the UCPD's effects on consumer trust vis-à-vis retailers and services located in consumers' home countries and on consumers trust vis-à-vis public enforcement authorities. By analyzing purchases consumer have made cross-border, i.e., from other EU member states, as well as purchases from their own country, we can compare consumers' shopping behavior and how it is affected by the UCPD. As online shopping has gained more and more relevance in recent years and the main channel for cross-border purchases is online-shopping, we are focusing on consumers' attitudes and shopping behavior towards online B2C purchases.

We use data from different sources: First, the Eurobarometer survey which contains information about consumer attitudes concerning trust as well as their behavior in terms of online shopping. Second, data from private consultancy Civic Consulting is used which includes different indicators, most importantly evaluations of consumer protection levels, provided by legal and consumer protection experts. As we expect different outcomes for different consumer protection levels, these evaluations allow us to build different groups of consumer protection level which are used for the empirical analysis.

Applying a multiple difference-in-difference (DiD) approach, we show that the UCPD has indeed a significant effect on (i) consumer trust and trust into public authorities as well as on (ii) cross-border purchases while homeshopping is not affected. The introduction of the UCPD increased consumer trust vis-à-vis retailers and services in their home country and trust vis-à-vis public authorities. Moreover, online purchases from other EU countries increased after the introduction of the UCPD. We show that the effect is increasing over time for both trust measures and relatively constant for cross-border purchases. Furthermore, the effects are estimated to be robust and not sensitive to our tests.

This paper is related to different strands in both the economics and legal literature. There are several studies that examine consumer trust in the digital age in general without any focus on the UCPD (Culnan and Armstrong 1999; Doney and Cannon 1997; Gefen and Straub 2004; Hoffman et al. 1999; Jarvenpaa et al. 2000; Lee and Turban 2001; Lim et al. 2006; McKnight and Choudhury 2006; Palvia 2009; Teo and Liu 2007; Wright et al. 2009). Conditions under which consumer trust in online retailing increases are, to some extent, addressed by the UCPD. Of course, other relevant but non-regulatory factors exist that contribute to consumers' trust in online retailers as Lim et al. (2006) have shown. Our study contributes to previous research by examining consumer trust and cross-border purchase after the introduction of minimum consumer protection regulations within the European Union. Previous studies have focused on the consumer-retailer relationship and how retailers may gain consumer trust. Our study analyzes the regulatory framework that may support consumer trust in retailers and services as well as cross-border purchase. We also contribute to the strand of regulation literature. To the best of our knowledge, the effects of the harmonization of consumer protection regulations in the European Union have not been empirically analyzed before. Hence, we are the first to investigate whether the UCPD did actually affect consumers' attitudes and shopping behavior.

This paper is also related to legal studies that have examined the introduction of the UCPD. In contrast to our study, these papers have analyzed the UCPD from a purely legal perspective (Collins 2005; Collins 2010; Gomez 2006; Schulte-Nölke 2007; Velentzas et al. 2012; Wright et al. 2009). As most studies suggest, the UCPD may be a first step to full harmonization in terms of consumer protection and to contribute to the goal of a digital single market. Among others, especially Collins (2010) and Osuji (2011) state that the UCPD alone will not be sufficient for full harmonization. This is especially relevant concerning our results. We contribute to this strand of literature as we show that the UCPD had a significant treatment effect on consumers' behavior, although it does not achieve a full harmonization of consumer protection regulations in the EU. We leave it open whether full harmonization is necessary or preferred over the current UCPD.

As our study analyses the effects of the Unfair Commercial Practice Directive, we contribute to the broad economic literature on policy evaluation. Early policy evaluation studies were conducted by Ashenfelter (1978); Ashenfelter and Card (1985); Heckman and Robb Jr (1985); Angrist (1990); Angrist and Krueger (1991); Angrist et al. (1996); Card (1990); Card et al. (1994); Heckman (1990); Manski (1990). More recently, policy evaluation focuses on the examination of treatments as we do in our study (among others Angrist and Lavy 1999; Angrist and Pischke 2008; Athey and Imbens 2017; Blundell and Dias 2002; Donald and Lang 2007)[49]. The growing literature on causal treatments in program evaluation often uses a difference-in-difference estimators with multiple treatments and multiple time periods. This method, developed by Athey and Imbens (2006) and refined by Imbens and Wooldridge (2009), is also used in this paper. With respect to consumer protection measures, the program evaluation

[49]A very good summary of policy evaluation and methods is provided by Abadie and Cattaneo 2018.

literature is relatively small. In fact, most of the consumer protection measures implemented at the EU level are not subject to any systematic ex post evaluation. Hence, our paper contributes to the growing literature on evidence-based policy analysis. In particular, we contribute to the literature by analyzing whether the UCPD has achieved its own objective, which has been formulated by the European Commission as follows: "The objective of the new EU rules on unfair commercial practices from 2005 was to boost consumer confidence and make it easier for businesses, especially small and medium-sized enterprises, to trade across borders."[50]

Our paper is structured as follows: Section 3.2 describes the underlying economic problem that the Unfair Commercial Practices Directives addresses and our theoretical expectations about its introduction. In Section 3.3, data and the identification strategy are discussed. Results are discussed in Section 3.4, before Section 3.5 concludes.

3.2 Regulation and the Unfair Commercial Practices Directive (UCPD)

3.2.1 Information problems in online cross-border shopping

The internet has greatly reduced information and travel or transport cost so that consumers can, in principle, easily purchase from retailers located far away from home. Shipping goods over long distances has become relatively cheap and the internet enabled consumers to inform themselves about offers of retailers that are located far away. For consumers to engage in online shopping, they need to trust retailers who promise to fulfill consumer orders and to guarantee certain quality and service levels. While retailers have developed various practices to build consumer trust, shoppers still need more trust than in brick and mortar stores where they immediately take away their purchases.

A particular problem of cross-border purchases is that consumers will be often unfamiliar with foreign consumer protection standards. While consumers may have some basic understanding about typical consumer protection levels at home, online

[50]See, e.g.: https://ec.europa.eu/info/law/law-topic/consumers/unfair-commercial-practices-law/unfair-commercial-practices-directive_en.

shopping abroad may be considered even more risky, as foreign consumer protection standards are less well known. In the European Union, consumers are unlikely to have expert or even lay knowledge about consumer laws of 28 different member states within the European Union. Given the costs involved in finding out and understanding foreign consumer protection legislation, consumers may refrain from shopping abroad, but rather shop at home. Put differently, consumers are likely to have some basic understanding of relevant consumer protection standards in their home country, but they are unlikely to be familiar with consumer protection standards abroad. Hence, consumers may be more reluctant to shop online abroad.

3.2.2 The Unfair Commercial Practices Directive (UCPD)

The UCPD intended to set minimum standards for consumer protection, but does not replace higher national standards. Hence, after the adoption of the UCPD consumers could rely, at minimum, on the rules provided in the UCPD. From an information economic perspective this means that, even if consumers lack knowledge about the particular consumer protection standards in place in any of the 28 member states, they could rely on the minimum standard provided by the UCPD.

The UCPD was one of the most significant European pieces of legislation that affects how markets operate in the European Union. The main focus are unfair commercial business-to-consumer practices in the internal market (Commission of the European Communities 2005). The directive has thereby two main goals: on the one hand, to achieve a minimum harmonization of national rules concerning unfair commercial practices, and on the other hand, to successfully implement a guaranteed consumer protection level. The first is a complex task, as many countries in the European Union had very few rules or relatively low standards concerning unfair commercial practices, making cross-border online shopping particularly risky.

It is sometimes argued that harmonized consumer protection standards can - possibly as an unintended consequence - reduce market competition, as (i) offers with lower standards are excluded from the market and (ii) firms can no longer compete in different standards. The latter is only true for full harmonization though. Minimum standards in contrast still allow for competition, even though lower protection standards are excluded, which is the first risk mentioned above. This argument, however, assumes that consumers make informed decisions about purchases from countries with different protection levels. In reality, it seems plausible that many consumers are not well-informed about 28 different standards and find it too costly or troublesome to acquire and process this information. In this case, risk averse consumers may prefer the shop from sellers in their home country, so that competition between home and foreign retailers becomes *less* intense. In this case, minimum standards even *foster* competition, as they resolve information problems and facilitate competition between home and foreign retailers.

In fact, Gomez (2006) argues that the directive is necessary to mitigate information asymmetries. These might arise especially from firm behavior affecting communication, advertising, sales promotion, contracting and pre-contracting conduct.

In terms of misleading commercial practices, the UCPD prohibits false information. The UCPD refers to the average consumer's right to correct and complete information. In addition, the UCPD prohibits aggressive commercial practices which include harassment, coercion or influence. The UCPD is intended to protect the freedom of choice of the average consumer which may not be given under aggressive commercial practice if the average consumer is caused to take a transactional decision that he or she would not have taken otherwise (European Parliament and Council 2005; Willett 2010).

3.2.3 Expectations

Many consumers are unfamiliar with consumer protection levels in foreign countries. Hence, consumers may be reluctant to shop abroad, as gathering correct information about foreign laws and regulations can be costly. The introduction of a minimum standard through the UCPD at EU level can mitigate this information problem, as consumers can now trust in a minimum level of consumer protection even if they are still unfamiliar with the detailed consumer protection level in any particular country. This effect should be particularly strong in countries with initially low levels of consumer protection, as consumers will learn that consumer protection levels rise after the introduction of the UCPD, both at home and abroad. In particular, they can infer that the same minimum protection level will be guaranteed EU wide. In contrast, consumers from countries with already high levels of consumer protection may not learn much about changed protection levels abroad if the level of consumer protection at home remains largely unchanged. Hence, we expect trust to rise in response to the minimum standard provided by the UCPD especially in countries with initially low levels of consumer protection. Consequently, we also expect cross-border trade to be affected the most in these countries.

The introduction of the UCPD should consequently lead to higher consumer protection standard in member states with initially low consumer protection standards. Hence, consumers should have an increased trust in retailers and services providers as well as in public authorities. This is especially true for consumers in countries with a low consumer protection level before the introduction of the UCPD. Consequently, we expect cross-border purchases to also increase.

3.3 Data and empirical strategy

3.3.1 Data

The main data is collected from Eurobarometer[51], which is a survey conducted on behalf of the European Commission. It was established in 1974 and contains beside the Standard Eurobarometer, which is collected once a year, Special and Flash Eurobarometer surveys. While the Standard Eurobarometer contains questions about general opinions concerning the European Union as well as demographic characteristics of the persons surveyed, Flash Eurobarometer are ad hoc thematic interviews. Special Eurobarometer are based on in-depth thematic studies carried out for various services of the European Commission or other EU institutions. Each survey consists of approximately 1,000 interviews per country, conducted partly by telephone and partly face-to-face in all European countries. Access to data from Eurobarometer is granted

[51]The used data sources are in detail: Special Eurobarometer 252 (2006), Special Eurobarometer 298 (2008), Flash Eurobarometer 282 (2009), Flash Eurobarometer 299 (2010), Flash Eurobarometer 332 (2011), Flash Eurobarometer 358 (2012), and Flash Eurobarometer 397 (2014).

by GESIS – the Institute for Social Sciences, which provides a collection of all waves of Standard, Special and Flash Eurobarometer surveys on the individual level. This leads to an overall sample of 179,724 respondents representing the 28 member states of the European Union[52] between 2006 and 2014.[53]

As we are analyzing attitudes and trust of consumers concerning cross-border purchases, we are focusing on four main outcome variables, namely consumer trust and public authority trust as well as cross-border purchase and homeshopping. Concerning consumer trust the respondents were asked how strongly they agree or disagree to the following statement: "In general, retailers and services providers respect your rights as a consumer". The resulting categorical variable of how strongly consumers trust in the retailers in services of their own country contains four different categories 'strongly agree', 'agree', 'disagree' and 'strongly disagree'.

For the variable public authority trust, respondents were asked to what extent the respondents trust the public authorities to protect their rights as consumers. Respondent had the same four different answer possibilities as for consumer trust.

For the third main variable, cross-border purchase, respondents were asked if they had at least one purchase in another EU country in the last 12 months. This variable is an indicator that turns one if the respondent had at least one purchase (via internet) in another EU country than their own in the last 12 months, and remains zero otherwise.[54]

The last main variable is called homeshopping. Here, respondents were asked

[52]The Unfair Commercial Practice Directive was not only implemented within member states of the European Union but rather within the European Economic Area (EEA) so that countries such Iceland and Norway also implemented the regulation into national law. As Civic Consulting is not providing data for countries other than EU member states, we excluded countries of the EEA which are not part of the EU from our dataset.

[53]No Eurobarometer surveys are available in 2007 and 2013 that focused on consumer attitude or shopping behavior.

[54]In general, respondents had four different answer possibilities: "Yes, via internet", "Yes, via telephone", "Yes, via door-to-door advertising" or "No". We chose to exclude the possibilities of ordering via telephone or door-to-door advertising from the sample as this study focuses on online shopping purchases. Unfortunately, in the years 2006 and 2008, the question did not distinguish between online and offline cross-border purchase so that shares of cross-border purchase do not exclusively refer to online shopping in these two years. In later years, the share of consumers who ordered products offline was extremely low. Although this may reflect a decreasing time trend, we believe that the share of offline cross-border purchases was also very low before 2008. However, in any case, purchases made during vacation or business trips in other countries are explicitly excluded.

whether they had at least one purchase in the past twelve months from their current home country. The same answer possibilities as for cross-border purchase are given which results in an indicator variable that turns one if respondent had at least one purchase in the past 12 months (via the internet) at a retailer or service provider located within their home country.

In a next step, other individual level data from the same Eurobarometer surveys were added, such as an indicator that turns one for female, a continuous variable for age ($\log(age)$) and its squared term ($\log(age)^2$) as well as an indicator whether nationality differs from the current living country. The data were then matched with country level data from Eurostat to control for country-specific effects such as the share of internet access (as percentage of population), the log of GDP per capita at respective prices ($\log(\text{GDP})$), unemployment shares (as percentage of population) as well as the actual share of cross-border purchases (as percentage of population).[55]

This sample was then matched with variables of consulting firm Civic Consulting which contributed an index for the level of consumer protection in the particular country before the introduction of the Unfair Commercial Practice Directive (pre-UCPD). This leads to an ordinal variable with five different outcomes, where the value 1 is the worst pre-UCPD evaluation level and 5 the best. Moreover, they provide an indicator (incident) that turned one if a country faced a crisis or unexpected event that may affected consumer trust.[56]

3.3.2 Identification strategy

We analyze the effect of the UCPD on four main outcomes: consumer trust and public authority trust as well as cross-border purchase and homeshopping. We firstly analyze descriptive statistics to identify suitable identification strategy for each dependent variable.[57] Figure 3.1 shows consumer trust over time by the different treatment

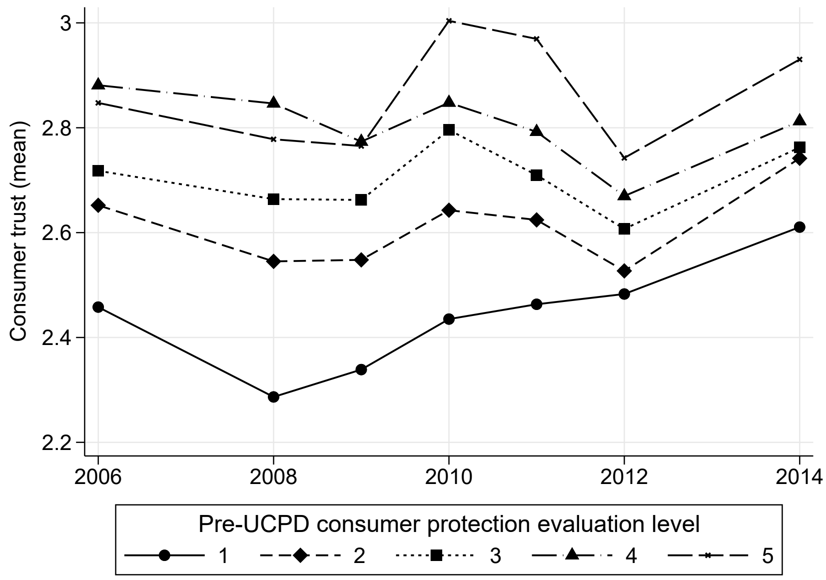
[55]Note that the variable "share of cross-border purchase" is not the same as the main variable "cross-border purchase" but the share of consumers within a country doing any cross-border purchase in another country as percentage of population given by Eurostat. We do not include this variable in the regression when estimating the effect of the introduction of the UCPD on individual cross-border purchases within the EU.

[56]Descriptive statistics for the mentioned variables are shown in Table 3.A1.

[57]As the variables consumer trust and public authority trust as well as cross-border purchase and homeshopping are very similar, we choose to only analyze the descriptives of one of each pair and use

groups, namely legal pre-UCPD experts' evaluation level of consumer protection. This figure shows that the different consumer protection levels perfectly fit consumer trust levels. A country with a high consumer protection standard before the UCPD correlates with high consumer trust in this country and vice versa. The overall shape of Figure 3.1 shows a decrease from 2006 to 2008 for all pre-UCPD consumer protection evaluation levels, followed by an increase for the lowest evaluation type. Especially, the very low evaluated countries strongly increase their trust during the observation time. Moreover, the lowest rating did not suffer from a decrease in consumer trust in 2012 as much as the other groups, although the increase lowers to a small extent.

Figure 3.1: Consumer trust over time by level of pre-UCPD evaluation



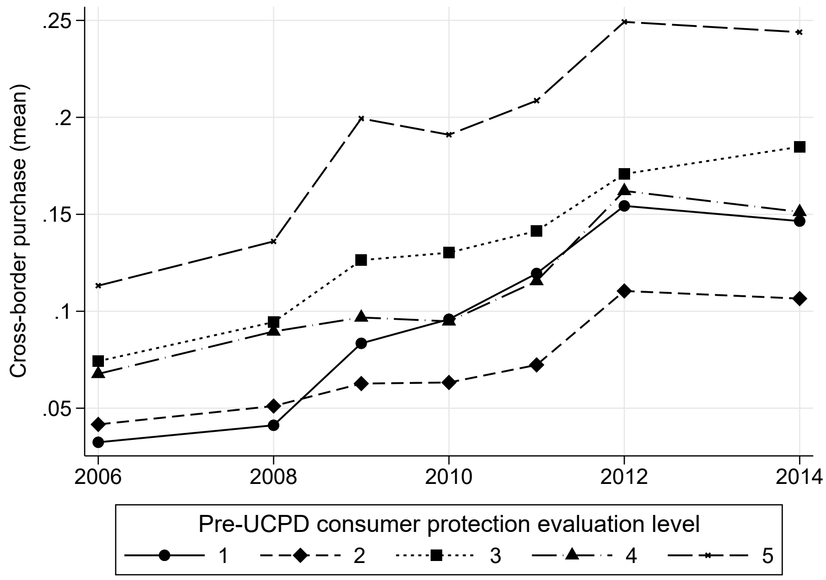
Note: This figure is based on Eurobarometer 2006-2014 and shows the correlation between the mean of consumer trust by the different legal experts' evaluation levels over time. Legal experts' pre-UCPD evaluation is based on data provided by Civic Consulting. These levels reach from one to five where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD.

This perfect fit of pre-UCPD legal expert's evaluation cannot be observed for cross border purchase, as can be seen in Figure 3.2. First thing to note is an overall increase in all five different evaluation groups. This is plausible as with an increase in internet consumption and the ongoing digital single market policy, more consumers are engaging in cross-border shopping. Countries with a pre-UCPD evaluation of one, three

the same identification strategy for both variables for comparison purposes.

or five have a similar development over time. Respondents of these countries did not purchase more from other EU-countries until 2008, but they all show a sharp increase from 2008 to 2009 and later a slighter increase until 2014. However, the most interesting part of this picture is the strong increase of cross-border purchase in countries with a pre-UCPD evaluation of one.

Figure 3.2: Cross-border purchase over time by level of pre-UCPD evaluation



Note: This figure is based on Eurobarometer 2006-2014 and shows the correlation between the mean of cross-border purchases by the different legal experts' evaluation levels over time. Legal experts' pre-UCPD evaluation is based on data provided by Civic Consulting. These levels reach from one to five where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD.

Figures 3.1 and 3.2 show that the trust outcome increases most for the lowest pre-UCPD consumer protection evaluation group. For cross-border purchase a different picture emerges. Still, countries with a very low pre-UCPD consumer protection evaluation level benefit in both cases most from the introduction of the UCPD. This is in line with previous literature, as, e.g., Collins (2010). Osuji (2011) suggests that the UCPD may only be a first step to full harmonization and therefore only provides a very low consumer protection level. The UCPD appears to strongly affect countries with a very low pre-UCPD consumer protection level. Countries with higher consumer protection level before the introduction of the UCPD will be not or at least less affected by its introduction. Consequently, we assume that consumers in countries with a very low pre-UCPD consumer protection level have a higher likelihood of an effect on trust and shopping behavior in result of the introduction of the UCPD compared to the other pre-UCPD evaluation groups.

A first relevant question in this context is how to choose appropriate treatment and control groups. The European market and its consumer protection regulation are rather unique which makes it complex to find an appropriate control group outside the European Union. As all EU countries are required to implement the regulation, finding a control group within the European Union is not trivial. However, the UCPD will, although introduced in all EU countries, eventually affect only countries with a very low pre-UCPD consumer protection evaluation level, as it is a minimum standard and as confirmed by the descriptive statistics. Consequently, we choose our treatment group so that it includes all countries with a very low pre-UCPD consumer protection evaluation level while countries with a higher pre-UCPD consumer protection evaluation level state the control group.

To analyze the effect of the UCPD on attitudes towards trust and shopping behavior within the EU, we utilize a difference-in-difference (DiD) approach with multiple time periods following Athey and Imbens (2006) as well as Imbens and Wooldridge (2009). They extended the standard DiD-estimator with two time periods and two groups to a general DiD-estimator with multiple time periods and multiple groups. As we have only one treatment group, countries with a very low pre-UCPD consumer protection evaluation level, the difference-in-difference estimator is only generalized in terms of time periods.[58] This is due to the fact that the UCPD was introduced at different times in different countries. The implementation dates vary across EU member states, as countries were required to implement UCPD by 2013 the latest. The directive was initially enacted in 2005 and it became effective in 2007. Member states then had up to six years to effectively implement the new regulation into their national provisions. The

[58]There is a growing literature on heterogeneous treatment effects applying a difference-in-difference approach with multiple time periods and varying treatment timing, e.g., Sun and Abraham (2021); Athey and Imbens (2022); Callaway and Sant'Anna (2021); De Chaisemartin and d'Haultfoeuille (2020); Goodman-Bacon (2021); Han (2021).

exact years when the directive was applied at the national level are shown in Table 3.1, Column (4). No country implemented the regulation later than 2010. However, we use the exact year when the UCPD went in place so that the treatment has different timings.

The difference-in-difference estimation equation looks as follows:

$$Y_{it} = \beta_0 + \beta_1(Post_{ct} \times L_{cj}) + \beta_2 X_{it} + \beta_3 Z_{ct} + \tau_t + \delta_c + u_{ict} \tag{3.1}$$

Here, Y_{it} is the outcome variable, namely consumer trust, public authority trust, cross-border purchase or homeshopping. Similar to consumer trust, we expect public authority trust to increase after the introduction of the UCPD. Cross-border purchase is also expected to increase after the introduction of the UCPD as the directive should make it easier to shop across borders. The other included outcome variable, homeshopping, gives an insight whether the UCPD only affects cross-border purchases or whether online purchases in home countries are also affected by the directive. On the one hand, a positive effect would be possible. As the consumer proetection level rises in the home country, consumers may shop more within their own country. On the other hand, no or even a negative effect is possible. As cross-border shopping becomes relatively easy and the UCPD only provides a minimum consumer protection standard, consumers of low pre-UCPD consumer protection standard level countries might shift their purchases towards other countries of the EU that provide an even higher consumer protection standard. Although consumer protection standard rises in their own country, consumers then prefer to shop cross-border. Expectations concerning homeshopping are therefore ambiguous although a negative effect is rather unlikely as distance and language effects still play a role.

The variable Post_{ct} is an indicator that turns one once the UCPD was implemented and it remains one from then on. Moreover, we assign L_{cj} to an indicator for legal experts that have evaluated the consumer protection before the UCPD was implemented. The variable L_{cj} can take five values $j \in \{1,...,5\}$, where 5 is the best evaluation and 1 is the worst. Countries with a pre-UCPD consumer protection evaluation level of 1 (very low) form our treatment group. This reflects the hypothesis that the introduction of UCPD only affects countries with a very low pre-UCPD consumer protection level. All other, higher pre-UCPD evaluation levels of consumer protection form the control group. Therefore, we measure the effect of the introduction of the UCPD for low consumer protection countries in comparison to higher consumer protection countries.[59] The exact evaluation levels of the legal and consumer protection experts are shown in the second and third column of Table 3.1. For the baseline regression, legal experts' evaluation levels are used while consumer protection experts' evaluation levels are later used as a robustness check.

[59]A detailed description concerning the choice of treatment and control group can be found in 3.C.

Table 3.1: Detailed descriptive statistics of countries, their pre-UCPD evaluation level and region within Europe

Country	Legal experts' evaluation	Protection experts' evaluation	UCPD in place	Region in Europe
Austria	5	5	2007	west
Belgium	3	3	2007	east
Bulgaria	1	1	2007	east
Croatia	3	3	2009	south
Cyprus (Republic)	3	3	2007	south*
Czech Republic	2	3	2009	east
Denmark	5	5	2007	north
Estonia	2	2	2007	north
Finland	4	4	2009	north
France	4	5	2009	west
Germany	5	5	2009	west
Greece	2	2	2007	south
Hungary	3	3	2007	east
Ireland	3	3	2007	north
Italy	3	3	2007	south
Latvia	2	2	2007	north
Lithuania	2	2	2009	north
Luxembourg	3	4	2010	west
Malta	1	1	2007	south
Poland	3	3	2007	east
Portugal	1	3	2009	south
Romania	2	2	2007	east
Slovakia	3	3	2007	south
Slovenia	2	2	2007	south
Spain	4	4	2010	south
Sweden	3	3	2007	north
The Netherland	2	3	2009	west
United Kingdom	4	4	2009	north

Note: This table shows the descriptive statistics of the EU member states, their pre-UCPD consumer protection level evaluated each by legal or by protection experts, the implementation date of the UCPD in each country and the region of the country within Europe. Legal and protection expert's evaluation as well as UCPD inplace information are part of the data provided by private consultancy Civic Consulting. Experts' evaluation level is an index which ranges from one to five, where one equals the worst and five the best consumer protection evaluation level. Regions are based on United Nations Statistics Division 2018 except of Cyprus which is by this definition not part of Europe. *We chose to define Cyprus in the region of "south" as different other sources suggest it similar (e.g., Bosco and Verney 2012; World Atlas 2018).

The interaction term $\text{Post}_{ct} \times \text{L}_{cj}$ between both variables is our variable of interest. Its coefficient is the effect of the introduction of the UCPD ($Post_{ct}$) on the outcome (consumer trust, public authority trust, cross-border purchase or homeshopping) for consumers in countries with a low pre-UCPD evaluation level by legal experts ($\text{L}_{cj} = 1$) in relation to consumers in higher pre-UCPD evaluated countries ($\text{L}_{cj} = 2 - 5$). For more detailed insights into our treatment and control group, Table 3.A2 provides an overview about the descriptive statistics for both groups before and after the treatment.

Returning to Equation 3.1, X_{it} are individual socio-demographic characteristics ($\log(age)$, $\log(age)^2$, female (indicator), nationality (indicator)) and Z_{ct} are the country specific economic characteristics (share of unemployment (as percentage of population), incident, share of internet access (as percentage of population), log(GDP), share of cross-border purchase (as percentage of population)) described above. Additionally, we include year and country fixed effects, τ_t and δ_c, respectively.

To account for the nature of our two dependent variables, we apply the following econometric models: For trust we apply as a baseline specification a linear probability model and later an ordered probit model due to the different categories of the variables. To analyze shopping behavior, we choose the probit model due to the binary outcome variables.

Additionally, we account for the correct inference. Bertrand et al. 2004 highlight that standard errors are inconsistent as state sizes vary. To address this problem, we cluster standard errors at the country level and, moreover, show the robustness of the effects, as we apply bootstrapped standard errors in the sensitivity analysis.

3.4 Results

Our analysis below examines aspects of consumer attitudes and consumer behavior within the European Union after the introduction of the Unfair Commercial Practice Directive, including their trust concerning retailers and services providers as well as the public authority, online cross-border purchases and online purchases in their home country.

3.4.1 Trust

In a first step, we report the results of the outcomes concerning trust attitudes. As baseline we use a linear probability model but we also show the results of an ordered probit model. With the marginal effects of the latter we are then able to show the specific effects on each category of the outcomes. The results of the linear probability and ordered probit estimation of Equation 3.1 are shown in detail in Table 3.2 and 3.3, respectively.[60] Two different panels are reported in each model: panel A constitutes the results for effects of the introduction of the Unfair Commercial Practice Directive on consumer trust. Panel B includes the effects of its introduction on public authority trust.[61]

The results for panel A and B in Table 3.2 suggest that with the introduction of the UCPD, consumer trust and public authority trust rise for consumers in countries with a low pre-UCPD consumer protection evaluation in comparison to consumers of all other countries.[62] Consequently, the results imply that the UCPD has indeed an effect on consumer trust and public authority trust.

[60]For the ordered probit model, we only report marginal effects due to simplicity and to interpret the results. The corresponding coefficients are available upon request.

[61]We estimated the reduced form as well as the full model for both panels. Adding the control variables to the model, the effect remains similar and the coefficient of interest, the interaction term $Post_{ct} \times L_{cj}$, even rises. For the control variables in panel A, coefficients of $\log(age)$, $\log(age)^2$ and the share of internet access (as percentage of population) show significant effects. In panel B coefficients female, nationality, the share of unemployment (as percentage of population) and the log (GDP) are additionally significant. For both panels, the reported marginal effects in Table 3.3 are estimated with the full model including individual and country control variables, year and country fixed effects as well as with clustered standard errors at the country level. Reduced form estimates and coefficients are available upon request.

[62]Consumers of countries with low pre-UCPD consumer protection levels are by roughly 20 percent (17 percent) more likely of answering the consumer trust (public authority) question with a higher category after the introduction of the UCPD in comparison to consumers of higher pre-UCPD consumer protection evaluation countries.

Table 3.2: Linear probability model estimation

	Panel A: Consumer trust		**Panel B**: Public authority trust	
Post_{ct} (indicator,	-0.073*	-0.065*	-0.014	-0.018
UCPD in place)	(0.042)	(0.038)	(0.042)	(0.033)
Treat ($\text{L}_{cj} = 1$)	-0.539***	-0.253*	-0.495***	-0.120
	(0.052)	(0.125)	(0.023)	(0.116)
Treat ($\text{L}_{cj} = 1$) × Post_{ct}	0.178**	0.198***	0.161***	0.168***
	(0.068)	(0.058)	(0.028)	(0.031)
Individual controls	No	Yes	No	Yes
Country controls	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Country cluster	Yes	Yes	Yes	Yes
Pseudo r^2	0.073	0.080	0.074	0.083
Observations	167,722		167,607	

Note: This table shows the results of the linear probability difference-in-difference estimation. Panel A reports the coefficients of introducing the Unfair Commercial Practice Directive on consumer trust, while panel B reports coefficients on public authority trust. Treatment and control groups are based on an index that shows the evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD. Here, the treatment group states the lowest pre-UCPD consumer protection evaluation, while the higher pre-UCPD consumer protection evaluation level are the summarized control group. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

The marginal effects of the ordered probit model in Table 3.3 allow detailed insight into the effects on the different outcomes. From these results, we can conclude that the effect is not only statistically significant but also economically relevant. The marginal effects are estimated for each outcome of the dependent variable separately so that the results can be interpreted as predicted probabilities for each outcome. Focusing on the interaction term $\text{Post}_{ct} \times \text{L}_{cj}$, every regression in both panels shows a highly statistically significant effect. In panel A, the outcome "strongly disagree" has a value of -0.04, meaning that after the introduction of the UCPD, consumers of countries with a very low pre-UCPD consumer protection evaluation level ($\text{L}_{cj} = 1$) are by 4 percentage points less likely to answer the question whether they trust retailers and services in their country with "strongly disagree" compared to countries with a higher pre-UCPD consumer protection evaluation ($\text{L}_{cj} = 2-5$). A similar value can be found for public authority trust in panel B where the probability of "strongly disagree" is decreased by 4.2 percentage points.

For the outcome "disagree" the change in probability is with 7.2 percentage points even higher. Consumers of lower consumer protection countries are by 7.2 percentage points less likely to disagree to the statement that retailers and services providers respect their rights as consumers after the introduction of the UCPD in comparison to countries with higher pre-UCPD consumer protection evaluation ($\text{L}_{cj} = 2-5$).

In contrast to this, the two outcomes "agree" and "strongly agree" have positive predicted probabilities. Therefore, consumers of countries with a low pre-UCPD consumer protection evaluation are by 6.6 percentage points and 4.8 percentage points (respectively) more likely to trust retailers and services providers after the introduction of the UCPD than before and in comparison to countries with a higher consumer protection evaluation ($\text{L}_{cj} = 2-5$). Changes in probabilities for trust into public authorities are with 4.6 ("agree") and 4.3 ("strongly agree") percentage points similar but lower. An overview of the marginal effects is provided in Figure 3.3.

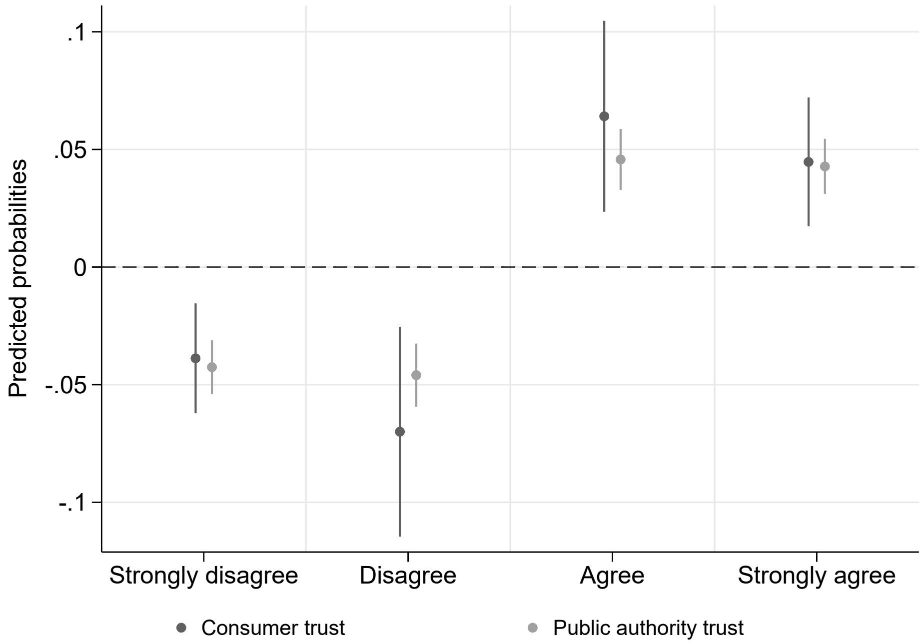
Overall, these estimation results show that consumers of countries with low pre-UCPD evaluation trust retailers and services providers as well as public authorities

Table 3.3: Marginal effects for consumer and public authority trust

	Strongly Disagree	Disagree	Agree	Strongly Agree
	Panel A: Consumer trust			
Post_{ct} (indicator,	0.013*	0.024*	−0.022*	−0.015*
UCPD inplace)	(0.008)	(0.014)	(0.013)	(0.009)
Treat (L_{cj} = 1)	0.052**	0.095**	−0.087**	−0.060**
	(0.026)	(0.046)	(0.043)	(0.029)
Treat (L_{cj} = 1) × Post_{ct}	−0.040***	−0.072***	0.066***	0.046***
	(0.011)	(0.021)	(0.019)	(0.013)
Observations	167,722			
	Panel B: Public authority trust			
Post_{ct} (indicator,	0.004	0.004	−0.004	−0.004
UCPD inplace)	(0.008)	(0.009)	(0.009)	(0.008)
Treat (L_{cj} = 1)	0.033	0.035	−0.035	−0.033
	(0.030)	(0.032)	(0.032)	(0.030)
Treat (L_{cj} = 1) × Post_{ct}	−0.042***	−0.046***	0.046***	0.043***
	(0.007)	(0.008)	(0.007)	(0.007)
Observations	167,607			
Individual controls	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Country cluster	Yes	Yes	Yes	Yes

Note: This table shows the marginal effects as predicted probabilities at means of all other variables. Baseline for the calculations is full model of the ordered probit difference-in-difference estimation. Panel A reports the marginal effects effects of the introduction of the UCPD on consumer trust while panel B reports marginal effects on public authority trust. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - “very low”, 2 - “low”, 3 - “middle”, 4 - “high”, 5 - “very high” consumer protection standards before the introduction of the UCPD. Here, the treatment group states the lowest pre-UCPD consumer protection evaluation while higher pre-UCPD consumer protection evaluation level are the summarized control group. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Figure 3.3: Marginal effects of consumer and public authority trust by outcomes



Note: This figure shows the marginal effects of the interaction term Treat(L_{cj} = 1)× Post_{ct} for panel A (consumer trust) and panel B (public authority trust) separately for each outcome (Table 3.3). The lines correspond to 95% confidence intervals.

more after the introduction of the UCPD as their probability of answering these questions with "strongly disagree" or "disagree" decreases and the probability for "agree" or "strongly agree" increases compared to other countries. This is especially the case as countries with a higher pre-UCPD consumer protection evaluation level already have a satisfying high consumer protection standard. In conclusion, consumer trust is increasing with the introduction of UCPD when the country was pre-evaluated by legal experts' indicator of one, compared to indicators between two and five. Trust rises, therefore, especially for consumers in countries where the evaluation of the pre-UCPD consumer protection was very low. The consumer protection standard that is introduced by the UCPD is thus comparable to a pre-UCPD protection evaluation of not higher than two. The minimum consumer protection standard provided by the UCPD is not high enough to change much for consumers in countries with a higher pre-UCPD consumer protection level so that trust in retailers and services providers as well as the public authority did not increase significantly.

With the results of the linear probability model (Table 3.2) and the marginal effects

(Table 3.3), we can conclude that the UCPD has indeed a significant effect on consumer trust and public authority trust, especially for countries with a low pre-UCPD consumer protection evaluation. We can confirm that consumers of countries with a low pre-UCPD consumer protection have, in comparison to higher pre-UCPD consumer protection evaluation, level a higher probability to trust retailers and services providers as well as public authorities after the introduction of the UCPD compared to before.

3.4.2 Online shopping

For online cross-border purchase and homeshopping (purchases from current home country), we implemented a probit model with the same difference-in-difference estimation as in Equation 3.1. Table 3.4 shows the marginal effects for both panels, cross-border purchase (panel A) and homeshopping (panel B), respectively.[63]

For panel A the results show a highly statistical significant and positive effect. Consumers of countries with a very low pre-UCPD consumer protection evaluation level are by 9 percentage points more likely of having a cross-border purchase after the introduction of the UCPD compared to consumers of countries with a higher pre-UCPD consumer protection evaluation level. For homeshopping in panel B we do find a positive but not statistically significant effect.

The results show that with the introduction of the UCPD, individuals of countries with a low pre-UCPD consumer protection evaluation are more likely to shop cross-border. Surprisingly, we do not find any effect for homeshopping. These results may appear counter-intuitive at first sight: Although the goal of the Unfair Commercial Practice Directive is to strengthen the digital single market, so that cross-border shopping is easier, there might be an effect on purchases within the own country. This is due to the fact that we still analyze countries with a very low pre-UCPD consumer protection evaluation level. Hence, consumers of countries with a very low consumer protection standard may increase their purchases at home when the consumer protection standard is

[63] The corresponding estimation results (coefficients) are available upon request. The basis for the computation of the marginal effects are the full models for both panels such that individual and country controls as well as year and country fixed effects are included.

increased there. This does not hold for countries with higher standards, as discussed, the UCPD only provides a very low consumer protection level. However, we do not find that consumers of low pre-UCPD consumer protection evaluation level countries rising their purchases at home significantly. An explanation may be that with knowing the consumer protection standard rising in their own country, consumers know that either the consumer protection standard in other countries is also rising or that the consumer protection is higher although the standard is rising in their country.

Table 3.4: Marginal effects for cross-border purchase and homeshopping

	Panel A: Cross-border purchase	**Panel B**: Homeshopping
Post_{ct} (indicator,	-0.035***	-0.025
UCPD in place)	(0.012)	(0.030)
Treat (L_{cj} = 1)	-0.219***	-0.164*
	(0.036)	(0.093)
Treat (L_{cj} = 1) × Post_{ct}	0.090***	0.040
	(0.011)	(0.036)
Individual controls	Yes	Yes
Country controls	Yes	Yes
Year fixed effects	Yes	Yes
Country fixed effects	Yes	Yes
Country cluster	Yes	Yes
Observations	179,724	173,479

Note: This table shows the marginal effects as predicted probabilities at means of all other variables. The baseline for the estimation is the full model of the probit difference-in-difference estimation. Panel A reports the marginal effects of introducing the UCPD on cross-border purchase, while panel B reports marginal effects on homeshopping. Treatment and control groups are based on an index that shows the evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five, where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD. Here, the treatment group states the lowest pre-UCPD consumer protection evaluation, while the higher pre-UCPD consumer protection evaluation level are the summarized control group. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

3.4.3 Changing effect sizes over time

In a next step, we analyze how the effect changes over time.[64] Countries had to choose on their own when to introduce the UCPD between 2007 and 2013 although no country introduced the UCPD later than 2010.

[64]The tables with marginal effects of this analysis can be found in 3.B.

We are implementing the same equation to estimate the baseline results, but now interact the variable of interest with year dummies, leaving the following estimation equation:

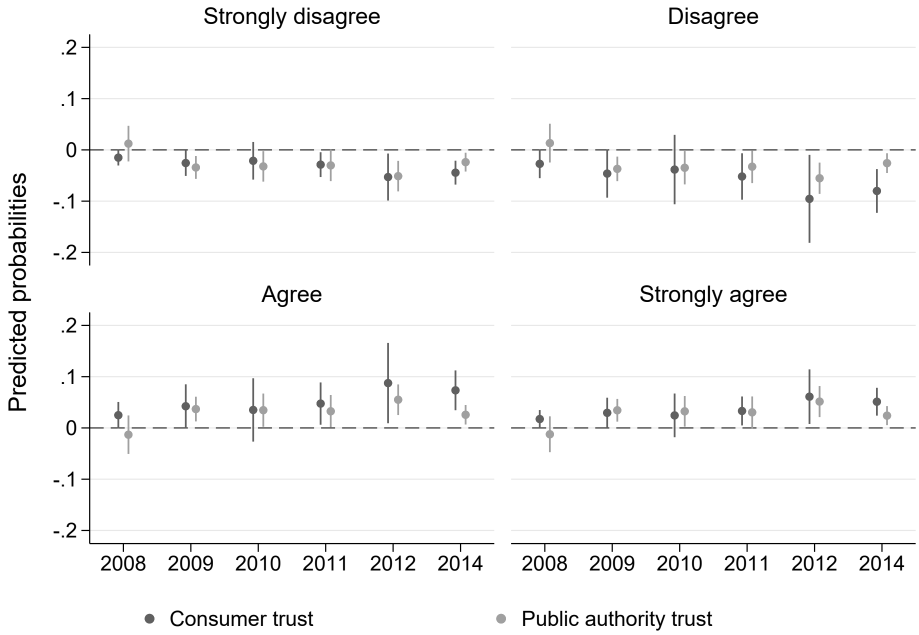
$$\mathrm{Y}_{ict} = \beta_0 + \beta_1 (Post_{ct} \times \mathrm{L}_{cj} \times \sum_{t=2008}^{2014} year_t) + \beta_2 \mathrm{X}_{ict} + \beta_3 \mathrm{Z}_{ct} + \tau_t + \delta_c + \varepsilon_{ict} \qquad (3.2)$$

Leaving out the indicator for 2006 is necessary to have a reference point. As countries implemented the regulation between 2007 and 2010 into national law, there was no effect of the UCPD in 2006. Therefore, 2006 serves as the reference year. As data is missing in 2007, the effect for the implementation is caught in 2008 data. However, delayed effects even after 2010 may be expected, as trust has to build up often over a long time (Williams 2007). Moreover the shopping variables reflect the shopping behavior of the past 12 months so that, for example, purchases in 2008 are caught only by the question in 2009.

The marginal effects for trust in Figure 3.4 support these considerations.[65] In panel A the effect is stable and highly statistically significant after 2010 for all possible outcomes. Similar results emerge for panel B, public authority trust, although the effect is not as strong. Panel A has lower effects in the beginning but highly increasing effects over time, so the full effect hits in 2012 where it almost reaches 10 percentage points for two ("disagree" and "agree") of the four outcomes. In panel B there is also an increase over time. The effect is highly statistically significant from 2009 onward, but the peak in 2012 only reaches 5 percentage points for all outcomes.

[65] Exact values can be found in Table 3.B1 in 3.B

Figure 3.4: Marginal effects of consumer and public authority trust over time



Note: This figure shows marginal effects of the interaction term Treat($L_{cj}=1$)$\times$ Post$_{ct}$ $\times \sum_{t=2008}^{2014}$year$_t$ for panel A (consumer trust) and panel B (public authority trust) separately for each outcome and over time (Table 3.B1). The lines correspond to 95% confidence intervals.

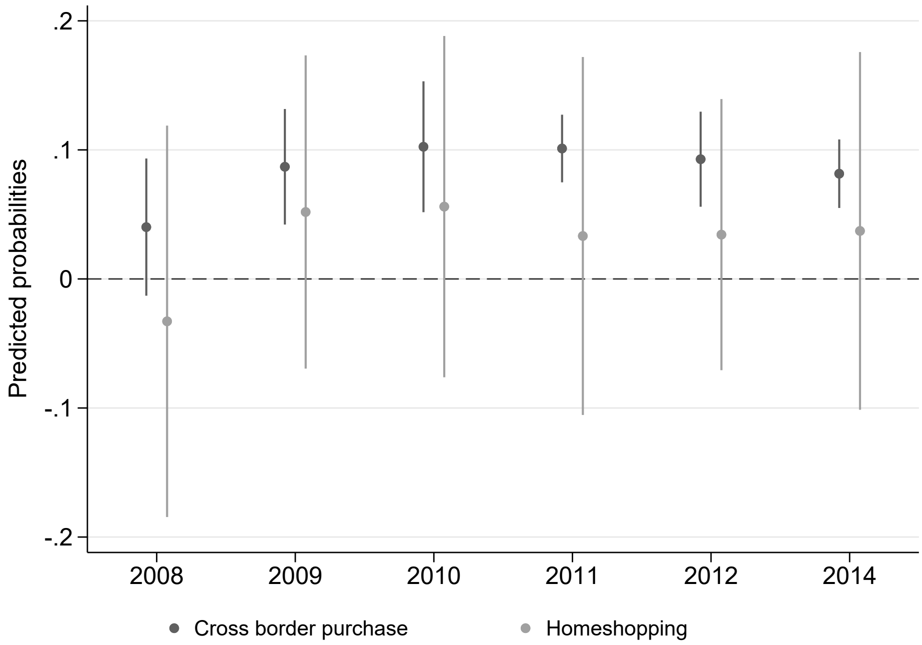
The variables for cross-border purchase and homeshopping catch the shopping behavior in the last 12 months. Therefore, the effect of the UCPD is also delayed in our estimation. Although the effect is increasing in the beginning, it stays constant over time and only decreases relatively less in the end. Most of the treated countries in our sample implemented the directive by 2007. Hence, it is not surprising that the positive and statistically significant effect is visible since 2008. However, a stable effect can only be shown by 2010 until the end of our sample. In contrast to the trust outcomes, the impact of the UCPD on cross-border purchase (panel A) is more long-lasting and more stable over time. For panel B, however, the effect shows a similar yet lower development over time which can be nicely seen in Figure 3.5. Nevertheless, the effect on homeshopping behavior is not statistically significant at any point in time.[66]

We provide various robustness checks. The results are robust to all these sensitivity tests.[67]

[66] Exact values can be found in Table 3.B2 in 3.B.

[67] Robustness checks include varying the method, varying the treatment and treatment groups, transforming the data and accounting for the correct inference of the standard error. The discussion and

Figure 3.5: Marginal effects of cross-border purchase and homeshopping over time



Note: This figure shows marginal effects of the interaction term Treat(L_{cj} = 1) × Post$_{ct}$ × $\sum_{t=2008}^{2014}$year$_t$ for panel A (cross-border purchase) and panel B (homeshopping) over time (Table 3.B2). The lines correspond to 95% confidence intervals.

3.4.4 Discussion

The results of this analysis show that consumers' trust vis-à-vis retailers, service providers, and vis-à-vis public authorities could be obtained by introducing the Unfair Commercial Practice Directive. We show that consumer trust rises for consumers of countries with a very low pre-UCPD consumer protection standard by roughly 11 percentage points, adding together the changes from strongly disagree and disagree as well as agree and strongly agree. For public authority trust, this effect is about 9 percentage points (see Table 3.3). The probability of a cross-border online purchase raised after the introduction by about 9 percentage points, while homeshopping increased by 4 percentage points and is not statistically significant (see Table 3.4).

The EU Digital Agenda (DAE)[68] has set different policy targets for e-commerce, e.g., by 2015, the EU would like to have 50 percent of its citizens buying online and 20 percent engaged in cross-border trade. We show for cross-border purchases an in-

results of the robustness checks are provided in the 3.D.

[68]See: https://ec.europa.eu/digital-single-market/en/policies/shaping-digital-single-market

crease by 9 percentage points, after the introduction of the UCPD, for consumers in countries with a low pre-UCPD consumer protection level. From an initial low cross-border shopping level of 6 percent in 2006, this is s crucial result (European Commission 2009) and therefore, the UCPD substantially contributed to the goal of increasing cross-border trade. Still, the general cross-border share within the EU member states was in 2017 only at 13 percent (Eurostat 2018). Our results showed that the discussed barriers in terms of language, culture or trust may be decreasing but cannot be vanished completely with the help of the UCPD. However, the ultimate objective of the DAE is to increase consumer welfare and not cross-border trade itself. These welfare effects are also achieved by minimum standard which implies, e.g., reduced information costs and thus higher trust.

However, the results have to be interpreted with caution. First, our sample only showed this effect for a small number of countries. Second, the analysis is based on a survey sample and does not reflect administrative data. However, this is partly necessary due to the trust outcomes. Third, there are only few studies that examine trust empirically. Either the studies have used different trust measures (e.g., Lewicki et al. 2006; Ennew and Sekhon 2007) or they examined trust in another context (e.g., Ha 2004; Cheung and Lee 2006; Xu et al. 2003). Our results are, therefore, difficult to interpret and discuss in their height compared to other studies.

Importantly, all effects increased over time and stay relatively constant so that the introduction of the UCPD had a constant effect over time and does not only affect the shown outcomes once. This is relevant as the effect does not vanish (at least until the end of our sample in 2014) and the regulation has a constant effects on attitudes concerning trust and shopping behavior.

3.5 Conclusion

In this paper, we present evidence that the introduction of a minimum consumer protection standard within the European Union significantly improves trust and online shopping behavior of consumers, especially in countries with initially low consumer protection levels. Our study analyses the Unfair Commercial Practice Directive (UCPD) which was implemented in EU member states between 2007 and 2010. We find that the introduction of the UCPD has lead to significant increase in consumer trust, public authority trust and cross-border purchases. The effects are only visible for consumers in countries with low pre-UCPD consumer protection levels which is in line with our expectations. The effects have been becoming stronger over time, and we find a peak for both trust outcomes in 2012 while shopping behavior stays on a constant high level from 2010 onwards. The results pass several robustness tests, including controlling for time invariant effects, changes on model specification and tests on treatment and control group. In general, the results imply that improved and standardized consumer protection within the European Union has positive effects on trust that consumers have vis-à-vis retailers and services providers as well as public authorities, and on online purchases.

To analyze the UCPD, we have use data for the years between 2006 and 2014 which was provided by different sources: First, we have used Eurobarometer survey data for the outcomes and controls on an individual level. Second, Civic Consulting provided data on the consumer protection level in each country before the introduction of the UCPD and specific time information on its implementation. Third, the data were merged with country-level data from Eurostat to control for country specific factors. The main identification was driven by the pre-UCPD consumer protection level. This index enables us to apply a difference-in-difference estimation method with multiple time periods. The European Union is a unique market so that it is difficult to find a suitable control group which did not introduce the UCPD or a similar consumer protection regulation outside the EU.

We argue that the UCPD – only providing a minimum consumer protection standard – affects countries with a very low pre-UCPD consumer protection evaluation level the most. Therefore, these countries were chosen as treated while countries with a higher initial protection level form the control group. Hence, the estimation results only measure a minimum effect the UCPD has on trust and shopping behavior of the treated countries. Our results indicate that consumers in countries with low pre-

UCPD consumer protection levels have on average more trust in retailers and services providers as well as in public authorities after the introduction. Additionally, these consumers shop more cross-border within the EU while the effect on homeshopping behavior is not statistically significant. An obvious reason for the different effect on cross-border shopping and homeshopping is that consumers tend to be familiar with consumer protection levels at home, but the UCPD removes uncertainties about the minimum protection levels provided abroad which is relevant for cross-border shopping. The UCPD is an important instrument of the European Union to strengthen the European single market policy. As discussed, the UCPD does not provide full harmonization and the implemented consumer protection standard is relatively low. Hence, countries with a low pre-UCPD consumer protection standard benefit the most, while countries with high levels of consumer protection remain largely unaffected.

More generally, market-wide minimum consumer protection levels, as now also provided by the General Data Protection Regulation (GDPR), may especially benefit consumers in countries with initially low standards. While it may not change their knowledge about regulation levels at home, it removes uncertainties about foreign protection levels, thereby, facilitating further market integration and, hence, more intense competition. The key idea is that consumers tend to be unfamiliar with regulations of all 28 EU member states, and that getting information about foreign regulation is not costless. Hence, harmonization at minimum level can reduce consumer information cost and thereby, facilitate trade and competition. While, at this point, it is too early to evaluate the effects of the GDPR on trust, trade and competition, it appears a worthwhile exercise for future research.

As mentioned, the European Commission has proposed a “New Deal for Consumers” in April of 2018 which shall revise existing consumer protection initiatives like the UCPD. This was also due to substantial critique that followed the implementation of the UCPD. Among others, the European Consumer Organisation (Bureau Européen des Unions de Consommateurs, BEUC) raised concerns in terms of harmonization, effectiveness and enforcement of the UCPD. While the UCPD only provides a minimum consumer protection standard, as of 2013 member states are no longer allowed to introduce or maintain higher level of consumer protection rules in this area.[69] It is unclear, however, whether full harmonization provides similar benefits as minimum standards. (Bureau Européan des Unions de Consommateurs 2013; Bureau Européan des Unions de Consommateurs 2016)

Our analysis has shown that the UCPD can, to some extent, contribute to trust in retailers and services within the EU and increase cross-border purchase. However, these results are only valid for countries with a very low pre-UCPD consumer protection standard. If policymakers also want to address consumers of countries with a high consumer protection level before the introduction of the UCPD, measures have to be carefully designed. On the one hand, standardized consumer protection regulations have to address different consumer preferences. On the other hand, replacing higher national standards can create uncertainty so that consumers still prefer to shop at home rather than cross-border within the internal market.

Moreover, the legal regime of the UCPD is largely based on enforcement through courts and public authorities. In some member states with a strong private enforcement tradition, not much has changed after the introduction of the UCPD while public enforcement is rather common in other member states (Bureau Européan des Unions de Consommateurs 2016). To address consumers' concerns, policy makers should be clear about the position of national authorities, consumer associations, and the European Commission. If consumer protection regulations are standardized and fully harmonized, a European consumer agency that replaces or complements the national agencies may be beneficial.

[69] As of June 2013 member states may not enact higher standard for unfair practices than those prescribed by the UCPD except of the areas relating to financial services and immovable property.

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Appendix

3.A Descriptive Statistics

Table 3.A1: Descriptive statistics

	Obs.	Mean	Std. Dev.	Min	Max	P1	P25	P50	P75	P99
Dependent variables										
Consumer trust	167,580	2.688	0.751	1	4	1	2	3	3	4
Public authority trust	167,475	2.633	0.844	1	4	1	2	3	3	4
Cross-border purchase	179,724	0.115	0.319	0	1	0	0	0	0	1
Homeshopping	173,479	0.293	0.455	0	1	0	0	0	1	1
Treatment variables										
Pre-UCPD consumer protection evaluation level by legal experts (L_{cj})	179,724	2.920	1.147	1	5	1	2	3	4	5
Pre-UCPD consumer protection evaluation level by protection experts (P_{cj})	179,724	3.136	1.098	1	5	1	2	3	4	5
Individual controls										
Female	179,724	0.579	0.494	0	1	0	0	1	1	1
Nation (indicator, nationality different to current country)	179,724	0.326	0.469	0	1	0	0	0	1	1
Age	179,724	49.173	17.695	15	99	16	35	50	63	85
$\log(age)$	179,724	3.818	0.414	2.708	4.595	2.773	3.555	3.912	4.143	4.443
Country controls										
Share of internet access (% of population)	179,724	65.687	16.792	23	96	25	54	67	78	94
Share of unemployment (% of population)	179,724	9.277	4.321	3.4	26.5	3.7	6.5	7.9	11	24.8
log(GDP)	179,724	9.914	0.633	8.517	11.402	8.517	9.384	10.012	10.463	11.280
Incident (indicator, consumer trust affected by crisis)	179,724	0.212	0.409	0	1	0	0	0	0	1
Share of border purchase (% of population)	167,580	13.190	10.582	1	51	1	6	10	17	45

Note: This table shows descriptive statistics of the sample used in the baseline model.

Table 3.A2: Descriptive statistics of treatment and control group

		Post_{ct}		Total
		0	1	
Treatment ($L_{cj} = 1$)	0	34,297	129,693	163,99
	1	2,512	14,057	16,569
Total		36,809	143,75	180,559

Note: This table shows detailed descriptive statistics of treatment and control group before and after the introduction of the Unfair Commercial Practice Directive (UCPD). Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD.

3.B Analysis over time

Table 3.B1: Marginal effects for consumer and public authority trust over time

	Strongly Disagree	Disagree	Agree	Strongly Agree
	Panel A: Consumer trust			
Treat (L_{cj} = 1) × $Post_{ct}$ × 2006	*Reference category*			
Treat (L_{cj} = 1) × $Post_{ct}$ × 2008	-0.015*	-0.027*	0.025*	0.017*
	(0.008)	(0.014)	(0.013)	(0.009)
Treat (L_{cj} = 1) × $Post_{ct}$ × 2009	-0.026**	-0.046*	0.042*	0.029**
	(0.013)	(0.024)	(0.022)	(0.015)
Treat (L_{cj} = 1) × $Post_{ct}$ × 2010	-0.021	-0.038	0.035	0.024
	(0.019)	(0.035)	(0.032)	(0.022)
Treat (L_{cj} = 1) × $Post_{ct}$ × 2011	-0.029**	-0.052**	0.048**	0.033**
	(0.012)	(0.023)	(0.021)	(0.014)
Treat (L_{cj} = 1) × $Post_{ct}$ × 2012	-0.053**	-0.096**	0.087**	0.061**
	(0.023)	(0.044)	(0.040)	(0.027)
Treat (L_{cj} = 1) × $Post_{ct}$ × 2014	-0.044***	-0.080***	0.073***	0.051***
	(0.012)	(0.022)	(0.020)	(0.014)
Observations	167,722			
	Panel B: Public authority trust			
Treat (L_{cj} = 1) × $Post_{ct}$ × 2006	*Reference category*			
Treat (L_{cj} = 1) × $Post_{ct}$ × 2008	0.012	0.013	-0.013	-0.012
	(0.018)	(0.019)	(0.019)	(0.018)
Treat (L_{cj} = 1) × $Post_{ct}$ × 2009	-0.034***	-0.037***	0.037***	0.034***
	(0.011)	(0.012)	(0.012)	(0.011)
Treat (L_{cj} = 1) × $Post_{ct}$ × 2010	-0.032**	-0.035**	0.035**	0.032**
	(0.015)	(0.017)	(0.017)	(0.015)
Treat (L_{cj} = 1) × $Post_{ct}$ × 2011	-0.030*	-0.033**	0.033**	0.030*
	(0.016)	(0.016)	(0.016)	(0.016)
Treat (L_{cj} = 1) × $Post_{ct}$ × 2012	-0.051***	-0.055***	0.055***	0.051***
	(0.015)	(0.016)	(0.015)	(0.015)
Treat (L_{cj} = 1) × $Post_{ct}$ × 2014	-0.024**	-0.026***	0.026***	0.024**
	(0.009)	(0.010)	(0.010)	(0.009)
Observations	167,607			
Individual controls	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Country Cluster	Yes	Yes	Yes	Yes

Note: This table shows the marginal effects as predicted probabilities at means of all other variables, separately for each outcome and over time. Baseline for the calculations is the full models of the ordered probit difference-in-difference estimation. The reference group states the year 2006 such that all other interactions are interpretable in reference to this year. Panel A reports the marginal effects effects of the introduction of the UCPD over time on consumer trust while panel B reports marginal effects on public authority trust. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD. Here, the treatment group states the lowest pre-UCPD consumer protection evaluation while higher pre-UCPD consumer protection evaluation level are the summarized control group. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 3.B2: Marginal effects for cross-border purchase and homeshopping over time

	Panel A: Cross-border purchase	**Panel B**: Homeshopping
Treat (L_{cj} = 1) × $Post_{ct}$ × 2006	*Reference category*	
Treat (L_{cj} = 1) × $Post_{ct}$ × 2008	0.040**	-0.033
	(0.017)	(0.077)
Treat (L_{cj} = 1) × $Post_{ct}$ × 2009	0.052	0.052
	(0.017)	(0.062)
Treat (L_{cj} = 1) × $Post_{ct}$ × 2010	0.102***	0.056
	(0.016)	(0.067)
Treat (L_{cj} = 1) × $Post_{ct}$ × 2011	0.101***	0.033
	(0.015)	(0.071)
Treat (L_{cj} = 1) × $Post_{ct}$ × 2012	0.093***	0.034
	(0.016)	(0.054)
Treat (L_{cj} = 1) × $Post_{ct}$ × 2014	0.082***	0.037
	(0.016)	(0.071)
Individual controls	Yes	Yes
Country controls	Yes	Yes
Year fixed effects	Yes	Yes
Country fixed effects	Yes	Yes
Country Cluster	Yes	Yes
Observations	179,724	173,479

Note: This table shows the marginal effects as predicted probabilities at means of all other variables and over time. Baseline for the calculations is full model of the probit difference-in-difference estimation. The reference group states the year 2006 such that all other interactions are interpretable in reference to this year. Panel A reports the marginal effects effects of the introduction on cross-border purchase for each year while panel B reports marginal effects on homeshopping over time. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD. Here, the treatment group states the lowest pre-UCPD consumer protection evaluation while higher pre-UCPD consumer protection evaluation level are the summarized control group. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

3.C Control groups

As a very first step, utilizing a difference-in-difference estimator with multiple time periods and multiple treatments was chosen. To do so, the regression estimation included all five pre-UCPD consumer protection evaluation levels. To approach this combination of periods and groups, we use the generalized DiD-estimator suggested by Athey and Imbens 2006 as well as Imbens and Wooldridge 2009. Here, all different pre-UCPD consumer protection levels represent an individual treatment. The estimation equation looks as follows:

$$Y_{it} = \beta_0 + \sum_{j=2}^{5} (\beta_j Post_{ct} \times L_{cj}) + \beta_5 X_{it} + \beta_6 T_{ct} + \tau_t + \delta_c + u_{ict} \tag{3.1}$$

Due to the five different treatments, we sum over the interaction term. The estimation will then automatically omit one of the treatments which state the reference category or control group. In this estimation the omitted category is the lowest consumer protection level, namely $L_{cj} = 1$. The results show indeed a significant effect of the introduction of the UCPD for all pre-UCPD consumer protection evaluation levels higher than one in comparison to a pre-UCPD consumer protection evaluation of one.[70] The results of the marginal effects shown in Tables 3.C1 and 3.C2 are counter-intuitive as they lead in the other direction than expected. Thus, it is more likely to answer the question whether retailers and services providers respect the rights of consumer with 'strongly disagree' or 'disagree' for consumers of countries with a pre-UCPD consumer protection evaluation level of two, three or four compared to consumers of countries with a very low pre-UCPD consumer protection evaluation level.

A control group that equals the lowest consumer protection evaluation level is more intuitive as countries of a very low pre-UCPD consumer protection evaluation level are by chance the ones which benefit the most of a general EU consumer protection standard. This is due to the higher consumer protection standard within their own country which should lead to a higher consumer trust. However, when using this argumenta-

[70] Coefficients of the results are available upon request.

tion as a base for the choice of treatment and control group, we start with using all pre-UCPD consumer protection levels lower than five as treatment groups while $P_{cj} = 5$ states the control group. In doing so, the results are ambiguous. (Tables 3.C3 and 3.C4). While all pre-UCPD consumer protection evaluation levels smaller than four face insignificant effects after the introduction of the UCPD compared to countries with a pre-UCPD consumer protection evaluation level of five, the evaluation level of four is statistical significant. The marginal effects reveal an increasing likelihood for consumers of countries with a low pre-UCPD consumer protection evaluation answering the trust question with strongly disagree or disagree and on the other hand a decreasing likelihood for the answers agree and strongly agree (Tables 3.C3 and 3.C4).

Literature (e.g., Collins 2010; Osuji 2011) suggest that the UCPD only leads to a very low minimum consumer protection level. That is why consumer trust should only be affected in the very low pre-UCPD consumer protection evaluation level countries. Countries with higher consumer protection evaluation level should not be affected by the minimum standard in the EU and therefore, consumers are not expected to have a higher trust in the retailers and services providers of their own country.

However, for shopping behavior we expect a similar picture, so that we choose the same treatment and control group for outcomes concerning shopping behavior. [71]

[71]Coefficients for the estimations for shopping behavior with different multiple difference-in-difference estimation are available upon request. Marginal effects are, however, shown in Table 3.C5 and 3.C6

Table 3.C1: Marginal effects of multiple difference-in-difference estimations with reference category $L_{cj} = 1$

	Strongly disagree	Disagree	Agree	Strongly agree
		Panel A: Consumer trust		
Post_{ct} (indicator,	-0.029***	-0.052***	0.048***	0.033***
UCPD in place)	(0.010)	(0.018)	(0.017)	(0.012)
Treat ($L_{cj} = 1$)		*Reference category*		
Treat ($L_{cj} = 2$)	0.020	0.036	-0.033	-0.023
	(0.023)	(0.042)	(0.039)	(0.027)
Treat ($L_{cj} = 3$)	0.007	0.013	-0.012	-0.008
	(0.028)	(0.050)	(0.046)	(0.032)
Treat ($L_{cj} = 4$)	-0.035*	-0.064*	0.058*	0.041*
	(0.020)	(0.036)	(0.034)	(0.023)
Treat ($L_{cj} = 5$)	-0.039	-0.071	0.065	0.045
	(0.029)	(0.052)	(0.048)	(0.033)
Treat ($L_{cj} = 1$) × Post_{ct}		*Reference category*		
Treat ($L_{cj} = 2$) × Post_{ct}	0.040***	0.072***	-0.066***	-0.046***
	(0.013)	(0.025)	(0.023)	(0.015)
Treat ($L_{cj} = 3$) × Post_{ct}	0.041***	0.074***	-0.068***	-0.047***
	(0.010)	(0.020)	(0.018)	(0.012)
Treat ($L_{cj} = 4$) × Post_{ct}	0.051***	0.092***	-0.084***	-0.059***
	(0.012)	(0.023)	(0.021)	(0.014)
Treat ($L_{cj} = 5$) × Post_{ct}	0.021	0.038	-0.035	-0.024
	(0.015)	(0.027)	(0.025)	(0.017)
Individual controls	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Country cluster	Yes	Yes	Yes	Yes
Observations		167,722		

Note: This table shows the marginal effects estimated as predicted probabilities at means all other variables. Panel A reports the marginal effects of the introduction of the UCPD on consumer trust. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five where one is the lowest and five the highest. The index is equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD. Here, the control group states the lowest pre-UCPD consumer protection evaluation. The multiple DiD approach leads to four different treatment groups which are all evaluation levels higher than one. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 3.C2: Marginal effects of multiple difference-in-difference estimations with reference category $L_{cj} = 1$

	Strongly disagree	Disagree	Agree	Strongly agree
	Panel B: Public authority trust			
$Post_{ct}$ (indicator,	-0.038***	-0.041***	0.041***	0.038***
UCPD in place)	(0.009)	(0.010)	(0.010)	(0.009)
Treat ($L_{cj} = 1$)	*Reference category*			
Treat ($L_{cj} = 2$)	0.025	0.027	-0.027	-0.025
	(0.032)	(0.034)	(0.034)	(0.032)
Treat ($L_{cj} = 3$)	0.017	0.019	-0.019	-0.017
	(0.035)	(0.038)	(0.038)	(0.035)
Treat ($L_{cj} = 4$)	-0.007	-0.007	0.007	0.007
	(0.024)	(0.026)	(0.026)	(0.024)
Treat ($L_{cj} = 5$)	-0.008	-0.009	0.008	0.008
	(0.029)	(0.032)	(0.031)	(0.029)
Treat ($L_{cj} = 1$) × $Post_{ct}$	*Reference category*			
Treat ($L_{cj} = 2$) × $Post_{ct}$	0.065***	0.071***	-0.070***	-0.066***
	(0.010)	(0.011)	(0.011)	(0.010)
Treat ($L_{cj} = 3$) × $Post_{ct}$	0.039***	0.042***	-0.042***	-0.039***
	(0.009)	(0.009)	(0.009)	(0.009)
Treat ($L_{cj} = 4$) × $Post_{ct}$	0.032***	0.035***	-0.034***	-0.032***
	(0.011)	(0.012)	(0.012)	(0.011)
Treat ($L_{cj} = 5$) × $Post_{ct}$	0.026***	0.028***	-0.028***	-0.026***
	(0.007)	(0.008)	(0.008)	(0.007)
Individual controls	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Country cluster	Yes	Yes	Yes	Yes
Observations	167,607			

Note: This table shows the marginal effects estimated as predicted probabilities at means all other variables. Panel B reports marginal effects of the introduction of the UCPD on public authority trust. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five where one is the lowest and five the highest. The index is equivalent to: 1 - “very low”, 2 - “low”, 3 - “middle”, 4 - “high”, 5 - “very high” consumer protection standards before the introduction of the UCPD. Here, the control group states the lowest pre-UCPD consumer protection evaluation. The multiple DiD approach leads to four different treatment groups which are all evaluation levels higher than one. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 3.C3: Marginal effects of multiple difference-in-difference estimations with reference category $L_{cj} = 5$

	Strongly disagree	Disagree	Agree	Strongly agree
		Panel A: Consumer trust		
Post_{ct} (indicator, UCPD in place)	-0.008	-0.014	0.013	0.009
	(0.013)	(0.024)	(0.022)	(0.015)
Treat ($L_{cj} = 1$)	0.039	0.071	-0.065	-0.045
	(0.029)	(0.052)	(0.048)	(0.033)
Treat ($L_{cj} = 2$)	0.059***	0.107***	-0.098***	-0.068***
	(0.015)	(0.026)	(0.024)	(0.017)
Treat ($L_{cj} = 3$)	0.047***	0.084***	-0.077***	-0.054***
	(0.014)	(0.026)	(0.024)	(0.017)
Treat ($L_{cj} = 4$)	0.004	0.007	-0.007	-0.005
	(0.016)	(0.028)	(0.026)	(0.018)
Treat ($L_{cj} = 5$)		*Reference category*		
Treat ($L_{cj} = 1$) × Post_{ct}	-0.021	-0.038	0.035	0.024
	(0.015)	(0.027)	(0.025)	(0.017)
Treat ($L_{cj} = 2$) × Post_{ct}	0.019	0.034	-0.031	-0.022
	(0.017)	(0.031)	(0.028)	(0.020)
Treat ($L_{cj} = 3$) × Post_{ct}	0.020	0.036	-0.033	-0.023
	(0.013)	(0.024)	(0.022)	(0.015)
Treat ($L_{cj} = 4$) × Post_{ct}	0.030**	0.054*	-0.050*	-0.035**
	(0.015)	(0.028)	(0.026)	(0.018)
Treat ($L_{cj} = 5$) × Post_{ct}		*Reference category*		
Individual controls	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Country cluster	Yes	Yes	Yes	Yes
Observations		167,722		

Note: This table shows the marginal effects estimated as predicted probabilities at means all other variables. Panel A reports the marginal effects of the introduction of the UCPD on consumer trust. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five where one is the lowest and five the highest. The index is equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD. Here, the control group states the highest pre-UCPD consumer protection evaluation. The multiple DiD approach leads to four different treatment groups which are all evaluation levels lower than five. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 3.C4: Marginal effects of multiple difference-in-difference estimations with reference category $L_{cj} = 5$

	Strongly disagree	Disagree	Agree	Strongly agree
	Panel B: Public authority trust			
$Post_{ct}$ (indicator,	-0.012	-0.013	0.013	0.012
UCPD in place)	(0.011)	(0.012)	(0.012)	(0.011)
Treat ($L_{cj} = 1$)	0.008	0.009	-0.008	-0.008
	(0.029)	(0.032)	(0.031)	(0.029)
Treat ($L_{cj} = 2$)	0.033**	0.036**	-0.035**	-0.033**
	(0.016)	(0.016)	(0.016)	(0.015)
Treat ($L_{cj} = 3$)	0.025	0.027*	-0.027	-0.025
	(0.016)	(0.017)	(0.017)	(0.016)
Treat ($L_{cj} = 4$)	0.001	0.001	-0.001	-0.001
	(0.016)	(0.017)	(0.017)	(0.016)
Treat ($L_{cj} = 5$)	*Reference category*			
Treat ($L_{cj} = 1$) × $Post_{ct}$	-0.026***	-0.028***	0.028***	0.026***
	(0.007)	(0.008)	(0.008)	(0.007)
Treat ($L_{cj} = 2$) × $Post_{ct}$	0.040***	0.043***	-0.043***	-0.040***
	(0.012)	(0.013)	(0.013)	(0.012)
Treat ($L_{cj} = 3$) × $Post_{ct}$	0.013	0.014*	-0.014*	-0.013
	(0.008)	(0.009)	(0.009)	(0.008)
Treat ($L_{cj} = 4$) × $Post_{ct}$	0.006	0.007	-0.007	-0.006
	(0.012)	(0.014)	(0.013)	(0.013)
Treat ($L_{cj} = 5\times$ $Post_{ct}$)	*Reference category*			
Individual controls	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Country cluster	Yes	Yes	Yes	Yes
Observations	167,607			

Note: This table shows the marginal effects estimated as predicted probabilities at means all other variables. Panel A reports the marginal effects of the introduction of the UCPD on public authority trust. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five where one is the lowest and five the highest. The index is equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD. Here, the control group states the highest pre-UCPD consumer protection evaluation. The multiple DiD approach leads to four different treatment groups which are all evaluation levels lower than five. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 3.C5: Marginal effects of multiple difference-in-difference estimations with reference category $L_{cj} = 1$

	Panel A: Cross-border purchase	**Panel B**: Homeshopping
$Post_{ct}$ (indicator,	0.060***	0.019
UCPD in place)	(0.015)	(0.038)
Treat ($L_{cj} = 1$)	*Reference category*	
Treat ($L_{cj} = 2$)	0.058	0.303***
	(0.042)	(0.106)
Treat ($L_{cj} = 3$)	0.061	0.330***
	(0.045)	(0.117)
Treat ($L_{cj} = 4$)	0.074**	0.422**
	(0.037)	(0.082)
Treat ($L_{cj} = 5$)	0.190***	0.144
	(0.040)	(0.102)
Treat ($L_{cj} = 1$) × $Post_{ct}$	*Reference category*	
Treat ($L_{cj} = 2$) × $Post_{ct}$	-0.101**	-0.028
	(0.022)	(0.040)
Treat ($L_{cj} = 3$) × $Post_{ct}$	-0.083***	-0.041
	(0.019)	(0.038)
Treat ($L_{cj} = 4$) × $Post_{ct}$	-0.105***	-0.068
	(0.013)	(0.043)
Treat ($L_{cj} = 5$) × $Post_{ct}$	-0.064***	-0.004
	(0.011)	(0.056)
Individual controls	Yes	Yes
Country controls	Yes	Yes
Year fixed effects	Yes	Yes
Country fixed effects	Yes	Yes
Country cluster	Yes	Yes
Observations	179,724	173,479

Note: This table shows the marginal effects estimated as predicted probabilities at means all other variables. Panel A reports the marginal effects of the introduction of the UCPD on cross-border purchase while panel B reports marginal effects on homeshopping. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five where one is the lowest and five the highest. The index is equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD. Here, the control group states the lowest pre-UCPD consumer protection evaluation. The multiple DiD approach leads to four different treatment groups which are all evaluation levels higher than one. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 3.C6: Marginal effects of multiple difference-in-difference estimations with reference category $L_{cj} = 5$

	Panel A: Cross-border purchase	**Panel B**: Homeshopping
$Post_{ct}$ (indicator,	-0.004	0.015
UCPD in place)	(0.013)	(0.052)
Treat ($L_{cj} = 1$)	-0.190***	-0.144
	(0.040)	(0.102)
Treat ($L_{cj} = 2$)	-0.132***	0.159***
	(0.014)	(0.051)
Treat ($L_{cj} = 3$)	-0.129***	0.186***
	(0.016)	(0.053)
Treat ($L_{cj} = 4$)	-0.116***	0.278***
	(0.009)	(0.051)
Treat ($L_{cj} = 5$)	*Reference category*	
Treat ($L_{cj} = 1$) × $Post_{ct}$	0.064***	0.004
	(0.011)	(0.056)
Treat ($L_{cj} = 2$) × $Post_{ct}$	-0.037*	-0.024
	(0.022)	(0.054)
Treat ($L_{cj} = 3$) × $Post_{ct}$	-0.019	-0.037
	(0.017)	(0.051)
Treat ($L_{cj} = 4$) × $Post_{ct}$	-0.041***	-0.065
	(0.010)	(0.059)
Treat ($L_{cj} = 5$) × $Post_{ct}$	*Reference category*	
Individual controls	Yes	Yes
Country controls	Yes	Yes
Year fixed effects	Yes	Yes
Country fixed effects	Yes	Yes
Country cluster	Yes	Yes
Observations	179,724	173,479

Note: This table shows the marginal effects estimated as predicted probabilities at means all other variables. Panel A reports the marginal effects of the introduction of the UCPD on cross-border purchase while panel B reports marginal effects on homeshopping. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five where one is the lowest and five the highest. The index is equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD. Here, the control group states the highest pre-UCPD consumer protection evaluation. The multiple DiD approach leads to four different treatment groups which are all evaluation levels lower than five. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

3.D Robustness checks

We present a variety of sensitivity analyses. First, we use a more simple method. It has been discussed in the literature (recently by, e.g., Bond and Lang 2019) that for a cardinal variable an ordered logit or probit model might be a problem. Results of the re-estimation of Equation 3.1 with an ordinary least squares model support the main results of our analysis for the trust outcomes (Table 3.D1).

Moreover, we added Worldwide Governance Indicators (WGI) for all member states in addition to individual and country controls in our baseline specification. The governance indicators include: voice and accountability, political stability and absence of violence/terrorism, government effectiveness, regulatory quality, rule of law as well as control of corruption. The data was provided by The World Bank 2018. The marginal effects for the variables of interest can be found in Tables 3.D2 and 3.D3, respectively for trust and shopping behavior. The results reveal that including additional governance indicators does not change the marginal effects substantially. The effects for consumer trust seem to be a little bit smaller while public authority trust is not affected by including the governance indicators. A different picture arises for shopping behavior. While the effect for cross-border purchase is a slightly lower, the former (non-statistically but positive) effect for homeshopping diminishes completely.[72]

In our data different implementation dates in different countries happen. This leads to a difference-in-difference approach with multiple time periods and varying timing. Comparing treated and non-treated observations before and after the treatment may then lead to a comparison of treated countries compared to other treated countries that simply are not treated at this time. To overcome this issue, we fixed the

[72]The coefficients show similar results for the main variable of interest as in the baseline estimations. Interestingly, the governance indicators may influence consumer trust but do not explain public authority trust. While the regulatory quality and rule of law have statistically significant effects on consumer trust, political stability has an influence on cross-border purchase and government effectiveness is in addition relevant for homeshopping. The governance indicators reflect the situation in the home country, so that it is especially interesting that political stability in the home country has a statistical influence on cross-border purchase. However, it would also be interesting to investigate how political stability in countries of retailers and service providers influence cross-border purchase. Unfortunately, we are not able to observe directions of cross-border shopping, but only the consumer's country of origin. These estimation results are available upon request.

treatment dates for all countries to 2010 as this is the latest year, countries have implemented the UCPD.[73] The results in Tables 3.D4 and 3.D5 confirm the previous results of a difference-in-difference approach with multiple time periods although the effects are not as high.

In the beginning, two different evaluation indexes were introduced. The first is an evaluation index by legal law expert's and their evaluation of the consumer protection situation before the introduction of the UCPD. The second is also an evaluation index of the pre-UCPD consumer protection standard but from consumer protection experts instead of legal experts. Similar to the first evaluation index, consumer protection experts evaluate the level of pre-UCPD consumer protection by a value from 1-5, where 1 is the lowest and 5 the highest. For analysis, we mainly focused on the evaluation of the legal experts. However, we re-estimated the main outcome variables (consumer trust, public authority trust, cross-border purchase and homeshopping) with a treatment and control group based on the protection experts' evaluation. The results indicating that our findings are robust across the evaluation indexes and can be found in Tables 3.D6 and 3.D7 for trust, while the results for shopping behavior are shown in Tables 3.D8 and 3.D9.

As the data are only available as repeated cross-section samples, it is not possible to account for time invariant effects by using a fixed effects estimation or to test for autocorrelation. To overcome this, we build a pseudo panel based on Deaton 1985.[74] Individual characteristics (home country, year of birth and gender) of the respondents are used to generate a panel that contains average persons from groups that are gathered by the mentioned characteristics. The groups contain between 1 to 7 individuals leaving a panel between 21,871 and 26,416 observation depending on the regression method. We utilized the synthetic panel to re-estimate Equation 3.1 with a fixed effects estimator and to tests for autocorrelation. The results of the fixed effects as well as (ordered) logit estimations with robust and clustered standard errors can be found

[73]We thank an anonymous referee for raising our awareness towards this issue and the suggestion for fixing the treatment date.

[74]This technique was, among others, applied by Verbeek and Vella 2005 and Guillerm 2017.

in Tables 3.D10 and 3.D11, respectively for trust attitudes and shopping behavior. All estimates show similar positive and significant effects of the introduction of the UCPD on the outcomes except of homeshopping which remains insignificantly although positive. The estimates are therefore robust in the pseudo panel. Tests for first-degree autocorrelation as discussed by Verbeek and Nijman 1992 show no statistically significant results so that estimation results are not suffering from first-degree autocorrelation.

As mentioned by Bertrand et al. 2004 standard errors may be inconsistent with varying state sizes, therefore, we bootstrap the standard errors in the baseline regression to account for the correct inference. The results in Tables 3.D12 and 3.D13 show more coefficients being statistically significant so that even homeshopping now shows a highly statistically significant effect. Thus, we can confirm our baseline results and will rely on them. In summary, our results are robust to all applied sensitivity tests.

Table 3.D1: Ordinary least squares estimation results

	Panel A: Consumer trust		**Panel B**: Public authority trust	
Post_{ct} (indicator, UCPD in place)	-0.073*	-0.065*	-0.014	-0.018
	(0.042)	(0.038)	(0.042)	(0.033)
Treat ($L_{cj} = 1$)	-0.539***	-0.253*	-0.495***	-0.120
	(0.052)	(0.125)	(0.023)	(0.116)
Treat ($L_{cj} = 1$) $\times \text{Post}_{ct}$	0.178**	0.198***	0.161***	0.168***
	(0.068)	(0.058)	(0.028)	(0.031)
Individual controls				
Female		0.000		0.037***
		(0.004)		(0.008)
Nation (indicator, nationality different to current country)		0.043**		0.096***
		(0.018)		(0.033)
$\log(age)$		-1.540***		-1.453***
		(0.147)		(0.196)
$\log(age)^2$		0.202***		0.180***
		(0.020)		(0.027)
Country controls				
Share of internet access (% of population)		0.010***		0.004**
		(0.003)		(0.002)
Share of unemployment (% of population)		0.004		-0.011***
		(0.005)		(0.003)
log (GDP)		0.256		0.327**
		(0.168)		(0.147)
Incident (indicator, consumer trust affected by crisis)		-0.013		-0.019
		(0.019)		(0.022)
Share of border purchase (% of population)		-0.001		-0.000
		(0.003)		(0.003)
Intercept	2.975***	2.743*	2.965***	2.276
	(0.023)	(1.596)	(0.024)	(1.436)
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Country Cluster	Yes	Yes	Yes	Yes
Pseudo r^2	0.073	0.080	0.074	0.083
Observations	167,722		167,607	

Note: This table shows the results of the ordinary least squares difference-in-difference estimation of the introduction of the Unfair Commercial Practice Directive. Panel A reports the coefficients of the introduction on consumer trust while panel B reports coefficients on public authority trust. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD. Here, the treatment group states the lowest pre-UCPD consumer protection evaluation while higher pre-UCPD consumer protection evaluation level are the summarized control group. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 3.D2: Marginal effects including governance indicators as additional control variables

	Strongly Disagree	Disagree	Agree	Strongly Agree
	Panel A: Consumer trust			
Post_{ct} (indicator,	0.013*	0.023*	-0.021*	-0.015*
UCPD in place)	(0.007)	(0.013)	(0.012)	(0.008)
Treat ($L_{cj} = 1$)	0.029	0.052	-0.047	-0.033
	(0.030)	(0.053)	(0.049)	(0.034)
Treat ($L_{cj} = 1$) × Post_{ct}	-0.025***	-0.046***	0.042***	0.029***
	(0.009)	(0.016)	(0.015)	(0.010)
Observations	167,722			
	Panel B: Public authority trust			
Post_{ct} (indicator,	0.004	0.004	-0.004	-0.004
UCPD in place)	(0.008)	(0.009)	(0.009)	(0.008)
Treat ($L_{cj} = 1$)	0.032	0.035	-0.035	-0.032
	(0.033)	(0.036)	(0.036)	(0.034)
Treat ($L_{cj} = 1$) × Post_{ct}	-0.042***	-0.046***	0.045***	0.043***
	(0.008)	(0.009)	(0.009)	(0.008)
Observations	167,607			
Individual controls	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes
Governance indicators	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Country cluster	Yes	Yes	Yes	Yes

Note: This table shows the marginal effects estimated as predicted probabilities at means all other variables. Panel A reports the marginal effects of the introduction of the UCPD on consumer trust while panel B reports marginal effects on public authority trust. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD. Here, the treatment group states the lowest pre-UCPD consumer protection evaluation while higher pre-UCPD consumer protection evaluation level are the summarized control group. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 3.D3: Marginal effects including governance indicators as additional control variables

	Panel A: Cross-border purchase	**Panel B**: Homeshopping
Post_{ct} (indicator,	-0.031***	-0.019
UCPD in place)	(0.010)	(0.029)
Treat ($\text{L}_{cj} = 1$)	-0.207***	-0.098
	(0.038)	(0.099)
Treat ($\text{L}_{cj} = 1$) × Post_{ct}	0.082***	-0.001
	(0.015)	(0.037)
Individual controls	Yes	Yes
Country controls	Yes	Yes
Governance indicators	Yes	Yes
Year fixed effects	Yes	Yes
Country fixed effects	Yes	Yes
Country cluster	Yes	Yes
Observations	179,724	173,479

Note: This table shows the marginal effects of the probit difference-in-difference estimation. Panel A reports the marginal effects of the introduction of the UCPD on cross-border purchase while panel B reports marginal effects on homeshopping. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - “very low”, 2 - “low”, 3 - “middle”, 4 - “high”, 5 - “very high” consumer protection standards before the introduction of the UCPD. Here, the treatment group states the lowest pre-UCPD consumer protection evaluation while higher pre-UCPD consumer protection evaluation level are the summarized control group. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 3.D4: Marginal effects with a fixed treatment implementation date

	Strongly Disagree	Disagree	Agree	Strongly Agree
	Panel A: Consumer trust			
Post_{ct} (indicator, UCPD in place in 2010)	0.055***	0.100***	-0.091***	-0.064***
	(0.019)	(0.035)	(0.032)	(0.022)
Treat ($\text{L}_{cj} = 1$)	0.033	0.059*	-0.054	-0.038
	(0.020)	(0.036)	(0.033)	(0.023)
Treat ($\text{L}_{cj} = 1$) × Post_{ct}	-0.021*	-0.038*	0.035*	0.024*
	(0.012)	(0.022)	(0.020)	(0.014)
Observations	167,722			
	Panel B: Public authority trust			
Post_{ct} (indicator, UCPD in place in 2010)	0.039**	0.042**	-0.041**	-0.039**
	(0.017)	(0.018)	(0.017)	(0.017)
Treat ($\text{L}_{cj} = 1$)	0.022	0.024	-0.024	-0.022
	(0.023)	(0.025)	(0.024)	(0.023)
Treat ($\text{L}_{cj} = 1$) × Post_{ct}	-0.026***	-0.028***	0.028***	0.026***
	(0.008)	(0.009)	(0.009)	(0.009)
Observations	167,607			
Individual controls	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Country cluster	Yes	Yes	Yes	Yes

Note: This table shows the marginal effects of an ordered probit difference-in-difference estimation. Panel A reports the marginal effects of the introduction of the UCPD on consumer trust while panel B reports marginal effects on public authority trust. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD. Here, the treatment group states the lowest pre-UCPD consumer protection evaluation while higher pre-UCPD consumer protection evaluation level are the summarized control group. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 3.D5: Marginal effects with a fixed treatment implementation date

	Panel A: Cross-border purchase	**Panel B**: Homeshopping
Post_{ct} (indicator, UCPD in	0.061**	0.178***
place in 2010)	(0.027)	(0.048)
Treat ($L_{cj} = 1$)	-0.166***	-0.148
	(0.031)	(0.094)
Treat ($L_{cj} = 1$) × Post_{ct}	0.038***	0.027
	(0.008)	(0.027)
Individual controls	Yes	Yes
Country controls	Yes	Yes
Year fixed effects	Yes	Yes
Country fixed effects	Yes	Yes
Country cluster	Yes	Yes
Observations	179,724	173,479

Note: This table shows the marginal effects of the probit difference-in-difference estimation. Panel A reports the marginal effects of the introduction of the UCPD on cross-border purchase while panel B reports marginal effects on homeshopping. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD. Here, the treatment group states the lowest pre-UCPD consumer protection evaluation while higher pre-UCPD consumer protection evaluation level are the summarized control group. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 3.D6: Estimation results with treatment group indicator $P_{cj} = 1$ (consumer protection evaluation by consumer protection experts)

	Panel A: Consumer trust		**Panel B**: Public authority trust	
$Post_{ct}$ (indicator, UCPD in place)	-0.112*	-0.099*	-0.017	-0.020
	(0.065)	(0.059)	(0.058)	(0.046)
Treat ($P_{cj} = 1$)	-0.797***	-0.494**	-0.202***	0.149
	(0.087)	(0.214)	(0.034)	(0.145)
Treat ($P_{cj} = 1$) $\times Post_{ct}$	0.268***	0.299***	0.220***	0.230***
	(0.098)	(0.085)	(0.039)	(0.037)
Individual controls				
Female		-0.003		0.045***
		(0.006)		(0.011)
Nation (indicator, nationality different to current country		0.069**		0.129***
		(0.028)		(0.041)
$\log(age)$		-2.449***		-1.972***
		(0.213)		(0.250)
$\log(age)^2$		0.322***		0.245***
		(0.030)		(0.035)
Country controls				
Share of internet access (% of population)		0.015***		0.006**
		(0.005)		(0.002)
Share of unemployment(% of population)		0.006		-0.015***
		(0.007)		(0.005)
log(GDP)		0.379		0.417**
		(0.253)		(0.197)
Incident (indicator, consumer trust affected by crisis)		-0.021		-0.028
		(0.028)		(0.029)
Border purchase (% of population)		-0.002		0.000
		(0.004)		(0.004)
Cut 1	-1.982***	-1.917	-1.722***	-1.040
	(0.042)	(2.406)	(0.037)	(1.947)
Cut 2	-0.874***	-0.805	-0.759***	-0.071
	(0.041)	(2.411)	(0.032)	(1.948)
Cut 3	0.874***	0.950	0.740***	1.436
	(0.036)	(2.410)	(0.039)	(1.939)
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Country Cluster	Yes	Yes	Yes	Yes
Pseudo r^2	0.034	0.037	0.031	0.035
Observations	167,722		167,607	

Note: This table shows the results of the ordered probit difference-in-difference estimation of the introduction of the Unfair Commercial Practice Directive. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level by consumer protection experts. These evaluation levels reach from one to five where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - “very low”, 2 - “low”, 3 - “middle”, 4 - “high”, 5 - “very high” consumer protection standards before the introduction of the UCPD. Here, the treatment group states the lowest pre-UCPD consumer protection evaluation while higher pre-UCPD consumer protection evaluation level are the summarized control group. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 3.D7: Marginal effects with treatment group indicator $P_{cj} = 1$ (consumer protection evaluation by consumer protection experts)

	Strongly Disagree	Disagree	Agree	Strongly Agree
	Panel A: Consumer trust			
$Post_{ct}$ (indicator, UCPD in place)	0.013*	0.024*	-0.022*	-0.015*
	(0.008)	(0.014)	(0.013)	(0.009)
Treat ($P_{cj} = 1$)	0.066**	0.118**	-0.108**	-0.076**
	(0.028)	(0.051)	(0.047)	(0.033)
Treat ($P_{cj} = 1$) × $Post_{ct}$	-0.040***	-0.072***	0.066***	0.046***
	(0.011)	(0.021)	(0.019)	(0.013)
Observations	167,722			
	Panel B: Public authority trust			
$Post_{ct}$ (indicator, UCPD in place)	0.004	0.004	-0.004	-0.004
	(0.008)	(0.009)	(0.009)	(0.008)
Treat ($P_{cj} = 1$)	-0.028	-0.030	0.030	0.028
	(0.027)	(0.029)	(0.029)	(0.027)
Treat ($P_{cj} = 1$) × $Post_{ct}$	-0.042***	-0.046***	0.046***	0.043***
	(0.007)	(0.008)	(0.007)	(0.007)
Observations	167,607			
Individual controls	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Country cluster	Yes	Yes	Yes	Yes

Note: This table shows the marginal effects of the ordered probit difference-in-difference estimation of the introduction of the Unfair Commercial Practice Directive. Panel A reports the marginal effects of the introduction on consumer trust while panel B reports marginal effects on public authority trust. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level by consumer protection experts. These evaluation levels reach from one to five where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD. Here, the treatment group states the lowest pre-UCPD consumer protection evaluation while higher pre-UCPD consumer protection evaluation level are the summarized control group. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 3.D8: Estimation results with treatment group indicator $P_{cj} = 1$ (consumer protection evaluation by consumer protection experts)

	Panel A: Cross-border purchase		**Panel B**: Homeshopping	
$Post_{ct}$ (indicator, UCPD in place in 2010)	-0.137**	-0.181***	-0.037	-0.069
	(0.060)	(0.061)	(0.087)	(0.083)
Treat ($P_{cj} = 1$)	-0.479***	-0.180	-1.249***	-1.097***
	(0.046)	(0.211)	(0.092)	(0.317)
Treat ($P_{cj} = 1$) $\times Post_{ct}$	0.493***	0.469***	0.186*	0.111
	(0.053)	(0.058)	(0.101)	(0.099)
Individual controls				
Female		-0.278***		-0.133***
		(0.020)		(0.020)
Nation (indicator, nationality different to current country		-0.049		-0.130***
		(0.089)		(0.033)
$\log(age)$		9.815***		10.836***
		(0.337)		(0.458)
$\log(age)^2$		-1.459***		-1.613***
		(0.048)		(0.064)
Country controls				
Share of internet access (% of population)		0.013***		0.019***
		(0.004)		(0.004)
Share of unemployment (% of population)		0.008		0.002
		(0.008)		(0.010)
log(GDP)		0.322		0.189
		(0.251)		(0.392)
Incident (indicator, consumer trust affected by crisis)		-0.004		-0.021
		(0.029)		(0.028)
Intercept	-0.918***	-20.929***	-0.981***	-21.606***
	(0.048)	(2.537)	(0.045)	(4.038)
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Country Cluster	Yes	Yes	Yes	Yes
Pseudo r^2	0.099	0.176	0.113	0.199
Observations	179,724		173,479	

Note: This table shows the results of the probit difference-in-difference estimation of the introduction of the Unfair Commercial Practice Directive. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level by consumer protection experts. These evaluation levels reach from one to five where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD. Here, the treatment group states the lowest pre-UCPD consumer protection evaluation while higher pre-UCPD consumer protection evaluation level are the summarized control group. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 3.D9: Marginal effects with treatment group indicator $P_{cj} = 1$ (consumer protection evaluation by consumer protection experts)

	Panel A: Cross-border purchase	**Panel B**: Homeshopping
$Post_{ct}$ (indicator, UCPD in place)	-0.035***	-0.025
	(0.012)	(0.030)
Treat ($L_{cj} = 1$)	-0.035	-0.399***
	(0.041)	(0.116)
Treat ($L_{cj} = 1$) × $Post_{ct}$	0.090***	0.040
	(0.011)	(0.036)
Individual controls	Yes	Yes
Country controls	Yes	Yes
Year fixed effects	Yes	Yes
Country fixed effects	Yes	Yes
Country cluster	Yes	Yes
Observations	179,724	173,479

Note: This table shows the marginal effects of the probit difference-in-difference estimation of the introduction of the Unfair Commercial Practice Directive. Panel A reports the marginal effects of the introduction on cross-border purchase while panel B reports marginal effects on homeshopping. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level by consumer protection experts. These evaluation levels reach from one to five where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD. Here, the treatment group states the lowest pre-UCPD consumer protection evaluation while higher pre-UCPD consumer protection evaluation level are the summarized control group. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 3.D10: Estimation results of the pseudo panel

	OLS FE	oLogit	oLogit
	Panel A: Consumer trust		
Post_{ct} (indicator, UCPD in place)	-0.025*	-0.231***	-0.231
	(0.014)	(0.077)	(0.198)
Treat ($L_{cj} = 1$)	-	-2.585***	-2.585***
		(0.308)	(0.629)
Treat ($L_{cj} = 1$) × Post_{ct}	0.250***	0.864***	0.864***
	(0.046)	(0.129)	(0.233)
Observations	21,871	26,416	26,416
	Panel B: Public authority trust		
Post_{ct} (indicator, UCPD in place)	0.016	-0.093	-0.093
	(0.016)	(0.072)	(0.147)
Treat ($L_{cj} = 1$)	-	-0.300	-0.300
		(0.250)	(0.493)
Treat ($L_{cj} = 1$) × Post_{ct}	0.242***	0.818***	0.818***
	(0.051)	(0.125)	(0.123)
Observations	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes
Country controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Country Cluster	No	No	Yes
Robust SE	No	Yes	Yes

Note: This table shows the results of the ordinary least squares and ordered logit difference-in-difference estimations. Panel A reports the coefficients of introducing the Unfair Commercial Practice Directive on consumer trust while panel B reports coefficients on public authority trust. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - “very low”, 2 - “low”, 3 - “middle”, 4 - “high”, 5 - “very high” consumer protection standards before the introduction of the UCPD. Here, the treatment group states the lowest pre-UCPD consumer protection evaluation while higher pre-UCPD consumer protection evaluation level are the summarized control group. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 3.D11: Estimation results of the pseudo panel

	OLS FE	Logit	Logit
	Panel A: Cross-border purchase		
Post_{ct} (indicator, UCPD in place)	-0.025***	-0.688***	-0.688***
	(0.006)	(0.169)	(0.177)
Treat ($\text{L}_{cj} = 1$)	–	-4.966***	-4.966***
		(0.849)	(1.322)
Treat ($\text{L}_{cj} = 1$) × Post_{ct}	0.033*	1.054***	1.054**
	(0.018)	(0.385)	(0.427)
Observations	22,152	26,744	26,744
	Panel B: Homeshopping		
Post_{ct} (indicator, UCPD in place)	-0.017**	-0.364***	-0.364
	(0.007)	(0.104)	(0.279)
Treat ($\text{L}_{cj} = 1$)	–	-1.402**	-1.402
		(0.573)	(0.872)
Treat ($\text{L}_{cj} = 1$) × Post_{ct}	0.036	0.101	0.101
	(0.023)	(0.483)	(0.198)
Observations	22,152	26,744	26,744
Individual controls	Yes	Yes	Yes
Country controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Country Cluster	No	No	Yes
Robust SE	No	Yes	Yes

Note: This table shows the results of the ordinary least squares and logit difference-in-difference estimations. Panel A reports the coefficients of introducing the Unfair Commercial Practices Directive on cross-border purchase while panel B reports coefficients on homeshopping. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - “very low”, 2 - “low”, 3 - “middle”, 4 - “high”, 5 - “very high” consumer protection standards before the introduction of the UCPD. Here, the treatment group states the lowest pre-UCPD consumer protection evaluation while higher pre-UCPD consumer protection evaluation level are the summarized control group. Standard errors clustered at the country level are in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 3.D12: Estimation results with bootstrapped standard errors

	Panel A: Consumer trust		**Panel B**: Public authority trust	
Post_{ct} (indicator, UCPD in place)	-0.112***	-0.099***	-0.017	-0.020
	(0.014)	(0.015)	(0.014)	(0.014)
Treat ($L_{cj} = 1$)	-0.836***	-0.394***	-0.677***	-0.177***
	(0.029)	(0.055)	(0.027)	(0.049)
Treat ($L_{cj} = 1$) $\times \text{Post}_{ct}$	0.268***	0.299***	0.220***	0.230***
	(0.029)	(0.028)	(0.025)	(0.026)
Individual controls				
Female (indicator)		-0.003		0.045***
		(0.006)		(0.006)
Nation (indicator, nationality		0.069***		0.129***
different to current country)		(0.017)		(0.017)
$\log(age)$		-2.449***		-1.972***
		(0.110)		(0.105)
$\log(age)^2$		0.322***		0.245***
		(0.015)		(0.014)
Country controls				
Share of internet access (% of		0.015***		0.006***
population)		(0.001)		(0.001)
Share of unemployment (% of		0.006***		-0.015***
population)		(0.002)		(0.001)
log(GDP)		0.379***		0.417***
		(0.052)		(0.049)
Incident (indicator, consumer		-0.021**		-0.028***
trust affected by crisis)		(0.010)		(0.009)
Share of border purchase (% of		-0.002*		0.000
population)		(0.001)		(0.001)
Cut 1	-1.982***	-1.917***	-1.722***	-1.040*
	(0.018)	(0.575)	(0.017)	(0.547)
Cut 2	-0.874***	-0.805	-0.759***	-0.071
	(0.017)	(0.575)	(0.017)	(0.547)
Cut 3	0.874***	0.950*	0.740***	1.436***
	(0.017)	(0.575)	(0.016)	(0.546)
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Country Cluster	Yes	Yes	Yes	Yes
Bootstrapped SE	Yes	Yes	Yes	Yes
Pseudo r^2	0.034	0.037	0.031	0.035
Observations	167,722		167,607	

Note: This table shows the results of the ordered probit difference-in-difference estimation. Panel A reports the coefficients of introducing the Unfair Commercial Practice Directive on consumer trust while panel B reports coefficients on public authority trust. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD. Here, the treatment group states the lowest pre-UCPD consumer protection evaluation while higher pre-UCPD consumer protection evaluation level are the summarized control group. Bootstrapped standard errors obtained by 200 replications in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 3.D13: Estimation results with bootstrapped standard errors

	Panel A: Cross-border purchase		**Panel B**: Homeshopping	
Post_{ct} (indicator, UCPD in place)	-0.137***	-0.181***	-0.037**	-0.069***
	(0.022)	(0.024)	(0.019)	(0.019)
Treat ($\text{L}_{cj} = 1$)	-1.418***	-1.139***	-0.829***	-0.450***
	(0.059)	(0.099)	(0.049)	(0.078)
Treat (L_{cj}) $\times \text{Post}_{ct}$	0.493***	0.469***	0.186***	0.111**
	(0.057)	(0.064)	(0.054)	(0.054)
Individual controls				
Female (indicator)		-0.278***		-0.133***
		(0.009)		(0.007)
Nation (indicator, nationality different to current country)		-0.049*		-0.130***
		(0.027)		(0.025)
$\log(age)$		9.815***		10.836***
		(0.178)		(0.155)
$\log(age)^2$		-1.459***		-1.613***
		(0.025)		(0.021)
Country controls				
Share of internet access (% of population)		0.013***		0.019***
		(0.001)		(0.001)
Share of unemployment (% of population)		0.008***		0.002
		(0.003)		(0.002)
log (GDP)		0.322***		0.189***
		(0.094)		(0.072)
Incident (indicator, consumer trust affected by crisis)		-0.004		-0.021*
		(0.014)		(0.011)
Intercept	-0.918***	-20.929***	-0.981***	-21.606***
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Country Cluster	Yes	Yes	Yes	Yes
Bootstrapped SE	Yes	Yes	Yes	Yes
Pseudo r^2	0.099	0.176	0.113	0.199
Observations	179,724		173,479	

Note: This table shows the results of the probit difference-in-difference estimation. Panel A reports the coefficients of introducing the Unfair Commercial Practices Directive on cross-border purchase while panel B reports coefficients on homeshopping. Treatment and control groups are based on an index that shows evaluation of the pre-UCPD consumer protection level. These evaluation levels reach from one to five where one is the worst and five the best pre-UCPD consumer protection index. The index is therefore equivalent to: 1 - "very low", 2 - "low", 3 - "middle", 4 - "high", 5 - "very high" consumer protection standards before the introduction of the UCPD. Here, the treatment group states the lowest pre-UCPD consumer protection evaluation while higher pre-UCPD consumer protection evaluation level are the summarized control group. Bootstrapped standard errors obtained by 200 replications in parentheses. Significance: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

4

Reaching for the Society: The Commercialization Effects of NASA Technology Transfer

with Marek Giebel

" NASA(...) ensures that innovations developed for exploration and discovery are broadly available to the public, maximizing the benefit to the Nation."

– NASA (2022b)

4.1 Introduction

The yearly federal R&D spending in the United States increased from about 61 to 128 billion US$ between 1990 and 2010 (Sargent 2022). Since this is a non-negligible share of the US gross domestic product, there is a lively debate related to the effectiveness and societal benefits of government-funded research (e.g., Fleming et al. 2019; Lach et al. 2021; Myers and Lanahan 2022; Nelson 1982), particularly that of government agencies like NASA (e.g., Evans 1976; United States Government Accountability Office 1977; Hertzfeld 2002). On the one hand, this fulfills important functions for society as it, for example, provides the ground for follow-on innovations that are important from a welfare perspective (e.g., Bezdek and Wendling 1992; Bresnahan and Trajtenberg 1995; Fleming et al. 2019; Scotchmer 1991).[75] On the other hand, however, the actual appropriation of benefits of these investments is often not trivial and below the socially desired level (e.g., Bezdek and Wendling 1992; Fleming et al. 2019; Lach et al. 2021). Consequently, it is particularly important to understand how to increase the societal returns from federally funded research.

In this paper, we analyze the effects of technology transfer of National Aeronautics and Space Administration (NASA) inventions on follow-on innovation. The significance of this question lies, among others, in the ongoing debate whether patenting and licensing are appropriate tools to foster subsequent innovation (e.g., Drivas et al. 2017; Gallini and Winter 1985; Heller and Eisenberg 1998; Nagler et al. 2022; Williams 2017). This is particularly rooted in the possible ambiguous effects of licensing on follow-on research. On the one hand, licensing could signal the commercial value of an invention, increase awareness for it, or provide additional information. On the other hand,

[75] These include scientific advances related to the successful realization of the Apollo mission or the development of the Global Positioning System (GPS) technology, which still exert indispensable positive impacts in the civil sector (e.g., Kantor and Whalley 2023; Mazzucato and Semieniuk 2017; Mazzucato 2021).

however, it could be used to block other inventors from entering. Although the literature has focused on either university-licensed research or innovation in the private sector (e.g., Arora and Fosfuri 2003; Arora et al. 2013; Arora and Gambardella 2010; Drivas et al. 2017; Thompson et al. 2018; Palermo et al. 2019), the in-between is underrepresented. This perspective, however, is utterly important as government-conducted research often serves as a bridge between science and markets. This makes it particularly important for firms that are more inclined to build on research that has characteristics of that from private entities, i.e., that is more useful and reliable (e.g., Bikard and Marx 2020). NASA bridges these elements as the research is geared toward technical applications.[76] To add novel evidence to this debate, we first investigate the determinants of exclusive licensed government-funded inventions. Second, we determine the relationship between the commercialization of government-funded research through licensing and how this affects the subsequent invention behavior of third parties.

Being aware of the importance of technology development and commercialization, the United States enacted a group of policies in the 1980s to promote government-funded research. Particularly, the Stevenson-Wydler Technology Innovation Act of 1980 aimed to foster the technology transfer of federally financed inventions to non-federal entities and led to the enactment of technology transfer programs (TTP). We use this legislation and leverage technological information from NASA's TTP. This includes technologies from various fields as NASA's yearly total budget to pursue several programs related to aeronautics, robotics, and technology development amounted to between about 12 and 19 billion US$ between 1990 and 2010 (Morgan 2022). In addition, we use the announcement of NASA technologies available for licensing or licensed in the Federal Register. Thus, we exploit a rich set of technology and licensing-related information for patents invented or financed by NASA between 1995 and 2010. We first analyze the NASA patent portfolio and how licensed technologies differ from those that are not. In the second step, we compare the degree of follow-on innovation measured by patent citations conditional on the technology's licensing

[76] Thereby, the Technology Transfer Program, licensing, and spin-offs of specific technologies facilitate follow-on research.

status.

Our analysis of the effect of commercialization of government-funded research on its diffusion has two main results. First, we analyze NASA's technology portfolio, which consists of about 4,000 patents invented by NASA or contracted third parties. The descriptive results show that the patent portfolio is quite diversified, concentrating in fields like 'Chemistry and materials', 'Engineering', and 'Physics'. This observation is similar within the sub-samples of NASA inventions and those of contracted third parties. Of the approximately 1,600 NASA-conducted inventions, an average of about 52% are announced to be available for licensing. However, only about 12% of the NASA-conducted inventions are part of an announcement in the Federal Register related to an intention for an exclusive license. Thus, only a small amount shows a high commercialization potential. When comparing available technologies and exclusively licensed technologies, we find that the latter are more novel, rely on more basic research, and are part of a larger patent family. This hints at a higher value of these technologies.

Second, we analyze how the commercializability and commercialization of NASA-invented technologies affect their degree of follow-on innovation. Thus, we first compare all technologies that are part of the licensing portfolio to those that are not. We account for endogeneity due to a potential selection bias by applying a matching approach using a set of technology and patent characteristics. Our results show that commercialized technologies, i.e., exclusively licensed patents, show a significantly higher follow-on innovation pattern. When considering the origin of follow-on research, we find considerable spillovers from licensed technologies. Subsequent developments stem largely from distinct inventors, locations, and technology fields. We extend these considerations by analyzing the impact of the licensing timing. First, the degree of follow-on innovation is comparably larger when the technology is licensed after the patent grant. Second, comparing the degree of follow-on innovation before and after the licensing event in a conditional difference-in-differences approach implies that a higher degree of commercialization is positively associated with more subsequent innovation. This indicates that licensing fosters the benefits of government-funded research for society. Our results are robust to various sensitivity tests, including alternative specifications, different sub-samples, changes to the outcome variables, and sample extensions.

We analyze the important relationship between technological commercialization and follow-on innovation for government-funded inventions. From the point of view of licensing through technology transfer on follow-on innovation, we provide novel evidence to strands of literature that determine the general economic effects of government-funded research (e.g., Fleming et al. 2019; Lach et al. 2021; Myers and Lanahan 2022), Small Business Innovation Research (SBIR) awards (e.g., Fini et al. 2023; Howell 2017; Myers and Lanahan 2022), and other research laboratories like CERN that are not located in the United States (e.g., Helmers and Overman 2017; Schmied 1977). In addition to these works, we also add to the literature that analyzes the economic impact of NASA-related research (e.g., Archibald and Finifter 2003; Bezdek and Wendling 1992; Evans 1976; Giga et al. 2022; Goldfarb 2008; Hertzfeld 2002; Jaffe et al. 1998; Kantor and Whalley 2023; Lockney and Glass 2011). We add to these studies by showing that spillovers from government inventions are related to the licensing status of the technology. In this context, especially exclusively licensed technologies provide social benefits due to an elevated degree of follow-on innovation. Moreover, in this way, this paper contributes to the ongoing discussion about the relationship between government funding, innovation, and innovation policy (e.g., Edler and Fagerberg 2017; Mazzucato and Semieniuk 2017). Thus, a valuable policy implication would be to extend and improve licensing programs to increase the benefits of government-funded research for the civil population. Second, and due to similar reasons, we add the perspective of government-funded inventions to studies that analyze the commercialization of academic research and particularly that of universities (e.g., Drivas et al. 2017; Marx and Hsu 2022; Shen et al. 2022; Thompson et al. 2018; Hsu et al. 2021). We provide further novel evidence to this strand of literature by showing that particularly exclusively licensed technologies are leading to the largest benefits for society.

By investigating the effects of the commercialization of government-developed technologies, we also contribute to the discussion surrounding the markets for technology that focuses primarily on the licensing of inventions carried out by private firms (e.g., Arora and Fosfuri 2003; Arora et al. 2013; Arora and Gambardella 2010; Palermo et al. 2019). We add a new and complementary perspective on government-funded inventions. More specifically, our evidence implies that these technologies can provide larger benefits for society if they are licensed out. Thereby, we also contribute to the theoretical discussion on whether licenses can reduce incentives for further research (e.g., Bessen 2004; Gallini 1984; Nelson 2004) or spurs follow-on research (e.g., Green and Scotchmer 1995; Heller and Eisenberg 1998). We add to these theoretical works by providing empirical evidence that exclusive licensing of government inventions leads to a higher degree of follow-on innovation. Due to this reason, we also contribute the perspective of government-funded inventions to empirical works that analyze the innovation-related effects of licensing of private inventions (e.g., Nagler et al. 2022; Watzinger et al. 2020).

The paper is structured as follows. Section 4.2 covers the description of the institutional background, with details on the policies to promote government-funded research, NASA's TTP, and a discussion of the expected results. The used data and the empirical strategy are described in Section 4.3 before Section 4.4 covers the results and sensitivity analyses. Section 4.5 concludes.

4.2 Institutional setting and related literature

4.2.1 Policies promoting government-funded research

Government-funded research plays a critical role in advancing scientific knowledge, fostering innovation, and addressing societal challenges. For instance, government-funded research is often focused on basic science expanding the knowledge of how the world works (e.g., Fleming et al. 2019), but also supports applied research aiming at solutions to real-world problems such as climate change, public health, and national security (e.g., Fleming et al. 2019, Lach et al. 2021). Commercializing government-funded research can help ensure that the results are put to practical use leading to new products and services (e.g., Bresnahan and Trajtenberg 1995). Additionally, commercializing can pay back the government's initial research investment and generate revenue for future reinvestments. Lastly, commercializing creates opportunities for collaborations between the public and the private sector by bringing together researchers, entrepreneurs, and investors (e.g., Fleming et al. 2019).

Being aware of the importance of technology development and commercialization, the United States enacted a group of policies in the 1980s that aimed at promoting and commercializing government-funded research. At least 14 bills were enacted during the 1980s (Katz and Ordover 1990). We focus on two acts that are aimed at patent ownership changes and licensing in particular. Both had a major impact on technology transfer and, thus, invention commercialization: The Bayh-Dole Act and the Stevenson-Wydler Technology Innovation Act.

First, the Bayh-Dole Act was enacted in 1980. This legislation is also known as the Trademark Law Amendments Act and governs the ownership of inventions and patents resulting from government-funded research conducted at universities, research institutes, and small businesses. The provisions of the Bayh-Dole Act allow these organizations to retain titles to inventions and patents financed by the government. This encouraged them to commercialize their research and consequently support the process of bringing new products and technologies to the market more quickly and efficiently (e.g., Kenny and Patton 2008, Link and van Hasselt 2019, Stevens 2004). The act also established a standardized process for universities, research institutions, and small businesses to obtain and retain patent ownership. This includes requirements for reporting the inventions, negotiations with the government for the rights to the inventions, and obligations for licensing and commercialization. Another significant change was the ability of federal agencies to give exclusive licenses to inventions that belong to the federal government (Latker 2019). Consequently, the Bayh-Dole Act had a significant impact on the commercialization of government-funded research and the development of new technologies and products (e.g., Mowery et al. 2001, Shane 2004), being called a "*landmark piece of legislation*" (Bremer 2001, p. 6).

A second policy promoting government-funded research is the Stevenson-Wydler Technology Innovation Act of 1980, which aimed to increase the licensing and, particularly, commercialization of federally financed inventions. The law mandates that federal laboratories allocate a portion of their budget specifically to promote technology transfer between federal institutions and the private sector. Under the Stevenson-Widler Technology Innovation Act, federal research institutions are authorized to enter into 'cooperative research and development agreements' (CRADAs) with private companies by providing them access to the institutions' research facilities, equipment, and expertise. Moreover, the legislation also established the Federal Laboratory Consortium for Technology Transfer (FLC). This serves as a central clearinghouse for the collection, dissemination, and transfer of information regarding federally-owned or originated technology that has the potential to be utilized by private industry as well as state and local governments (Jolly 1980).

In line with the technology transfer-promoting policies of the Stevenson-Wydler Technology Innovation Act, technology transfer programs (TTPs) were enacted. TTPs transfer federally funded and developed technology to industry, academia, and other research organizations. Those programs usually enable third parties to license selected patents from the respective agencies' patent portfolios. Departments and agencies with a TTP include the Department of Agriculture, the Department of Commerce, the Department of Defense, the Department of Energy, the Department of Health and Human Services, and the National Aeronautics and Space Administration. Although these policies aim at increasing the benefits of government conducted research, it remains questionable how effective they are.

4.2.2 NASA's Technology Transfer Program

In this study, we analyze the effects of the commercialization of NASA technologies. NASA serves as a perfect example to study the effects of TTPs as it fulfills three main characteristics. First, NASA was one of the first agencies to promote and foster technology transfer to the private sector. Second, NASA's technology portfolio is broad, and the application areas are not limited to a few specific technology classes[77]. Third, NASA bridges the public and private sectors as it is government-funded research with high technology applicability.

In response to a recommendation to increase government effectiveness in 1993 (Gore 1993; NASA 1994)[78], NASA launched "NASA's Commercial Technology: Agenda for Change". Besides implementing the recommendations, it set out the Agency's newly defined Commercial Technology Mission. This included, amongst others, aiming at 20% of NASA's R&D budget to support commercial partnership. Additionally, all NASA contracts require a clearly defined technology transfer plan for the commercial application of technologies developed for NASA missions. Although NASA's efforts in technology transfer originate much earlier and date back to its founding year in 1958, these implementations in 1994 are set to boost the commercialization of NASA technology in particular. This way was paved and supported by different legislations as discussed in 4.2.1 and shown in more detail Appendix 4.A, Figure 4.A1.

The program is designed to promote innovation, economic growth, and job creation by facilitating the transfer of NASA's technological expertise and resources to the private sector (NASA 2022b).[79] The TTP provides opportunities for companies, universities, and other organizations to license and commercialize NASA-developed technologies, including patents, software, and hardware. NASA also provides support and technical assistance to help companies commercialize the technologies, and it participates in joint development agreements and other partnerships to facilitate the transfer of technology. The TTP is managed by the Office of the Chief Technologist at NASA headquarters, with support from NASA field centers, the respective Center Technol-

[77]As described by NASA itself: '*NASA develops all sorts of technology to solve the tough challenges of exploring space, advancing the understand of our home planet, and improving air transportation. Often, those same inventions have other untapped applications. Through patent licensing, those technologies, can be transformed into commercial products and solutions that can give your business a competitive edge.*" (NASA 2022a).

[78]These recommendations include, amongst others, technology transfer training for all employees, 10-20% of R&D budget goes to industry-partnerships, and improving metrics to measure technology transfers.

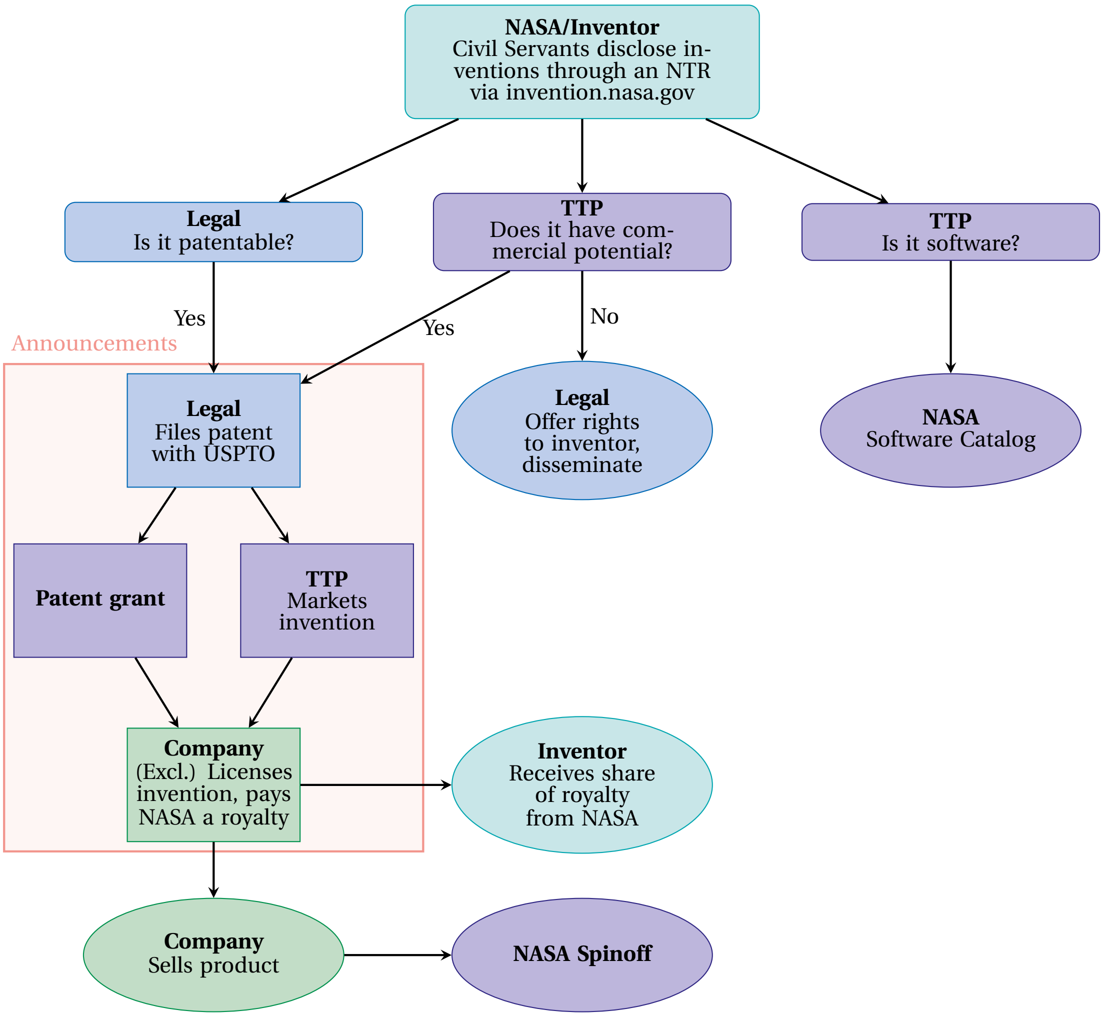
[79]See NASA (2022b) and NASA (2022a) for details about the program and its description. Additionally, NASA's patent portfolio can be accessed via https://technology.nasa.gov/patents.

ogy Transfer Officer, and Center Patent Counsels.[80] The program is designed to be flexible and responsive to the needs of the private sector, and it is continuously reviewed and updated to ensure that it is meeting the needs of technology transfer and commercialization stakeholders.[81] The TTP plays a crucial role in transforming NASA's innovative research and developments into practical applications that benefit society. Overall, NASA tries to ensure with the structural approach of its technology program that technological advancements are protected, effectively utilized, and transitioned from federal laboratories to private industry, resulting in real and useful products on the marketplace. Figure 4.1 visualizes the structural process, which is described below.

[80]In general, other agencies may also play a role in implementing the TTP and support NASA and its centers in ensuring the quality of the program and its resulting inventions. Additionally, NASA compromises different centers which also may apply different additional strategies than the one that is described in this paper. However, the general implementation remains the same.

[81]Although NASA is, in principle, also licensing to foreign companies, the focus lies on domestic companies to benefit US society. Foreign companies have additional requirements to fulfill when applying for a patent. Thus, NASA intends to reach society by benefiting technologies and innovation through commercialization within the US. This is also reinforced by the following statement: "*NASA's priority is to license its U.S. taxpayer-funded technologies to benefit the American tax payers, through increasing US economic competitiveness and/or promoting public availability of new products and services.*" (NASA 2022a).

Figure 4.1: Structural process of NASA's TTP



Note: This figure shows the structured process of NASA's technology transfer program. It includes legal steps and the time frame of the availability or exclusive licensing announcement of patents.

NASA employees and contractors who develop new technologies (innovators) are required to report, document, and identify the potential commercial applications of their work by submitting New Technology Reports (NTR). Thus, the technology transfer process begins when civil servants at NASA disclose their inventions through an NTR via `invention.nasa.gov`. Once an invention is disclosed, it undergoes an initial assessment to determine its commercial potential and its patentability. On the one hand, the Center Technology Transfer Officer (CTTO) is tasked with managing all received NTRs, including conducting assessments of both commercialization and technical viability for technologies that have the potential to be transferred to industry. On the other hand, the responsibility of the Patent Counsel is to perform a patentability assessment as necessary or as the CTTO recommends. This process is based primarily on the recommendations of the CTTO or their delegate assessing the technology's commercial potential.[82]

If the CTTO finds the invention to have commercial potential and, concurrently, the Patent Counsel decides an invention is patentable, they file a patent application with the United States Patent and Trademark Office (USPTO). Parallel to this, the TTP actively markets these technologies to potential commercial partners. Companies interested in the technology can enter into licensing agreements with NASA, paying a royalty for the use of the patented invention. As an incentive, inventors receive a percentage of the royalty payments generated from these agreements. Licensed companies then develop and bring products based on NASA's technology to market. This often leads to the creation of NASA spinoff companies, which leverage these innovations to develop new products and services.

There are two different types of announcements related to the licensability of technologies: either the technology will be announced as available or exclusively licensed. The latter originates in the legal requirement to release a public notice of the intent to grant an exclusive or partially exclusive license (35 U.S.C. 209(e) and 37 CFR 404.7(a)). The announcement of the availability of technologies for licensing, however, is related to the organization and administration statutes of NASA (e.g., NASA 1997). Thereby, the publications of the availability and exclusivity announcements in the Federal Register originate in NASA's requirement to inform the public about the agency's activities, manifested in the NASA policy directive NPD 1400.2 (NASA 1997) that is the successor of the NASA management instruction NMI 1410.10 (NASA 1993).[83]

In case the invention lacks commercial potential, NASA's legal team may offer the rights back to the inventor or choose to disseminate the technology through other appropriate channels. In the case of software inventions, a distinct path is followed.

[82] A more detailed description of the technology transfer process and its goals can be found in NASA OIG (2012) and NASA OIG (2019).

[83] It must be noted that the timing of these announcements is not directly bound to the patenting procedures (or patent grant) of the respective technologies. However, the majority of announcements contain references to patents (applications or granted).

These inventions are directed to the NASA Software Catalog, a comprehensive repository where NASA's software is made available to the public, ensuring wide dissemination and accessibility. Consequently, NASA technologies announced to be available for licensing could be assumed to be commercially valuable.

4.2.3 Licensing government-funded research

As outlined in the previous sections, government-funded entities are incentivized to license technologies to third parties. Thereby, it has to be noted that the incentives to emit exclusive licenses differ between private and non-private entities (e.g., Shen et al. 2022). While a firm might use a license to constrain competition (e.g., Arora and Fosfuri 2003), a government-funded entity has no production facilities and is earning revenue from licensing such as universities (Barirani et al. 2017). Accordingly, public entities' incentives to grant an exclusive license, as codified in 35 U.S.C. 209(a), are rooted in promoting the utilization of the specific technology by the public. This also becomes evident by the description in Section 4.2.2 that government agencies like NASA have to announce the intent to license a technology exclusively to one firm publicly. Consequently, whether exclusive licensing of government inventions spurs or impedes subsequent technology developments remains questionable.

The question about the impact of licensing on innovation has been debated for some time (e.g., Gallini and Winter 1985). On the one hand, it could be argued that licensing spurs follow-on research (e.g., Green and Scotchmer 1995; Heller and Eisenberg 1998). This is mainly related to a license facilitating or enabling subsequent research (e.g., Green and Scotchmer 1995). Moreover, it could be a positive signal about the value of a specific technology, increase attention to a specific technology, suggest market opportunities, and lead to additional information about the technology (e.g., Drivas et al. 2017; Thompson et al. 2018). These factors could, therefore, increase the degree of follow-on innovation. In contrast to this statement, it could be argued that licenses can diminish or block further research. This might lie in the protection by intellectual property rights itself (e.g., Bessen and Maskin 2009; Boldrin and Levine 2013). More specifically, the reduction in follow-on innovation might be related to incentives of the licensee or patent holder to enforce their monopoly rights against potential infringers (e.g., Bessen 2004; Nelson 2004), but also diminished incentives for further research of entrants (e.g., Gallini 1984). Thus, potential follow-on innovators would rather invent around the patent or use other technologies to build on. This, in turn, would reduce the amount of innovation building on licensed research. Although this is the case, whether the positive or negative effects are stronger remains to be discussed.

Empirical findings imply mixed evidence concerning the effects of licensing or research from private or academic entities on subsequent technological developments. First, the effects of licensing of private inventions might be detrimental to the flow of knowledge and market activities (e.g., Arora and Fosfuri 2003; Arora et al. 2013; Arora and Gambardella 2010; Palermo et al. 2019). However, in contrast to this finding, research also highlights the positive effects of forms of compulsory licensing (Nagler et al. 2022; Watzinger et al. 2020), which fostered follow-on developments. Second, related to academic research, there is a long-lasting discussion about the effect of its commercialization through licensing (e.g., Larsen 2011). Thereby, a particular concern is that licensing might hinder the application and dissemination of scientific knowledge (Larsen 2011). There exists, however, evidence that licensing of university research can have positive effects (e.g., Drivas et al. 2017; Marx and Hsu 2022; Thompson et al. 2018). In this context, it has been shown that the granting of licenses to universities is advantageous for subsequent innovations, which is at least partly due to the signaling of market opportunities (Drivas et al. 2017).

NASA-conducted research available for licensing has features that are both private and academic. On the one hand, NASA inventions are built on basic research (e.g., Archibald and Finifter 2003; Reichhardt 1998). On the other hand, however, they are geared towards applications (e.g., Archibald and Finifter 2003; Goldfarb 2008). The applied nature of the inventions is underlined by the fact that technologies offered for licensing are evaluated as potentially commercially valuable (see Section 4.2.2). The conditions under which an exclusive license may be granted include that the technology's utilization by the public will be promoted (35 U.S.C. §209). Furthermore, licensing entails that the public is served by the granting of the license and that the invention is practically applied within a reasonable time frame (35 U.S.C. §209). Consequently, we assume a positive association between the licensing of government inventions and follow-on innovation, which is particularly pronounced for exclusive licenses.

4.3 Data and empirical strategy

4.3.1 Data and variables

To determine the association between commercializing government inventions by licensing and follow-on innovation, we use three main data sources: USPTO patent data, NASA technology information, and announcements from the US Federal Register. Our basis is formed from NASA technology information that is available via the NASA Technical Reports Server (NTRS) and the NASA TTP homepage. Both sources provide details concerning the technologies that are invented by NASA itself or non-government parties that NASA has contracted.[84] This allows us to extract the information in which NASA research center the technology was developed and to which of the about 100 NASA technology subject categories (e.g., energy production and conversion, optics, spacecraft design) it belongs. For our analysis, we sort these about 100 subject categories according to the NASA documentation into eleven main subject categories (e.g., aeronautics, math and computational science, physics)[85]. Furthermore, and important for our analysis, we obtain two important identifiers from this data source. First, the NASA case number, and second, related US patent numbers. Both allow us to combine this data source with further information concerning patent characteristics and the licensing status of the specific technology. We restrict the information from this source to the years after 1994, as the TTP was finally enacted in 1995.

Using the patent number allows us to combine the NASA technology information with USPTO PatentsView patent data. From this data source, we extract several patent characteristics. This first includes the type of prior art the patent builds on. Namely, we

[84] See Appendix 4.A, Figure 4.A4 for the location of the NASA research centers and the distribution of technologies.

[85] The technology classes are categorized as follows: Space Science, Social Sciences, Physics, Mathematical and Computer Science, Life Science, Geo Science, Engineering, Chemistry and Materials, Astronautics, Aeronautics.

use the information on whether the focal patent cites granted US or foreign patents and whether it builds on non-patent literature. In addition, second, we exploit information on the patent family. This allows us further to account for the degree of related patents covering a similar or the same technology in the US or other legislation. More precisely, we determine the patent family size in terms of the number of related patents. Moreover, we use the information whether it includes any patent granted in the European Patent Office (EPO) or any other office. Moreover, third, we leverage information related to the description of the technology in the patent document. In that regard, we consider the number of figures in the patent document and the number of claims. Besides these patent features, we also account for the characteristics of the patented technology. Therefore, we extract the main International Patent Classification (IPC) code as indicated on the patent front sheet.[86] In addition, we use data from Arts et al. (2021) to account for the novelty of the technology. Therefore, we include a measure comprising the number of new keyword combinations that is positively correlated with patent novelty. We are finally interested in the follow-on innovation pattern. Therefore, we follow the literature (e.g., Balsmeier et al. 2023; Drivas et al. 2017; Sampat and Williams 2019) and consider the patent citations of the focal patent as a proxy for subsequent innovation. We use the aggregate citation count but also disaggregate it into applicant and examiner citations, the assignee type (same or different), the geographical origin, and the technological origin of the invention. To prevent biased estimates due to outlier citation counts, we winsorize the citation measures at the 5 percent level.[87] To avoid the problem of right truncation due to missing citation information, we restrict the set of patent data to application years before 2014. Therefore, our baseline citation measure is the aggregate citation count in the first five years after the grant. We extend this definition by also analyzing the periods from one to seven years after the grant.[88]

Finally, we make use of the licensing status of a specific technology. For this pur-

[86]See Appendix 4.A, Figure 4.A4 for the distribution of technologies over IPC sections and NASA research centers or subject categories.

[87]Robustness tests concerning this threshold and other choices made when generating the dataset are discussed and presented in Section 4.4.7. They lead to similar conclusions.

[88]These time windows also coincide with NASA's strategy that technologies are patented that should be marketable within seven years (Olivari et al. 2021).

pose, we leverage information from the US Federal Register (USFR). We particularly use two sets of announcements that are regularly made in the USFR as described in Section 4.2.2. First, we use the listing of available NASA technologies for licensing (e.g., Appendix 4.A, Figure 4.A2 (a)). These announcements contain either a list of NASA technology codes or patents that are available for licensing. In the next step, we extend this information even further by obtaining the details on whether a third party intends to license a specific technology exclusively. Thus, we leverage the related announcement in the federal register (e.g., Appendix 4.A, Figure 4.A2 (b)). This, again, allows us to extract the respective technology codes or patents, if available. To combine this information with the patent dataset, we use the extracted relation between NASA case numbers and patent numbers from the NTRS. For patent applications at the time of addition to the NTRS, we complete the entry by adding the respective number of the granted patent. This finally allows us to generate a dataset containing NASA technologies, those available for licensing, and technologies that have been at least partly exclusively licensed to third parties.

4.3.2 Empirical strategy

The aim of this paper is to determine the impact of technology transfer on follow-on innovation. For this purpose, we trace subsequent technological developments by citations of patents following works like Balsmeier et al. (2023), Galasso and Schankerman (2015), or Sampat and Williams (2019) and account for observable differences between technologies by combining this with a matching approach. In the second step, we extend this procedure by accounting for time-invariant unobservable factors by applying the conditional difference-in-differences methodology (e.g., Caliendo and Kopeinig 2008; Heckman et al. 1998; Roth et al. 2023).

Our baseline estimation equation to analyze the relationship between licensing and technological follow-on developments is the following:

$$\text{Citations}_{it+k} = \beta_0 + \beta_1 \text{Licensing}_i + \gamma \text{T}_i + \varepsilon \text{P}_i + \mu_i \tag{4.1}$$

We use the plain citation measure in future period $t + k$ as outcome variable Citations_{it+k}.[89] The indicator of interest is 'Licensing,' which takes unit value if the focal patent is licensed or not. Thus, the coefficient β_1 informs us about the impact of licensing on subsequent developments of the specific technology. We add several control variables to account for further factors that could affect future technological developments. These include vectors of technology (T_i) and patent (P_i) characteristics, such as the technology group, as indicated by NASA, or the prior knowledge the technology builds on, as indicated in the patent document. The latter also includes a set of IPC section times class fixed effects, application cohort dummies, and grant year effects. While the first accounts for technological citation paths, the time cohort dummies incorporate potential citation trends due to the application timing.

Since licensing could be assumed to be a non-random event, the effect of licensing on follow-on technology developments is likely subject to various biases that might affect the results. First, unobserved factors might drive the licensing decision. These include, for example, the quality of the patent holder in terms of inventors. To account for this issue, we restrict the analysis to one specific entity – the NASA. Furthermore, we control for the NASA technology subject categories and research centers to account for time-invariant differences in these. This allows us to rule out the impact of unobserved heterogeneity due to entity characteristics at least partially.[90] Second, however, also observed factors play likely a role, even when all technologies are offered by one entity. Thus, it could be technology-related parameters, like the specific technology field, that affect the decision of a firm or individual to apply for a license. Furthermore, it could also be that prior technological input is necessary to invent the technology that could drive the licensing decision. To account for this and other influences, we make use of the rich set of patent characteristics described in Section 4.3.1.

To account for the potential endogeneity issue due to observable differences,

[89] This follows the suggestion of Mullahy and Norton (2024) concerning how to handle count variables with a non-negligible number of zeros. We provide robustness tests concerning this choice in Section 4.4.7.

[90] We provide the results when applying a conditional difference-in-differences approach in Section 4.4.6. Using this methodology allows us to account for time-invariant unobserved factors.

we augment the estimation of equation (4.1), by applying a re-weighting approach (e.g., Imbens and Wooldridge 2009).[91] More specifically, we use inverse probability weights, which allows us to account for observable differences between licensed and non-licensed technologies. To do so, we proceed in three steps. First, we estimate the propensity to license as a function of the control variables explained in Section 4.3.1. The probit estimation result is shown in Appendix 4.B, Table 4.B1. In a second step, this allows us to calculate the related propensity score (ps_i), in which we restrict the propensity score to the region of common support, such that the scores of the treatment and control groups overlap. Next, we calculate the inverse probability weights (w_i) as follows:

$$w_i = \begin{cases} \dfrac{1}{ps_i} & \text{if licensed} \qquad (4.2) \\ \dfrac{1}{1 - ps_i} & \text{if not licensed} \qquad (4.3) \end{cases}$$

Using these calculated weights, we are able to assess the quality of our matching approach by comparing the means of the licensing predictors after the weighting. As shown in Appendix 4.B, Table 4.B2, the differences between the variables are minimal and not statistically significant on conventional levels. This implies that the re-weighting approach is successful in constructing a counterfactual control group. Consequently, we combine the estimation of equation (4.1) with inverse probability weighting to account for potential endogeneity due to observable differences.

4.4 Results

4.4.1 NASA licensing technology portfolio characteristics

We present descriptive statistics for the sample used in this analysis in Figure 4.2 and Table 4.1. We first focus on all patents funded by NASA but could be invented internally or by third parties (panels a and b). In that context, Figure 4.2 shows the patent composition of technology categories defined by NASA and the funding centers in panel (a). A relatively high share of technologies is related to the NASA headquarter (HQ). From the

[91] We discuss a test regarding unobserved time-invariant heterogeneity and its result in Section 4.4.6.

heat map, it interestingly becomes evident that within this, the highest share of granted patents are related to the fields 'Engineering', 'Chemistry and materials', and 'Physics'. Fields like 'Space sciences' and 'Social sciences', however, comprise the minority of patents in the sample. Next, in panel (b), we report the sub-sample of firm-invented patents that NASA funds. This figure implies that, on average, about 61% of the patents are invented by firms and that there is some variation among the fields without exceptional outliers.

In the next step, we consider only those patents invented by NASA (panels c and d). In panel (c), we show a heat map similar to panel (a) but without the third-party invented patents. The pattern is similar. Again, a small share of granted patents is related to the fields 'Space sciences' and 'Social sciences'. The field 'Engineering' in contrast, still covers the highest share of the granted patents. Finally, we turn to the licensing information related to the individual patents with the share of licensed patents shown in panel (d). First, on average, about 53% of the patents invented by NASA are announced to be available for licensing. Again, there is some heterogeneity among the technology categories. Thus, in the field 'Chemistry and materials', for example, about 57% of the patents are announced to be available for licensing. Regarding the announcement of exclusive licensing agreements, panel (d) of Figure 4.2 implies that this is the case for about 14% of the patents. While the share in fields like 'Chemistry and Materials' and 'Life sciences' is relatively high, it is low or even zero in fields like 'Social sciences', 'Astronautics', and 'Aeronautics'.

The descriptive statistics of further variables used in this analysis are presented in Table 4.1. The overall variable means for the sample of 4,044 patents are shown in column (1). Regarding the patent characteristics, the results imply that about 52% of the patents rely on non-patent references like published articles in academic journals. Furthermore, about 36% cite foreign patents, and about 98% cite US patents. The latter does not only imply that the patents rely on foreign knowledge but that almost all of them rely on an invention patented in the United States. A similar high mean is shown by about 98%, which represents the share of patents that include a figure. Related to the novelty of patents, the descriptive statistics imply that about 56% of the patents include at least one new combination of two keywords. However, the descriptive results also imply that the patents part of a patent family of patents registered in the US or other patent offices. Thus, we find that the patents belong to families with an average size of 4.5. Furthermore, within the families, 19% contain patents registered in the EPO, and about 36% contain at least one patent registered in another office. The average patent is invented by a team of three researchers.

4.4.2 The difference between licensed and not licensed technologies

Next, we compare the different categories of NASA inventions to those that NASA invents but are not part of an availability announcement or are exclusively licensed (column 4). First, comparing columns (4) and (5) indicates the following: Patents that are part of the licensing portfolio cite more scientific and foreign patent references. Moreover, a higher share of these patents contains a new keyword combination that points to a higher degree of novelty. What becomes evident as well is that these patents belong to a larger patent family that contains international patents (EPO and non-EPO patents). Regarding the citation outcomes, we do not find significant differences for the time after the patent grant. For the firm patents funded by NASA (column 2), we make similar observations for the patent characteristics but observe higher post-grant citation counts.

Next, when it comes to comparing those patents that are available for licensing and those that are exclusively licensed, we find the following (columns 7 and 9): Patents in both groups rely less on scientific but more on foreign patent references. Although both show a higher share of new keyword combinations, the differences are statistically insignificant. However, both groups show a statistically significantly higher number of patents in the respective patent families and a stronger degree of international patents within these. For the citation measures, we find that patents available for licensing show a significantly lower citation count beginning two years after the patent grant. In contrast, those that are exclusively licensed are cited to a higher degree in the first four years after the patent grant. The latter observation first hints towards a higher degree of follow-on innovation of exclusively licensed technologies.

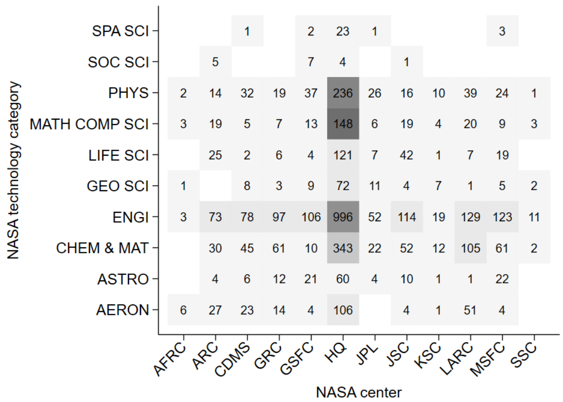
We extend these considerations and determine the probability that a patent is part of the licensing portfolio in logit and multinomial logit regressions.[92] The results are shown in Table 4.2. The estimates for the determinants of being part of the licensing portfolio in column (1) largely reinforce the observations made in the simple mean comparisons before (Table 4.1, columns 4-6). Additionally, when applying a multinomial logit regression to determine the probability that a patent is available for licensing or exclusively licensed (Table 4.2, columns 2 and 3), we observe similar effects to those described before (Table 4.1, columns 7-10). However, what becomes evident is that patents part of the NASA licensing portfolio now show a significant difference in terms of novelty. This is consistent with the idea that these technologies show a higher commercialization potential due to the possibility of creating a new market.

[92] NASA research center fixed effects are excluded due to convergence issues. Including an aggregated set of research center dummy variables does not alter the results remarkably.

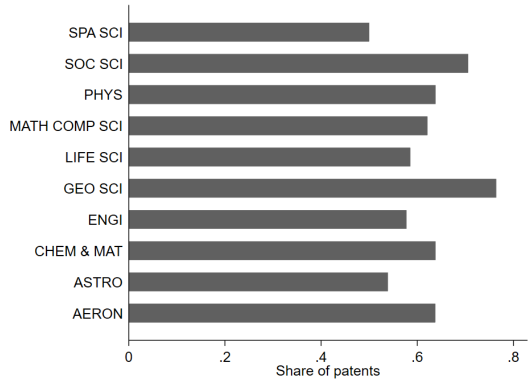
Figure 4.2: NASA technologies and patent classification

NASA inventions and NASA-financed firm patents

(a) Technology groups

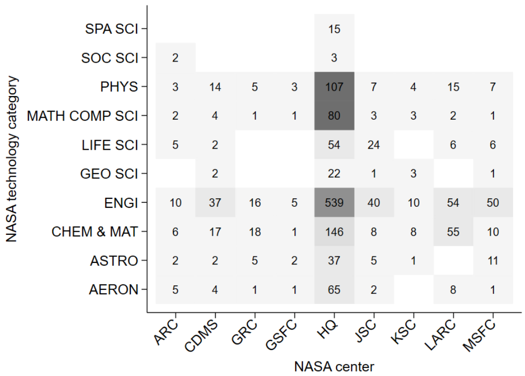


(b) Share of financed firm patents

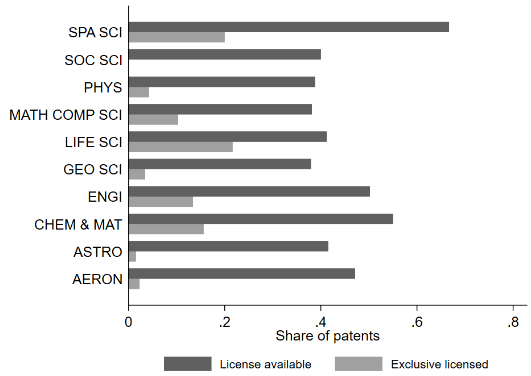


NASA inventions without NASA-financed firm patents

(c) Technology groups



(d) Share of licensed patents



Note: This figure shows the absolute amount and shares of NASA-invented or NASA-financed patents. Panel (a) shows NASA inventions and NASA-financed firm patents by technology groups and research centers. Panel (b) shows the share of financed firm patents within the whole sample of NASA inventions and NASA-financed firm patents. Panels (c) and (d) refer to NASA inventions without NASA-financed firm patents. Panel (c) shows NASA inventions by technology group and research center. Panel (d) shows the share of licensed patents within the NASA inventions sample comparing the groups of the patents available for licensing and those exclusively licensed.
The technology classes are defined as follows: SPA SCI - Space Science, SOC-SCI - Social Sciences, PHYS - Physics, MATH COMP SCI - Mathematical and Computer Science, LIFE SCI - Life Science, GEO SCI - Geo Science, ENGI - Engineering, CHEM & MAT - Chemistry and Materials, ASTRO - Astronautics, AERON - Aeronautics. The research centers are abbreviated as follows: AFRC - Armstrong Flight Research Center, ARC - Ames Research Center, CDMS - Center Directives Management System (i.e., not assigned to any specific center), GRC - Glenn Research Center, GSFC - Goddard Space Flight Center, HQ - Head Quater, JPL - Jet Propulsion Laboratory, JSC - Johnson Space Center, KSC - Kennedy Space Center, LARC - Langley Research Center, MSFC - Marshall Space Flight Center, SSC - Stennis Space Center.

Table 4.1: Descriptive statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
							Announcement type			
	Sample	Third party invented		Any announcement			Availability		Exclusivity	
				No	Yes					
	Mean	Mean	(3)=(4)	Mean	Mean	(4)=(5)	Mean	(4)=(7)	Mean	(4)=(9)
Patent characteristics										
Cites scientific references	0.524	0.553	(0.018)	0.506	0.450	(0.026)	0.435	(0.008)	0.497	(0.830)
Cites foreign patent references	0.356	0.431	(0.000)	0.198	0.287	(0.000)	0.277	(0.001)	0.317	(0.000)
Cites US patent references	0.975	0.978	(0.381)	0.972	0.970	(0.775)	0.965	(0.447)	0.984	(0.350)
Number of claims	19.877	20.581	(0.003)	18.816	18.760	(0.930)	18.415	(0.569)	19.804	(0.341)
Figure in patent document	0.980	0.975	(0.000)	0.996	0.982	(0.004)	0.983	(0.008)	0.979	(0.008)
New keyword combination	0.556	0.548	(0.879)	0.551	0.591	(0.109)	0.586	(0.186)	0.603	(0.190)
Number of patents in family	4.485	5.511	(0.000)	2.360	3.488	(0.000)	3.241	(0.000)	4.238	(0.000)
Family contains EPO patent	0.189	0.264	(0.000)	0.039	0.110	(0.000)	0.101	(0.000)	0.138	(0.000)
Family contains non-EPO patent	0.362	0.459	(0.000)	0.138	0.291	(0.000)	0.250	(0.000)	0.418	(0.000)
Team size	2.730	2.823	(0.000)	2.562	2.615	(0.560)	2.574	(0.902)	2.741	(0.219)
Citation measures										
Citations 1 year after patent grant	1.232	1.443	(0.000)	0.865	0.953	(0.371)	0.857	(0.937)	1.243	(0.022)
Citations 2 years after patent grant	2.779	3.279	(0.000)	1.972	2.045	(0.694)	1.726	(0.152)	3.011	(0.001)
Citations 3 years after patent grant	4.349	5.117	(0.000)	3.135	3.193	(0.833)	2.661	(0.073)	4.804	(0.000)
Citations 4 years after patent grant	5.980	7.020	(0.000)	4.424	4.323	(0.778)	3.644	(0.030)	6.381	(0.001)
Citations 5 years after patent grant	7.510	8.791	(0.000)	5.618	5.440	(0.692)	4.628	(0.032)	7.899	(0.002)
Citations 6 years after patent grant	9.083	10.645	(0.000)	6.825	6.503	(0.554)	5.562	(0.026)	9.354	(0.005)
Citations 7 years after patent grant	10.570	12.385	(0.000)	7.973	7.543	(0.496)	6.455	(0.022)	10.841	(0.005)
Observations	4044	2454	3282	828	762	1590	573	1401	189	1017

Note: The table shows the descriptive statistics for the variables used in the analysis. Mean values are reported in columns 1, 2, 4, 5, 7, and 9. The values in parentheses in columns 3, 6, 8, and 10 represent p-values of the test with the null hypothesis indicated in the column heading. The alternative hypothesis is the inequality of the values in the respective values.

Table 4.2: Probability that a technology is part of NASA licensing portfolio

	(1)	(2)	(3)
		Licensing status	
	Part of portfolio	Available	Exclusive
Cites scientific references	0.736***	0.695***	0.907
	(0.066)	(0.071)	(0.112)
Cites foreign patent references	1.379***	1.405***	1.311**
	(0.148)	(0.183)	(0.177)
Cites US patent references	0.655	0.547	1.512
	(0.201)	(0.207)	(0.525)
Number of claims	0.996	0.994***	1.001
	(0.003)	(0.002)	(0.007)
Figure in patent document	0.561**	0.526*	0.656
	(0.162)	(0.194)	(0.261)
New keyword combination	1.368***	1.388***	1.327*
	(0.157)	(0.162)	(0.198)
Number of patents in family	1.046**	1.042***	1.052
	(0.021)	(0.016)	(0.042)
Family contains EPO patent	0.875	1.031	0.585
	(0.210)	(0.208)	(0.219)
Family contains non-EPO patent	1.724**	1.352	3.358***
	(0.387)	(0.292)	(1.052)
Team size	0.994	0.988	1.015
	(0.050)	(0.048)	(0.072)
Patent controls	Yes	Yes	Yes
Patent technology fixed effects	Yes	Yes	Yes
NASA technology fixed effects	Yes	Yes	Yes
NASA research center fixed effects	No	No	No
Application year fixed effects	Yes	Yes	Yes
Grant year fixed effects	Yes	Yes	Yes
R-squared	0.091	0.097	
Observations	1590	1590	

Note: The table shows the results of logit estimations to determine the odds that a patent is part of the technology licensing portfolio in column (1). In columns (2) and (3) multinomial logit estimations to determine the odds that a patent is available for licensing or exclusively licensed. The reference category is formed from NASA-invented patents not part of the technology licensing portfolio. Patent controls are added according to the description in Section 4.3.1. These include dummy variables for patents that include scientific references, foreign patent references, US patent references, a figure in the patent document, a new keyword combination, an EPO patent in their family, or a non-EPO patent in their family. Moreover, control variables are added that account for the number of claims, the number of patents in the family, and the inventor team size. Standard errors clustered at the NASA technology category level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

4.4.3 The association between licensing and follow-on innovation

In the next step, we determine the relation between the licensing status of a technology and follow-on innovation in terms of patent citations. We first turn to the results in Table 4.3, which displays the coefficients of estimating equation (4.1) for the aggregate citations five years after the patent grant. In columns (1) - (2), we show the effect of offering the technologies for licensing, regardless of the actual licensing status. For both, the results for the sample with and without control variables, we find a positive effect that is not significantly different from zero on conventional levels. In the next step, we extend these results by considering the announcements of the availability of a technology for licensing or of an exclusive license in the Federal Register. Thus, we split the 'Any licensing announcement' variable into the categories 'Availability announcement' and 'Exclusive licensing announcement'. The coefficients in columns (3) - (4) imply that particularly exclusively licensed technologies benefit in terms of follow-on developments. When restricting the sample to only those patents for which an announcement is available (columns 5 and 6), we find that exclusive licensed patents gain about two citations more than not exclusive licensed patents in the first five years after the grant.

We extend the considerations before by analyzing the pattern of citations over time. The results are shown in Figure 4.3, panels (a) and (b). It becomes evident that the effect remains not statistically significant on conventional levels for the first seven years after the patent grant in panel (a). Thus, technological developments are not fostered if a technology is only part of the licensing portfolio. In panel (b), however, it can be seen that the coefficients are positive and relatively stable for the exclusively licensed technologies but become even more negative for those not exclusively licensed but available for licensing. We interpret these effects as a sign that exclusive licenses reflect higher commercialization potential associated with more follow-on developments.

Table 4.3: Licensing announcement and follow-on innovation of NASA inventions

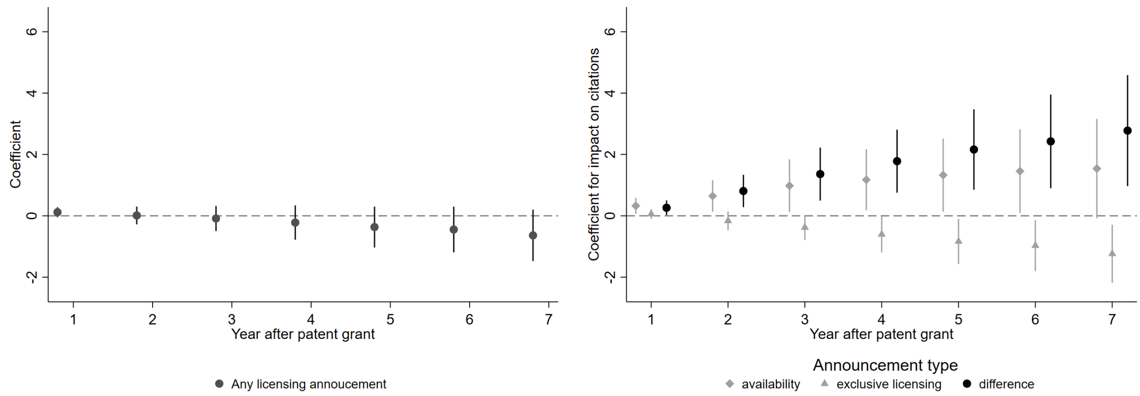
	(1)	(2)	(3)	(4)	(5)	(6)
	Citations$_{t+5}$					
Any licensing announcement	0.735	0.438				
	(0.442)	(0.436)				
Availability announcement			-0.595	-0.821		
			(0.376)	(0.494)		
Exclusive licensing announcement			1.355**	1.256**	1.950***	2.170***
			(0.595)	(0.515)	(0.624)	(0.541)
Constant	4.787***	0.108	4.787***	0.282	4.192***	-2.369
	(0.366)	(2.213)	(0.366)	(2.266)	(0.259)	(3.269)
Test for coefficient difference – Availability vs. Exclusive licensing announcement						
p-value	-	-	0.003	0.000	-	-
Patent controls	No	Yes	No	Yes	No	Yes
Patent technology fixed effects	No	Yes	No	Yes	No	Yes
NASA technology fixed effects	No	Yes	No	Yes	No	Yes
NASA research center fixed effects	No	Yes	No	Yes	No	Yes
Application year fixed effects	No	Yes	No	Yes	No	Yes
Grant year fixed effects	No	Yes	No	Yes	No	Yes
R-squared	0.003	0.314	0.018	0.327	0.021	0.437
Observations	1379	1379	1379	1379	689	689

Note: The table shows the results of linear fixed effects estimations of equation (4.1) for the inverse probability weighted sample of patents. The primary outcome variable is 'Citations$_{t+5}$', the aggregate citation count five years after the patent grant. The indicator variable 'Any licensing announcement' takes unit value if the patent was announced to be available for license, regardless of the licensing status. The variable 'Availability announcement' reflects whether the patent was announced to be available for licensing but not exclusively licensed. The indicator 'Exclusive licensing announcement' is constructed from the exclusive licensing announcement information and takes unit value if the patent was exclusively licensed and zero else. The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. Patent controls include dummy variables for patents that include scientific references, foreign patent references, US patent references, a figure in the patent document, a new keyword combination, an EPO patent in their family, or a non-EPO patent in their family. Moreover, control variables are added that account for the number of claims, the number of patents in the family, and the inventor team size. Standard errors clustered at the main IPC section times class level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

Figure 4.3: Follow-on innovation pattern of NASA inventions

(a) All inventions

(b) Available for and exclusive licensed

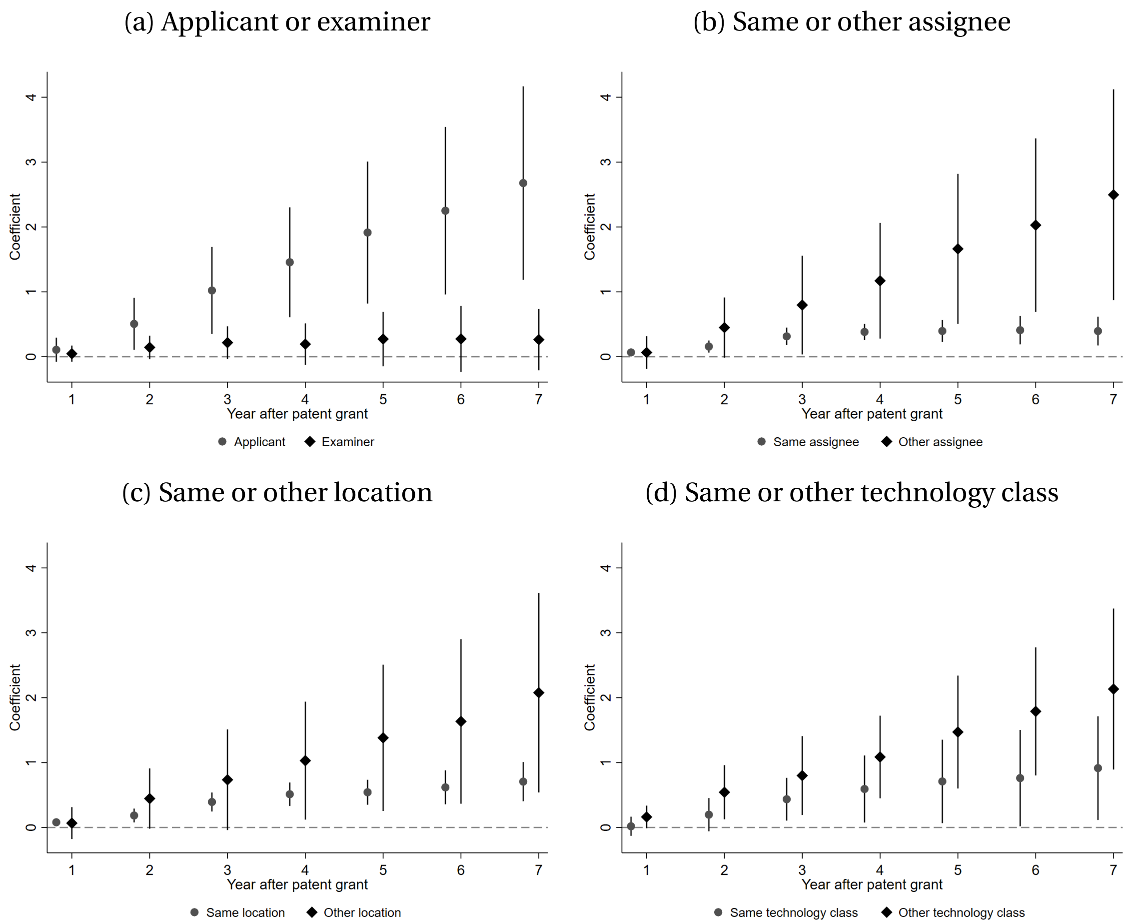


Note: This figure shows the coefficients of regressing the aggregate citations of NASA patents between 1 and 7 years after the patent grant against a set of dummies characterizing the licensing status of NASA patents. The baseline category is constructed from patents invented by NASA but not announced as available for licensing or exclusively licensed. Panel (a) shows the aggregate citation pattern for all patents of technologies that are part of the NASA technology licensing portfolio. Panel (b) displays the patents distinguished into those announced as available for licensing and those exclusively licensed. The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. 95% confidence intervals are indicated by vertical lines.

4.4.4 Origin of citations

The results in the previous section show that exclusive licensing is associated with a higher citation pattern after the patent grant. In the next step, we analyze the origin of the increase in citations. This is particularly important because we assume that the increase in citations stems from inventors building on commercially valuable technology. However, the increase in citations might also be attributed to other events, such as policy changes (e.g., Salter and Martin 2001). To test for this relation, we distinguished the aggregate citations used in the previous part of the analysis in various sub-types, such as the type of the entity, its location, and the technological origin. Table 4.4 and Figure 4.4 show the results when re-running the regressions to determine the rise in follow-on innovation. First, in columns (1) and (2), we show that applicants increase the citation count by about 3.5-fold compared to examiners. Next, the results in columns (3) and (4) indicate that the elevated citation count has its origin likely in follow-on research by other assignees. Although the increase is about three times as large as that of the same assignee, it has to be noted that we also find a stronger increase in self-citations for exclusively licensed technologies. Regarding the location of citations (columns 5 and 6), the results imply spillovers to other regions. Still, a considerable amount of citations also stem from the same location. In the context of the previous results, this indicates that there are spillovers to distinct entities, but these are likely located near the respective NASA research centers. Finally, when analyzing the technological origin of the follow-on inventions (columns 7 and 8), we find that the increase is driven by technologies that follow a different direction than the cited research. This result adds further evidence to the narrative that the licensing of technologies leads to follow-on research from distinct entities in different regions. Thus, the commercialization of NASA-funded research benefits society through knowledge spillovers.

Figure 4.4: Origin of follow-on innovation pattern of NASA inventions



Note: This figure shows the coefficients of regressing the aggregate citations of NASA patents between 1 and 7 years after the patent grant against a dummy characterizing the exclusive licensing status of NASA patents. The baseline category is constructed from patents invented by NASA and announced as available for licensing but not exclusively licensed. Thereby, citations are distinguished into applicant or examiner (panel a), the same or any other assignee (panel b), being from the same location or any other (panel c), having the same technological origin or any other (panel d). The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. 95% confidence intervals are indicated by vertical lines.

Table 4.4: Licensing announcement and follow-on innovation of NASA inventions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Citations$_{t+5}$							
	Applicant or examiner		Assignee		Location		Technology	
	Applicant	Examiner	Same	Other	Same	Other	Same	Other
Exclusive licensing announcement	1.531***	0.433**	0.429***	1.383**	0.577***	1.083**	0.720**	1.239***
	(0.493)	(0.214)	(0.088)	(0.526)	(0.096)	(0.519)	(0.307)	(0.362)
Constant	-2.086	-0.598	-0.426	-1.397	-0.817	-1.207	-1.318	-1.755
	(3.074)	(0.391)	(0.446)	(3.537)	(0.516)	(3.558)	(1.675)	(1.904)
Patent controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patent technology fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NASA technology fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NASA research center fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Application year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grant year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.436	0.472	0.439	0.420	0.505	0.417	0.497	0.429
Observations	683	683	683	683	683	683	683	683

Note: The table shows the results of linear fixed effects estimations of equation (4.1) for the inverse probability weighted sample of patents. The primary outcome variable is 'Citations$_{t+5}$', the aggregate citation count five years after the patent grant. The indicator variable 'Part of licensing portfolio' takes unit value if the patent was announced as available for license, regardless of the licensing status. The variable 'Available for licensing' reflects whether the patent was announced as available for licensing but not exclusively licensed. The indicator 'Exclusive licensed' is constructed from the exclusive licensing announcement information and takes unit value if the patent was exclusively licensed and zero else. The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. Patent controls include dummy variables for patents that include scientific references, foreign patent references, US patent references, a figure in the patent document, a new keyword combination, an EPO patent in their family, or a non-EPO patent in their family. Moreover, control variables are added that account for the number of claims, the number of patents in the family, and the inventor team size. Standard errors clustered at the main IPC section times class level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

4.4.5 Timing of availability and exclusive licensing announcement

The result in the previous section indicates that technologies that are licensed exclusively benefit particularly. However, it could be questioned whether this is due to the exclusive licensing agreement or rather an effect of the interest in the technology itself due to the announcement of the availability for licensing. Thus, in this section, we test whether it is the availability that signals value or whether it is the exclusive license itself that drives follow-on development. We take the grant event as a potential cut-off point in time as this could also affect the patents' citations. The idea is that patents licensed before the grant might follow a parallel citation path to those part of the NASA patent portfolio but not announced to be available for licensing. However, if exclusive licensing facilitates follow-on developments, licensed technologies should increase citations after the patent grant event. We include exclusive licenses between five years before and three years after the patent grant using the last announcement date to test for this relation. First, it is a reasonable time frame to test for the impact on our outcome variable – citations between the first and fifth year after the patent grant. Second, including exclusively licensed technologies beyond that point would not allow us to determine whether the citation change is due to the exclusive license or any other event before the licensing. Third, this period includes the largest share of exclusively licensed technologies.[93]

In the first step, we analyze the impact on aggregate citations in columns (1) and (2) of Table 4.5. In column (1), we distinguish the exclusively licensed technologies according to the announcement of the availability of the license. If the availability announcement would drive the results, we expect to observe significant effects for exclusively licensed patents, either announced to be available for a license before the grant or after. While we see positive effects for the availability of an exclusively licensed patent before and after the patent grant in column (1), only the estimate of

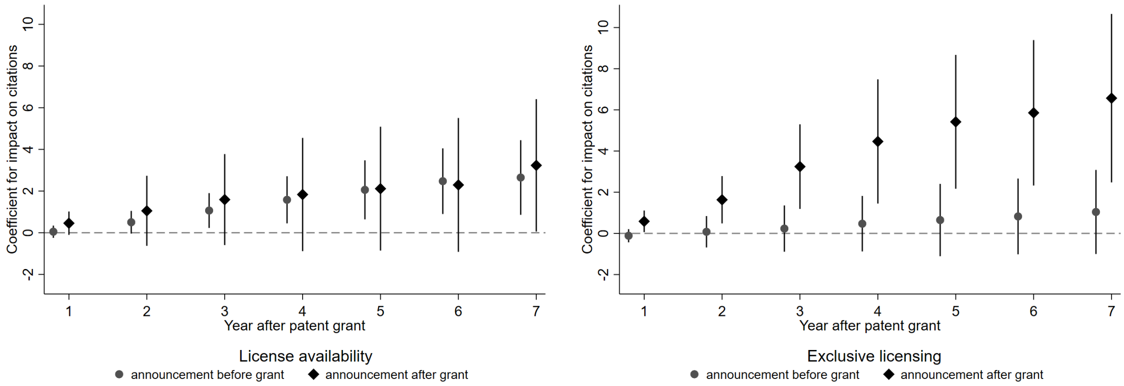
[93]The share of exclusively licensed technologies and availability announcements in the period of five years before the grant and three years after is about two-thirds. See Appendix 4.A, Figure 4.A5 for details. Results for the full-time period before and after the grant remain comparable. Results for the baseline estimates for the reduced sample of exclusively licensed technologies are comparable to the baseline estimates in Section 4.4.3, Table 4.3. Robustness tests concerning these choices are presented in Section 4.4.7.

the pre-grant effect is statistically significantly different from zero. Next, we distinguish the group of exclusively licensed patents into those licensed before and after the grant. The results in column (2) indicate that the licensing after the patent grant is associated with a higher citation count. For the comparison between the groups, we find that technologies that are exclusively licensed do not only benefit compared to non-licensed patents but also in comparison to their earlier licensed counterparts. This result is a further indication that exclusive licensing drives follow-on developments. Additionally, we show the results of the effects over time for the regressions in Table 4.5, columns (1) and (2) in Figure 4.5 panels (a) and (b). The individual results in each considered period point in the same direction as those described before. Thus, it becomes evident that the gap between exclusively licensed patents and those that are either not licensed or exclusively licensed before the patent grant increases over time. Next, we consider the subsample of exclusive licensed patents and the impact of the availability announcement (columns 3 and 4). we find that the effect is indeed driven by the patents announced to be exclusively licensed after the patent grant (column 4). We extend these findings by considering the sub-sample of exclusively licensed patents whose availability is announced before (column 5) or after (column 6) the grant. The results imply that the exclusivity announcement after the grant is driving the effect for both samples.

Figure 4.5: Licensing timing and follow-on innovation pattern of NASA inventions

(a) Available for license

(b) Exclusively licensed



Note: This figure shows the coefficients of regressing the aggregate citations of NASA patents between 1 and 7 years after the patent grant against a dummy characterizing the exclusive licensing status of NASA patents. The baseline category is constructed from patents invented by NASA and announced as available for licensing but not exclusively licensed. Panel (a) shows the aggregate citation pattern for all patents of technologies available for licensing, announced to be available for licensing five years before or three years after the patent grant. Panel (b) shows the aggregate citation pattern for all patents for technologies that are available for licensing and announced to be exclusively licensed five years before or three years after the patent grant. The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. 95% confidence intervals are indicated by vertical lines.

Table 4.5: Licensing timing and follow-on innovation NASA inventions

	(1)	(2)	(3)	(4)	(5)	(6)
	Citations$_{t+5}$					
	Full sample		Exclusivity announcement		Availability announcement	
			Before grant	After grant	Before grant	After grant
Exclusive licensed						
Availability announcement before grant	2.347***		0.435	4.670**		
	(0.738)		(0.999)	(2.077)		
Availability announcement after grant	1.232		0.179	5.675***		
	(1.340)		(1.397)	(1.999)		
Exclusivity announcement before grant		0.929			0.335	1.461
		(0.877)			(0.994)	(0.992)
Exclusivity announcement after grant		4.643***			4.664**	5.254***
		(1.132)			(1.987)	(1.679)
Constant	-0.741	0.783	1.555	1.747	0.312	1.368
	(2.949)	(2.627)	(1.852)	(2.100)	(2.630)	(1.676)
Test for coefficient differences (p-values)						
Announcement before grant vs. after grant	0.532	0.007	0.809	0.711	0.025	0.027
Patent controls	Yes	Yes	Yes	Yes	Yes	Yes
Patent technology fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
NASA technology fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
NASA research center fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Application year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Grant year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.452	0.426	0.383	0.380	0.398	0.340
Observations	642	601	561	522	573	510

Note: The table shows the results of linear fixed effects estimations of equation (4.1) for the inverse probability weighted sample of patents. The primary outcome variable in columns (1) and (2) is 'Citations$_{t+5}$', which is the aggregate citation count five years after the patent grant. The variable 'Available for licensing' reflects whether the patent was announced as available for licensing but not exclusively licensed. The indicator 'Exclusive licensed' is constructed from the exclusive licensing announcement information and takes unit value if the patent was exclusively licensed and zero else. The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. Patent controls include dummy variables for patents that include scientific references, foreign patent references, US patent references, a figure in the patent document, a new keyword combination, an EPO patent in their family, or a non-EPO patent in their family. Moreover, control variables are added that account for the number of claims, the number of patents in the family, and the inventor team size. Standard errors clustered at the main IPC section times class level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

4.4.6 Difference in differences results

Although we account for observable differences and determine that post-grant licensing likely drives the effect, it might still be a concern that unobserved differences between the patents in the analysis drive the effect. Thus, in further tests, we extend equation (4.1) by using the difference of the citation measure between two points in time after the patent grant. Combining this adjusted version of equation (4.4) with inverse probability weighting, we apply a conditional difference-in-differences (CDID) regression approach (e.g., Heckman et al. 1998; Heckman et al. 1999; Roth et al. 2023). This approach helps to mitigate biases from time-invariant unobserved factors to a strong degree by constructing the differences in outcomes for treated and control units and determining the difference between the weighted units (Caliendo and Kopeinig 2008).[94] Thus, our adjusted baseline estimation equation to determine the impact of licensing on the change in citations is the following:

$$\Delta \text{Citations}_{i(t+k-t=1)} = \tau_0 + \tau_1 \text{Licensing}_i + \gamma \text{T}_i + \varepsilon \text{P}_i + \eta_i \tag{4.4}$$

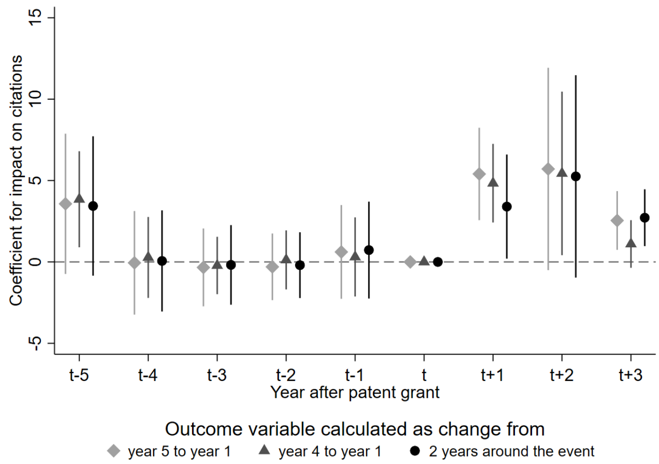
We construct the respective outcome measure $\Delta\text{Citations}_{(t+k-t=1)}$ as the difference of citations in the k-th year and the first year after the patent grant. Thereby, the parameter τ_1 reflects the change in citations for the licensed technologies compared to those that are not caused by the change in the licensing status.

The results when applying the conditional difference-in-differences approach are shown in Table 4.6 and Figure 4.6. These results reinforce the conclusion from before that it is the exclusive licensing event that fosters follow-on innovation. We find that exclusively licensed patents receive about 1.5 to 1.8 more citations compared to the patents that are only available in the years after the patent grant surrounding the licensing event (columns 1, 3, 5). When further distinguishing the driver of that effect, we find evidence that the announcement after the grant leads to a higher citation

[94]We cannot rule out the influence of time-variant unobserved factors on our results. However, we provide baseline results and subsequent robustness tests to analyze the consistency of our results along various dimensions. The results of these tests imply that the influence of this bias, if any, is minor.

count (columns 2, 4, 6). Furthermore, the coefficients in Figure 4.6 imply that the citation pattern is indeed parallel for the exclusively licensed technologies before the grant. Moreover, the effect is significantly different from zero in the post-grant period, indicating that the licensing is associated with a citation uptake compared to patents only available for licensing. The finding also implies that the effect is higher than that of patents exclusively licensed before the grant. This finding underlines that exclusive licensing is most likely the driver of the citation increase. Thus, exclusive licenses are associated with higher commercial value, triggering more follow-on developments.

Figure 4.6: Change in follow-on innovation pattern of NASA inventions



Note: This figure shows the coefficients of regressing the citation differences as indicated in the headline of Table 4.6 on the exclusive licensing status of NASA patents. The baseline category is constructed from patents invented by NASA and announced as available for licensing but not exclusively licensed. The announcement time window is five years before or three years after the patent grant. The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. 95% confidence intervals are indicated by vertical lines.

Table 4.6: Change in follow-on innovation pattern of NASA inventions

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔCitations$_{t=1,t=5}$		ΔCitations$_{t=1,t=4}$		ΔCitations$_{t=1,t+2}$	
Exclusive licensing announcement	1.807***		1.526***		1.638**	
	(0.651)		(0.486)		(0.701)	
Exclusivity announcement before grant		0.877		0.831		0.866
		(0.802)		(0.585)		(0.810)
Exclusivity announcement after grant		4.387***		3.451***		3.778***
		(1.015)		(0.912)		(1.078)
Constant	-0.258	0.868	-0.319	0.521	-0.357	0.578
	(2.441)	(2.403)	(1.977)	(1.922)	(2.314)	(2.336)
Test for coefficient differences (p-values)						
Announcement before grant vs. after grant		0.005		0.016		0.016
Patent controls	Yes	Yes	Yes	Yes	Yes	Yes
Patent technology fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
NASA technology fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
NASA research center fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Application year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Grant year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.409	0.434	0.373	0.395	0.408	0.426
Observations	601	601	601	601	601	601

Note: The table shows the results of linear fixed effects estimations of equation (4.1) for the inverse probability weighted sample of patents. The primary outcome variable in columns (1) to (6) is 'ΔCitations$_{t=l,t=u}$', which is the difference of the aggregate citation count between year u and l after the patent grant. The variable 'Available for licensing' reflects whether the patent was announced as available for licensing but not exclusively licensed. The indicator 'Exclusive licensed' is constructed from the exclusive licensing announcement information and takes unit value if the patent was exclusively licensed and zero else. The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. Patent controls include dummy variables for patents that include scientific references, foreign patent references, US patent references, a figure in the patent document, a new keyword combination, an EPO patent in their family, or a non-EPO patent in their family. Moreover, control variables are added that account for the number of claims, the number of patents in the family, and the inventor team size. Standard errors clustered at the main IPC section times class level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

4.4.7 Further robustness and sensitivity tests

The results presented in the previous sections imply that exclusive licensed technologies facilitate follow-on innovations. The provided graphical evidence already points towards the robustness of the results concerning the long-term impact. However, in the following paragraphs, we will provide further tests to underline the robustness of the results. We begin with testing whether the baseline results rely on the transformation outcome variable, discussed in Section 4.3. First, we test for the extensive and intensive margin of citations, that is, whether any citation is received (extensive margin) or the number of non-zero citations (intensive margin). The results in Appendix 4.D, Table 4.D1, and Table 4.D2 imply that exclusive licensed patents receive more likely any citation and also a higher non-zero count. This reinforces the baseline results. Next, we apply the pure citation count and winsorize the variable at the 1% level, or truncate it at the 1% or 5% level, which leads to similar results (Appendix 4.D, Table 4.D3, Table 4.D4, Table 4.D5). Furthermore, we apply the inverse hyperbolic sine transformation of the plain citation variable or use the count variable in fixed effects poison estimations. Although the size of the coefficients changes, the interpretation of the results remains comparable (Appendix 4.D, Table 4.D6, Table 4.D7).

Besides the citation variable, it might be argued that the timing of the patent disclosure is important for its citations and the firm's licensing decision. To test for this relation, we perform different tests. First, we restrict the sample of application cohorts to those after 2001 that are affected by the American Inventors Protection Act (AIPA). This act required disclosing the patent application for patents filed before November 29, 2000. Applying this adjustment, the results do not change to a strong degree (Appendix 4.D, Table 4.D8). In a second test, we analyze whether the effects differ for patents filed before the AIPA went into force. We find that the effects (Appendix 4.D, Table 4.D9) remain comparable to the baseline estimates.

In our empirical analysis, we use the assumption that the timing of the exclusive licensing announcement is the driver of the increase in follow-on innovation. Although this result is fairly robust when applying various empirical specifications, we employ additional tests related to the availability and exclusivity variables. A more detailed investigation of the exclusively licensed technologies reveals that about one-third are licensed more than once. Thus, we restrict the sample to technologies announced to be exclusively licensed once to exclude that patents drive the effect that have multiple announcements. Although the count of treated observations decreases, the results in Appendix 4.D, Table 4.D10, and Table 4.D11 are comparable to the baseline results.

Furthermore, we restricted the post-grant period to three years in the analysis. Thus, we modify our approach by using up to 5 years after the grant, which yields similar results (Appendix 4.D, Table 4.D12). Finally, we apply the same change to the conditional difference-in-differences approach presented in Section 4.4.6. The estimates are shown in Appendix 4.D, Table 4.D13. Although the sample size increases and the outcome variable differences are adjusted for a longer time period, the results lead to conclusions similar to those before. Therefore, we can conclude that the results are fairly robust to changes.

4.5 Conclusion

How does the technology transfer of government(-funded) inventions affect follow-on innovations? Government-funded research is important as it focuses on basic research and thereby serves as a basis for practical solutions to real-world problems, such as climate change. However, commercialization of this research can bring additional benefits by spurring innovation, stimulating economic growth, and generating revenue that can be reinvested in future research. After laws like the Bayh-Dole Act and the Stevenson-Wydler Technology Innovation Act paved the way in the 1980s, NASA implemented its Technology Transfer Program in 1995 to commercialize its invented technologies by licensing. In this paper, we used this program to analyze the effects of licensing on follow-on innovations. We combine data from the NASA TTP, USPTO, and US Federal Register, allowing us to distinguish between exclusively licensed and non-exclusively licensed patents. We use this information to determine the impact of licensing on follow-on innovation. We find that exclusively licensed technologies spur subsequent innovation to a strong degree. This is consistent with the idea that these technologies have the highest commercialization potential, triggering follow-on innovation. When analyzing the origin of these, we show that they stem from distinct inventors from distinct regions and technology fields. This implies considerable spillover effects. Thus, particularly exclusive licensed technologies provide high benefits to society.

The results of this paper have important implications for policymakers and firms. First, making government-funded research available for licensing is benefiting society. However, particularly exclusively licensed technologies show high commercialization potential and are related to an increase in follow-on developments. Thus, further evaluations of technology potentials and analysis of existing technologies are needed. These can help bridge the gap between government-funded inventions, firms, and consumers. Moreover, the increase in follow-on innovation implies positive spillover effects that are beneficial for economic growth. Consequently, the TTP is a valuable policy. An implication would be to extend and improve licensing programs to increase the benefits of government-funded research for the civil population. Second, this paper's results imply a high potential for firms to license government-funded research. While this is related to the market potential of new technology, it also relates to the development of follow-on applications. Thus, licensing government-funded inventions could be an efficient way to source external knowledge, which yields further private benefits.

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Appendix

4.A Additional figures

Figure 4.A1: Legislations, executive orders and other events related to NASA technology transfer

Decade	Year	Event
1950s	1958	National Aeronautics and Space Act of 1958; *Creating the agency, & beginning of the 'technology transfer' movement*
1980s	1980	Bayh-Dole Act of 1980 *Small businesses, universities & nonprofit organizations permitted to obtain titles to inventions*
		Stevenson-Wydler Technology Innovation Act of 1980 *Federal laboratories to establish formal* ***technology transfer program***
	1986	Federal Technology Transfer Act of 1986 *Authorized CRADAs, laboratories invention licensing, royalty payments to government employees*
	1987	Executive Order 12591 *Federal laboratories to assist universities, private sector through technology transfer, e.g., two-way knowledge transfer*
	1988	Omnibus Trade and Competitiveness Act of 1988 *Extended royalty payments to non-government employees of government laboratories*
	1989	National Competitiveness Technology Transfer Act of 1989 *Innovations created through CRADAs protected from disclose to third parties*
1990s	1993	Report of the National Performance Review of 1993 *Recommendation to increase government's effectiveness of 1993*
	1994	NASA's Commercial Technology: Agenda for Change of 1994 *Implementing recommendations of 1993, e.g., 20% of R&D budget to industry partnerships*
	1995	National Technology Transfer and Advancement Act of 1995 *Makes CRADAs more attractive to federal laboratories, scientists, and private industry;* ***allows licensing of inventions developed under a CRADA***
2000s	2000	Technology Transfer Commercialization Act of 2000 *Laboratories may license preexisting federally-owned inventions under a CRADA*
	2005	NASA Authorization Act of 2005 *Asked NASA to develop a commercialization plan that outlines technology transfer activities, including commercial R&D partnerships between NASA, universities, and the private sector*
	2006	NASA Strategic Plan of 2006 *Emphasized the engagement of the private sector in the NASA mission; Encouraged prize competitions to advance needed technologies, and encouraged partnerships with the emerging commercial space sector*
2010s	2011	Presidential Memorandum of 2011 *Emphasized technology transfer goals and requires all federal laboratories to have a 5-year technology transfer plan to accelerate and promote technology transfer*

Note: This figure shows the development of legislation related to NASA technology transfer (NASA OIG 2019), own visualization.

Figure 4.A2: Federal register announcements related to the licensing of inventions

(a) Availability of technologies

NATIONAL AERONAUTICS AND SPACE ADMINISTRATION

[Notice (04–068)]

Government-Owned Inventions, Available for Licensing

AGENCY: National Aeronautics and Space Administration.

ACTION: Notice of availability of inventions for licensing.

SUMMARY: The inventions listed below are assigned to the National Aeronautics and Space Administration, have been filed in the United States Patent and Trademark Office, and are available for licensing.

DATES: May 18, 2004.

FOR FURTHER INFORMATION CONTACT: Linda Blackburn, Patent Counsel, Langley Research Center, Mail Code 212, Hampton, VA 23681–2199; telephone (757) 864–9260; fax (757) 864–9190.

NASA Case No. LAR–16324–2: Self-Activating System and Method for Alerting When an Object or a Person Is Left Unattended;

NASA Case No. LAR–16406–1–CU: Ultrasonic Apparatus and Method To Assess Compartment Syndrome;

NASA Case No. LAR 16606–1: Catalytic Oxidation System.

Dated: May 12, 2004.

Keith T. Sefton,

Chief of Staff, Office of the General Counsel.

[FR Doc. 04–11176 Filed 5–17–04; 8:45 am]

BILLING CODE 7510–01–P

(b) Exclusive licensing intent

NATIONAL AERONAUTICS AND SPACE ADMINISTRATION

[Notice 07–028]

Notice of Intent To Grant Exclusive License

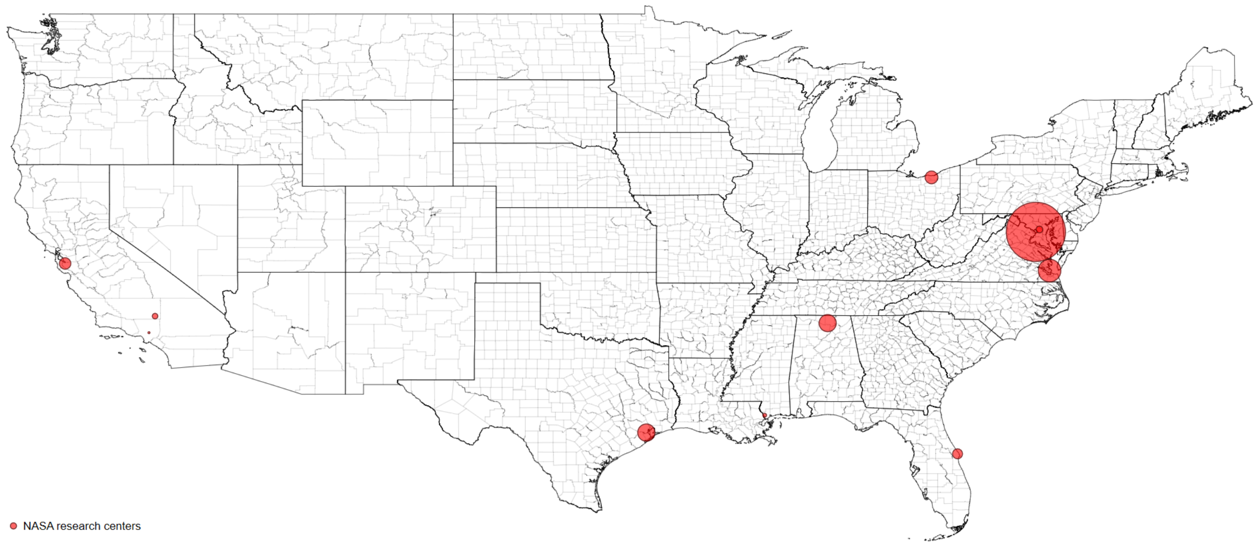
AGENCY: National Aeronautics and Space Administration.

ACTION: Notice of intent to grant exclusive license.

SUMMARY: This notice is issued in accordance with 35 U.S.C. 209(c)(1) and 37 CFR 404.7(a)(1)(i). NASA hereby gives notice of its intent to grant an exclusive license in the United States to practice the inventions described and claimed in NASA Case Number LAR–16324–1 entitled “Self-Activating System and Method for Alerting When an Object or a Person is Left Unattended,” U.S. Patent Number 6,714,132; LAR–16324–2 entitled “Self-Activating System and Method for Alerting When an Object or a Person is Left Unattended,” U.S. Patent Number 7,106,203 to MaxTec, Inc. having its principal place of business in Wellington, Florida. The patent rights in these inventions have been assigned to the United States of America as represented by the Administrator of the National Aeronautics and Space Administration. The prospective exclusive license will comply with the terms and conditions of 35 U.S.C. 209 and 37 CFR 404.7.

Note: The figure shows NASA technology announcements in the Federal Register. Panel (a) shows the announcement of technologies available for licensing. Panel (b) shows an exclusive licensing announcement.

Figure 4.A3: Research centers locations and number of patents

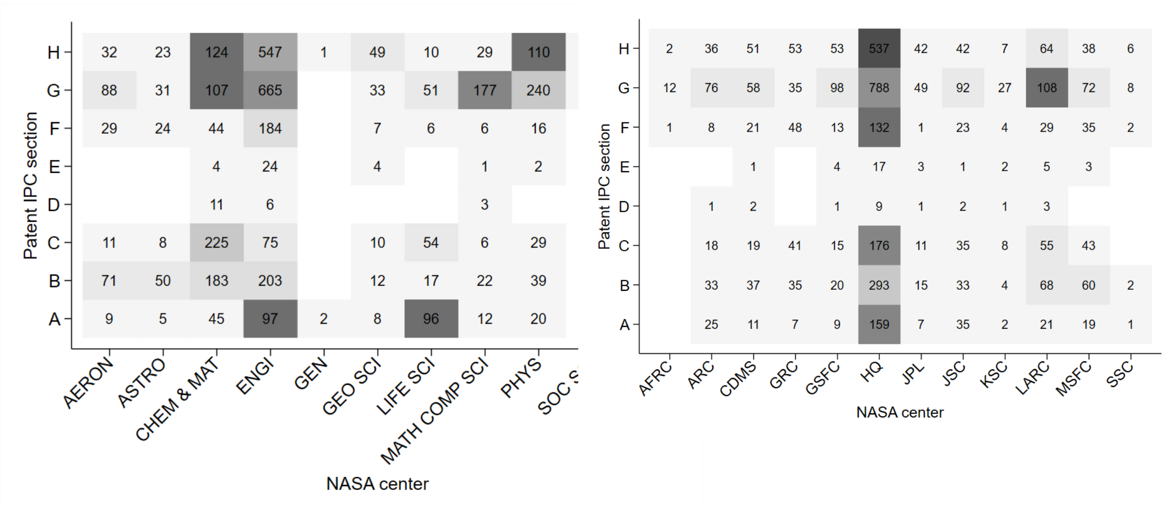


Note: The figure shows the geographical location of NASA research centers. The size of the red dots reflects the patent count relative to the total number of patents in the NASA technology portfolio.

Figure 4.A4: NASA technologies and patent classification

(a) Technology groups

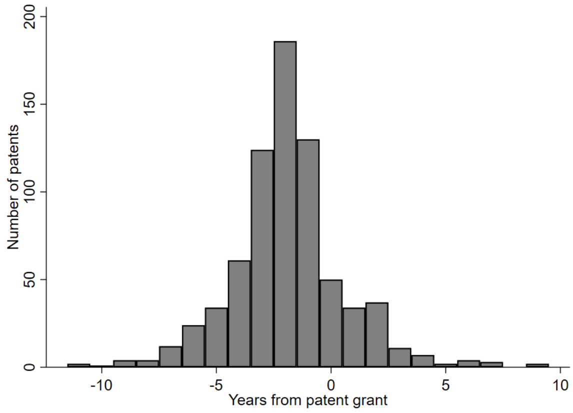
(b) NASA research centers



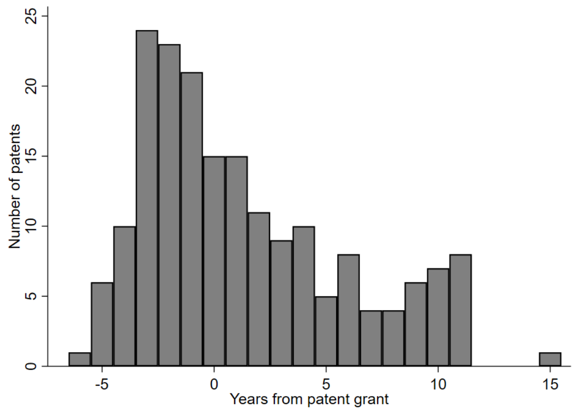
Note: The figure shows the distribution of patents over NASA technology groups and NASA research centers in relation to patent IPC classes.

Figure 4.A5: Timing of availability and exclusivity announcements

(a) Timing of availability announcement



(b) Timing of exclusivity announcement



Note: The figure shows the timing of the availability and exclusivity announcements relative to the patent grant year. In case of more than one announcement, the date of the last is taken to calculate the difference.

4.B Additional results for weighting approach

Table 4.B1: Propensity of being part of the licensing portfolio

	(1) Part of the licensing portfolio
Cites scientific references	0.102
	(0.095)
Cites foreign patent references	0.058
	(0.110)
Cites US patent references	0.453
	(0.316)
Number of claims	0.004
	(0.003)
Figure in patent document	0.115
	(0.385)
New keyword combination	0.059
	(0.095)
Number of patents in family	0.024
	(0.015)
Family contains EPO patent	-0.494**
	(0.217)
Family contains non-EPO patent	0.571***
	(0.132)
Team size	0.002
	(0.025)
Constant	-3.770***
	(0.781)
Patent controls	Yes
Patent technology fixed effects	Yes
NASA technology fixed effects	Yes
NASA research center fixed effects	Yes
Application year fixed effects	Yes
Grant year fixed effects	Yes
Pseudo R-squared	0.150
Observations	1444

Note: The table shows the results of a probit estimation to determine the inverse probability weights as described in Section 4.3.2. The dependent variable takes unit value if the patent is part of the licensing portfolio of NASA, and zero else. Patent controls are added according to the description in Section 4.3.1. These include dummy variables for patents that include scientific references, foreign patent references, US patent references, a figure in the patent document, a new keyword combination, an EPO patent in their family, or a non-EPO patent in their family. Moreover, control variables are added that account for the number of claims, the number of patents in the family, and the inventor team size. Standard errors clustered at the main IPC section times class level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

Table 4.B2: Mean comparison of technologies in the licensing portfolio and those which are not

	(1)	(2)	(3)	(4)
	Mean		Difference	p-value
	Treatment	Control	(2)-(1)	(1)=(2)
Cites scientific references	0.484	0.477	-0.007	0.902
Cites foreign patent references	0.248	0.321	0.073	0.229
Cites US patent references	0.972	0.985	0.013	0.210
Number of claims	18.673	19.212	0.539	0.563
Figure in patent document	0.989	0.988	-0.002	0.832
New keyword combination	0.556	0.544	-0.012	0.843
Number of patents in family	2.995	3.210	0.215	0.517
Family contains EPO patent	0.075	0.078	0.003	0.877
Family contains non-EPO patent	0.222	0.217	-0.005	0.888
Team size	2.604	2.478	-0.126	0.413
Citations 1 year after patent grant	0.797	1.195	0.398	0.097
Citations 2 years after patent grant	1.769	2.846	1.077	0.041
Citations 3 years after patent grant	2.810	4.435	1.625	0.023
Citations 4 years after patent grant	3.938	5.753	1.815	0.032
Citations 5 years after patent grant	5.051	7.293	2.242	0.021
Citations 6 years after patent grant	6.107	8.687	2.580	0.021
Citations 7 years after patent grant	7.149	10.128	2.979	0.019

Note: The table shows the comparison of the inverse-probability weighted means for the treatment and control group. The treatment group is formed of technologies that are part of the NASA licensing technology portfolio. The control group consists of technologies invented by NASA, but not announced to be available for licensing.

Supplementary material

4.C Description of the application process for NASA's TTP

The application process is described in the following to better understand how the TTP works and which options a company has when it wants to license technology from NASA. As a first step, the company has to find the technology that is a matter of licensing. To do so, it can search NASA's patent portfolio for a suitable technology which can be found on their website[95]. NASA's portfolio of available technologies is broad and diverse, and it covers a wide range of areas, including communications, electrical, environment, medicine/biotech, mechanical/fluid systems, aerospace, instrumentation, manufacturing, materials/coatings, sensors, optics, IT/software, power generation, propulsion, and robotics. The website provides a search tool to find a respective patent for licensing by entering a keyword to minimize search costs for a potentially interested company. In the second step, the company applies for a patent. This can be done online using NASA's Automated Technology Licensing Application System (ATLAS). The system guides the whole process and keeps the applicant updated about the application status. In general, there are three different application paths possible: (i) a standard commercial license (SCL), (ii) an evaluation license (EL), and (iii) a startup license (SL).

The standard commercial license (SCL) allows companies to make and sell products using NASA's patented technologies. Generally, these will be offered with a standard licensing template but will in the process negotiated case-by-case. An SCL is not restricted to domestic companies but is also available for international organizations. A patent under an SCL can either be exclusive, partially exclusive, or non-exclusively licensed. The agreements include an upfront payment, a minimum annual license fee, and an ongoing license fee. A company must fulfill in general two parts to fulfill the requirements of an SCL application. The first part includes a list of the requested technologies, the company's contact information, a basic plan for the use of the technology, and the proposed fees. The second part of the requirements must include a technology development plan, a marketing and sales plan, a projected financial statement with investment requirements, a current balance sheet and incoming statement, a management and staffing plan, and a risk assessment and mitigation.

An evaluation license (EL) allows short-term permission to explore a technology's potential and learn whether it fits the company's business development goals. An EL is a non-exclusive agreement and usually lasts 12 months at a cost of $US 2,500. Important to notice is that an EL not permits to commercialize or sell the technology. To do so, the company first has to sign an SCL. A contrast to this, a non-disclosure agreement (NDA) allows for answering basic questions. With an EL, however, the company can discuss the specific technology adoption in their case with NASA and is allowed to conduct testing, experiment, create prototypes or discuss the technology with other third parties, like investors. However, this kind of licensing is not relevant to the research question in this paper as it does not allow for commercializing.

[95]NASA's patent portfolio can be accessed via https://technology.nasa.gov/patents. This website gives an overview of a fraction of the available technologies.

The third option to license is a startup license (SL). An SL offers a company a license with no up-front costs for the commercial use of NASA-patented technologies. Technologies available for an SL have already been evaluated for technical and commercial feasibility by NASA and external sources. These patents are administrated and protected by the US government. NASA also offers to provide technical personnel and facilities as additional support. SLs offer companies to keep their cash while securing the intellectual property they need to enter a competitive market. An SL is designed for companies that intend to commercialize licensed NASA technologies. While the initial licensed fees as well as the annual fees for the first three years are waived, NASA will collect an annual fee of $US 3,000 from year four onwards. Additionally, NASA collects a royalty fee of 4.2% once the company starts selling the product. NASA passes this money mainly to the inventor and uses it to maintain the technology transfer activities and support. An SL can only be licensed non-exclusively so that other companies, and thus possible competitors to the applicant, can apply for similar rights to use the technology for commercial purposes. It is however possible to negotiate over a possible exclusive agreement in the further process. In contrast to the SCLs, SLs are only available to companies in the United States.

In the third step of the application process, the terms for the agreement are set up between NASA and the company. In this step, the fees and royalties are discussed and depend on various factors. In principle, NASA collects three different fees: (i) upfront fees, (ii) yearly minimum royalties, and (iii) running royalty percentage. The amount of each depends on the licensing option, the exclusivity, the industry the technology will be used or sold, and the maturity of the technology. The upfront fees, for example, can vary between zero for SL, $5,000-10,000 for non-exclusive licensed, and more than $50,000 for exclusively licensed technologies. With these upfront fees, NASA is trying to recoup part of its investment in the costs of the patent application and its maintenance. Conversely, this means that the costs for application and maintenance for exclusively licensed patents seem to be much higher than for other technologies. The second fee, yearly minimum royalties, is based on the company's business plan and is intended to ensure that licensees are actively working on the development of commercial applications. The last fee, the running royalty percentage, is negotiated based on sales, but generally ranges from three to seven percent. A higher upfront payment can reduce this fee and vary depending on the readiness or maturity of the technology, the industrial application of the technology, and the level of exclusivity desired by the company.

In the last step of the application process, NASA and the company execute the license in accordance with the terms of the agreement. After the license is granted, NASA monitors the licensee's sales of products and services that use the licensed technologies. Additionally, NASA writes success stories that may be published on its website, in NASA's Spinoff magazine, or in other publications. One reason for this is to make the effort in commercializing visible.

4.D Results of robustness tests

Table 4.D1: Licensing announcement and follow-on innovation of NASA inventions – Extensive margin

	(1)	(2)	(3)	(4)	(5)	(6)
			$\mathbb{1}$(Citations$_{t+5}$>0)			
Any licensing announcement	0.066***	0.049**				
	(0.023)	(0.024)				
Availability announcement			-0.023	-0.015		
			(0.023)	(0.022)		
Exclusive licensing announcement			0.107***	0.090***	0.130***	0.100**
			(0.028)	(0.032)	(0.032)	(0.038)
Constant	0.801***	0.648***	0.801***	0.657***	0.779***	0.689***
	(0.014)	(0.071)	(0.014)	(0.072)	(0.020)	(0.096)
Test for coefficient difference – Availability vs. Exclusive licensing announcement						
p-value	-	-	0.000	0.002	-	-
Patent controls	No	Yes	No	Yes	No	Yes
Patent technology fixed effects	No	Yes	No	Yes	No	Yes
NASA technology fixed effects	No	Yes	No	Yes	No	Yes
NASA research center fixed effects	No	Yes	No	Yes	No	Yes
Application year fixed effects	No	Yes	No	Yes	No	Yes
Grant year fixed effects	No	Yes	No	Yes	No	Yes
R-squared	0.007	0.208	0.027	0.218	0.032	0.305
Observations	1379	1379	1379	1379	689	683

Note: The table shows the results of linear fixed effects estimations of equation (4.1) for the inverse probability weighted sample of patents. The primary outcome variable is '$\mathbb{1}$(Citations$_{t+5}$>0)', an indicator of whether the aggregate citation count five years after the patent grant is larger than zero. The indicator variable 'Any licensing announcement' takes unit value if the patent was announced as available for license, regardless of the licensing status. The variable 'Availability announcement' reflects whether the patent was announced as available for licensing but not exclusively licensed. The indicator 'Exclusive licensing announcement' is constructed from the exclusive licensing announcement information and takes unit value if the patent was exclusively licensed and zero else. The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. Patent controls include dummy variables for patents that include scientific references, foreign patent references, US patent references, a figure in the patent document, a new keyword combination, an EPO patent in their family, or a non-EPO patent in their family. Moreover, control variables are added that account for the number of claims, the number of patents in the family, and the inventor team size. Standard errors clustered at the main IPC section times class level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

Table 4.D2: Licensing announcement and follow-on innovation of NASA inventions – Intensive margin

	(1)	(2)	(3)	(4)	(5)	(6)
	Citations$_{t+5}$|Citations$_{t+5}$>0					
Any licensing announcement	0.499	0.461				
	(0.509)	(0.474)				
Availability announcement			-0.582	-0.634		
			(0.470)	(0.605)		
Exclusive licensing announcement			0.949	1.141**	1.531**	1.907***
			(0.666)	(0.569)	(0.734)	(0.702)
Constant	5.984***	1.399	5.984***	1.158	5.401***	-2.407
	(0.395)	(3.284)	(0.395)	(3.359)	(0.309)	(4.174)
Test for coefficient difference – Availability vs. Exclusive licensing announcement						
p-value	-	-	0.041	0.010	-	-
Patent controls	No	Yes	No	Yes	No	Yes
Patent technology fixed effects	No	Yes	No	Yes	No	Yes
NASA technology fixed effects	No	Yes	No	Yes	No	Yes
NASA research center fixed effects	No	Yes	No	Yes	No	Yes
Application year fixed effects	No	Yes	No	Yes	No	Yes
Grant year fixed effects	No	Yes	No	Yes	No	Yes
R-squared	0.001	0.326	0.010	0.335	0.012	0.461
Observations	1103	1103	1103	1103	554	549

Note: The table shows the results of linear fixed effects estimations of equation (4.1) for the inverse probability weighted sample of patents. The primary outcome variable is 'Citations$_{t+5}$', the aggregate non-zero citation count five years after the patent grant. The indicator variable 'Any licensing announcement' takes unit value if the patent was announced as available for license, regardless of the licensing status. The variable 'Availability announcement' reflects whether the patent was announced as available for licensing but not exclusively licensed. The indicator 'Exclusive licensing announcement' is constructed from the exclusive licensing announcement information and takes unit value if the patent was exclusively licensed and zero else. The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. Patent controls include dummy variables for patents that include scientific references, foreign patent references, US patent references, a figure in the patent document, a new keyword combination, an EPO patent in their family, or a non-EPO patent in their family. Moreover, control variables are added that account for the number of claims, the number of patents in the family, and the inventor team size. Standard errors clustered at the main IPC section times class level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

Table 4.D3: Licensing announcement and follow-on innovation of NASA inventions – 1% winsorized

	(1)	(2)	(3)	(4)	(5)	(6)
			Citations$_{t+5}$			
Any licensing announcement	0.944	0.501				
	(0.634)	(0.620)				
Availability announcement			-0.658	-1.010		
			(0.431)	(0.633)		
Exclusive licensing announcement			1.691*	1.482*	2.349***	2.583***
			(0.861)	(0.775)	(0.847)	(0.840)
Constant	5.127***	-1.268	5.127***	-1.060	4.469***	-5.940
	(0.445)	(3.046)	(0.446)	(3.110)	(0.329)	(4.670)
Test for coefficient difference – Availability vs. Exclusive licensing announcement						
p-value	-	-	0.007	0.001	-	-
Patent controls	No	Yes	No	Yes	No	Yes
Patent technology fixed effects	No	Yes	No	Yes	No	Yes
NASA technology fixed effects	No	Yes	No	Yes	No	Yes
NASA research center fixed effects	No	Yes	No	Yes	No	Yes
Application year fixed effects	No	Yes	No	Yes	No	Yes
Grant year fixed effects	No	Yes	No	Yes	No	Yes
R-squared	0.002	0.305	0.014	0.315	0.015	0.436
Observations	1379	1379	1379	1379	689	689

Note: The table shows the results of linear fixed effects estimations of equation (4.1) for the inverse probability weighted sample of patents. The primary outcome variable is 'Citations$_{t+5}$', the aggregate citation count five years after the patent grant. The indicator variable 'Any licensing announcement' takes unit value if the patent was announced as available for license, regardless of the licensing status. The variable 'Availability announcement' reflects whether the patent was announced as available for licensing but not exclusively licensed. The indicator 'Exclusive licensing announcement' is constructed from the exclusive licensing announcement information and takes unit value if the patent was exclusively licensed and zero else. The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. Patent controls include dummy variables for patents that include scientific references, foreign patent references, US patent references, a figure in the patent document, a new keyword combination, an EPO patent in their family, or a non-EPO patent in their family. Moreover, control variables are added that account for the number of claims, the number of patents in the family, and the inventor team size. Standard errors clustered at the main IPC section times class level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

Table 4.D4: Licensing announcement and follow-on innovation of NASA inventions – 1% truncation

	(1)	(2)	(3)	(4)	(5)	(6)
			Citations$_{t+5}$			
Any licensing announcement	0.466	0.236				
	(0.479)	(0.406)				
Availability announcement			-0.793*	-0.941*		
			(0.441)	(0.512)		
Exclusive licensing announcement			1.059*	1.001**	1.852***	1.969***
			(0.616)	(0.472)	(0.614)	(0.573)
Constant	5.047***	0.463	5.047***	0.611	4.253***	-1.362
	(0.442)	(1.955)	(0.442)	(1.998)	(0.295)	(2.866)
Test for coefficient difference – Availability vs. Exclusive licensing announcement						
p-value	-	-	0.004	0.000	-	-
Patent controls	No	Yes	No	Yes	No	Yes
Patent technology fixed effects	No	Yes	No	Yes	No	Yes
NASA technology fixed effects	No	Yes	No	Yes	No	Yes
NASA research center fixed effects	No	Yes	No	Yes	No	Yes
Application year fixed effects	No	Yes	No	Yes	No	Yes
Grant year fixed effects	No	Yes	No	Yes	No	Yes
R-squared	0.001	0.303	0.011	0.312	0.016	0.437
Observations	1374	1374	1374	1374	685	685

Note: The table shows the results of linear fixed effects estimations of equation (4.1) for the inverse probability weighted sample of patents. The primary outcome variable is 'Citations$_{t+5}$', the aggregate citation count five years after the patent grant. The indicator variable 'Any licensing announcement' takes unit value if the patent was announced as available for license, regardless of the licensing status. The variable 'Availability announcement' reflects whether the patent was announced as available for licensing but not exclusively licensed. The indicator 'Exclusive licensing announcement' is constructed from the exclusive licensing announcement information and takes unit value if the patent was exclusively licensed and zero else. The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. Patent controls include dummy variables for patents that include scientific references, foreign patent references, US patent references, a figure in the patent document, a new keyword combination, an EPO patent in their family, or a non-EPO patent in their family. Moreover, control variables are added that account for the number of claims, the number of patents in the family, and the inventor team size. Standard errors clustered at the main IPC section times class level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

Table 4.D5: Licensing announcement and follow-on innovation of NASA inventions – 5% truncation

	(1)	(2)	(3)	(4)	(5)	(6)
	Citations$_{t+5}$					
Any licensing announcement	0.828**	0.711*				
	(0.362)	(0.372)				
Availability announcement			-0.258	-0.308		
			(0.319)	(0.412)		
Exclusive licensing announcement			1.344***	1.374***	1.602***	1.814***
			(0.503)	(0.457)	(0.561)	(0.493)
Constant	4.134***	1.082	4.134***	1.200	3.875***	0.328
	(0.262)	(1.890)	(0.262)	(1.926)	(0.225)	(2.826)
Test for coefficient difference – Availability vs. Exclusive licensing announcement						
p-value	-	-	0.006	0.000	-	-
Patent controls	No	Yes	No	Yes	No	Yes
Patent technology fixed effects	No	Yes	No	Yes	No	Yes
NASA technology fixed effects	No	Yes	No	Yes	No	Yes
NASA research center fixed effects	No	Yes	No	Yes	No	Yes
Application year fixed effects	No	Yes	No	Yes	No	Yes
Grant year fixed effects	No	Yes	No	Yes	No	Yes
R-squared	0.005	0.325	0.020	0.337	0.020	0.446
Observations	1344	1344	1344	1344	665	665

Note: The table shows the results of linear fixed effects estimations of equation (4.1) for the inverse probability weighted sample of patents. The primary outcome variable is 'Citations$_{t+5}$', the aggregate citation count five years after the patent grant. The indicator variable 'Any licensing announcement' takes unit value if the patent was announced as available for license, regardless of the licensing status. The variable 'Availability announcement' reflects whether the patent was announced as available for licensing but not exclusively licensed. The indicator 'Exclusive licensing announcement' is constructed from the exclusive licensing announcement information and takes unit value if the patent was exclusively licensed and zero else. The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. Patent controls include dummy variables for patents that include scientific references, foreign patent references, US patent references, a figure in the patent document, a new keyword combination, an EPO patent in their family, or a non-EPO patent in their family. Moreover, control variables are added that account for the number of claims, the number of patents in the family, and the inventor team size. Standard errors clustered at the main IPC section times class level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

Table 4.D6: Licensing announcement and follow-on innovation of NASA inventions – inverse hyperbolic sine transformation

	(1)	(2)	(3)	(4)	(5)	(6)
	Citations$_{t+5}$					
Any licensing announcement	0.228***	0.160*				
	(0.086)	(0.088)				
Availability announcement			-0.081	-0.096		
			(0.064)	(0.081)		
Exclusive licensing announcement			0.372***	0.326***	0.453***	0.431***
			(0.116)	(0.114)	(0.123)	(0.110)
Constant	1.652***	0.504*	1.652***	0.539*	1.571***	0.095
	(0.067)	(0.297)	(0.067)	(0.304)	(0.051)	(0.432)
Test for coefficient difference – Availability vs. Exclusive licensing announcement						
p-value	-	-	0.000	0.000	-	-
Patent controls	No	Yes	No	Yes	No	Yes
Patent technology fixed effects	No	Yes	No	Yes	No	Yes
NASA technology fixed effects	No	Yes	No	Yes	No	Yes
NASA research center fixed effects	No	Yes	No	Yes	No	Yes
Application year fixed effects	No	Yes	No	Yes	No	Yes
Grant year fixed effects	No	Yes	No	Yes	No	Yes
R-squared	0.008	0.324	0.031	0.339	0.034	0.428
Observations	1379	1379	1379	1379	689	689

Note: The table shows the results of linear fixed effects estimations of equation (4.1) for the inverse probability weighted sample of patents. The primary outcome variable is 'Citations$_{t+5}$', the aggregate citation count five years after the patent grant. The indicator variable 'Any licensing announcement' takes unit value if the patent was announced as available for license, regardless of the licensing status. The variable 'Availability announcement' reflects whether the patent was announced as available for licensing but not exclusively licensed. The indicator 'Exclusive licensing announcement' is constructed from the exclusive licensing announcement information and takes unit value if the patent was exclusively licensed and zero else. The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. Patent controls include dummy variables for patents that include scientific references, foreign patent references, US patent references, a figure in the patent document, a new keyword combination, an EPO patent in their family, or a non-EPO patent in their family. Moreover, control variables are added that account for the number of claims, the number of patents in the family, and the inventor team size. Standard errors clustered at the main IPC section times class level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

Table 4.D7: Licensing announcement and follow-on innovation of NASA inventions – fixed effects poison estimations

	(1)	(2)	(3)	(4)	(5)	(6)
	Citations$_{t+5}$					
Any licensing announcement	0.201	0.124				
	(0.123)	(0.102)				
Availability announcement			-0.115	-0.150		
			(0.086)	(0.111)		
Exclusive licensing announcement			0.320**	0.268**	0.435***	0.472***
			(0.152)	(0.120)	(0.153)	(0.103)
Constant	1.636***	0.671	1.636***	0.675	1.521***	-0.024
	(0.087)	(0.547)	(0.087)	(0.583)	(0.081)	(0.769)
Test for coefficient difference – Availability vs. Exclusive licensing announcement						
p-value	-	-	0.005	0.000	-	-
Patent controls	No	Yes	No	Yes	No	Yes
Patent technology fixed effects	No	Yes	No	Yes	No	Yes
NASA technology fixed effects	No	Yes	No	Yes	No	Yes
NASA research center fixed effects	No	Yes	No	Yes	No	Yes
Application year fixed effects	No	Yes	No	Yes	No	Yes
Grant year fixed effects	No	Yes	No	Yes	No	Yes
Pseudo R-squared	0.004	0.325	0.018	0.334	0.019	0.430
Observations	1379	1379	1379	1379	689	689

Note: The table shows the results of linear fixed effects estimations of equation (4.1) for the inverse probability weighted sample of patents. The primary outcome variable is 'Citations$_{t+5}$', the aggregate citation count five years after the patent grant. The indicator variable 'Any licensing announcement' takes unit value if the patent was announced as available for license, regardless of the licensing status. The variable 'Availability announcement' reflects whether the patent was announced as available for licensing but not exclusively licensed. The indicator 'Exclusive licensing announcement' is constructed from the exclusive licensing announcement information and takes unit value if the patent was exclusively licensed and zero else. The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. Patent controls include dummy variables for patents that include scientific references, foreign patent references, US patent references, a figure in the patent document, a new keyword combination, an EPO patent in their family, or a non-EPO patent in their family. Moreover, control variables are added that account for the number of claims, the number of patents in the family, and the inventor team size. Standard errors clustered at the main IPC section times class level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

Table 4.D8: Licensing announcement and follow-on innovation of NASA inventions – pre AIPA

	(1)	(2)	(3)	(4)	(5)	(6)
	Citations$_{t+5}$					
Any licensing announcement	0.338	0.759				
	(1.172)	(1.013)				
Availability announcement			-2.085***	-1.546**		
			(0.708)	(0.630)		
Exclusive licensing announcement			1.604	2.255*	3.688**	4.643***
			(1.656)	(1.320)	(1.454)	(0.943)
Constant	6.982***	1.184	6.982***	2.669	4.898***	-0.277
	(0.811)	(5.156)	(0.812)	(5.018)	(0.407)	(5.959)
Test for coefficient difference – Availability vs. Exclusive licensing announcement						
p-value	-	-	0.015	0.000	-	-
Patent controls	No	Yes	No	Yes	No	Yes
Patent technology fixed effects	No	Yes	No	Yes	No	Yes
NASA technology fixed effects	No	Yes	No	Yes	No	Yes
NASA research center fixed effects	No	Yes	No	Yes	No	Yes
Application year fixed effects	No	Yes	No	Yes	No	Yes
Grant year fixed effects	No	Yes	No	Yes	No	Yes
R-squared	0.000	0.392	0.033	0.416	0.045	0.555
Observations	472	472	472	472	270	270

Note: The table shows the results of linear fixed effects estimations of equation (4.1) for the inverse probability weighted sample of patents. The primary outcome variable is 'Citations$_{t+5}$', the aggregate citation count five years after the patent grant. The indicator variable 'Any licensing announcement' takes unit value if the patent was announced as available for license, regardless of the licensing status. The variable 'Availability announcement' reflects whether the patent was announced as available for licensing but not exclusively licensed. The indicator 'Exclusive licensing announcement' is constructed from the exclusive licensing announcement information and takes unit value if the patent was exclusively licensed and zero else. The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. Patent controls include dummy variables for patents that include scientific references, foreign patent references, US patent references, a figure in the patent document, a new keyword combination, an EPO patent in their family, or a non-EPO patent in their family. Moreover, control variables are added that account for the number of claims, the number of patents in the family, and the inventor team size. Standard errors clustered at the main IPC section times class level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

Table 4.D9: Licensing announcement and follow-on innovation of NASA inventions – post AIPA

	(1)	(2)	(3)	(4)	(5)	(6)
	Citations$_{t+5}$					
Any licensing announcement	0.588	0.281				
	(0.535)	(0.527)				
Availability announcement			-0.095	-0.293		
			(0.501)	(0.604)		
Exclusive licensing announcement			0.897	0.770	0.992*	1.531***
			(0.642)	(0.539)	(0.581)	(0.476)
Constant	3.811***	1.448	3.811***	1.551	3.716***	-2.138
	(0.353)	(2.294)	(0.353)	(2.342)	(0.298)	(3.502)
Test for coefficient difference – Availability vs. Exclusive licensing announcement						
p-value	-	-	0.093	0.002	-	-
Patent controls	No	Yes	No	Yes	No	Yes
Patent technology fixed effects	No	Yes	No	Yes	No	Yes
NASA technology fixed effects	No	Yes	No	Yes	No	Yes
NASA research center fixed effects	No	Yes	No	Yes	No	Yes
Application year fixed effects	No	Yes	No	Yes	No	Yes
Grant year fixed effects	No	Yes	No	Yes	No	Yes
R-squared	0.003	0.303	0.008	0.307	0.008	0.469
Observations	876	876	876	876	401	401

Note: The table shows the results of linear fixed effects estimations of equation (4.1) for the inverse probability weighted sample of patents. The primary outcome variable is 'Citations$_{t+5}$', the aggregate citation count five years after the patent grant. The indicator variable 'Any licensing announcement' takes unit value if the patent was announced as available for license, regardless of the licensing status. The variable 'Availability announcement' reflects whether the patent was announced as available for licensing but not exclusively licensed. The indicator 'Exclusive licensing announcement' is constructed from the exclusive licensing announcement information and takes unit value if the patent was exclusively licensed and zero else. The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. Patent controls include dummy variables for patents that include scientific references, foreign patent references, US patent references, a figure in the patent document, a new keyword combination, an EPO patent in their family, or a non-EPO patent in their family. Moreover, control variables are added that account for the number of claims, the number of patents in the family, and the inventor team size. Standard errors clustered at the main IPC section times class level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

Table 4.D10: Licensing announcement and follow-on innovation of NASA inventions – licensed once

	(1)	(2)	(3)	(4)	(5)	(6)
	Citations$_{t+5}$					
Any licensing announcement	0.374	0.062				
	(0.505)	(0.361)				
Availability announcement			-0.598	-0.914*		
			(0.376)	(0.488)		
Exclusive licensing announcement			0.991	1.017*	1.589*	2.221***
			(0.806)	(0.535)	(0.897)	(0.737)
Constant	4.787***	-0.614	4.787***	-0.606	4.189***	-3.394
	(0.366)	(2.373)	(0.366)	(2.438)	(0.259)	(3.812)
Test for coefficient difference – Availability vs. Exclusive licensing announcement						
p-value	-	-	0.081	0.010	-	-
Patent controls	No	Yes	No	Yes	No	Yes
Patent technology fixed effects	No	Yes	No	Yes	No	Yes
NASA technology fixed effects	No	Yes	No	Yes	No	Yes
NASA research center fixed effects	No	Yes	No	Yes	No	Yes
Application year fixed effects	No	Yes	No	Yes	No	Yes
Grant year fixed effects	No	Yes	No	Yes	No	Yes
R-squared	0.001	0.312	0.012	0.323	0.016	0.446
Observations	1379	1317	1317	1317	627	627

Note: The table shows the results of linear fixed effects estimations of equation (4.1) for the inverse probability weighted sample of patents. The primary outcome variable is 'Citations$_{t+5}$', the aggregate citation count five years after the patent grant. The indicator variable 'Any licensing announcement' takes unit value if the patent was announced as available for license, regardless of the licensing status. The variable 'Availability announcement' reflects whether the patent was announced as available for licensing but not exclusively licensed. The indicator 'Exclusive licensing announcement' is constructed from the exclusive licensing announcement information and takes unit value if the patent was exclusively licensed and zero else. The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. Patent controls include dummy variables for patents that include scientific references, foreign patent references, US patent references, a figure in the patent document, a new keyword combination, an EPO patent in their family, or a non-EPO patent in their family. Moreover, control variables are added that account for the number of claims, the number of patents in the family, and the inventor team size. Standard errors clustered at the main IPC section times class level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

Table 4.D11: Licensing timing and follow-on innovation NASA inventions – licensed once

	(1)	(2)	(3)	(4)	(5)	(6)
	Citations$_{t+5}$					
	Full sample		Exclusivity announcement		Availability announcement	
			Before grant	After grant	Before grant	After grant
Exclusive licensed						
Availability announcement before grant	2.301**		-0.455	5.040**		
	(0.980)		(0.743)	(1.988)		
Availability announcement after grant	2.940**		-0.127	6.494***		
	(1.358)		(1.063)	(1.960)		
Exclusivity announcement before grant		0.068			-0.548	2.241
		(0.716)			(0.765)	(1.343)
Exclusivity announcement after grant		4.357***			4.417*	5.735***
		(1.157)			(2.255)	(1.778)
Constant	-1.295	-0.146	1.054	2.708*	-0.527	2.200
	(3.234)	(2.476)	(1.857)	(1.602)	(2.479)	(1.725)
Test for coefficient differences (p-values)						
Announcement before grant vs. after grant	0.746	0.000	0.756	0.595	0.019	0.056
Patent controls	Yes	Yes	Yes	Yes	Yes	Yes
Patent technology fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
NASA technology fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
NASA research center fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Application year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Grant year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.440	0.380	0.330	0.389	0.360	0.343
Observations	593	587	555	518	565	508

Note: The table shows the results of linear fixed effects estimations of equation (4.1) for the inverse probability weighted sample of patents. The primary outcome variable in columns (1) and (2) is 'Citations$_{t+5}$', which is the aggregate citation count five years after the patent grant. The variable 'Available for licensing' reflects whether the patent was announced as available for licensing but not exclusively licensed. The indicator 'Exclusive licensed' is constructed from the exclusive licensing announcement information and takes unit value if the patent was exclusively licensed and zero else. The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. Patent controls include dummy variables for patents that include scientific references, foreign patent references, US patent references, a figure in the patent document, a new keyword combination, an EPO patent in their family, or a non-EPO patent in their family. Moreover, control variables are added that account for the number of claims, the number of patents in the family, and the inventor team size. Standard errors clustered at the main IPC section times class level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

Table 4.D12: Licensing timing and follow-on innovation NASA inventions – longer post-grant period

	(1)	(2)	(3)	(4)	(5)	(6)
	Citations$_{t+5}$					
	Full sample		Exclusivity announcement		Availability announcement	
			Before grant	After grant	Before grant	After grant
Exclusive licensed						
Availability announcement before grant	2.296***		0.435	3.533**		
	(0.769)		(0.999)	(1.666)		
Availability announcement after grant	2.720**		0.179	5.119***		
	(1.277)		(1.397)	(1.632)		
Exclusivity announcement before grant		1.036			0.544	1.394
		(0.802)			(0.891)	(1.084)
Exclusivity announcement after grant		3.753***			3.333*	5.096***
		(1.066)			(1.702)	(1.481)
Constant	-2.166	-0.130	1.555	1.085	-1.245	1.518
	(3.519)	(2.904)	(1.852)	(2.081)	(3.100)	(1.665)
Test for coefficient differences (p-values)						
Announcement before grant vs. after grant	0.804	0.044	0.809	0.519	0.136	0.013
Patent controls	Yes	Yes	Yes	Yes	Yes	Yes
Patent technology fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
NASA technology fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
NASA research center fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Application year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Grant year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.461	0.415	0.383	0.385	0.394	0.344
Observations	648	611	561	530	578	513

Note: The table shows the results of linear fixed effects estimations of equation (4.1) for the inverse probability weighted sample of patents. The primary outcome variable in columns (1) and (2) is 'Citations$_{t+5}$', which is the aggregate citation count five years after the patent grant. The variable 'Available for licensing' reflects whether the patent was announced as available for licensing but not exclusively licensed. The indicator 'Exclusive licensed' is constructed from the exclusive licensing announcement information and takes unit value if the patent was exclusively licensed and zero else. The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. Patent controls include dummy variables for patents that include scientific references, foreign patent references, US patent references, a figure in the patent document, a new keyword combination, an EPO patent in their family, or a non-EPO patent in their family. Moreover, control variables are added that account for the number of claims, the number of patents in the family, and the inventor team size. Standard errors clustered at the main IPC section times class level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

Table 4.D13: Change in follow-on innovation pattern of NASA inventions – longer post-grant period

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔCitations$_{t=1,t=7}$		ΔCitations$_{t=1,t=6}$		ΔCitations$_{t-2,t+2}$	
Exclusive licensing announcement	2.204***		1.910***		1.614**	
	(0.707)		(0.605)		(0.623)	
Exclusivity announcement before grant		1.179		1.122		0.949
		(0.830)		(0.777)		(0.749)
Exclusivity announcement after grant		4.329***		3.545***		2.993***
		(1.094)		(0.952)		(0.955)
Constant	-1.731	-0.839	-0.910	-0.224	-0.925	-0.345
	(3.616)	(3.535)	(3.384)	(3.322)	(2.472)	(2.470)
Test for coefficient differences (p-values)						
Announcement before grant vs. after grant		0.015		0.052		0.073
Patent controls	Yes	Yes	Yes	Yes	Yes	Yes
Patent technology fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
NASA technology fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
NASA research center fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Application year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Grant year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.422	0.433	0.408	0.417	0.404	0.413
Observations	611	611	611	611	611	611

Note: The table shows the results of linear fixed effects estimations of equation (4.1) for the inverse probability weighted sample of patents. The primary outcome variable in columns (1) to (6) is 'ΔCitations$_{t=l,t=u}$', which is the difference of the aggregate citation count between year u and l after the patent grant. The variable 'Available for licensing' reflects whether the patent was announced as available for licensing but not exclusively licensed. The indicator 'Exclusive licensed' is constructed from the exclusive licensing announcement information and takes unit value if the patent was exclusively licensed and zero else. The regressions include control variables described in Section 4.3 and a set of fixed effects related to the NASA technology subject category, NASA research center, patent IPC section, and application year cohort. Patent controls include dummy variables for patents that include scientific references, foreign patent references, US patent references, a figure in the patent document, a new keyword combination, an EPO patent in their family, or a non-EPO patent in their family. Moreover, control variables are added that account for the number of claims, the number of patents in the family, and the inventor team size. Standard errors clustered at the main IPC section times class level are shown in parentheses. Significance: *, **, *** significant at the 10%, 5%, 1% level.

Declaration of Authorship

Eidesstattliche Versicherung

Ich, Frau Anja Rösner, versichere an Eides statt, dass die vorliegende Dissertation von mir selbstständig und ohne unzulässige fremde Hilfe unter Beachtung der „Grundsätze zur Sicherung guter wissenschaftlicher Praxis an der Heinrich-Heine-Universität Düsseldorf“ erstellt worden ist.

25. August 2023

Anja Rösner