

# **Market Power, Productivity, and the Firm: Three Essays in Industrial Organization**

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# Coauthors and Publications

### **Chapter 1:**

#### **Rising Markups, Common Ownership, and Technological Capacities**

*Coauthor:* Jan Philip Schain (Monopolies Commission)

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### **Chapter 2:**

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#### **The Impact of Profit Taxation on Prices, Product Quality, Investment, and Productivity**

*Coauthors:* Andreas Lichter (TU Dortmund), Joel Stiebale (Heinrich Heine University)

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# Introduction

Rising market power, first documented in the seminal study by De Loecker et al. (2020), has raised concerns about its potential origins, causes, and consequences. The global increase of concentration has coincided with other secular trends, such as *slowbalisation* (The Economist, 2019) and a slowdown in productivity growth (Duval et al., 2020), leaving many questions unanswered. In this cumulative dissertation, I study possible contributing factors with a focus on Europe, particularly Germany: common ownership, the 2008 financial crisis, and corporate profit taxes. I apply methods from empirical industrial organisation and causal inference, while relying on insights from several other strands of academic work in other related fields, such as international trade and public finance. Together, these studies aim to address different angles of how firm behaviour and product market outcomes respond to changes in market structures, demand disruptions, and tax policy.

The *first* chapter, coauthored with Jan Philip Schain, investigates common ownership as a potential driver of rising market power. Networks of overlapping ownership of institutional investors have expanded globally, leading to increased ownership concentration within markets. Although many of these investors are termed as passive, both theory and empirical evidence suggest that they exert influence (Appel et al., 2016; McCahery et al., 2016). When competitors share at least one institutional investor, the strategic environment changes as firms internalise rivals’ profits (Azar, 2012). This may lead to anti-competitive effects of common ownership (Azar et al., 2018). Proposed mechanisms include weakened performance-based managerial incentives (Antón et al., 2023) and direct interventions, such as a call for increased profits and reduced quantities with U.S. shale-oil-and-gas producers.<sup>1</sup> At the same time, common ownership can foster innovation if technological spillovers are sufficiently strong, since firms internalise competitors’ research and development (R&D) efforts and the associated profit increases, thereby increasing the marginal benefit of investment in R&D (López and Vives, 2019). Taken together, these opposing forces highlight how common ownership can simultaneously strengthen and reshape market power.

Our paper provides the first large-scale evidence on the effects of common ownership on markups and citation-weighted patents across a broad sample of European manufacturing firms. We estimate firm-level price-cost markups following De Loecker and Warzynski (2012) and analyse the first occurrence of common ownership in a product market in a difference-in-difference setting. Firms active in markets without common ownership during the observation period serve as the control group. To address selection on observables, we apply propensity score reweighting using pre-treatment variables at the firm, market, and industry levels.

We find that common ownership raises average markups. Positive effects on innovation become apparent only once we account for heterogeneity across industries. A further contribution of our study is to identify where these effects are most pronounced. We explore technological

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<sup>1</sup>(<https://www.wsj.com/articles/wall-streets-fracking-frenzy-runs-dry-as-profits-fail-to-materialize-1512577420>, last accessed: 03.03.2021. For an extensive collection of anecdotal evidence, see Shekita (2022).

spillovers, measured by firms' technological proximity based on the similarity of their patent portfolios across technology fields (Bloom et al., 2013), as a key dimension of variation. In high-spillover industries, the average effect on markups reaches up to 6 percent. In the same industries, the entry of a common owner also promotes innovation, increasing citation-weighted patents by up to 13 percent. The results align with the theoretical predictions of López and Vives (2019).

In addition, we investigate a dimension that has received little attention in the literature: firms without a common owner that compete in the same product market as firms with shared institutional investors. We find that in industries with high spillovers, markups rise for all firms. However, innovation increases only among firms that are commonly owned, while it decreases for firms indirectly exposed to common ownership within a market. This pattern also aligns with the framework of López and Vives (2019), where spillovers weaken innovation incentives in the absence of profit internalisation through common ownership. These results highlight that the influence of common ownership extends beyond directly affected firms across entire markets.

Beyond the common ownership literature, this paper also contributes to the broader discussion of rising market power. First, we document rising markups across European manufacturing firms, complementing evidence previously focused mainly on the United States. Second, we show that common ownership may be a driver contributing to these increases in markups, linking concentration in institutional ownership to the evolution of market power.

From a policy perspective, the results imply that in industries with low spillovers, higher markups associated with common ownership may lead to anti-competitive effects. Without gains in innovation, these effects may be meaningful for the whole industry. Moreover, mergers between institutional investors do not only raise direct antitrust concerns but may also unintentionally strengthen shareholder concentration.

So far, the first chapter has established common ownership as one contributing element in rising market power across European manufacturing. Nonetheless, market power is determined by many forces. In particular, large economic shocks or changes in corporate taxation can shift firms' long-run competitive behaviour and cost structures. Motivated by this broader perspective, I move beyond ownership networks and concentrate on the 2008 financial crisis and changes in local business taxes. The following two chapters focus on the German manufacturing sector, where highly granular administrative data allow a closer examination of firm behaviour and production decisions. Germany provides an ideal setting, given its economic size and export orientation, to complement the broader European evidence on market power and firm performance with product-level analysis.

The *second* chapter is single-authored and studies the 2008 financial crisis as a large-scale economic shock. Alongside the global rise in market power (De Loecker et al., 2020), the years after the financial crisis marked the beginning of the slowdown of globalisation, or *slowbalisation*

(The Economist, 2019), and the productivity slowdown (Duval et al., 2020). The driving factors remain not fully identified. Characterised by a contraction of GDP and a much sharper decline in global trade, the financial crisis represented a significant economic disruption. By studying its impact on German firms’ behaviour and product-market outcomes, I characterise firms that did not contribute to the rise of market power, but find evidence for role of the crisis in the productivity slowdown.

In this chapter, I aim to shed light on how this large-scale shock materialised in product market outcomes and firm behaviour. A detailed administrative dataset covering the whole German manufacturing sector allows me to study firm responses at the micro level by providing granular production information. I estimate markups and marginal costs at the firm-product level using the procedure described by De Loecker et al. (2016). To capture exposure to the financial crisis, I construct a product-category-level variable based on the respective decline in exports (Aghion et al., 2021). Product categories that suffer large export drops are considered treated, while control products are those that experience smaller changes in exports and are produced by firms that do not carry treated products. Using a difference-in-differences specification, I estimate year-specific effects on the outcome variables. These include markups, prices, marginal costs, and quantities at the firm-product level, as well as total factor productivity, employment, and wages at the firm level.

The first main finding of this chapter is that markups decline for firm-products most exposed to the financial crisis, as measured by the export shock. I further examine the two components of price-cost markups and document that prices remain essentially unchanged, while marginal costs rise significantly. Both the negative effect on markups and the positive impact on marginal costs are highly persistent and reach their respective maximum of -18 percent and 22 percent five years after the crisis in 2013.

In search of potential channels of the rise in marginal costs, I investigate three drivers: changes in output in the presence of economies of scale, total factor productivity, and input costs. First, I observe a substantial drop in production quantities. Although this finding aligns with global output contraction, I do not find evidence of more pronounced effects in industries with larger scale economies. Second, I uncover a persistent negative impact on total factor productivity. The effect remains significantly lower across all observed post-crisis periods. A decrease in total factor productivity is generally consistent with higher costs. Third, my analysis shows that average wages decrease slightly, ruling out wage increases as a driver of marginal costs. Information on the cost of intermediate inputs or capital is unavailable. However, empirical evidence shows that the latter increased sharply during the crisis and may have been an important driving factor

Moreover, I examine different margins of heterogeneous responses. In addition to products directly exposed to the export shocks described above, I estimate the effect of the large export declines on other products in the treated firms’ portfolios. I find evidence of within-firm

spillovers: markups decline, and marginal costs rise similarly for these indirectly treated products, suggesting the presence of economies of scope. Lastly, I examine the role of production networks and show that the observed effects are more pronounced for products that intensively use intermediate inputs and for those that are heavily used as intermediates.

To my knowledge, this study is the first to apply the approach of De Loecker et al. (2016) to estimate granular firm-product markups and marginal costs for Germany. The rich administrative data allow me to analyse micro-level adjustments and disentangle the effects of the financial crisis on markups and marginal costs, revealing several of its effects. In the final chapter, I use the same dataset and introduce another dimension of firms' margins of adjustment to external changes, in particular corporate taxes: product quality.

The *third* chapter is joint work with Andreas Lichter and Joel Stiebale and examines the effect of corporate profit taxation on product market outcomes. Recent and ongoing global corporate tax cuts raise an important question: do such reductions benefit only firms by boosting their after-tax profits, or do they genuinely encourage economic growth? In particular, we ask whether these tax changes are passed on to consumers through higher prices or are instead reflected in lower product quality and prices.

We study firms' responses to tax changes at the product level, extending the focus beyond widely researched firm-level outcomes such as wages (Fuest et al., 2018), investment (Chodorow-Reich et al., 2024), and innovation (Akcigit et al., 2022; Lichter et al., 2024). Using the same administrative data covering Germany's entire manufacturing sector as in chapter two, we observe prices and output and estimate product quality as in Khandelwal et al. (2013). Our identification strategy exploits tax variation stemming from more than 28,000 changes in local business tax rates set by municipalities and their geographically varying interactions with 14 federal tax reforms. Specifically, we estimate an event study with staggered implementation to capture how taxation influences firm-product outcomes.

Standard tax pass-through would imply that firms shift the tax burden to consumers through higher prices in response to tax hikes. Instead, we document a price decrease of 0.32 percent after a one percent increase in the statutory total tax rate. Further analysis reveals no change in produced quantities, but a decline in product quality: following a one percent rise in the statutory tax rate, product quality decreases by 0.41 percent. We attribute this pattern to reductions in employment and investment using firm-level event studies on the same dataset. These findings are consistent with existing empirical evidence (Cornelissen et al., 2022; Chodorow-Reich et al., 2024; Lichter et al., 2024).

We provide additional evidence that the effect on quality is symmetric. A one percent decrease in the tax rate increases product quality, with an estimated elasticity of 0.51. This result adds a novel perspective to the literature by highlighting potential consumer gains from corporate tax cuts through improvements in product quality, an aspect that has received little attention so far.

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## Chapter 1

# Rising Markups, Common Ownership, and Technological Capacities

## 1.1 Introduction

The recently observed pattern of a long term rise in market power accompanied by increasing industry concentration (De Loecker et al., 2020; Autor et al., 2020; Syverson, 2019) has sparked interest and worries in the economic consequences and causes of this phenomenon. Simultaneously, the rapidly increasing prevalence of diversified institutional investors has changed industry concentration by creating ownership links between competing companies (Azar et al., 2018). Common ownership, defined as indirect corporate networks of at least two competing firms held by overlapping sets of institutional investors, is potentially one reason that we observe rising markups across many industries and countries.

Institutional investors held on average around 40% of Western European countries' GDP in assets under management in 2018 (OECD, 2019), with common ownership emerging from a concentration of few but large investors within the same industry<sup>1</sup>. Investors owning larger shares of an industry are in a position to exert a certain degree of influence on directly competing companies. Economists (for example Azar et al., 2018) argue that in settings of common ownership, firms might no longer take strategic decisions independently. Aligned shareholder value maximisation incentives of firms provide room for possible anti-competitive behaviour regarding prices or innovation. Particular cases of interventions by common owners have gained attention from the media<sup>2</sup>. Apart from direct interventions, a reduction in performance-based managerial incentives by common owners constitutes a possible mechanism leading to anti-competitive outcomes (Antón et al., 2023).

Overlapping ownership structures affect the competitive landscape of firms in several dimensions. Early theoretical articles, (such as Reynolds and Snapp, 1986; Bresnahan and Salop, 1986; Salop and O'Brien, 2000) extend the classical concentration measure Herfindahl-Hirschman Index (HHI) to a modified Herfindahl-Hirschman Index (MHHI), taking into account ownership links at the industry level, and conclude that common ownership exerts an upward pressure on prices through rivals' profit internalisation and may facilitate collusion (Gilo et al., 2006; Shelegia and Spiegel, 2012). Firms compete less aggressively, as the negative effect on competing firms' profit is partly taken into account through the common owners. Bayona et al. (2022) show that even monopoly profits can be replicated allowing for endogenous common ownership links. A relatively new theoretical paper (López and Vives, 2019) calls this the cartelisation effect of common ownership. In addition to these anti-competitive results, the authors find that common ownership can also have a beneficial effect. Depending on technological spillovers in a given in-

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<sup>1</sup>Considerable volumes of common ownership can be found in publicly listed companies, for instance in the airline, banking, or pharmacy sector in the USA (Azar et al., 2018), as well as in the chemical sector and car industry in Germany (Seldeslachts et al., 2017).

<sup>2</sup>E.g. the discussions of shareholders with U.S. shale-oil-and-gas producers with the intention of generating larger profits and reducing quantities (<https://www.wsj.com/articles/wall-streets-fracking-frenzy-runs-dry-as-profits-fail-to-materialize-1512577420>, last accessed: 03.03.2021.). For a comprehensive overview, see Shekita (2022).

dustry, common ownership can spur innovation by increasing the marginal benefit of investment in research and development (R&D). They conclude that in markets with high technological spillovers, firms internalise the *spilled over* decrease in competitors’ marginal costs caused by their own innovation through common ownership. Thus, this increases the marginal benefit of innovation which leads to higher innovation levels and possibly lower prices, also described by Shelegia and Spiegel (2024). On the contrary, Gutiérrez and Philippon (2017) show empirically that higher concentration and higher levels of common ownership tend to characterise industries with less investment in capital and R&D (i.e. industries with lower technological capacities). Also adding to the ambiguity, others find no significant effects or challenge the methodologies used for identification of anti-competitive effects (O’Brien and Waehrer, 2017; Rock and Rubinfeld, 2018; Patel, 2018; Lambert and Sykuta, 2019; Koch et al., 2021 and Lewellen and Lowry, 2021)<sup>3</sup>. More empirical research on the effects of common ownership is required, as the theoretical predictions on competition are ambiguous.

This article investigates the relationship of common ownership, markups, and innovation on a broad European manufacturing sample of large firms, as categorised by the European Commission, between 2005 and 2016. Using data from Bureau van Dijk’s Amadeus database and accounting for input endogeneity following Akerberg et al. (2015), we estimate industry-specific production functions and calculate markups as in De Loecker and Warzynski (2012). Innovation activity by firms is measured by patents weighted with forward citations. Furthermore, we use the detailed ownership information available in Amadeus to construct the MHHI as used in other empirical studies (for example Azar et al., 2018), which we exploit as a measure of treatment intensity. We use a measure of technology spillovers by Bloom et al. (2013) at the three-digit NACE industry level as well as an industry classification of technological capacities by the European Commission (2019) to investigate in more detail how the effect of common ownership on markups and innovation varies along these dimensions, and to contribute to the further disambiguation of the effects of common ownership.

We use a propensity score reweighting estimator to control for biases due to observational characteristics. We define a binary treatment indicator taking the value one in markets in which at least one additional investment by an institutional investor creates common ownership links between competitors for the first time. This constitutes the first occurrence of common ownership in a given market. Control firms operate in markets that never experience common ownership. Commonly used approaches of exploiting institutional mergers (e.g. He and Huang, 2017; Azar et al., 2018) and stock index inclusion of firms and rivals (e.g. Kennedy et al., 2017; Boller and Scott Morton, 2020) are less appropriate here, as we observe only a small number

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<sup>3</sup>Discussions by Kennedy et al. (2017) and Dennis et al. (2022), specifically targeted at the empirical strategy by Azar et al. (2018), have been refuted in Azar et al. (2021) and Azar et al. (2022b). The latter shows that original estimates were in fact biased towards zero and that even higher anti-competitive price effects can be found. Elhauge (2020) provides further insights in how addressing these methodological critiques may actually reveal larger anti-competitive effects.

of firms listed in a stock index relative to the whole sample.

We find a positive effect of common ownership on firm markups that is significantly increasing with technological spillovers and ranges up to 6% in high spillover industries. The positive effect of common ownership on markups becomes stronger with increasing treatment intensity, relying on percentiles of the distribution of MHHI delta. Splitting the sample into four groups of increasing technological capacities (low, medium-low, medium-high, and high technology) according to the European Commission (2019), we find pronounced effects on markups in low-tech and high-tech industries.

Considering the impact on innovation activity, the emergence of common ownership has in fact a positive and statistically significant effect on citation-weighted patents in high spillover markets for inside firms, which are firms directly held by common investors. For these firms, the effect is increasing in spillovers and reaches up to 13% in high-spillover industries. By splitting up the sample with respect to technological capacities as defined by the European Commission (2019), we confirm the finding of a positive effect on inside firms that is increasing with technological capacities. For outside firms competing in the same market with commonly owned firms, we find only insignificant results for innovation activity. Both findings for markups and innovation activity are consistent with theoretical findings in López and Vives (2019). Our results are robust with respect to the measure of common ownership, regression and production function specifications, as well as a one-to-one propensity score matching approach combined with a difference-in-differences setup.

Although there are some empirical industry-specific studies that analyse anti-competitive effects of common ownership on prices<sup>4</sup> in the airline and banking industry (Azar et al., 2018, 2022a), there is less work on a wider firm panel containing multiple industries. Backus et al. (2021) perform a calibration exercise on firms in the S&P500 index with initial markup estimates taken from De Loecker and Eeckhout (2021). In our analysis we abstract from general equilibrium effects as in Azar and Vives (2021a,b); Ederer and Pellegrino (2025). Kini et al. (2024) investigate the effect of common ownership on product differentiation of US listed companies. They also analyse firm markups and investment as outcome variables and find no average effect on markups, but a positive effect in industries characterised by high technological spillovers. For investments, they find an average positive effect that is more pronounced in high-spillover industries. The results on investments are consistent with our findings on innovation, but our results differ in terms of markups. Antón et al. (2025) find positive correlations of common ownership in US firms with innovation activities and R&D expenditures, which are amplified differently in settings of either technological or product market spillovers. Kostovetsky and Manconi (2020) show increased intensity of patent citations among firms owned by overlapping

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<sup>4</sup>Apart from prices, markups, and innovation, researchers have also dealt with managerial incentives (Antón et al., 2023), market entry and exit (Xie, 2020; Newham et al., 2025), and mergers and acquisitions (Antón et al., 2022) that are influenced by common ownership structures in industries. Schmalz (2021); Elhauge (2021) provide comprehensive overviews of the literature on competitive effects of common ownership.

institutional investors.

This article is substantially different from the existing literature and contributes in five main ways. First, we analyse a broad manufacturing sample in Europe that mostly consists of non-listed firms, whereas almost the entire empirical literature on common ownership is based on data sets of US listed firms and often focuses on specific industries. Second, we shed some light on the effect of common ownership on firms which are not directly commonly owned but which, in fact, compete in a market where there are common ownership links between rivals. This aspect has been largely neglected in the literature. Third, we offer a detailed analysis of industry characteristics regarding technological capacities and spillovers that drive the results of common ownership. Fourth, in direct comparison to Kini et al. (2024), this article focuses solely on citation-weighted patents as a more precise measure of innovation activity, as opposed to a wider range of investments as an outcome variable, consisting of capital expenditures, R&D expenditures, and acquisitions. This is advantageous, because innovation output is more important for welfare than innovation input, and the theoretical foundation given in López and Vives (2019) focuses on innovation spillovers only and may not be trivially extended to general investments in capital. Fifth, on a broader scale, our article also contributes to the rising market power discussion, as we find a pattern of rising markups in our sample for the top 10 percent of companies in the markup distribution.

The rest of this article proceeds as follows. Section 1.2 gives an overview of the data set and markup estimation. The identification strategy and the measure for common ownership are presented in Section 1.3. Results of the propensity reweighting estimator follow in Section 1.4 and robustness checks are reported in Section 1.5. Section 1.6 discusses the results and draws conclusions for future investigations and applications.

## **1.2 Data and Markups**

This section presents the data at hand in Subsection 1.2.1. The procedures for the estimation of the production function (according to Akerberg et al., 2015) and markups (adapted from De Loecker and Warzynski, 2012) are discussed in Subsection 1.2.2. In this context, we show how the markup distribution has developed over time.

### **1.2.1 Data Description**

#### **Manufacturing Firms' Financial Data**

The Amadeus data base by Bureau van Dijk provides a comprehensive collection of financial data and information on corporate structure of European companies, which also covers non-listed firms. Our analyses are conducted using a rich firm-level panel of the manufacturing sector (NACE two-digit codes 10 to 32) for the observation period 2005 to 2016. We rely on

the standard definition of large firms by the European Commission, restricting our sample to firms with more than 250 employees and over EUR 50 million in turnover on average, with a total of 7229 unique firms. Large firms follow better reporting standards, which leads to better data availability and quality, and institutional investors have a strong preference for large firms, as shown in the literature (Ferreira and Matos, 2008; Dahlquist and Robertsson, 2001). Compared to small and medium enterprises (SMEs), more than twice as many large firms have an institutional owner at some point in our sample, and the average firm revenue weighted by institutionally owned shares of large firms is 32 times larger than of SMEs in the data set. Small firms are likely to be non-strategic price-takers (Deneckere and Kovenock, 1992), which are targeted less by institutional investors. Assuming monitoring costs by institutional investors, we would expect common ownership to be a more important factor in large firms, as in larger firms the benefit of being active outweighs monitoring costs.

Markets are defined using the Statistical Classification of Economic Activities in the European Community (NACE) at the three-digit level in the product dimension and for geographical differentiation at the country level, such that each NACE three-digit and country combination in the European manufacturing sector defines a separate market. Each firm is assigned its main three-digit industry in the dataset Amadeus by Bureau van Dijk, such that a firm occurs only once per time period and not in several markets. The market definition implies that for example, a German company assigned to a specific German three-digit industry<sup>5</sup> neither competes with firms in another three-digit industry in Germany nor with firms in the same or other three-digit industries in another country. Our raw sample incorporates 35 European countries and 1398 markets, i.e. NACE three-digit code and country combinations, over the complete sample period. Not all three-digit codes are prevalent in each country, and on average, there are 1217 markets per year and around 8 firms per market per year.

Common ownership arises when any institutional investor holds any equity share in two or more companies within the same market. We assume proportionate control, where the percentages held in equity are proportional to control rights, as there is no distinction between ownership and control shares in the data<sup>6</sup>. In order to acknowledge holding structures, different subsidiaries of some of the largest investors are manually aggregated under the parent investor name. Ownership stakes are consolidated at the corporation level as far as possible, relying on names, the Amadeus data base and other external information. This is justified by the finding that votes are cast on a mutual fund family level and not singularly for individual

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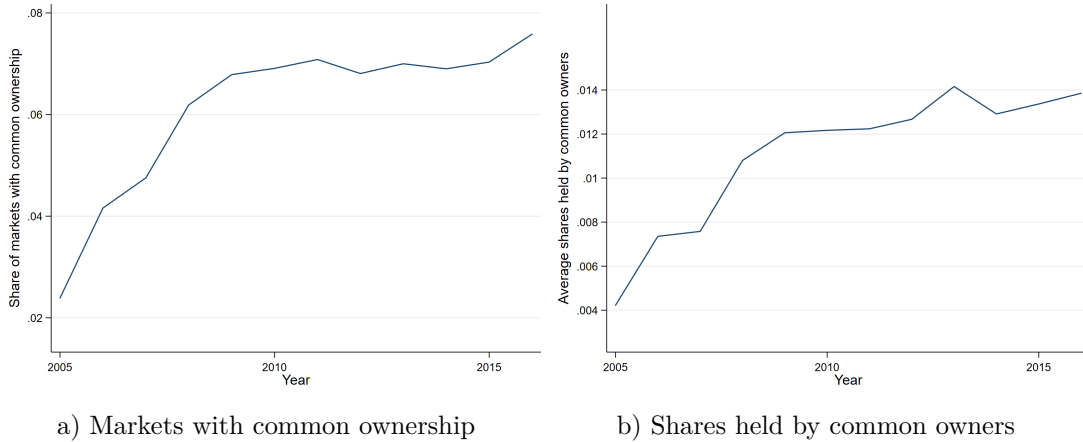
<sup>5</sup>One example for a NACE three-digit code: 106 “*Manufacture of grain mill products, starches and starch products: This group includes the milling of flour or meal from grains or vegetables, the milling, cleaning and polishing of rice, as well as the manufacture of flour mixes or doughs from these products. Also included in this group are the wet milling of corn and vegetables and the manufacture of starch and starch products*” Source: Statistical Classification of Economic Activities in the European Community (NACE Rev. 2, 2008).

<sup>6</sup>For example, in the US, around 90% of publicly listed companies issue shares with equal voting rights with a single class of stock. Council of Institutional Investors (13.02.2022). Dual-class stock. Available at [https://www.cii.org/dualclass\\_stock](https://www.cii.org/dualclass_stock).



affiliated funds (He et al., 2019). On the full sample, there are on average 2.3% firms affected by common ownership. In a market exposed to common ownership, around 27.7% of firms are directly affected by common ownership, on average. In our dataset, common ownership becomes more prevalent over time. The percentage of markets with common ownership increases from roughly 2.5% to almost 8% from 2005 to 2016 as shown in Figure 1.1a. During the same period, the average share held by common owners increases from 0.4% to 1.4%, as shown in Figure 1.1b. This rising pattern of common ownership is consistent with findings in other studies, such as Backus et al. (2021) for the S&P500 and Boot et al. (2022) for the S&P Europe 350. Figures 1.7a and 1.7b show the percentage of markets and the share of firms with common ownership per NACE two-digit industry, respectively. In the graphs, we distinguish between the industries in high, medium-high, medium-low, and low-technology classes.

Figure 1.1: Market-level and firm-level evolution of common ownership



*Note:* The figure on the left shows the percentage of affected markets, defined as NACE three-digit and country combinations. The figure on the right shows the average share held by common owners over the whole sample. We use European ownership data from the Amadeus data base by Bureau van Dijk. Common ownership in a market is defined as two competing firms being held by overlapping sets of institutional investors.

For structural estimation of production functions, it is common practice to use accounting data proxies as information on produced quantities are not widely available. The data contain sales as a variable approximating output, tangible fixed assets for capital, material expenses for physical materials, and the costs of employment for labour. All of these variables are converted to constant 2010 Euros using annual producer price indices per two-digit industry and country for the years 2005 to 2016 from Eurostat<sup>7</sup>.

Table 1.1 reports summary statistics of the main variables used in the estimation procedure for productivity and markups, as used in our main analysis in Section 1.4. These exhibit a large dispersion of values for sales and input factors, all reported in million Euros. Around 5%

<sup>7</sup>Short term statistics, code sts\_inpp\_a. Available at <https://ec.europa.eu/eurostat/web/short-term-business-statistics/data/database>, last accessed: 20.06.2019.

of large firms in our sample are publicly quoted, and 27% of observations have a positive count of patents in a given year. The average number of patent citations is around 4.

Table 1.1: Summary statistics, firm-level

|                  | Characteristics |         |       |          |
|------------------|-----------------|---------|-------|----------|
|                  | Mean            | SD      | Min   | Max      |
| Sales            | 373.84          | 1623.19 | 23.76 | 65657.08 |
| Labour           | 52.54           | 195.34  | 0.90  | 13561.66 |
| Materials        | 226.45          | 1179.97 | 2.60  | 53756.88 |
| Capital          | 80.94           | 330.14  | 0.31  | 12063.22 |
| Investment       | 13.06           | 66.31   | 0.00  | 4325.21  |
| Wages            | 45.70           | 20.07   | 5.24  | 110.58   |
| Age              | 35.47           | 33.39   | 0.00  | 731.00   |
| Public           | 0.05            | 0.21    | 0.00  | 1.00     |
| Innovating       | 0.27            | 0.44    | 0.00  | 1.00     |
| Patent Citations | 4.43            | 71.49   | 0.00  | 9938.00  |
| Unique firms     | 7229            |         |       |          |
| N                | 38566           |         |       |          |

*Note:* This table shows summary statistics of the sample at the firm-level. Financial information taken from the Amadeus data base by Bureau van Dijk. Labour denotes costs of employees, materials the material expenditures, and capital tangible fixed assets. Investment is calculated as the change of tangible fixed assets between periods plus depreciation. Wages are calculated as the ratio of costs of employment over number of employees. For some companies, information on employment is incomplete, for which then the two-digit industry-country median wage is assumed. Sales, costs of employees, material expenditures, tangible fixed assets, investment, and wages in million Euro, deflated by two-digit industry-country-year-specific producer prices. Innovating is a dummy variable that takes the value of one if the firm has more than zero patents in a specific year. Patent citations is the number of forward-citation weighted patents in a given year. Public is a dummy variable that takes the value of one if the firm is publicly listed.

## Additional Data Sources

We analyse additional heterogeneous effects, as described further below in Subsection 1.4.2. For this purpose we employ data on knowledge spillovers and technological capacities of industries. The first data source is made available by Bloom et al. (2013) comprising data on technological spillovers at the three-digit industry-level (US SIC codes) which we concord to the NACE three-digit classification in our main financial data outlined above. Bloom et al. (2013) rely on a firm’s position in technology space, which is measured by the patenting distribution across an international classification of technology fields, and serves to determine the distance of rivals in terms of technological advances. The proximity between firms is used to weight respective R&D stocks, as firms closer to one another have a higher chance to profit from each other’s R&D expenditures (Bloom et al., 2013). Their firm-level measure of technological spillovers is therefore the sum of the firm’s competitors’ R&D stock (in million USD) weighted with

the pairwise degree of overlap in technology. We use the pre-sample average of each NACE three-digit industry.

As an additional measure, we obtain a classification of technology intensity of the manufacturing industries. According to the definition by the European Commission (2019), each two-digit and some three-digit NACE code industries can be categorised by their technological capacities (see Table 1.5). The technological intensity of an industry is measured by R&D expenditures over value added (European Commission, 2020). With increasing technological intensity, industries have higher R&D expenditures, more patent applications, and a larger share of innovating firms (see Table 1.6).

### 1.2.2 Productivity and Markup Estimation

Estimation of markups relies on preceding estimation of a production function and respective output elasticities using the standard procedure proposed by Akerberg et al. (2015). We assume a logarithmic Cobb-Douglas production function to account for substitutability of inputs. The production function of firm  $j$  in year  $t$  (note that each firm only operates in one market  $p$ , their main line of business) for output  $q_{jt}$  includes the inputs capital  $k_{jt}$ , labour  $l_{jt}$ , materials  $m_{jt}$ , unobserved productivity  $\omega_{jt}$ , and a measurement error  $\epsilon_{jt}$ , such that  $q_{jt} = \beta^0 + \beta^k k_{jt} + \beta^l l_{jt} + \beta^m m_{jt} + \omega_{jt} + \epsilon_{jt}$ . The estimation consists of a two-step procedure. In the first stage, we correct for measurement error without identifying any of the input coefficients by predicting output using inverted material input demand that consists of a third order polynomial in input factors labour, capital, and materials, as well as country fixed effects. In the second step following Akerberg et al. (2015), the serial correlation of productivity is modelled as a controlled first order Markov process, in which we allow for common ownership to endogenously impact future productivity. The exogenous part of this process is used for the identification of the coefficients of the production function. We estimate output elasticities for nine subsets of the manufacturing industry. A more detailed description of the estimation procedure, information on the pooled industry subsets, and the results of the production function estimation can be found in the Appendix 1.B<sup>8</sup>.

Using the elasticity of output with respect to materials and the revenue share of material expenditures following De Loecker and Warzynski (2012), we compute markups as

$$\mu_{jt} = \frac{\beta^m}{\hat{\alpha}_{jt}^m} = \left( \frac{P_{jt}Q_{jt}}{w_{jt}^m m_{jt}} \right) \frac{\partial Q_{jt}(\cdot)}{\partial m_{jt}} \frac{m_{jt}}{Q_{jt}}, \quad (1.1)$$

where  $\mu_{jt}$  is the markup of firm  $j$  in year  $t$ . The product of output prices and quantities  $P_{jt}Q_{jt}$  is given as sales, and the product of the price and quantities of materials  $w_{jt}^m m_{jt}$  is given as

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<sup>8</sup>In a robustness check we also estimate a Translog production function. In another robustness check we control for wages in the first stage to mitigate potential endogeneity concerns resulting from unobserved price data as described in De Loecker (2021).

material expenditures in the data. The second term,  $\frac{\partial Q_{jt}(\cdot)}{\partial m_{jt}} \frac{m_{jt}}{Q_{jt}}$ , denotes the elasticity of output with respect to material inputs, obtained by the previous estimation of the production function and the respective input coefficients. An error correction is applied to deflated sales in the calculation of the revenue share of the costs of materials, such that  $\hat{\alpha}_{jt}^m = \frac{w_{jt}^m m_{jt}}{P_{jt} Q_{jt} \exp(\epsilon_{jt})}$ . Markups are calculated for each firm from the estimated material elasticities, starting in 2006<sup>9</sup>.

Figure 1.2 shows the evolution of markups weighted with labour input costs. The construction of the percentiles follows the same methodology as in De Loecker et al. (2020), in order to make the percentiles comparable to the weighted average. We see that the 90<sup>th</sup> and 95<sup>th</sup> percentiles of markups show a rising pattern<sup>10</sup>, similar to the results in De Loecker et al. (2020) for the USA, and globally in De Loecker and Eeckhout (2021). The authors also show weighted average markups specifically for Europe, which are relatively flat, similar to our results in the respective time period. However, their sample displays a sharp rise in the last periods, where our sample remains flat. Another study with similar markup patterns on a global sample is Caligaris et al. (2025). A recent working paper (Ciapanna et al., 2024) analyses markup evolution with Italian data. The manufacturing sample shows very similar dynamics as in this article. The weighted average is relatively flat and only the upper ten percent of markups show a rising pattern. Flat average markups in Europe for the periods of our sample are also reported in Cavalleri et al. (2020); De Loecker et al. (2018); Gradzewicz and Mućk (2024).

## 1.3 Empirical Strategy

This section presents the identification strategy employed to determine the effect of common ownership on markups and citation-weighted patents. The propensity score reweighting procedure following Guadalupe et al. (2012) including the construction of inverse probability weights is detailed in Subsection 1.3.1, and a discussion of reweighted regressions follows in Subsection 1.3.2.

### 1.3.1 Propensity Score Reweighting

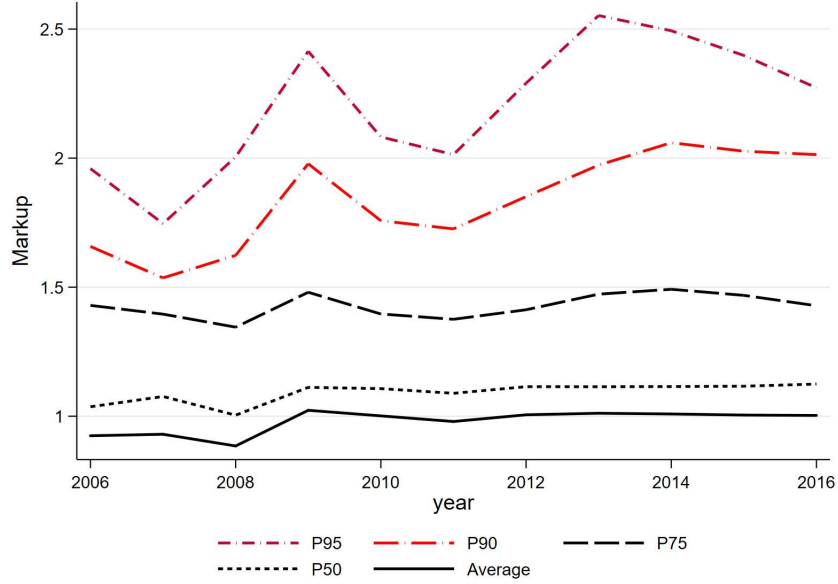
The investment strategies of asset managers are clearly not independent of the performance or profitability of their potential portfolio firms. It seems plausible that they may choose firms that have initially high markups, or that are more productive or innovative. Determinants of the investment decision at the market level are also possible: firms may invest in markets where they already hold shares in competing firms, or choose a market in which larger investments by other institutional investors signal profitability.

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<sup>9</sup>The year 2005 drops out, due to the lag specification in the estimation routine.

<sup>10</sup>Using alternative weighting variables (see Figures 1.6a and 1.6b in the Appendix) does not change markup patterns.

Figure 1.2: Evolution of markups, weighted with labour input costs



*Note:* The figure illustrates the evolution of the weighted distribution of firm markups from 2006 to 2016. Labour input costs are used as weights. Markups are estimated using European accounting data from the Amadeus data base by Bureau van Dijk and the method proposed by De Loecker and Warzynski (2012), relying on production function elasticities from the Akerberg et al. (2015) procedure. For the construction of the percentiles we follow the methodology of De Loecker et al. (2020).

We apply a propensity score reweighting approach following Guadalupe et al. (2012) using weighted panel fixed-effects regressions to account for these potential biases. The propensity score controls for selection on time-varying observed covariates, as the observables and treatment assignment are independent conditional on the propensity score under the unconfoundedness assumption (Rosenbaum and Rubin, 1983; Heckman et al., 1997)<sup>11</sup>. The aim of this method is to construct a sample with a control group that can approximate the counterfactual outcome of the treated group absent treatment by assigning weights corresponding to the inverse probability of treatment to observations (Hirano and Imbens, 2001; Hirano et al., 2003; Imbens, 2004). Fixed-effects models control for time-constant characteristics and identify the effects using only within-firm variation.

Propensity score reweighting encompasses a two-stage procedure: In a first stage, a probit model is estimated to determine the propensity towards exposure to treatment given the observed covariates. Treatment probabilities are used to assign corresponding inverse probability weights to the observations. In the second stage, weighted least squares regressions using

<sup>11</sup>There are numerous other studies relying on estimates under selection on observables that have applied propensity score procedures. Examples include firm-level studies (Alfaro and Chen, 2012; Aghion et al., 2013; Smeets and Warzynski, 2013; Bena and Li, 2014; Geurts and Van Biesebroeck, 2019; Cunningham et al., 2021), notably also regarding common ownership (He and Huang, 2017), and applications within other contexts (Heckman et al., 1997; Acemoglu et al., 2019).

the inverse probability weights are estimated to determine the average treatment effect (ATE) (Hirano and Imbens, 2001; Imbens, 2004).

In our application, firms in markets where we observe new occurrences of common ownership links are considered to be in the treatment group. For each NACE three-digit industry and country combination, we construct the common ownership measure MHHI delta to denote treated markets (i.e. there is common ownership when MHHI delta  $> 0$ )<sup>12</sup>. The MHHI delta reflects common ownership concentration in a market and is calculated as the difference between the MHHI and the classical HHI (Salop and O’Brien, 2000). For each market at a given point in time,  $MHHI = \sum_j s_j^2 + \sum_j \sum_{f \neq j} s_j s_f \frac{\sum_i \beta_{ij} \beta_{if}}{\sum_i \beta_{ij}^2}$ , where subscripts  $j$  and  $f$  denote firms and competitors,  $i$  indexes the investors, and  $\beta_{ij}$  are ownership shares assuming proportionate control, such that ownership shares equal control shares. Individual profit weights between each pair of commonly owned firms are weighted with the product of market shares  $s_j$  and  $s_f$  of the firm and respective rival. The average change in MHHI delta around treatment is 0.01 which constitutes  $\frac{1}{4}$  standard deviation of the MHHI delta distribution.

We closely follow the identification strategy employed by Guadalupe et al. (2012). In the first stage probit model, the outcome variable is one if the market experiences the first occurrence of common ownership in the following year, and zero otherwise. The following firm-level variables are included to estimate the propensity score, using only pre-treatment covariates for the treated firms: the logarithm of markups and TFP, firm age, number of patent citations, labour, capital, and output in logarithms, and the share of institutional holdings. As treatment varies at the market level (defined by three-digit-industry code and country combinations), we also include market and industry-level covariates HHI, technological spillovers and technological gap between firms. A year trend is also included, following Guadalupe et al. (2012). Observations belonging to treatment group and control group are pooled together, but two separate probit models are estimated for firms in low-tech and high-tech industries to allow for the relationship to vary across these categories. Table 1.9 shows that the majority of covariates significantly determine treatment.

Following Hirano and Imbens (2001); Guadalupe et al. (2012), we calculate the propensity score  $\hat{p}$  as the estimated treatment probability of new common ownership links in the market, conditional on having no common ownership in the period before, from the probit regressions and calculate the inverse probability weights. To obtain an estimate of the ATE in the second stage weighted regressions, treated firms are assigned weights of  $1/\hat{p}$ , and weights for the control observations are  $1/(1 - \hat{p})$ . Following Guadalupe et al. (2012), we only use observations that fulfil the common support condition and sum over the firms to generate weights for control

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<sup>12</sup>For a clearly defined treatment group, we discard markets that always show common ownership and that only contain discontinuation of previous common ownership links, and remove observations with periods of discontinuation and second emergence of common ownership in a market. We also remove NACE two-digit industries and countries that never experience common ownership. For a more detailed description, see Appendix 1.C.1. More information on the MHHI delta can be found in Appendix 1.C.2.

observations that are used multiple times. Finally, weights are winsorised at the 99<sup>th</sup> percentile to account for large outliers in the weights.

After reweighting the sample with propensity scores, treatment and control group should not differ systematically in observables. We test the balancing condition for pre-treatment variables on the full sample. Table 1.8 in the Appendix reports the difference in pre-treatment means for the treatment group and control group for the unweighted and the weighted sample after demeaning at the year level. In the unweighted sample, there are substantial differences in firm and market characteristics. Reweighting observations with their inverse treatment probability weights leads to an active correction, as this sample shows no significant difference in means. Figures 1.10, 1.11 in the Appendix plot the empirical cumulative distribution functions of the pre-treatment covariates in the unweighted and weighted sample for the treatment group and control group. In the weighted sample, the distributions of the treated firms lie very close to those of the control firms. Compared to the unweighted sample, balancing is clearly improved. Figure 1.9 shows yearly averages<sup>13</sup> of markups and patent citations in logarithms, using only pre-treatment observations for the treatment group. The yearly means for the treatment group follow a similar pattern as the control markets, not giving rise to concerns of diverging pre-treatment trends.

### 1.3.2 Regression Specification

Having obtained the propensity score weights, we estimate weighted fixed-effects regressions in the second stage to determine the effects of common ownership on the outcome variables. Our main variable of interest is the binary variable indicating the first occurrence of common ownership in a market. The main specification with firm  $j$ 's logarithm of markups in market  $p$ <sup>14</sup> and period  $t$  as the outcome variable includes year and firm-fixed effects  $\tau_t$  and  $\nu_j$ , such that

$$\ln(\mu)_{jt} = \beta_1 \mathbf{1}[\text{MHHI delta} > 0]_{pt} + \beta_2 \text{HHI}_{pt} + \beta_3 \text{Inst}_{jt} + \tau_t + \nu_j + \epsilon_{jt}. \quad (1.2)$$

$\mathbf{1}[\text{MHHI delta} > 0]_{pt}$  is the common ownership treatment indicator variable, taking the value of one for  $\text{MHHI delta}_{pt} > 0$ , i.e. a market with common ownership, and zero for a market without common ownership, where  $\text{MHHI delta}_{pt} = 0$ . Firm-fixed effects rather than market-specific or industry-specific fixed effects are included to control for unobserved heterogeneity at the firm level, which might be correlated with the variable measuring common ownership. We therefore analyse only within-firm variation. In addition to the year and firm-fixed effects, we control for the standard concentration measure  $\text{HHI}$  at the NACE three-digit-country and year-level and the variable  $\text{Inst}$  at the firm-year level, capturing institutional holdings in each firm, measured by the percentage of shares held by institutional investors. By including additional

<sup>13</sup>Both variables are demeaned at the company level before averaging at a yearly level. For the logarithm of patent citations, we additionally control for zero patent citations.

<sup>14</sup>In the data, firms are only assigned to a single market, therefore  $\ln(\mu)_{jpt} = \ln(\mu)_{jt}$  and  $\nu_{jp} = \nu_j$ .

control variables, the precision of the weighted least squares model is enhanced (Imbens, 2004). Standard errors are clustered at the market level, as the treatment indicator varies at the aggregated market level and unobserved shocks might lead to correlation of errors of firms in the same market. There are a total of 468 unique market clusters.

We incorporate an analysis of treatment intensity effects by estimating the model in several subsets of the data. We always keep all control observations, but discard treated firms with an MHHI delta below different percentiles of the distribution of non-zero MHHI delta. We first regard the full sample, and then only keep treated firms above the 5<sup>th</sup>, 10<sup>th</sup>, 15<sup>th</sup>, 20<sup>th</sup> and above the 25<sup>th</sup> percentile of MHHI delta larger than zero<sup>15</sup>. Additionally, we estimate a model on the full sample and include dummy variables for different values of MHHI delta in the regression, indicating observations below 15% of the distribution of positive MHHI delta, between 15 and 25%, and above 25%. As a robustness check, we also employ alternative firm-specific continuous measures of common ownership.

Our second outcome variable is innovation output measured by citation-weighted patents. We follow Hausman et al. (1984) by replacing zero patent citations with unity before taking the logarithm and consequently adding a dummy variable indicating zero citations in the regression. The regression specification for patent citations as the outcome variable is richer than for markups, as additional control variables  $\mathbf{X}_{jt}$  are introduced. The firm-level covariates included are the logarithm of TFP, capital intensity measured as the ratio of capital to labour, firm age, and the indicator of zero citations. As market-level control variables, we also include market size measured by average market sales, and as an additional measure for competition,  $1 - Lerner$  at the market level. For innovation output, we estimate the model

$$\ln(cites)_{jt} = \beta_1 \mathbf{1}[\text{MHHI delta} > 0]_{pt} + \beta_2 \text{HHI}_{pt} + \beta_3 \text{Inst}_{jt} + \mathbf{X}_{jt}\theta + \tau_t + \nu_j + \epsilon_{jt}. \quad (1.3)$$

We repeat the exercise using the same subsets and indicator variables as before to account for treatment intensity along different values of the distribution of non-zero MHHI delta.

## 1.4 Empirical Results

The empirical results relying on the propensity score reweighting method are reported in this section. Subsection 1.4.1 presents the results of the reweighting estimator, where we test whether upon emergence of new common ownership links in the market, firms set higher markups, and engage in more innovation activity. We show results for the full sample and varying treatment intensity as described above, and examine average direct and indirect effects of common ownership. In Subsection 1.4.2, we explore the interaction of the effect of common ownership with the level of technological spillovers in an industry, and analyse further

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<sup>15</sup>Balancing for each of the subsamples is shown in Table 1.10.



heterogeneity with respect to technological capacities of specific industries.

### 1.4.1 Treatment Intensity

#### Markups

Figure 1.3 shows the effect of the treatment indicator for new common ownership links in the market, as estimated from firm-level propensity score reweighted regressions of the logarithm of markups on the common ownership treatment dummy. Observations are assigned weights according to their treatment group status as described in Subsection 1.3.1. To examine how the effect changes with increasing treatment intensity, the different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to zero and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. In all subsets, we control for HHI at the three-digit industry-country level, share of institutional holdings, firm and year-fixed effects. By including firm-fixed effects, we account for selection based on time-invariant firm idiosyncrasies. Standard errors are clustered at the three-digit industry-country level. The positive average treatment effect is increasing in treatment intensity and becomes statistically significant when discarding the lower 15% of the distribution of positive MHHI delta. The effect size implies a 0.9 to 1.5% increase in markups after a market's first exposure to common ownership.

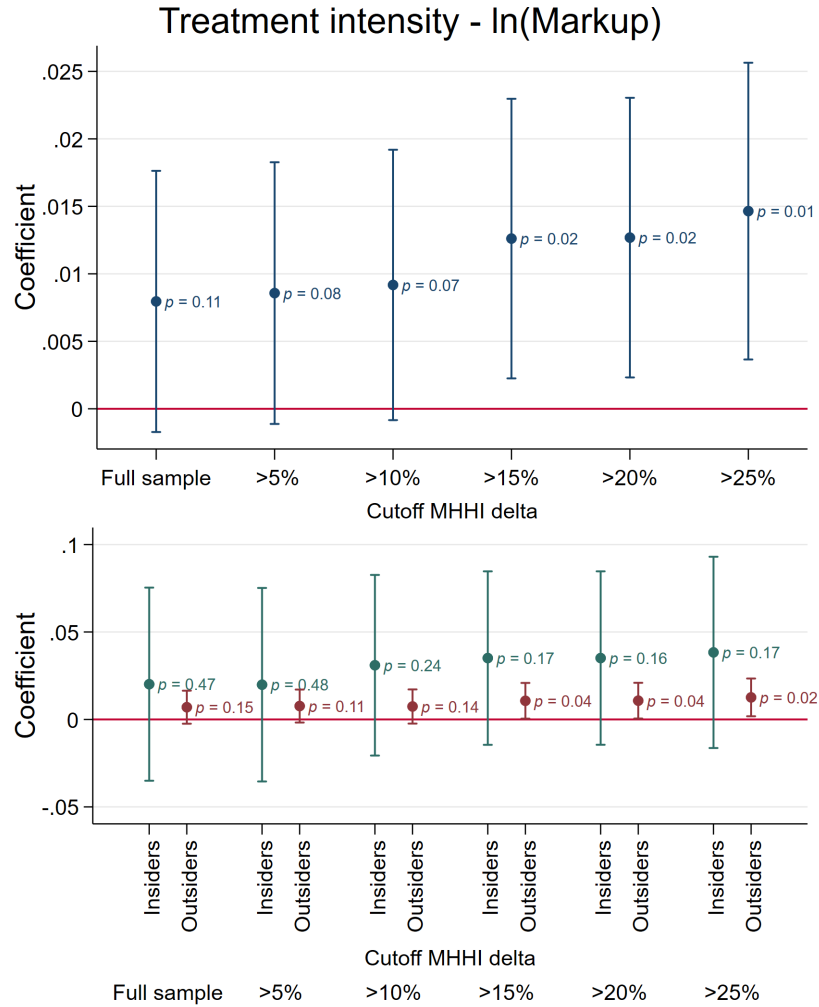
As we define treated firms as all firms operating in a market that is first exposed to common ownership, we would expect different responses of firms directly and only indirectly affected by common ownership. We define directly affected firms, or insiders, as competitors in the same market which are held by overlapping sets of institutional investors in the same period, resulting in a common ownership link between these firms. Indirectly affected firms, or outsiders, operate in the same market as these jointly held firms, but do not have any common owners and are therefore not directly linked to another rival firm<sup>16</sup>. We interact the treatment effect with two dummies indicating the insider and outsider status in the different subsamples as before, and find that the positive effect of treatment on log markups differs in strength between inside and outside firms, and also increases with treatment intensity. In all subsamples, the point estimate for inside firms is insignificant but always larger than the indirect effect for the competing firms, and ranges from 2 to 3.8%. The effect for outside firms lies between 0.7 and 1.3%. Table 1.11 and 1.12 in the Appendix show the corresponding weighted least squares regression results.

In addition to estimating the treatment effect for different percentiles of the MHHI distribution, we estimate a model on the full sample including dummy variables for MHHI delta below 15%, between 15% and 25%, and above 25% of the distribution of positive MHHI delta.

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<sup>16</sup>There is only little known about the effects of common ownership on outsiders in the literature. Papadopoulos (2022) analyses common ownership in the form of cross-ownership as minority stakes in rivals. He finds that firms that are not part of a cross-ownership scheme always benefit from their competitors that are forming cross-ownership links and shows that outsiders increase output as a response to the change in market structure.

Figure 1.3: Reweighting estimator: Markups - Treatment intensity



*Note:* The graph plots the estimated coefficients of the treatment indicator and respective confidence intervals and p-values. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, share of institutional holdings, firm and year-fixed effects and cluster standard errors at the three-digit industry-country level. The red line indicates zero.

Table 1.15 shows the result of this regression of the logarithm of markups including additional models controlling for time-heterogeneous country and three-digit NACE industry fixed effects. The average treatment effect is increasing in treatment intensity as measured by the percentile indicator variables. For a small MHHI delta below the 15<sup>th</sup> percentile the effect is negative, but

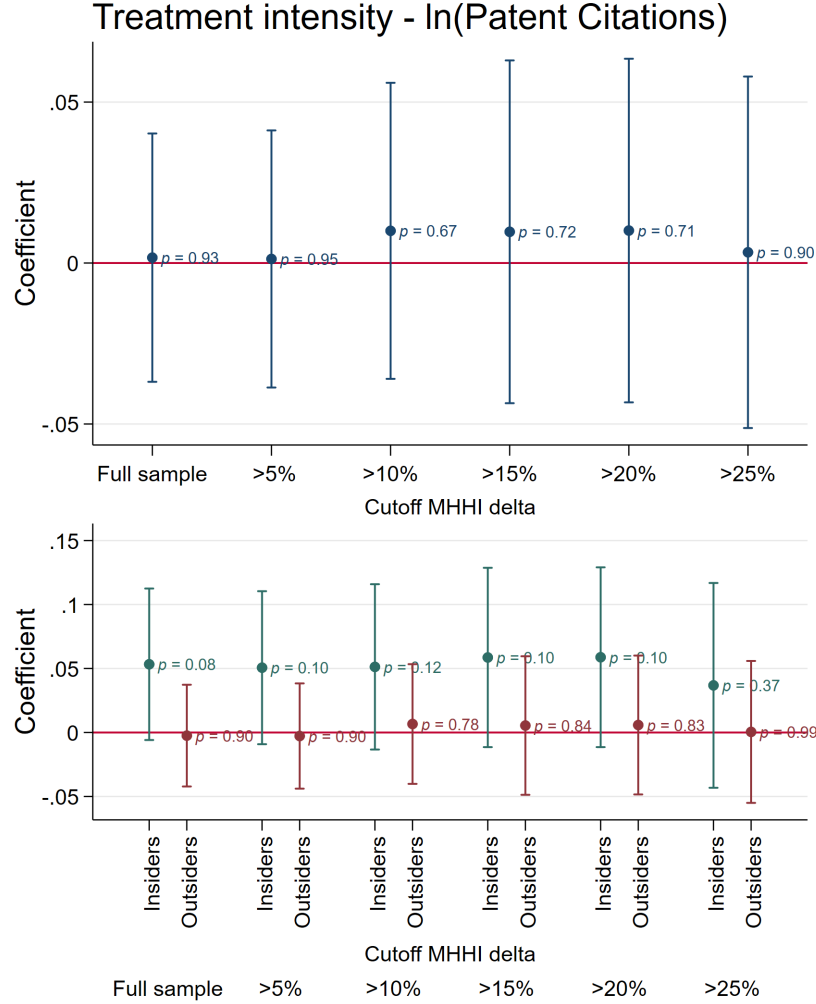
becomes statistically significant and amounts to around 1.4% increase in markups for MHHI delta above the 25<sup>th</sup> percentile.

## Innovation

We are interested in whether also the innovation output of the firms changes with common ownership. The same propensity score reweighting procedure is performed using a linear count data model with the logarithm of patent citations as the outcome variable. Propensity score weights are assigned as in Subsection 1.3.1. Pooling directly held firms and indirectly affected competitors together, the treatment effect is not statistically significant. Distinguishing between inside and outside firms in Figure 1.4 reveals that the first occurrence of common ownership only affects the innovation output of directly commonly held firms. The average treatment effect on inside firms is positive in all subsamples, and does not increase with increasing treatment intensity. The magnitude of the effect for insiders is weakly significant for the full sample and for the subsample discarding the lower 5<sup>th</sup> percentile of the MHHI. The effect for insiders lies between 5 and 5.9%. Coefficients of the outside firms are very close to zero and insignificant. The corresponding regression results are reported in Tables 1.13 and 1.14.

We also estimate a model on the full sample containing dummy variables for MHHI delta below 15%, between 15% and 25%, and above 25% of the distribution of positive MHHI delta. In Table 1.16, we show the effects on innovation output accounting for different time-heterogeneous fixed effects. Here, the largest positive and highly statistically significant average effect is found in firms with MHHI delta between the 15<sup>th</sup> and 25<sup>th</sup> percentile, implying an average increase of 8.5% percent in patent citations.

Figure 1.4: Reweighting estimator: Innovation - Treatment intensity



*Note:* The graph plots the estimated coefficients of the treatment indicator and respective confidence intervals and p-values. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, share of institutional holdings,  $\ln(\text{TFP})$ , market size measured by average sales at the market level, capital intensity, 1-Lerner index, age, and a dummy for zero citations. Zero patent citations are set to one. We also include firm and year-country-fixed effects and cluster standard errors at the three-digit industry-country level. The red line indicates zero.

### 1.4.2 Heterogeneous Effects

This section further explores the driving factors of the effects of common ownership on markups and innovation activity. Following López and Vives (2019), technological market characteristics play a major role in determining the effects of common ownership on strategic variables. First, we briefly discuss the main model by López and Vives (2019). Second, the results regarding the effects of common ownership for varying levels of technological spillovers are presented. Third, the results of splitting the sample according to different technological capacities are shown<sup>17</sup>.

#### Theoretical Background

A recent article by López and Vives (2019) presents an integrated theoretical framework to analyse competitive effects of common ownership. Their main model is a symmetric Cournot oligopoly with a symmetric overlapping ownership structure. Firms have two strategic variables: output and marginal cost-reducing R&D spending. Innovation of a given firm spills over to a certain degree to other firms operating in the same market. The authors characterise an equilibrium under some regularity conditions and perform a comparative static exercise showing how equilibrium output and innovation activity is impacted by an increase in common ownership for varying degrees of technological spillovers.

An increase in common ownership impacts innovation through two distinct channels. Possible internalisation of R&D efforts in the presence of positive spillovers increases the incentives to innovate. The strength of this positive incentive depends on the degree of spillovers. The second mechanism is rather indirect. The cartelisation effect has a negative effect on output, which in turn leads to lower marginal incentives to innovate as now the overall gain of innovation is lower with fewer units of output. They find three different regions along the spillover dimension, characterised by low, intermediate and high spillovers. Table 1.2 summarises the predictions of their model and our interpretation of the response of markups to common ownership for each spillover region.

In the first region, categorised by low-spillover markets, common ownership has a negative effect on output, thus a positive effect on prices, and a negative or no effect on innovation. The non-positive impact on innovation in this region stems from the low spillovers that lead to relatively small internalisation effects of common ownership on innovation, such that the negative impact of the reduced output on innovation outweighs the positive effects due to internalisation. In this region, we would expect to find a positive effect on firm markups if innovation is not impacted by common ownership.

For increasing spillovers in the second region, we would expect to find an increasing effect on markups, because in the adjacent region with higher spillovers the effect of common ownership on output is still negative, and thus positive on prices, and also positive on equilibrium

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<sup>17</sup>We also explore heterogeneity with respect to different levels of HHI and investor concentration in the Appendix in Section 1.E.2.

Table 1.2: Summary of predictions by López and Vives (2019)

| Technological Spillovers | Low | Intermediate | High (may not exist) |
|--------------------------|-----|--------------|----------------------|
| Output                   | –   | –            | +                    |
| Prices                   | +   | +            | –                    |
| Cost-reducing innovation | 0/– | +            | ++                   |
| Price-over-cost markup   | 0/+ | ++           | ?                    |

*Note:* The first three rows refer to the predictions directly taken from the theoretical model by López and Vives (2019) of how common ownership affects firms’ output, prices and cost-reducing innovation activity under different degrees of technological spillovers. The last row includes our interpretation of the response of markups to common ownership in these settings.

innovation, such that marginal costs are decreasing in common ownership. Here, the spillovers are sufficiently large for the positive internalisation effects of common ownership on innovation to outweigh the reduced incentives to innovate due to lower output.

In the third region, characterised by very high spillovers, common ownership has a positive effect on output and innovation, thus the effect on markups is ambiguous. Here, the positive spillover effect on innovation is expected to be the largest, such that the increased incentives to innovate let marginal costs decrease, even resulting in increased output. However, this region is not guaranteed to exist by the assumptions of the model by López and Vives (2019).

One aspect that is not addressed in the article by López and Vives (2019) is how the effect of common ownership changes in the presence of firms that are not directly commonly owned, but that compete with commonly owned firms in the same market. The authors only consider a symmetric setup where all firms are commonly owned. Regarding price changes of insiders and outsiders due to the cartelisation effect, neglecting innovation, one would expect the effects to go in the same direction. However, the impact of common ownership on the innovation activity of outside firms in this context is unclear. To the best of our knowledge, there is no theoretical or empirical work that analyses this aspect in terms of common ownership specifically. There are also only relatively few articles in the literature on mergers and acquisitions that focus on rivals’ responses to mergers in terms of innovation activity. Theoretical predictions for rivals are ambiguous in this regard (Haucap et al., 2019). Federico et al. (2018) show merger effects on innovation incentives and on consumer surplus where non-merging firms increase innovation effort, but this increase does not compensate for reduction of the innovation effort by merging firms. Motta and Tarantino (2021) show that in case of mergers without or weak synergy gains insiders decrease and outsiders increase innovation effort. While insiders increase prices, outsiders may increase or decrease prices.

## Technological Spillovers

This section now turns to the empirical evidence on how the effects of common ownership on markups and innovation vary with different degrees of technological spillovers. We interact the treatment variable with a three-digit industry-level, pre-sample measure of technological spillovers by Bloom et al. (2013) and perform sample splits. Figures 1.5a and 1.5b display the treatment effect along the spillover dimension on markups and innovation, respectively<sup>18</sup>. Each graph contains, from top to bottom, effects for insiders and outsiders combined, for insiders only, and effects for outsiders only. The shaded area in each graph shows a 95% confidence interval. For markups, we see that the effect of common ownership is increasing in the degree of spillovers for insiders and outsiders. The effect only becomes statistically significant for all treated firms combined and for outsiders. The combined effect reaches up to roughly 6% in high-spillover industries. A one standard deviation increase in spillovers increases the effect of common ownership on markups by 1.4 percentage points. For example, the treatment effect at the 75<sup>th</sup> percentile of the spillover distribution is highly significant and 1.9%. An increase of one standard deviation in spillovers increases the effect to 3.3%. The effect for insiders, although insignificant, is larger and reaches a magnitude of up to 12% in high-spillover industries. For innovation, we find an increasing effect in the degree of spillovers for firms that are directly commonly owned, which is statistically significant for medium-high and high-spillover industries. For insiders a one standard deviation increase in spillovers increases the effect of common ownership on patent citations by 2 percentage points. The effect for outsiders is decreasing in spillovers, such that it is positive for lower levels of spillovers and becomes negative for high spillovers.

We also perform sample splits with respect to spillovers in columns 2 to 5 of Tables 1.17 and 1.18 for markups and innovation, respectively. Columns 2 in both tables show the effects for the lower 25% of the spillover distribution. Columns 3 and 4 show the effects for observations below and above the median value of technological spillovers. Columns 5 in both tables show the effects for the upper 25% of the spillover distribution. The results of the sample splits are consistent with the interaction results shown in Figures 1.5a and 1.5b. In the sample splits, we see that the effect on markups is increasing with the levels of spillovers and reaches up to 3.3% for observations above the 75<sup>th</sup> percentile of the spillover distribution. For the innovation activity of inside firms, we also see an increase of the effects with the degree of spillovers, where observations above the 75<sup>th</sup> percentile experience an increase of 9.6% in patent citations.

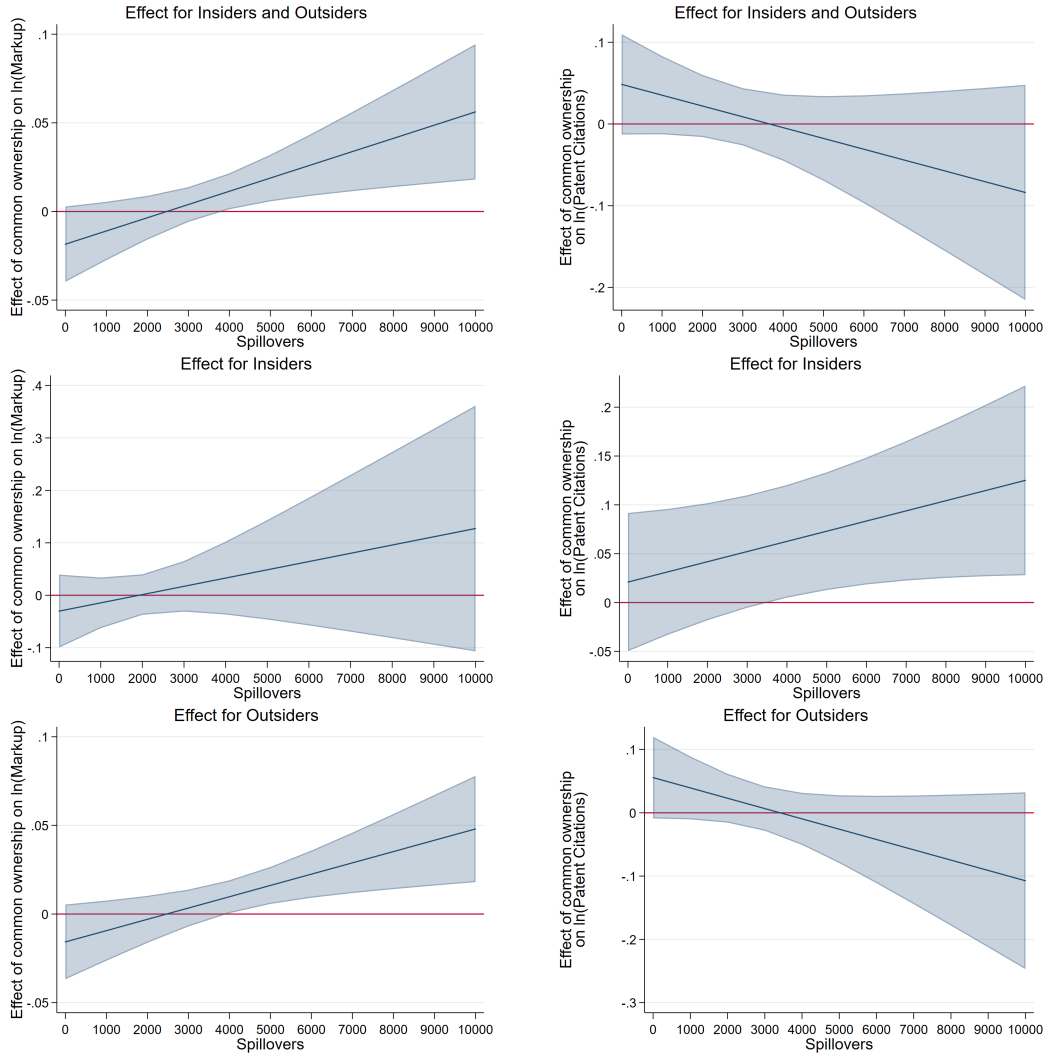
## Technological Capacities

As shown in López and Vives (2019), the effects of common ownership highly depend on the industry structure the companies are operating in. This implies the necessity of developing reliable readily available heuristics regarding industry classifications for policy and decision-makers

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<sup>18</sup>The treatment effect from the first columns in Tables 1.17 and 1.18 is plotted for markups and innovation, respectively. The first columns in both tables interact the treatment effect with spillovers.

Figure 1.5: Reweighting estimator: Spillover interaction effect



a) Markups - Spillover interaction effect

b) Innovation - Spillover interaction effect

*Note:* Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, share of institutional holdings, firm and year-fixed effects and cluster standard errors at the three-digit industry-country level. Additionally for patent citations we control for  $\ln(\text{TFP})$ , market size measured by average sales at the market level, capital intensity, 1-Lerner index, age, and a dummy for zero citations. Zero patent citations are set to one. The red line indicates zero. The blue shaded area is a 95% CI.

to assess the impact of common ownership, similar to what has been done for mergers and acquisitions (European Commission, 2004). This section exploits an industry classification by the European Commission based on technological capabilities to further explore the heterogeneity



of the effect of common ownership on markups and innovation. This classification could be used as first guidance to policy and decision-makers as to which effects of common ownership are likely to matter in the industry under consideration.

We apply the classification of NACE two-digit and some three-digit industries by means of technological capacities by the European Commission (2019), as described in Subsection 1.2.1, to our data. We estimate the treatment effect separately for each technological class. The results for markups and patent citations are presented in Tables 1.3 and 1.4, respectively. In both tables, columns 1 to 4 show the results in ascending order from low-technology to high-technology industries. Following our results regarding spillovers and considering theoretical predictions by López and Vives (2019), we would expect to find a positive effect on markups and innovation in high-tech industries and a positive effect for markups in low-tech industries. This is exactly what we find, as the medium-high-tech and high-tech models in columns 3 and 4 in Table 1.4 show the largest and statistically significant results on patent citations for firms directly commonly owned. Here, treatment increases patent citations for insiders by 16.6% and 20.2%, respectively. For markups, we find the largest effect in high-tech industries in column 4 of Table 1.3, where treatment increases markups by 2.2%. We also find a significant effect of 2.1% in low-tech industries in column 1. We would only expect to find a positive effect in these low-tech-low-spillover industries if innovation is not an important strategic variable. As shown in Table 1.5, low-technology industries include manufacturing of food, beverages, tobacco, different kinds of textile industries, wood and paper, furniture and other manufacturing industries, which are arguably industries where innovation does not play a major role. High-technology industries comprise the pharmaceutical industry, computer and optical products, and the air and spacecraft industry. For innovation, we also find a positive effect in the medium-high-tech industries consisting of chemicals, weapons, electrical equipment, machinery, motor vehicles and other transport equipment, and medical instruments and supplies.

The empirical results investigating heterogeneous effects with respect to technological spillovers are consistent with predictions derived from the model by López and Vives (2019) regarding the implications for markups and innovation. The effect of common ownership on markups in Figure 1.5a is increasing in the degree of spillovers. For directly commonly owned firms, the positive effect of common ownership on citation-weighted patents in Figure 1.5b is also increasing in spillovers. By contrast, the results using technological capacities as a proxy for technological spillovers diverge from theory for markups. A positive effect of similar size can only be found for firms in low-tech and high-tech industries, while the effects in both intermediate categories are statistically insignificant and small. For innovation, splitting the sample according to technological capacities, the effects are again consistent with the findings using the measure of technological spillovers.

Table 1.3: Reweighting estimator: Markups - Technology classes split

| Dep. Variable:         | ln(Markup)          |                     |                   |                    |
|------------------------|---------------------|---------------------|-------------------|--------------------|
|                        | (1)                 | (2)                 | (3)               | (4)                |
| Technology             | Low                 | Medium-Low          | Medium-High       | High               |
| $1_{(MHHI\delta > 0)}$ | 0.021**<br>(0.009)  | 0.004<br>(0.011)    | -0.006<br>(0.009) | 0.022**<br>(0.009) |
| HHI                    | 0.069<br>(0.066)    | 0.041<br>(0.047)    | 0.041<br>(0.039)  | -0.030<br>(0.052)  |
| Inst. Holdings         | -0.036**<br>(0.016) | 0.046***<br>(0.017) | 0.006<br>(0.023)  | -0.027<br>(0.047)  |
| Firm FE                | Yes                 | Yes                 | Yes               | Yes                |
| Year FE                | Yes                 | Yes                 | Yes               | Yes                |
| Adj. $R^2$             | 0.98                | 0.92                | 0.95              | 0.94               |
| N                      | 3654                | 4975                | 5117              | 1664               |
| Market clusters        | 120                 | 138                 | 158               | 52                 |

*Note:* Standard errors in parentheses and clustered at the three-digit industry-country level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

Table 1.4: Reweighting estimator: Innovation - Technology classes split

| Dep. Variable:                                | ln(Patent Citations) |                    |                    |                     |
|-----------------------------------------------|----------------------|--------------------|--------------------|---------------------|
|                                               | (1)                  | (2)                | (3)                | (4)                 |
| Technology                                    | Low                  | Medium-Low         | Medium-High        | High                |
| $1_{(MHHI\delta > 0)} \times \text{Insider}$  | 0.000<br>(0.021)     | -0.010<br>(0.056)  | 0.166**<br>(0.073) | 0.202***<br>(0.069) |
| $1_{(MHHI\delta > 0)} \times \text{Outsider}$ | -0.013<br>(0.015)    | -0.004<br>(0.027)  | 0.038<br>(0.053)   | -0.016<br>(0.060)   |
| HHI                                           | -0.050<br>(0.069)    | -0.123<br>(0.136)  | 0.053<br>(0.149)   | -0.425*<br>(0.218)  |
| Inst. Holdings                                | -0.031<br>(0.041)    | 0.316**<br>(0.145) | 0.018<br>(0.068)   | -0.065<br>(0.142)   |
| Firm FE                                       | Yes                  | Yes                | Yes                | Yes                 |
| Year FE                                       | Yes                  | Yes                | Yes                | Yes                 |
| Adj. $R^2$                                    | 0.59                 | 0.77               | 0.79               | 0.87                |
| N                                             | 3654                 | 4975               | 5117               | 1664                |
| Market clusters                               | 120                  | 138                | 158                | 52                  |

*Note:* Standard errors in parentheses and clustered at the three-digit industry-country level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level,  $\ln(\text{TFP})$ , market size measured by average sales at the market level, capital intensity, 1-Lerner index, and age, share of institutional holdings, a dummy for zero citations, firm and year-fixed effects. Zero patent citations are set to one. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

## 1.5 Robustness Checks

This section reports the results of a variety of robustness checks with regard to the common ownership measure in Subsection 1.5.1 and different regression and production function specifications in Subsection 1.5.2. In Subsection 1.5.3 we further investigate industry balance, and apply propensity score matching combined with a difference-in-differences estimator. Neither robustness check changes our conclusion regarding the effect of common ownership on markups and innovation.

### 1.5.1 Firm-level Common Ownership

Our main specification uses a binary treatment indicator for common ownership. Even though we show treatment intensity by leveraging different percentiles of the MHHI delta distribution and we differentiate between insiders and outsiders, the measure estimates an average effect for affected firms. One might be concerned how robust the findings are with respect to other measures for common ownership. To mitigate this issue, we use two different continuous firm-level measures of common ownership on the weighted sample as a robustness check.

First, we follow Azar et al. (2018) and use a firm-level average of the weights placed on competitors' profits, reflecting the degree of rival profit internalisation. Their *carrier-route common ownership variable* (CRCO) is calculated for each combination of airline carrier and route. As each firm is only assigned to one market in our data, the corresponding measure is defined at the firm level and termed *firm common ownership* (FCO)<sup>19</sup>. This measure represents by how much a given firm internalises its competitors' profits. For each firm  $j$  in year  $t$ , using the profit weights relative to all firms  $f \neq j$ , the market-share weighted average FCO can be specified as

$$FCO_{jt} = \sum_{f \neq j} \frac{\sum_i \beta_{ij} \beta_{if}}{\sum_i \beta_{ij}^2} \frac{s_{ft}}{1 - s_{jt}}.$$

We replicate the main results using this firm-level measure for markups in Table 1.19 and Figure 1.14a, and for innovation in Table 1.20 and Figure 1.14b.

Second, we use the aggregate holdings of common owners at the firm level. This measure has the advantage that it does not include any market shares. It is known that common ownership measures that utilise market shares suffer from endogeneity (Azar et al., 2018). The results of this robustness check for markups are reported in Table 1.21 and Figure 1.15a, and for innovation in Table 1.22 and Figure 1.15b.

All models for both measures of common ownership include the respective firm-specific measure of common ownership for directly impacted firms (insiders), and a dummy variable for indirectly affected firms (outsiders). The results seem to be sensitive to the measure of common ownership. Using the firm-level profit weights, the effect for insiders on markups

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<sup>19</sup>Figure 1.8 shows the sample average of this measure over time.

is driven in low-spillover industries, while the effect for outsiders is driven in high-spillover industries. The effects on patent citations are of equal size in low and high-spillover industries, but weakly significant in low-spillover industries and non-significant in high-spillover industries. The results using the firm-level measure of commonly held shares are similar to the main findings. For markups, the effects of insiders and outsiders seem to be concentrated in high-spillover industries. Furthermore, the effect on patent citations of inside firms is roughly twice as large in high-spillover industries.

### 1.5.2 Regression and Production Function Specification

Using a propensity score reweighting estimator as before, we additionally control for changes in marginal costs when regressing markups on the binary treatment indicator. We add a polynomial function of TFP as regressors to reflect changes in marginal costs. The results of this exercise are reported in Figures 1.16a and 1.16b. Furthermore, as our sample consists of many different countries that are subject to different governmental policy shocks, we include country-specific time-fixed effects in the markup and patent citation models. We also include broad two-digit industry-time-fixed effects to absorb industry-specific cost shocks. Figures 1.17a, 1.17b display the results for markups, and Figures 1.18a, 1.18b show the results for citation-weighted patents of these specifications.

Furthermore, we present results for markups under different assumptions of the production function estimation. First, we use a translog specification which produces more variation in markups. Figure 1.19a shows the treatment effect in this setup for different degrees of treatment intensity. Figure 1.19b shows how the treatment effect on markups varies with spillovers in the translog specification. Second, as a further robustness check on the production function specification, we follow De Loecker and Scott (2016) by including the logarithm of wages in the first stage of predicting output in response to the critique by Gandhi et al. (2020), who illustrate identification problems of gross output production functions. Results are reported in Figure 1.20a and Figure 1.20b.

The results are robust with respect to controlling for TFP and including country-time and industry-time-fixed effects in the regression specifications as well as different assumptions of the production function estimation.

### 1.5.3 Further Robustness Checks

While the propensity score does take into account industry characteristics, such as HHI, technology dispersion and technology ranking, and probit regressions are estimated separately for low and high-technological capacity industries, the question remains if the industries in the treatment and control group are balanced. To address this question we proceed as follows. First, Figure 1.21 shows the distributions of two-digit NACE industries for treatment and control group in the weighted sample. Visual inspection suggests that the distributions do not

differ much. Second, we perform a balancing test for each two-digit NACE industry. The result of this exercise is presented in Table 1.23, showing that all but three industries are balanced. In order to ensure that this does not influence our results, we drop these three industries and show that the main results remain unchanged. The results for markups are shown in Figures 1.22a and 1.22b and the results for innovation are shown in Figures 1.23a and 1.23b.

As a further robustness check on our identification strategy, we combine a propensity score matching approach with a difference-in-differences design. As before, firms in markets where we observe entry of common ownership are considered to be in the treatment group. We assign treated and control observations based on a one-to-one matching, and only use firms on common support. After matching, we use difference-in-differences estimation to determine the average treatment effect on the treated of common ownership on markups and innovation output<sup>20</sup>. Table 1.24 shows the results of the difference-in-differences estimator on the matched sample. Columns 1 and 2 show results with markups and columns 3 and 4 results with patent citations as the outcome variables. Tables 1.25 and 1.26 show how the effect varies with technological spillovers for markups and innovation, respectively. The conclusion regarding the effect of common ownership on markups and innovation remains unchanged.

## 1.6 Conclusion

This article analyses the relationship between common ownership and markups and innovation using a broad European manufacturing sample. We use balance sheet variables to estimate firm-level productivity, recover markups, and construct a measure of common ownership using comprehensive firm ownership information. As an additional outcome variable, citation-weighted patents measure the innovation output of firms. A propensity reweighting estimator corrects for observational biases. We define treatment as the first exposure of a market to common ownership and explore detailed heterogeneous treatment effects in various ways.

We find a positive effect of common ownership on markups that is increasing in technological spillovers. Using an industry classification by the European Commission (2019), we distinguish between effects in industries characterised by different technological capabilities. We find positive effects of common ownership on markups for high-tech industries that consist of highly innovative and high-spillover industries. We also find a positive effect for low-tech industries which are characterised by little innovation activity and low technological spillovers. Our findings also help to shed light on the ambiguous effects of common ownership on markups and innovation. Whereas a large part of the literature has focused on anti-competitive implications, our results contribute to a further disambiguation of the influence of common ownership structures. We find that common ownership increases innovation output measured as patent citations in high-spillover industries for firms directly commonly owned. Our results are ro-

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<sup>20</sup>For a more detailed description of the estimation see Section 1.E.3

bust with respect to the measure of common ownership, production function and regression specifications and the identification strategy.

This article shows that common ownership has a positive impact on average markups in Europe. However, the evolution of the markup distribution suggests a rising pattern for the top 10 percent of the companies. Our findings have direct policy implications for competition authorities. First, common ownership may have economically meaningful anti-competitive effects for the entire industry. In particular, in low-tech industries with low technological spillovers, where there is no positive effect on innovation by common ownership, decision makers should be concerned about a rise in markups. We provide evidence that in high-tech industries, common ownership can also lead to more innovation activity together with an increase in markups. Second, when competition authorities are confronted with mergers between institutional investors, portfolio firms of the parties have to be carefully analysed, as the merger could lead to more common ownership, which could then lead to the described effects. In the future, regulations on the degree of common ownership may be required to tackle these issues. Further empirical research is needed on the net effects of common ownership. This article delivers reduced form evidence that industry structure, prices, and innovation output play a major role for assessing competitive effects of common ownership. A full structural model taking into account multiple strategic variables, such as prices and innovation could be promising for future research, in order to help to disentangle the multiple effects of common ownership and to develop guidelines on how to approach this issue.

## 1.A Technology Classification

According to the definition of the European Commission, NACE two-digit and three-digit industries are grouped into the following technology classes as can be seen in Table 1.5.

Table 1.5: Technology classification

| NACE 2 digit                  | NACE 3 digit       | Description                                                   |
|-------------------------------|--------------------|---------------------------------------------------------------|
| <i>High-technology</i>        |                    |                                                               |
| 21                            |                    | Basic pharmaceutical products and pharmaceutical preparations |
| 26                            |                    | Computer, electronic and optical products                     |
|                               | 30.3               | Air and spacecraft and related machinery                      |
| <i>Medium-high-technology</i> |                    |                                                               |
| 20                            |                    | Chemicals and chemical products                               |
|                               | 25.4               | Weapons and ammunition                                        |
| 27                            |                    | Electrical equipment                                          |
| 28                            |                    | Machinery and equipment not elsewhere classified              |
| 29                            |                    | Motor vehicles, trailers and semi-trailers                    |
| 30                            | (excl. 30.1, 30.3) | Other transport equipment                                     |
|                               | 32.5               | Medical and dental instruments and supplies                   |
| <i>Medium-low-technology</i>  |                    |                                                               |
| 19                            |                    | Coke and refined petroleum products                           |
| 22                            |                    | Rubber and plastic products                                   |
| 23                            |                    | Other non-metallic mineral products                           |
| 24                            |                    | Basic metals                                                  |
| 25                            | (excl. 25.4)       | Fabricated metal products, except machinery and equipment     |
|                               | 30.1               | Building of ships and boats                                   |
| <i>Low-technology</i>         |                    |                                                               |
| 10                            |                    | Food products                                                 |
| 11                            |                    | Beverages                                                     |
| 12                            |                    | Tobacco products                                              |
| 13                            |                    | Textiles                                                      |
| 14                            |                    | Wearing apparel                                               |
| 15                            |                    | Leather and related products                                  |
| 16                            |                    | Wood and products of wood and cork                            |
| 17                            |                    | Paper and paper products                                      |
| 31                            |                    | Furniture                                                     |
| 32                            | (excl. 32.5)       | Other manufacturing                                           |

Table 1.6: Technology classification characteristics

|                  | Patents          | Patents<br>before 2005 | Percent inno-<br>vating firms | Capital<br>investment  | Technological<br>spillovers |
|------------------|------------------|------------------------|-------------------------------|------------------------|-----------------------------|
| High-tech        | 13.7***<br>(0.6) | 7.4***<br>(0.4)        | 41.0***<br>(0.7)              | 18364.9***<br>(1055.7) | 6014.7***<br>(25.1)         |
| Medium-high-tech | 6.4***<br>(0.3)  | 3.1***<br>(0.2)        | 35.0***<br>(0.4)              | 13246.7***<br>(539.2)  | 4148.1***<br>(12.8)         |
| Medium-low-tech  | 2.1***<br>(0.4)  | 1.6***<br>(0.3)        | 24.2***<br>(0.4)              | 13645.6***<br>(665.2)  | 3231.9***<br>(15.8)         |
| Low-tech         | 0.8**<br>(0.4)   | 0.6**<br>(0.3)         | 11.7***<br>(0.4)              | 9993.5***<br>(676.5)   | 2037.7***<br>(16.3)         |
| Observations     | 38566            | 38566                  | 38566                         | 38566                  | 37842                       |

*Note:* This table shows sample averages of characteristics indicative for technology classification. Patents, patents before 2005, a dummy for innovation activity, and capital investment (in thousand Euros) are measured at the firm level, and technological spillovers at the two-digit industry-level according to calculations by Bloom et al. (2013). Standard errors in parentheses. \* p<0.10, \*\* p<0.05, \*\*\* p<0.01



## 1.B Production Function Estimation Appendix

Estimation of markups relies on preceding estimation of total factor productivity (TFP) using the procedure proposed by Akerberg et al. (2015). A Cobb-Douglas technology accounts for substitutability of inputs and a logarithmic specification of this production function is chosen for the estimation of output elasticities. The production function of firm  $j$  in market  $p$  (note that each firm only operates in one market  $p(j)$ , their main line of business) and year  $t$  for output  $q_{jt}$  is designed with the inputs capital  $k_{jt}$ , labour  $l_{jt}$ , materials  $m_{jt}$ , unobserved productivity  $\omega_{jt}$ , and a measurement error  $\epsilon_{jt}$ , such that

$$q_{jt} = \beta^0 + \beta^k k_{jt} + \beta^l l_{jt} + \beta^m m_{jt} + \omega_{jt} + \epsilon_{jt}. \quad (1.4)$$

In the first stage, predicted output corrects for measurement error without identifying any of the input coefficients. Inverted material input demand is included in the production function to proxy productivity. Therefore a third order polynomial in input factors labour, capital, and materials is included as well as country fixed effects.

Following the assumption of Hopenhayn and Rogerson (1993), and later Olley and Pakes (1996); Levinsohn and Petrin (2003); Akerberg et al. (2015), the serial correlation of productivity is modelled as a controlled first order Markov process. The estimation also allows for common ownership to impact future productivity in an endogenous process, such that it is included in the law of motion of productivity

$$\omega_{jt} = g(\omega_{jt-1}, \text{MHHIdelta}_{pt-1}, \text{HHI}_{pt-1}) + \xi_{jt} \quad (1.5)$$

where  $g(\omega_{jt-1}, \text{MHHIdelta}_{pt-1}, \text{HHI}_{pt-1})$  is a flexible function of cubic lagged productivity, the common ownership measure, and the HHI, both of which are measured at the market level.  $\xi_{jt}$  is an exogenous firm-level productivity shock.

We estimate output elasticities for nine subsets of the manufacturing industry. For ease of notation, we omit the subscript of the industry subsets for the estimated elasticities. Information on the pooled industry subsets and the results of the production function estimation can be found in Table 1.7. We follow Collard-Wexler and De Loecker (2022) and correct for measurement error in capital, using lagged investment as an instrument for capital<sup>21</sup>. Constructed with the innovation to productivity  $\xi_{jt} = \omega_{jt} - E[\omega_{jt} | \omega_{jt-1}, \text{MHHIdelta}_{pt-1}, \text{HHI}_{pt-1}]$  from the law of motion, the objective function minimises the moment conditions

$$E[\xi_{jt}(l_{jt}, m_{jt-1}, i_{jt-1})] = 0.$$

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<sup>21</sup>For one subset of industries, we additionally include  $i_{jt-2}$  as an instrument for capital.

The empirical analogue for these moment conditions is

$$Q(\beta) = (\xi \mathbf{Z})'(\mathbf{Z}'\mathbf{Z})^{-1}(\xi \mathbf{Z}),$$

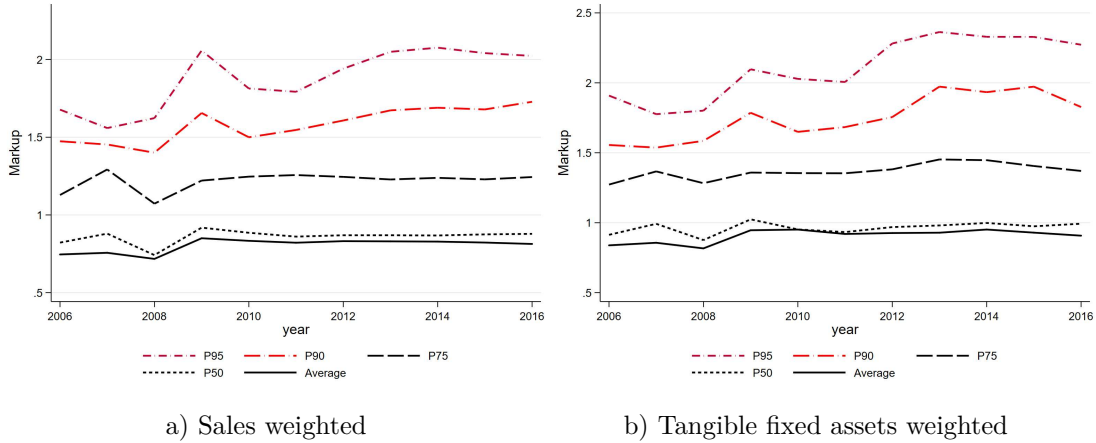
with  $\xi$  as a vector of productivity shocks  $\xi_{jt}$  and  $\mathbf{Z}$  as a stacked matrix containing instruments for the input factors (Collard-Wexler and De Loecker, 2022).

Table 1.7: Production function estimates

| NACE code  | Industries                           | $\beta_k$ | $\beta_l$ | $\beta_m$ | $N$  | $\mu_{jt}$ | $TFP_{jt}$ |
|------------|--------------------------------------|-----------|-----------|-----------|------|------------|------------|
| 10, 11, 12 | Food, beverages, tobacco             | 0.106     | 0.442     | 0.300     | 2585 | 0.592      | 2.483      |
| 13, 14, 15 | Textiles, wearing apparel, leather   | 0.015     | 0.407     | 0.614     | 637  | 1.397      | 0.549      |
| 16, 17     | Wood, paper                          | 0.150     | 0.404     | 0.412     | 962  | 0.850      | 0.121      |
| 19, 20, 21 | Coke, chemicals, pharmaceuticals     | 0.134     | 0.538     | 0.314     | 2239 | 0.817      | 3.220      |
| 22, 23     | Rubber, plastic, minerals            | 0.117     | 0.170     | 0.568     | 2060 | 1.391      | 6.590      |
| 24, 25     | Basic, fabricated metals             | 0.048     | 0.376     | 0.596     | 2612 | 1.316      | 1.170      |
| 26, 27     | Computer, electronic, electrical eq. | 0.076     | 0.437     | 0.478     | 2149 | 1.153      | 0.927      |
| 28, 29, 30 | Machinery, motor, transport          | 0.125     | 0.341     | 0.448     | 4941 | 1.005      | 2.930      |
| 31, 32     | Furniture, other manufacturing       | 0.012     | 0.361     | 0.660     | 452  | 1.586      | 0.344      |

*Note:* This table presents output elasticities obtained from production function estimation (Cobb-Douglas) following the method of Akerberg et al. (2015). For estimation of output elasticities, nine subsets of the data were regarded separately, pooling these NACE two-digit codes.  $\mu_{jt}$  and  $TFP_{jt}$  denote the firm-level average of estimated markup and productivity, respectively.

Figure 1.6: Evolution of markups

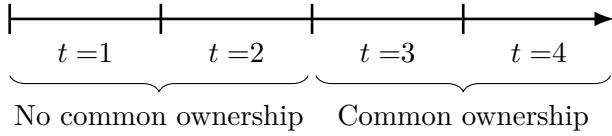


*Note:* The figures illustrate the evolution of the weighted distribution of firm markups from 2006 to 2016. The left figure uses sales as weights and the right figure uses tangible fixed assets as weights. Markups are estimated using European accounting data from the Amadeus data base by Bureau van Dijk and the method proposed by De Loecker and Warzynski (2012), relying on production function elasticities from the Akerberg et al. (2015) procedure. For the construction of the percentiles we follow the methodology of De Loecker et al. (2020).

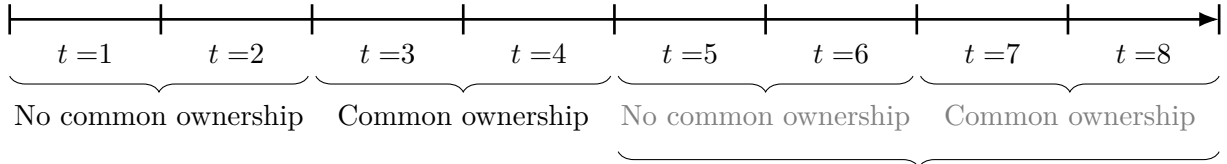
## 1.C Common Ownership Appendix

### 1.C.1 Market-level Binary Treatment Indicator

In the simple treatment case, there are periods without common ownership (treatment dummy equal to zero) followed by the first exposure to common ownership after the formation of a new horizontal ownership link between two or more firms in a market (treatment dummy equal to one), as illustrated below:

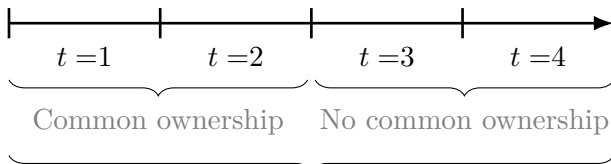


Additionally, there are two cases of intermittent common ownership. First, markets, defined at the NACE three-digit and country-level, can have multiple “entries” of common owners. The common ownership indicator starts at zero and then switches to one when the common ownership link occurs for the first time. As soon as the ownership link is terminated, we keep the markets while they experience new common ownership for the first time, but we drop the observations in all of the following periods, such that there cannot be multiple “new” occurrences of common ownership. Example of a market with intermittent common ownership:



Drop these periods, i.e. all observations after termination

Second, markets can have common ownership in the first period they appear in the data. It might either stay that way, with the indicator variable always being equal to one, or the common ownership link between firms within that market can be dissolved. In this case, the common ownership indicator variable switches from one to zero. It may even return to one, but we cannot be sure if this is due to new ownership links forming, or data errors. In any case, the effects of the common owners of the first periods may still be prevalent, such that the effect of a new ownership link might not be fully disentangled. Example of a market with common ownership links from the beginning of the sample, which then get dissolved in period 3:



Drop these periods, i.e. all observations of market

### 1.C.2 Market-level MHHI Delta

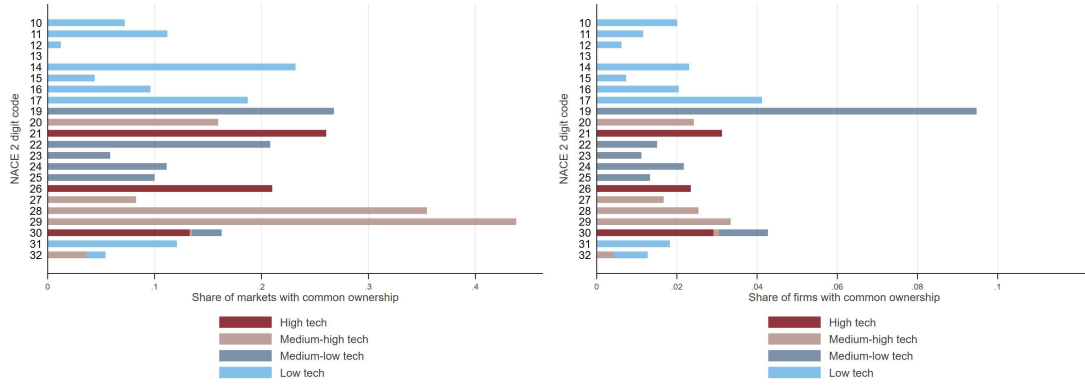
We introduce a frequently used measure for common ownership, the MHHI. The MHHI delta reflects common ownership concentration in a market and is constructed as the difference between the MHHI and the classical HHI (Salop and O'Brien, 2000), such that for a single market at a given point in time

$$\text{MHHI} = \sum_j \sum_f s_j s_f \frac{\sum_i \beta_{ij} \beta_{if}}{\sum_i \beta_{ij}^2} = \underbrace{\sum_j s_j^2}_{\text{HHI}} + \underbrace{\sum_j \sum_{f \neq j} s_j s_f \frac{\sum_i \beta_{ij} \beta_{if}}{\sum_i \beta_{ij}^2}}_{\text{MHHI delta}}.$$

The first part of the equation is the classical HHI as sum of squared market shares  $s_j$  of all market participants  $j$ , and the second part, MHHI delta, captures the degree of common ownership networks. Subscripts  $j$  and  $f$  denote firms and competitors,  $i$  indexes the investors, and  $\beta_{ij}$  are ownership shares. We assume proportionate control, such that ownership shares equal control shares. Summing over all combinations of firms and competitors in the industry, the individual profit weights between each pair of commonly owned firms in the fraction are weighted with the product of market shares  $s_j$  and  $s_f$  of the firm and respective rival.

Corresponding to the market definition partitioning NACE three-digit industry codes per country, the MHHI delta is calculated on a three-digit industry-country level to capture possible competition of firms operating in more than one four-digit industry. Whereas other articles exploit exogenous variation in the MHHI due to mergers at the investor level, we use the MHHI as a measure for treatment intensity.

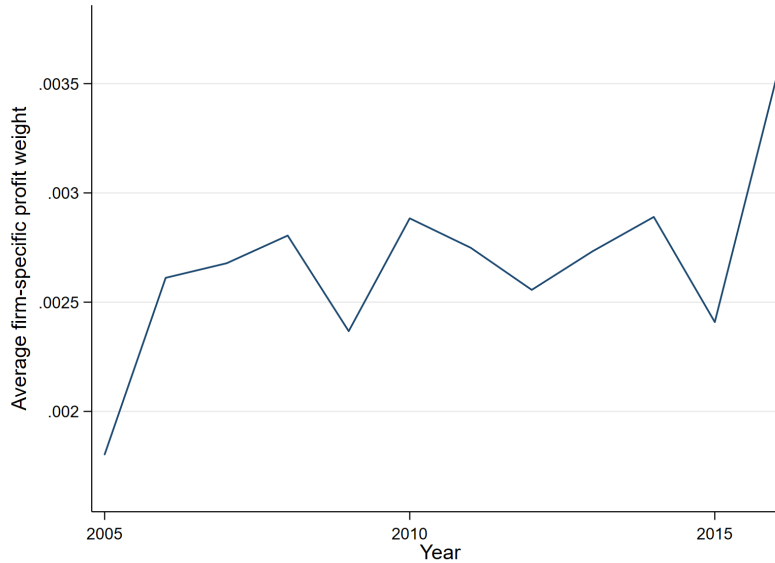
Figure 1.7: Common ownership by NACE two-digit industry



a) Share of markets with common ownership per NACE two-digit industry b) Share of firms with common ownership per NACE two-digit industry

*Note:* The figure on the left shows the percentage of markets with common ownership by NACE two-digit industry code. The figure on the right shows the percentage of manufacturing firms with common ownership by NACE two-digit industry code. We use European ownership data from the Amadeus data base by Bureau van Dijk. Common ownership in a market is defined as two competing firms being held by overlapping sets of institutional investors.

Figure 1.8: Common ownership profit weight

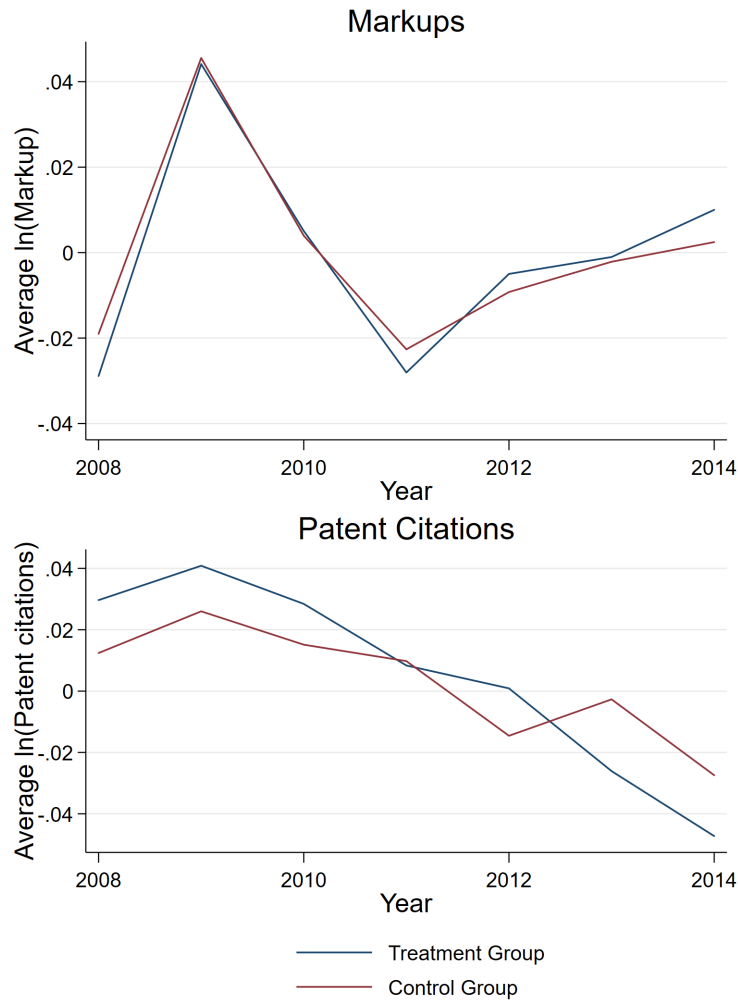


*Note:* The figure plots the firm-specific profit weights as in Azar et al. (2018) as an average over the whole sample. We use European ownership data from the Amadeus data base by Bureau van Dijk. Common ownership in a market is defined as two competing firms being held by overlapping sets of institutional investors.

## 1.D Propensity Score Reweighting Appendix

### 1.D.1 Parallel Trends

Figure 1.9: Pre-treatment averages of outcome variables



*Note:* The figures show yearly averages of markups and patent citations in logarithms. Markups are estimated using European accounting data from the Amadeus data base by Bureau van Dijk and the method proposed by De Loecker and Warzynski (2012), relying on production function elasticities from the Akerberg et al. (2015) procedure. Data on patent citations is obtained from the Amadeus patent data base by Bureau van Dijk. Both variables are demeaned at the company level before averaging at the yearly level. For patent citations, we also control for also zero citations. For the treatment group, only observations before treatment are used. For the control group, the yearly averages contain all observations.

### 1.D.2 Balancing Property

Table 1.8: Balancing property - unweighted and weighted sample

| Sample           | Balancing            |                   |
|------------------|----------------------|-------------------|
|                  | Unweighted           | Weighted          |
| ln(Markup)       | 0.138**<br>(0.057)   | 0.084<br>(0.084)  |
| ln(TFP)          | -0.048<br>(0.149)    | -0.145<br>(0.168) |
| Age              | 1.481<br>(2.189)     | 1.469<br>(2.698)  |
| Patent citations | 3.412**<br>(1.493)   | -0.091<br>(0.990) |
| ln(Capital)      | -0.280***<br>(0.103) | -0.132<br>(0.159) |
| ln(Labour)       | 0.105*<br>(0.059)    | 0.018<br>(0.076)  |
| ln(Sales)        | -0.110*<br>(0.062)   | -0.101<br>(0.102) |
| Inst. Holdings   | 0.020**<br>(0.010)   | 0.014<br>(0.016)  |
| HHI              | -0.071***<br>(0.025) | -0.013<br>(0.041) |
| Techn. gap       | 0.026<br>(0.027)     | 0.013<br>(0.034)  |
| Techn. ranking   | 4.332<br>(4.906)     | 0.038<br>(6.118)  |

*Note:* Standard errors in parentheses and clustered at the market level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . The table shows the differences in pre-treatment means between treatment and control group after controlling for year fixed effects. Propensity scores are the predicted values from the Probit model in Table 1.9. Markups and TFP are estimated using the methods proposed by De Loecker and Warzynski (2012) and Akerberg et al. (2015). Data on patent citations is obtained from the Amadeus patent data base by Bureau van Dijk. Institutional holdings are the shares held by institutional investors per firm. Calculation of technological gap is based on Aghion et al. (2005), and data on three-digit industry ranking (US SIC codes) according to their technological spillovers is obtained from Bloom et al. (2013). Market definition: HHI calculated at the three-digit industry-country level and rescaled by division by 10,000, such that it ranges from 0 to 1.

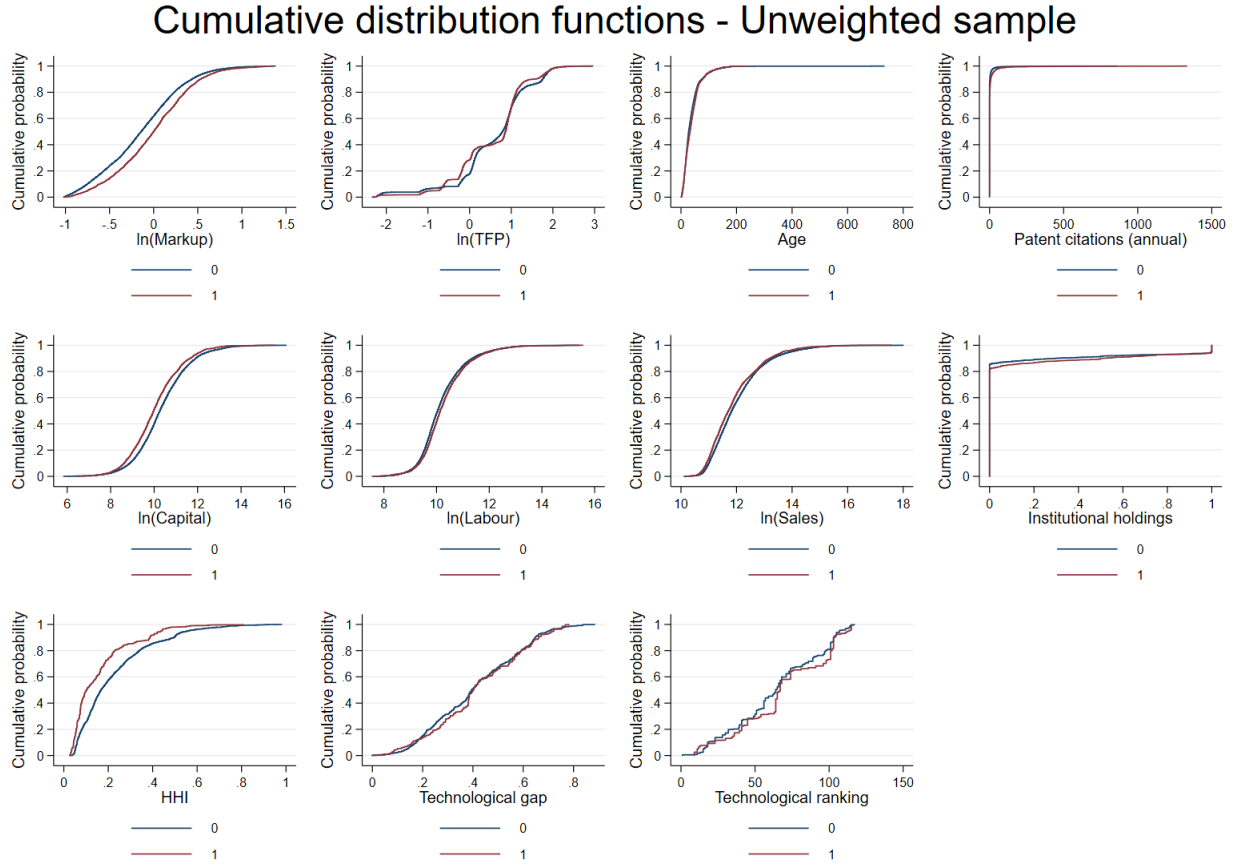
Table 1.9: Probit regressions: Propensity scores

| Technology       | Dependent Variable: Treatment |                      |
|------------------|-------------------------------|----------------------|
|                  | LOW                           | HIGH                 |
| Markup           | 0.487***<br>(0.112)           | 0.613***<br>(0.145)  |
| ln(TFP)          | 0.038<br>(0.036)              | 0.187***<br>(0.071)  |
| Age              | 0.001<br>(0.001)              | -0.001<br>(0.001)    |
| Patent citations | 0.002<br>(0.002)              | 0.001*<br>(0.001)    |
| ln(Capital)      | -0.138***<br>(0.042)          | -0.165***<br>(0.038) |
| ln(Labour)       | 0.116<br>(0.103)              | 0.137<br>(0.101)     |
| ln(Sales)        | 0.061<br>(0.104)              | 0.003<br>(0.100)     |
| Inst. Holdings   | 0.206*<br>(0.117)             | 0.160<br>(0.140)     |
| HHI              | -1.481***<br>(0.284)          | -1.322***<br>(0.256) |
| Techn. gap       | -0.555***<br>(0.197)          | 0.876***<br>(0.186)  |
| Techn. ranking   | -0.003**<br>(0.001)           | 0.005***<br>(0.002)  |
| Year Trend       | Yes                           | Yes                  |
| Pseudo $R^2$     | 0.08                          | 0.14                 |
| N                | 6136                          | 4457                 |
| Firm clusters    | 1638                          | 1349                 |

*Note:* Standard errors in parentheses and clustered at the firm level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . The table shows the results from Probit regressions. The dependent variable takes a value of one if common ownership occurs in the industry for the first time in year  $t+1$ , and zero otherwise. HIGH is a dummy that takes a value of one if the firm operates in a two-digit industry classified by the European Commission (2019) as high or medium-high technology, and zero if it operates in a low and medium-low-technology industry (LOW sample). Market definition: HHI delta calculated at the three-digit industry-country level. HHI rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

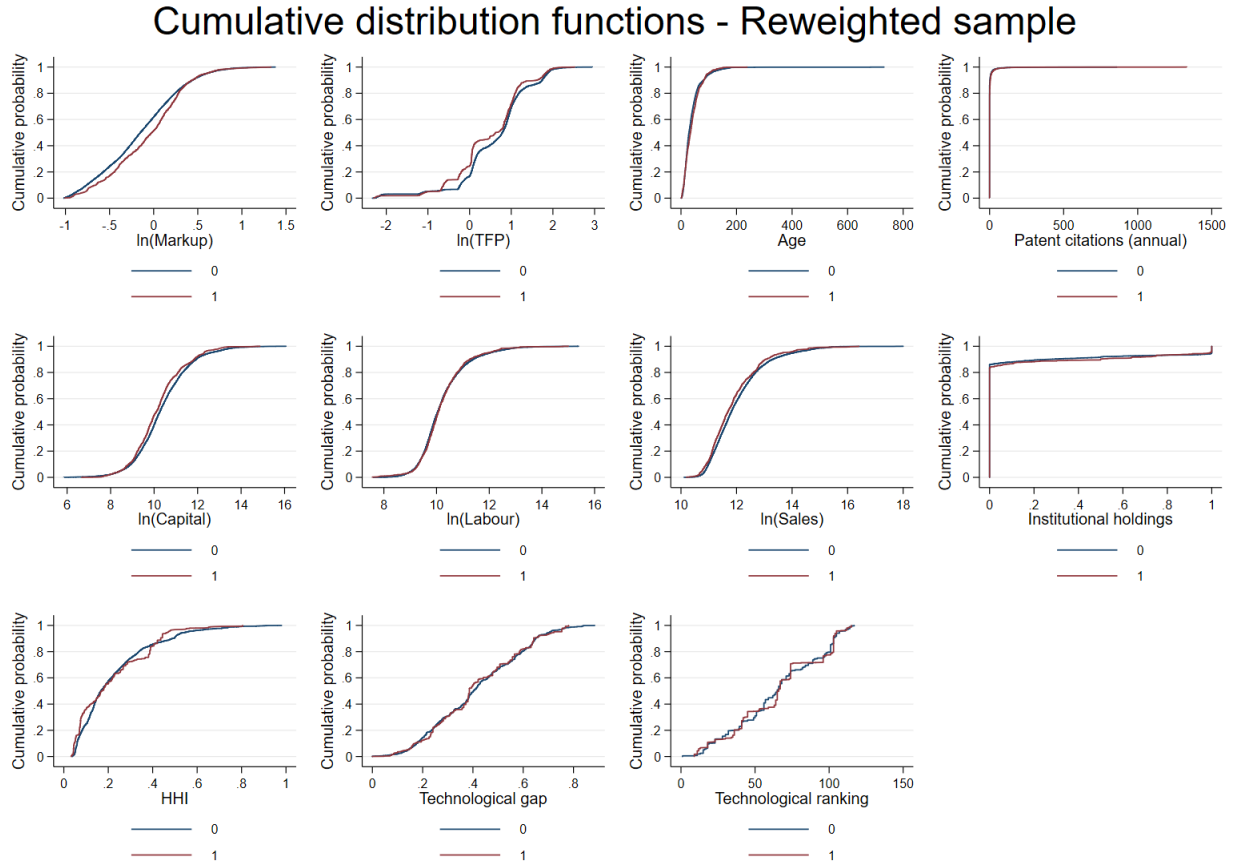


Figure 1.10: Cumulative distribution functions - Unweighted



*Note:* This graph shows the cumulative distribution function (cdf) of the respective variables measured as below for the unweighted regression sample. The blue line shows the cdf of the control group for firms in markets that never experience common ownership. The red line shows the cdf for the treatment group in pre-treatment periods.  $\ln(\text{Markup})$  and  $\ln(\text{TFP})$  are measured as the logarithm of markups and total factor productivity using a Cobb-Douglas production function. Additional variables are the firm age, the number of annual patent citations, the logarithm of capital, labour, and sales, the share of institutional holdings in a firm, three-digit-country level HHI, the technological gap as in Aghion et al. (2005), and the ranking in terms of technological spread.

Figure 1.11: Cumulative distribution functions - Reweighted



*Note:* This graph shows the cumulative distribution function (cdf) of the respective variables measured as below for the reweighted regression sample using propensity score weights. The blue line shows the cdf of the control group for firms in markets that never experience common ownership. The red line shows the cdf for the treatment group in pre-treatment periods.  $\ln(\text{Markup})$  and  $\ln(\text{TFP})$  are measured as the logarithm of markups and total factor productivity using a Cobb-Douglas production function. Additional variables are the firm age, the number of annual patent citations, the logarithm of capital, labour, and sales, the share of institutional holdings in a firm, three-digit-country level HHI, the technological gap as in Aghion et al. (2005), and the ranking in terms of technological spread.

Table 1.10: Balancing: Weighted sample - MHHI delta cutoffs

| Sample           | Balancing         |                   |                   |                   |                   |
|------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
|                  | >5%               | >10%              | >15%              | >20%              | >25%              |
| ln(Markup)       | 0.084<br>(0.084)  | 0.077<br>(0.088)  | 0.075<br>(0.091)  | 0.075<br>(0.091)  | 0.092<br>(0.087)  |
| ln(TFP)          | -0.143<br>(0.168) | -0.100<br>(0.173) | -0.081<br>(0.173) | -0.082<br>(0.173) | -0.093<br>(0.175) |
| Age              | 1.481<br>(2.684)  | 2.282<br>(2.607)  | 1.798<br>(2.834)  | 1.811<br>(2.836)  | 2.124<br>(3.026)  |
| Patent citations | -0.078<br>(0.995) | -0.209<br>(1.007) | 0.067<br>(1.068)  | 0.066<br>(1.067)  | 0.005<br>(1.008)  |
| ln(Capital)      | -0.131<br>(0.159) | -0.128<br>(0.168) | -0.104<br>(0.173) | -0.104<br>(0.173) | -0.092<br>(0.181) |
| ln(Labour)       | 0.020<br>(0.076)  | 0.012<br>(0.080)  | 0.031<br>(0.083)  | 0.031<br>(0.083)  | 0.063<br>(0.089)  |
| ln(Sales)        | -0.100<br>(0.102) | -0.096<br>(0.108) | -0.076<br>(0.112) | -0.076<br>(0.112) | -0.056<br>(0.121) |
| Inst. Holdings   | 0.014<br>(0.016)  | 0.019<br>(0.017)  | 0.017<br>(0.017)  | 0.017<br>(0.017)  | 0.020<br>(0.016)  |
| HHI              | -0.013<br>(0.041) | -0.011<br>(0.042) | -0.015<br>(0.042) | -0.015<br>(0.042) | -0.011<br>(0.041) |
| Techn. gap       | 0.013<br>(0.034)  | 0.019<br>(0.036)  | 0.022<br>(0.038)  | 0.022<br>(0.038)  | 0.015<br>(0.034)  |
| Techn. ranking   | 0.087<br>(6.113)  | 0.247<br>(6.450)  | 1.449<br>(6.696)  | 1.471<br>(6.698)  | 0.740<br>(6.205)  |

*Note:* Standard errors in parentheses and clustered at the market level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . The table shows the differences in pre-treatment means of the weighted sample between treatment and control group after controlling for year fixed effects. Each column shows a sub-sample where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. Markups and TFP are estimated using the methods proposed by De Loecker and Warzynski (2012) and Akerberg et al. (2015). Data on patent citations is obtained from the Amadeus patent data base by Bureau van Dijk. Institutional holdings are the shares held by institutional investors per firm. Calculation of technological gap is based on Aghion et al. (2005), and data on three-digit industry ranking (US SIC codes) according to their technological spillovers is obtained from Bloom et al. (2013). Market definition: HHI calculated at the three-digit industry-country level and rescaled by division by 10,000, such that it ranges from 0 to 1.

## 1.E Further Tables and Results

### 1.E.1 Main Results

#### Treatment Intensity

Table 1.11: Reweighting estimator: Markups - Treatment intensity

| Dep. Variable:         | ln(Markup)        |                   |                   |                    |                    |                     |
|------------------------|-------------------|-------------------|-------------------|--------------------|--------------------|---------------------|
|                        | (1)               | (2)               | (3)               | (4)                | (5)                | (6)                 |
| Cutoff MHHI delta      | >0                | >5%               | >10%              | >15%               | >20%               | >25%                |
| $1_{(MHHI\delta > 0)}$ | 0.008<br>(0.005)  | 0.009*<br>(0.005) | 0.009*<br>(0.005) | 0.013**<br>(0.005) | 0.013**<br>(0.005) | 0.015***<br>(0.006) |
| HHI                    | 0.043*<br>(0.025) | 0.043*<br>(0.025) | 0.038<br>(0.024)  | 0.033<br>(0.024)   | 0.033<br>(0.024)   | 0.031<br>(0.024)    |
| Inst. Holdings         | 0.003<br>(0.013)  | 0.003<br>(0.014)  | 0.005<br>(0.015)  | 0.004<br>(0.015)   | 0.004<br>(0.015)   | 0.003<br>(0.015)    |
| Firm FE                | Yes               | Yes               | Yes               | Yes                | Yes                | Yes                 |
| Year FE                | Yes               | Yes               | Yes               | Yes                | Yes                | Yes                 |
| Adj. $R^2$             | 0.96              | 0.96              | 0.96              | 0.96               | 0.96               | 0.96                |
| N                      | 15410             | 15305             | 15339             | 15149              | 15127              | 14944               |
| Market clusters        | 468               | 468               | 468               | 468                | 468                | 468                 |

*Note:* Standard errors in parentheses and clustered at the three-digit industry-country level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

Table 1.12: Reweighting estimator: Markups - Treatment intensity, insiders vs. outsiders

| Dep. Variable:                                | ln(Markup)        |                   |                  |                    |                    |                    |
|-----------------------------------------------|-------------------|-------------------|------------------|--------------------|--------------------|--------------------|
|                                               | (1)               | (2)               | (3)              | (4)                | (5)                | (6)                |
| Cutoff MHHI delta                             | >0                | >5%               | >10%             | >15%               | >20%               | >25%               |
| $1_{(MHHI\delta > 0)} \times \text{Insider}$  | 0.020<br>(0.028)  | 0.020<br>(0.028)  | 0.031<br>(0.026) | 0.035<br>(0.025)   | 0.035<br>(0.025)   | 0.038<br>(0.028)   |
| $1_{(MHHI\delta > 0)} \times \text{Outsider}$ | 0.007<br>(0.005)  | 0.008<br>(0.005)  | 0.007<br>(0.005) | 0.011**<br>(0.005) | 0.011**<br>(0.005) | 0.013**<br>(0.005) |
| HHI                                           | 0.043*<br>(0.025) | 0.043*<br>(0.025) | 0.037<br>(0.024) | 0.033<br>(0.024)   | 0.033<br>(0.024)   | 0.031<br>(0.024)   |
| Inst. Holdings                                | 0.002<br>(0.014)  | 0.002<br>(0.014)  | 0.001<br>(0.015) | 0.001<br>(0.016)   | 0.001<br>(0.016)   | -0.000<br>(0.017)  |
| Firm FE                                       | Yes               | Yes               | Yes              | Yes                | Yes                | Yes                |
| Year FE                                       | Yes               | Yes               | Yes              | Yes                | Yes                | Yes                |
| Adj. $R^2$                                    | 0.96              | 0.96              | 0.96             | 0.96               | 0.96               | 0.96               |
| N                                             | 15410             | 15305             | 15339            | 15149              | 15127              | 14944              |
| Market clusters                               | 468               | 468               | 468              | 468                | 468                | 468                |

*Note:* Standard errors in parentheses and clustered at the three-digit industry-country level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

Table 1.13: Reweighting estimator: Innovation - Treatment intensity

| Dep. Variable:         | ln(Patent Citations) |                   |                   |                   |                   |                   |
|------------------------|----------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
|                        | (1)                  | (2)               | (3)               | (4)               | (5)               | (6)               |
| Cutoff MHHI delta      | >0                   | >5%               | >10%              | >15%              | >20%              | >25%              |
| $1_{(MHHI\delta > 0)}$ | 0.002<br>(0.020)     | 0.001<br>(0.020)  | 0.010<br>(0.023)  | 0.010<br>(0.027)  | 0.010<br>(0.027)  | 0.003<br>(0.028)  |
| HHI                    | -0.144<br>(0.104)    | -0.142<br>(0.105) | -0.137<br>(0.107) | -0.129<br>(0.111) | -0.129<br>(0.111) | -0.118<br>(0.105) |
| Inst. Holdings         | 0.100<br>(0.074)     | 0.113<br>(0.075)  | 0.089<br>(0.075)  | 0.086<br>(0.072)  | 0.085<br>(0.072)  | 0.090<br>(0.072)  |
| Firm FE                | Yes                  | Yes               | Yes               | Yes               | Yes               | Yes               |
| Year FE                | Yes                  | Yes               | Yes               | Yes               | Yes               | Yes               |
| Adj. $R^2$             | 0.80                 | 0.80              | 0.80              | 0.80              | 0.80              | 0.80              |
| N                      | 15410                | 15305             | 15339             | 15149             | 15127             | 14944             |
| Market clusters        | 468                  | 468               | 468               | 468               | 468               | 468               |

*Note:* Standard errors in parentheses and clustered at the three-digit industry-country level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. We control for HHI at the three-digit industry country level,  $\ln(\text{TFP})$ , market size measured by average sales at the market level, capital intensity, 1-Lerner index, and age, share of institutional holdings, a dummy for zero citations, firm and year-fixed effects. Zero patent citations are set to one. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

Table 1.14: Reweighting estimator: Innovation - Treatment intensity, insiders vs. outsiders

| Dep. Variable:                                | ln(Patent Citations) |                   |                   |                   |                   |                   |
|-----------------------------------------------|----------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
|                                               | (1)                  | (2)               | (3)               | (4)               | (5)               | (6)               |
| Cutoff MHHI delta                             | >0                   | >5%               | >10%              | >15%              | >20%              | >25%              |
| $1_{(MHHI\delta > 0)} \times \text{Insider}$  | 0.053*<br>(0.030)    | 0.051*<br>(0.030) | 0.051<br>(0.033)  | 0.059<br>(0.036)  | 0.059<br>(0.036)  | 0.037<br>(0.041)  |
| $1_{(MHHI\delta > 0)} \times \text{Outsider}$ | -0.002<br>(0.020)    | -0.003<br>(0.021) | 0.007<br>(0.024)  | 0.005<br>(0.028)  | 0.006<br>(0.028)  | 0.000<br>(0.028)  |
| HHI                                           | -0.144<br>(0.103)    | -0.143<br>(0.104) | -0.137<br>(0.107) | -0.130<br>(0.110) | -0.130<br>(0.111) | -0.118<br>(0.105) |
| Inst. Holdings                                | 0.093<br>(0.076)     | 0.106<br>(0.077)  | 0.083<br>(0.077)  | 0.079<br>(0.075)  | 0.078<br>(0.075)  | 0.085<br>(0.075)  |
| Firm FE                                       | Yes                  | Yes               | Yes               | Yes               | Yes               | Yes               |
| Year FE                                       | Yes                  | Yes               | Yes               | Yes               | Yes               | Yes               |
| Adj. $R^2$                                    | 0.80                 | 0.80              | 0.80              | 0.80              | 0.80              | 0.80              |
| N                                             | 15410                | 15305             | 15339             | 15149             | 15127             | 14944             |
| Market clusters                               | 468                  | 468               | 468               | 468               | 468               | 468               |

*Note:* Standard errors in parentheses and clustered at the three-digit industry-country level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level,  $\ln(\text{TFP})$ , market size measured by average sales at the market level, capital intensity, 1-Lerner index, and age, share of institutional holdings, a dummy for zero citations, firm and year-fixed effects. Zero patent citations are set to one. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

Table 1.15: Reweighting estimator: Markups - Dummy MHHI delta distribution

| Dep. Variable:  | ln(Markup)           |                    |                    |
|-----------------|----------------------|--------------------|--------------------|
|                 | (1)                  | (2)                | (3)                |
| MHHI 25-100%    | 0.014***<br>(0.006)  | 0.010**<br>(0.005) | 0.015**<br>(0.007) |
| MHHI 15-25%     | -0.001<br>(0.005)    | 0.011<br>(0.010)   | 0.011<br>(0.010)   |
| MHHI 0-15%      | -0.016***<br>(0.006) | -0.013*<br>(0.007) | -0.002<br>(0.007)  |
| HHI             | 0.044*<br>(0.024)    | 0.039<br>(0.031)   | -0.002<br>(0.039)  |
| Inst. Holdings  | 0.002<br>(0.013)     | 0.005<br>(0.014)   | 0.001<br>(0.013)   |
| Firm FE         | Yes                  | Yes                | Yes                |
| Year FE         | Yes                  | Yes                | Yes                |
| Year×Country FE | No                   | Yes                | Yes                |
| Year×NACE3 FE   | No                   | No                 | Yes                |
| Adj. $R^2$      | 0.96                 | 0.96               | 0.96               |
| N               | 15410                | 15409              | 15334              |
| Market clusters | 468                  | 468                | 463                |

*Note:* Standard errors in parentheses and clustered at the three-digit industry-country level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.



Table 1.16: Reweighting estimator: Innovation - Dummy MHHI delta distribution

| Dep. Variable:  | ln(Patent Citations) |                     |                    |
|-----------------|----------------------|---------------------|--------------------|
|                 | (1)                  | (2)                 | (3)                |
| MHHI 25-100%    | -0.002<br>(0.021)    | 0.013<br>(0.020)    | -0.016<br>(0.019)  |
| MHHI 15-25%     | 0.085***<br>(0.028)  | 0.061***<br>(0.018) | 0.072**<br>(0.031) |
| MHHI 0-15%      | -0.016<br>(0.016)    | 0.001<br>(0.023)    | -0.002<br>(0.031)  |
| HHI             | -0.142<br>(0.106)    | -0.061<br>(0.129)   | 0.039<br>(0.088)   |
| Inst. Holdings  | 0.103<br>(0.086)     | 0.097<br>(0.088)    | 0.104<br>(0.092)   |
| Firm FE         | Yes                  | Yes                 | Yes                |
| Year FE         | Yes                  | Yes                 | Yes                |
| Year×Country FE | No                   | Yes                 | Yes                |
| Year×NACE3 FE   | No                   | No                  | Yes                |
| Adj. $R^2$      | 0.80                 | 0.80                | 0.81               |
| N               | 15410                | 15409               | 15334              |
| Market clusters | 169                  | 169                 | 168                |

*Note:* Standard errors in parentheses and clustered at the three-digit industry-country level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. We control for HHI at the three-digit industry country level,  $\ln(\text{TFP})$ , market size measured by average sales at the market level, capital intensity, 1-Lerner index, and age, share of institutional holdings, a dummy for zero citations, firm and year-fixed effects. Zero patent citations are set to one. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

## Technological Spillovers Interaction Effect

Table 1.17: Reweighting estimator: Markups - Spillover interaction effect

| Dep. Variable:                              | ln(Markup)          |                   |                   |                     |                     |
|---------------------------------------------|---------------------|-------------------|-------------------|---------------------|---------------------|
|                                             | (1)<br>ALL          | (2)<br><25%       | (3)<br><50%       | (4)<br>>50%         | (5)<br>>75%         |
| Spillover                                   |                     |                   |                   |                     |                     |
| $1_{(MHHIdelta>0)} \times \text{Spillover}$ | 0.000***<br>(0.000) |                   |                   |                     |                     |
| $1_{(MHHIdelta>0)}$                         | -0.018*<br>(0.011)  | 0.016*<br>(0.008) | -0.001<br>(0.007) | 0.021***<br>(0.007) | 0.033***<br>(0.011) |
| HHI                                         | 0.035<br>(0.023)    | 0.053<br>(0.059)  | 0.051<br>(0.043)  | 0.031<br>(0.029)    | 0.024<br>(0.043)    |
| Inst. Holdings                              | 0.005<br>(0.013)    | -0.017<br>(0.018) | -0.004<br>(0.018) | 0.007<br>(0.018)    | -0.008<br>(0.031)   |
| Firm FE                                     | Yes                 | Yes               | Yes               | Yes                 | Yes                 |
| Year FE                                     | Yes                 | Yes               | Yes               | Yes                 | Yes                 |
| Adj. $R^2$                                  | 0.96                | 0.98              | 0.97              | 0.95                | 0.95                |
| N                                           | 15410               | 3745              | 7922              | 7488                | 3593                |
| Market clusters                             | 468                 | 143               | 272               | 237                 | 125                 |

*Note:* Standard errors in parentheses and clustered at the three-digit industry-country level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

Table 1.18: Reweighting estimator: Innovation - Spillover interaction effect

| Dep. Variable:                                                        | ln(Patent Citations) |                   |                   |                   |                    |
|-----------------------------------------------------------------------|----------------------|-------------------|-------------------|-------------------|--------------------|
|                                                                       | (1)                  | (2)               | (3)               | (4)               | (5)                |
| Spillover                                                             | ALL                  | <25%              | <50%              | >50%              | >75%               |
| $1_{(MHHI\delta > 0)} \times \text{Insider} \times \text{Spillover}$  | 0.000*<br>(0.000)    |                   |                   |                   |                    |
| $1_{(MHHI\delta > 0)} \times \text{Outsider} \times \text{Spillover}$ | -0.000*<br>(0.000)   |                   |                   |                   |                    |
| $1_{(MHHI\delta > 0)} \times \text{Insider}$                          | 0.021<br>(0.036)     | 0.021<br>(0.019)  | 0.063<br>(0.039)  | 0.043<br>(0.043)  | 0.096**<br>(0.045) |
| $1_{(MHHI\delta > 0)} \times \text{Outsider}$                         | 0.056*<br>(0.033)    | 0.026<br>(0.018)  | 0.014<br>(0.032)  | -0.023<br>(0.031) | -0.026<br>(0.040)  |
| HHI                                                                   | -0.131<br>(0.097)    | -0.080<br>(0.131) | -0.210<br>(0.132) | -0.090<br>(0.144) | -0.169<br>(0.205)  |
| Inst. Holdings                                                        | 0.096<br>(0.076)     | 0.024<br>(0.049)  | 0.046<br>(0.037)  | 0.137<br>(0.131)  | -0.008<br>(0.084)  |
| Firm FE                                                               | Yes                  | Yes               | Yes               | Yes               | Yes                |
| Year FE                                                               | Yes                  | Yes               | Yes               | Yes               | Yes                |
| Adj. $R^2$                                                            | 0.80                 | 0.68              | 0.76              | 0.83              | 0.86               |
| N                                                                     | 15410                | 3745              | 7922              | 7488              | 3593               |
| Market clusters                                                       | 468                  | 143               | 272               | 237               | 125                |

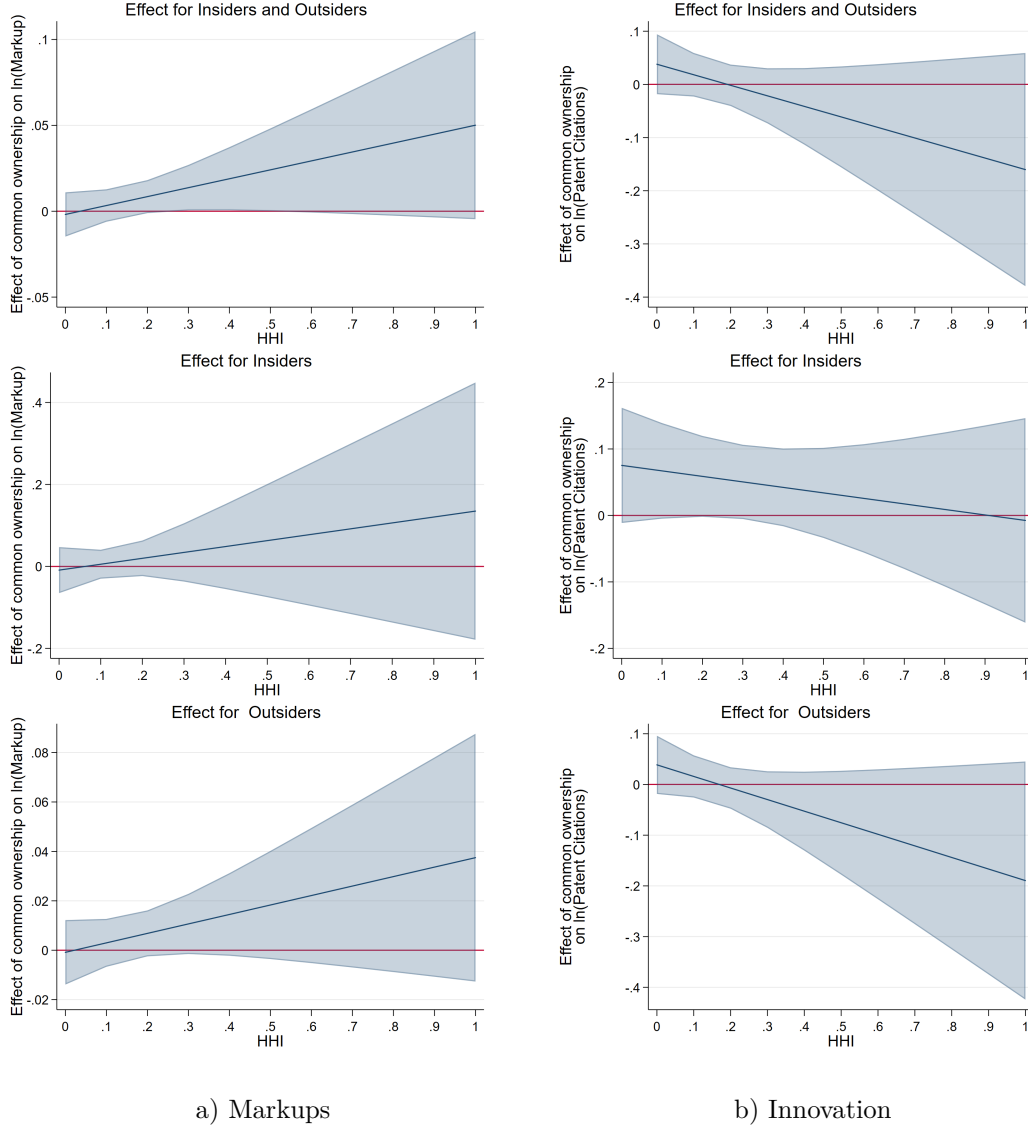
*Note:* Standard errors in parentheses and clustered at the three-digit industry-country level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level,  $\ln(\text{TFP})$ , market size measured by average sales at the market level, capital intensity, 1-Lerner index, and age, share of institutional holdings, a dummy for zero citations, firm and year-fixed effects. Zero patent citations are set to one. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

## 1.E.2 Heterogeneity

### HHI

Here, we analyse how the effect of common ownership varies with levels of HHI. This heterogeneity captures how the effect of common ownership varies with competition as measured by the HHI. Figures 1.12a and 1.12b below show the results of this exercise for markups and innovation, respectively. The combined effect on markups is increasing with HHI and significant or weakly significant for most levels of HHI. The effect for insiders and outsiders go in the same direction as the combined effect. The impact of common ownership on innovation is lower for higher levels of HHI but insignificant.

Figure 1.12: Reweighting estimator: HHI interaction effect

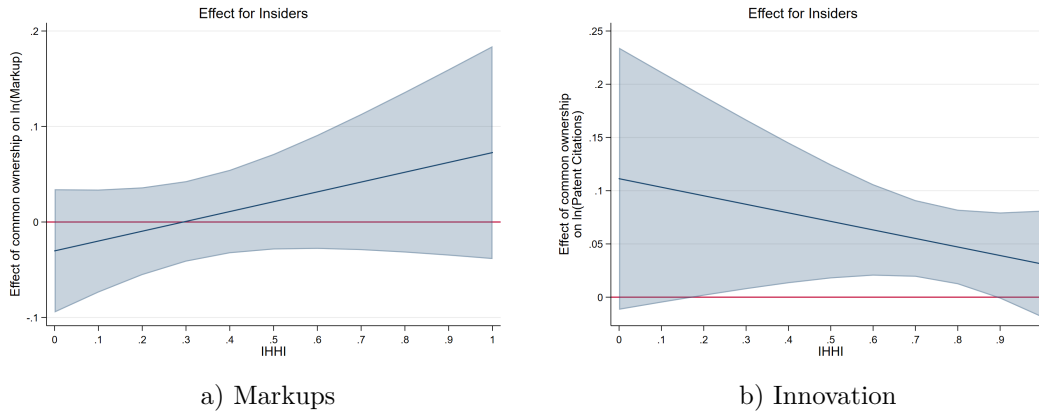


*Note:* Both graphs plot the treatment effect for varying degrees of HHI. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for institutional holdings and firm and year-fixed effects in all models. The combined models include an interaction term of treatment group and HHI. The models with insiders and outsiders include interaction terms of insider and outsider with HHI. The innovation models further control for  $\ln(\text{TFP})$ , market size measured by average sales at the market level, capital intensity, 1-Lerner index, and age, a dummy for zero citations. Zero patent citations are set to one. HHI is calculated at the three-digit industry-country level and rescaled by division by 10,000, such that it ranges from 0 to 1. The red line indicates zero.

## Investor HHI

Here, we analyse how the effect of common ownership varies with levels of Investor HHI (IHHI) (also used in e.g. Backus et al., 2021), which is the sum of squared investor holdings similar to the classical HHI, but is calculated at the firm level using ownership shares instead of market shares. The effect of common ownership on inside firms may vary with the concentration of the investors, as investors with larger shares may exert more monitoring or indirect control in a firm. However, we do not find that common ownership varies significantly with the IHHI. Figures 1.13a and 1.13b below show the results for markups and innovation, respectively. Effects are not statistically significant for most of the IHHI region.

Figure 1.13: Reweighting estimator: Investor HHI interaction effect



*Note:* Both graphs plot the treatment effect for varying degrees of Investor-HHI (IHHI). Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for institutional holdings and firm and year-fixed effects in all models. The models include an interaction term of insiders and IHHI. The innovation model further control for  $\ln(\text{TFP})$ , market size measured by average sales at the market level, capital intensity, 1-Lerner index, and age, a dummy for zero citations. Zero patent citations are set to one. IHHI is calculated firm specific and rescaled by division by 10,000, such that it ranges from 0 to 1. The red line indicates zero.

### 1.E.3 Robustness Checks

#### Firm-level Common Ownership Measure

Table 1.19: Reweighting estimator: Markups - Firm-level profit weight

| ln(Markup)           | Average effect    | Spillovers          |                     |                     |
|----------------------|-------------------|---------------------|---------------------|---------------------|
|                      | (1)<br>ALL        | (2)<br>Interaction  | (3)<br><50%         | (4)<br>>50%         |
| FCO                  | 0.211*<br>(0.112) | -0.033<br>(0.239)   | 0.183***<br>(0.032) | 0.255<br>(0.252)    |
| Outsider             | 0.007<br>(0.006)  | -0.016<br>(0.011)   | -0.003<br>(0.007)   | 0.021***<br>(0.006) |
| FCO × Spillover      |                   | 0.000<br>(0.000)    |                     |                     |
| Outsider × Spillover |                   | 0.000***<br>(0.000) |                     |                     |
| Adj. $R^2$           | 0.96              | 0.96                | 0.97                | 0.94                |
| N                    | 15404             | 15404               | 7918                | 7486                |
| Market clusters      | 2983              | 467                 | 272                 | 236                 |

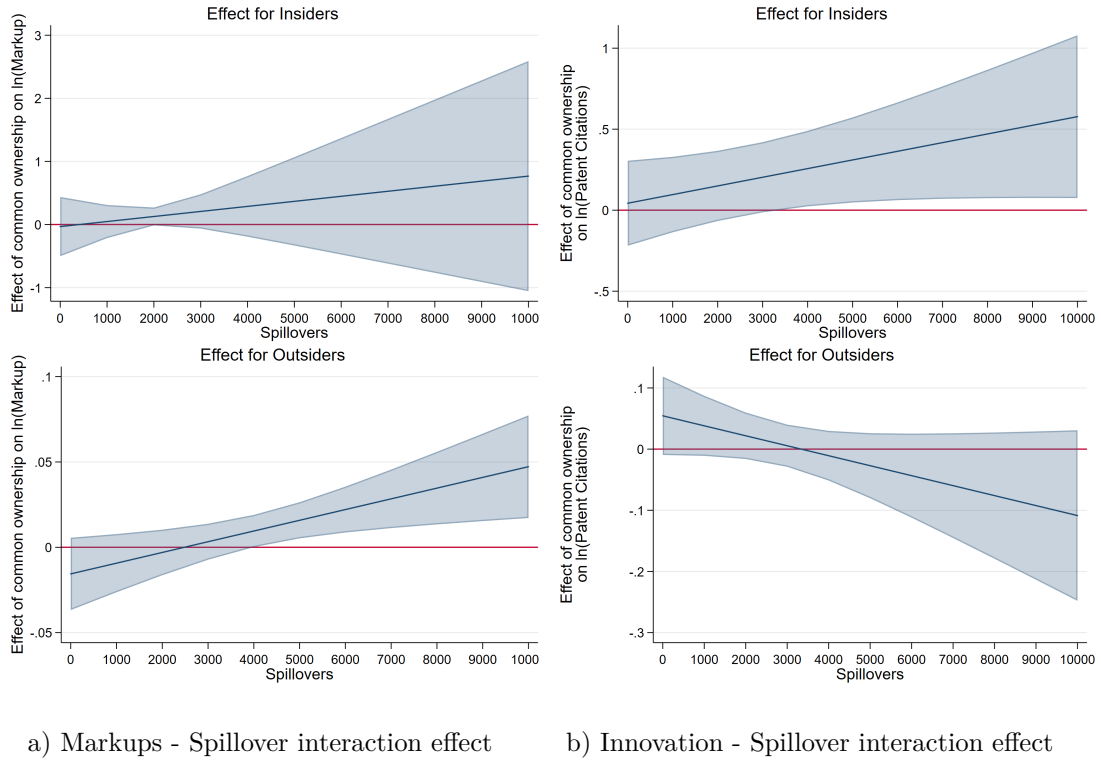
*Note:* Standard errors in parentheses and clustered at the market level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. We control for HHI at the three-digit industry country level, share of institutional holdings, firm and year-fixed effects. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

Table 1.20: Reweighting estimator: Innovation - Firm-level profit weight

| ln(Patent Citations) | Average effect    | Spillovers         |                   |                   |
|----------------------|-------------------|--------------------|-------------------|-------------------|
|                      | (1)<br>ALL        | (2)<br>Interaction | (3)<br><50%       | (4)<br>>50%       |
| FCO                  | 0.206*<br>(0.112) | 0.043<br>(0.134)   | 0.216*<br>(0.127) | 0.200<br>(0.223)  |
| Outsider             | -0.004<br>(0.022) | 0.054*<br>(0.033)  | 0.013<br>(0.031)  | -0.024<br>(0.031) |
| FCO × Spillover      |                   | 0.000*<br>(0.000)  |                   |                   |
| Outsider × Spillover |                   | -0.000*<br>(0.000) |                   |                   |
| Adj. $R^2$           | 0.80              | 0.80               | 0.76              | 0.83              |
| N                    | 15404             | 15404              | 7918              | 7486              |
| Market clusters      | 2983              | 467                | 272               | 236               |

*Note:* Standard errors in parentheses and clustered at the market level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level,  $\ln(TFP)$ , market size measured by average sales at the market level, capital intensity, 1-Lerner index, age, share of institutional holdings less commonly owned shares, a dummy for zero citations, firm and year-fixed effects. Zero patent citations are set to one. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

Figure 1.14: Reweighting estimator: Spillover interaction effect with firm-level profit weight



*Note:* The graph plots the treatment effect for varying degrees of spillovers for the outcome markups in the left graph and innovation in the right graph. Common ownership is measured as the firm-level profit weight in Azar et al. (2018). Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, share of institutional holdings less commonly owned shares, firm and year-fixed effects. For innovation, we additionally control for  $\ln(\text{TFP})$ , market size measured by average sales at the market level, capital intensity, 1-Lerner index, age, a dummy for zero citations. Zero patent citations are set to one. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1. The red line indicates zero.



Table 1.21: Reweighting estimator: Markups - Commonly held shares

| ln(Markup)                  | Average effect   | Spillovers         |                   |                     |
|-----------------------------|------------------|--------------------|-------------------|---------------------|
|                             | (1)<br>ALL       | (2)<br>Interaction | (3)<br><50%       | (4)<br>>50%         |
| CO share                    | 0.067<br>(0.049) | -0.015<br>(0.022)  | 0.005<br>(0.020)  | 0.127<br>(0.078)    |
| Outsider                    | 0.007<br>(0.006) | -0.015<br>(0.011)  | -0.003<br>(0.008) | 0.022***<br>(0.008) |
| CO share $\times$ Spillover |                  | 0.000*<br>(0.000)  |                   |                     |
| Outsider $\times$ Spillover |                  | 0.000**<br>(0.000) |                   |                     |
| Adj. $R^2$                  | 0.96             | 0.96               | 0.97              | 0.95                |
| N                           | 15410            | 15410              | 7922              | 7488                |
| Market clusters             | 2985             | 468                | 1567              | 1418                |

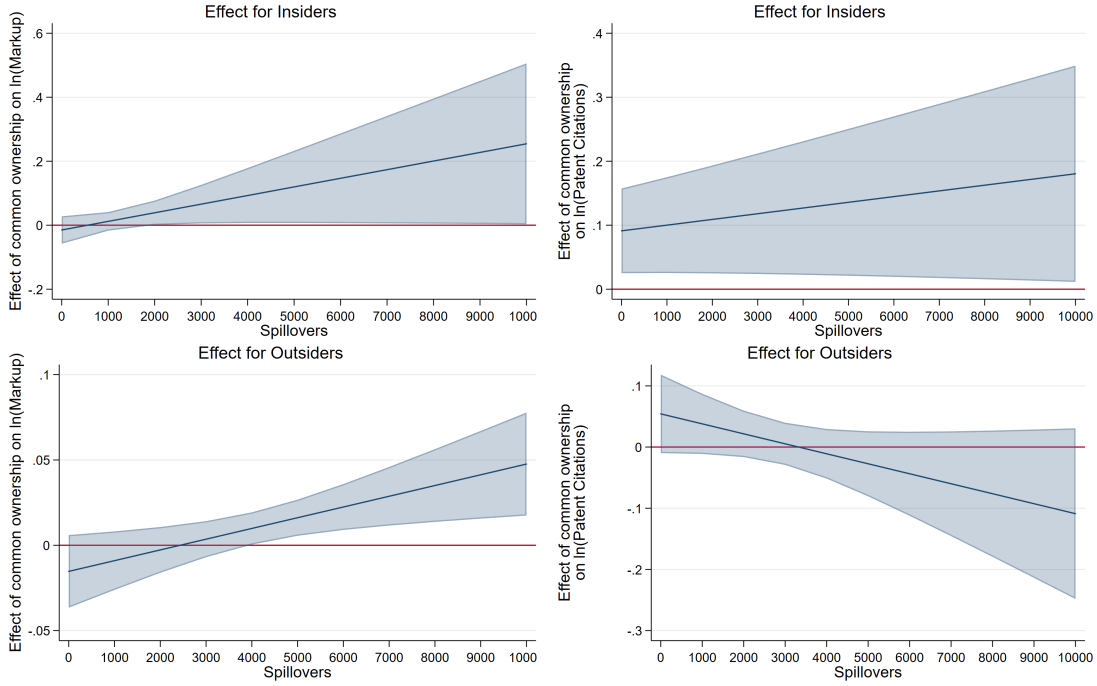
*Note:* Standard errors in parentheses and clustered at the market level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. We control for HHI at the three-digit industry country level, share of institutional holdings less commonly owned shares, firm and year-fixed effects. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

Table 1.22: Reweighting estimator: Innovation - Commonly held shares

| ln(Patent Citations)        | Average effect      | Spillovers          |                     |                    |
|-----------------------------|---------------------|---------------------|---------------------|--------------------|
|                             | (1)<br>ALL          | (2)<br>Interaction  | (3)<br><50%         | (4)<br>>50%        |
| CO share                    | 0.118***<br>(0.037) | 0.091***<br>(0.034) | 0.084***<br>(0.023) | 0.156**<br>(0.079) |
| Outsider                    | -0.004<br>(0.022)   | 0.054*<br>(0.033)   | 0.013<br>(0.028)    | -0.024<br>(0.033)  |
| CO share $\times$ Spillover |                     | 0.000<br>(0.000)    |                     |                    |
| Outsider $\times$ Spillover |                     | -0.000*<br>(0.000)  |                     |                    |
| Adj. $R^2$                  | 0.80                | 0.80                | 0.76                | 0.83               |
| N                           | 15410               | 15410               | 7922                | 7488               |
| Market clusters             | 2985                | 468                 | 1567                | 1418               |

*Note:* Standard errors in parentheses and clustered at the market level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level,  $\ln(TFP)$ , market size measured by average sales at the market level, capital intensity, 1-Lerner index, age, share of institutional holdings less commonly owned shares, a dummy for zero citations, firm and year-fixed effects. Zero patent citations are set to one. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

Figure 1.15: Reweighting estimator: Spillover interaction effect with commonly held shares



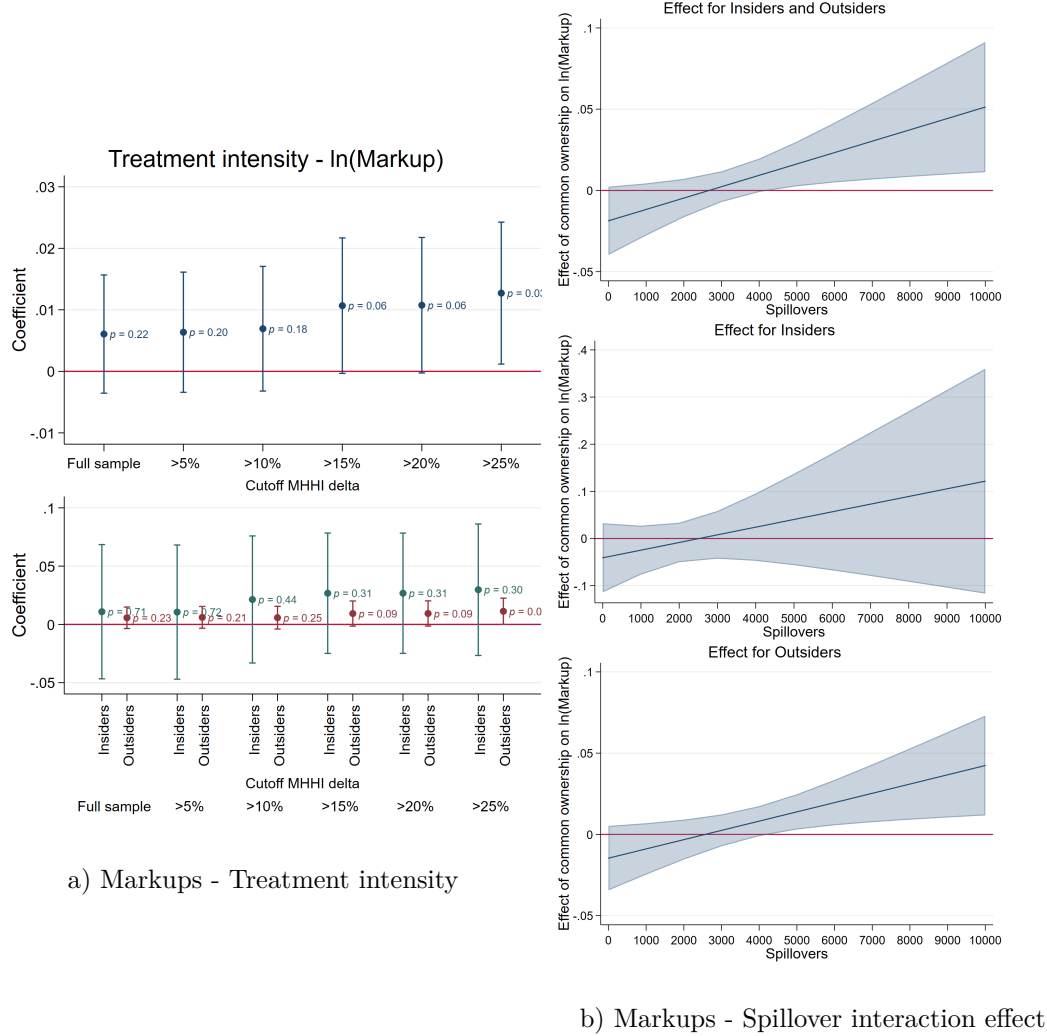
a) Markups - Spillover interaction effect

b) Innovation - Spillover interaction effect

*Note:* The graph plots the treatment effect for varying degrees of spillovers for the outcome markups in the left graph and innovation in the right graph. Common ownership is measured as commonly held shares at the firm level. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, share of institutional holdings less commonly owned shares, firm and year-fixed effects. For innovation, we additionally control for  $\ln(\text{TFP})$ , market size measured by average sales at the market level, capital intensity, 1-Lerner index, age, a dummy for zero citations. Zero patent citations are set to one. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1. The red line indicates zero.

## Controlling for TFP

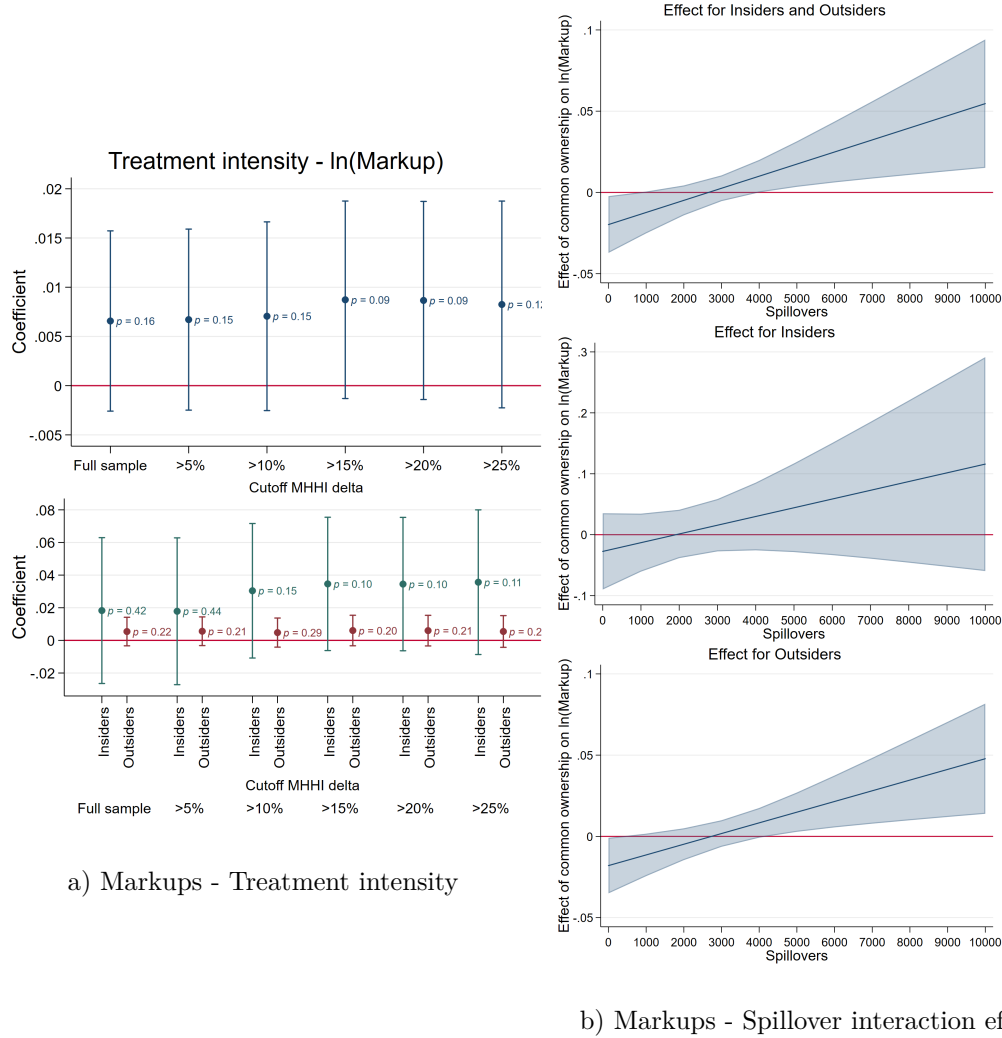
Figure 1.16: Reweighting Estimator: Markups - Controlling for polynomial of TFP



*Note:* The graph on the left plots the estimated coefficients of the treatment indicator and respective confidence intervals and p-values. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. The graph on the right plots the treatment effect for varying degrees of spillovers. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, share of institutional holdings, firm and year-fixed effects and cluster standard error at the three-digit industry-country level. The red line indicates zero.

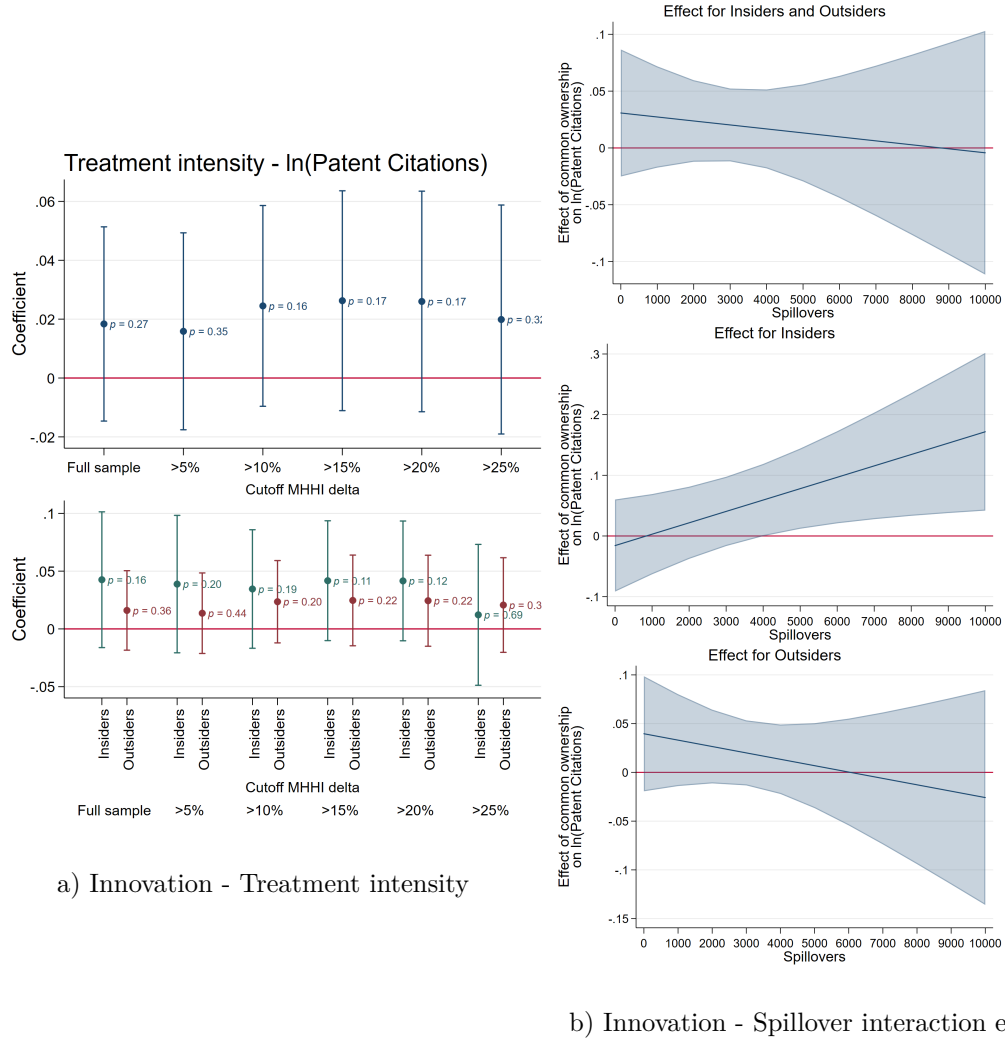
## Country-specific and Industry-specific Time-fixed Effects

Figure 1.17: Reweighting estimator: Markups - Country-specific and industry-specific time-fixed effects



*Note:* The graph on the left plots the estimated coefficients of the treatment indicator and respective confidence intervals and p-values. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. The graph on the right plots the treatment effect for varying degrees of spillovers. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, share of institutional holdings, firm and year-fixed effects and cluster standard error at the three-digit industry-country level. The red line indicates zero.

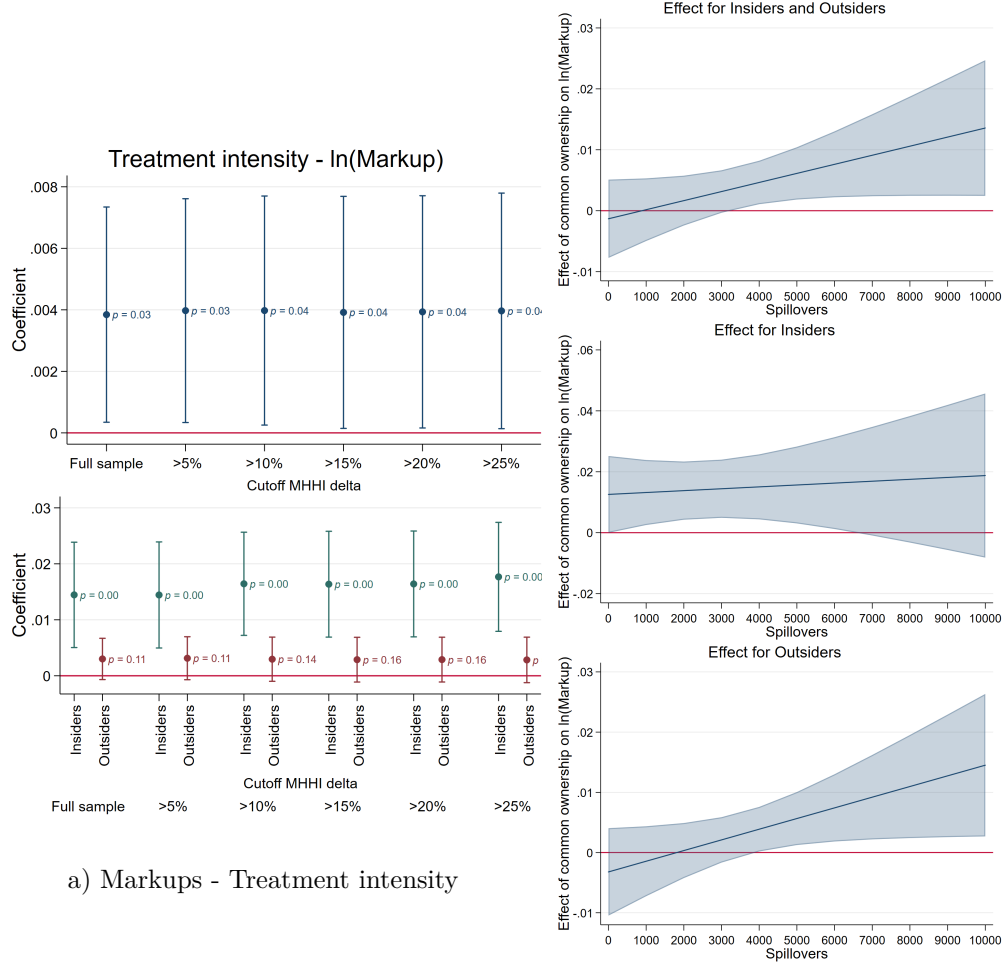
Figure 1.18: Reweighting estimator: Innovation - Country-specific and industry-specific time-fixed effects



*Note:* The graph on the left plots the estimated coefficients of the treatment indicator and respective confidence intervals and p-values. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. The graph on the right plots the treatment effect for varying degrees of spillovers. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, share of institutional holdings,  $\ln(\text{TFP})$ , market size measured by average sales at the market level, capital intensity, 1-Lerner index, age, and a dummy for zero citations. Zero patent citations are set to one. We also include firm and year-country-fixed effects and cluster standard errors at the three-digit industry-country level. The red line indicates zero. The blue shaded area is a 95% CI.

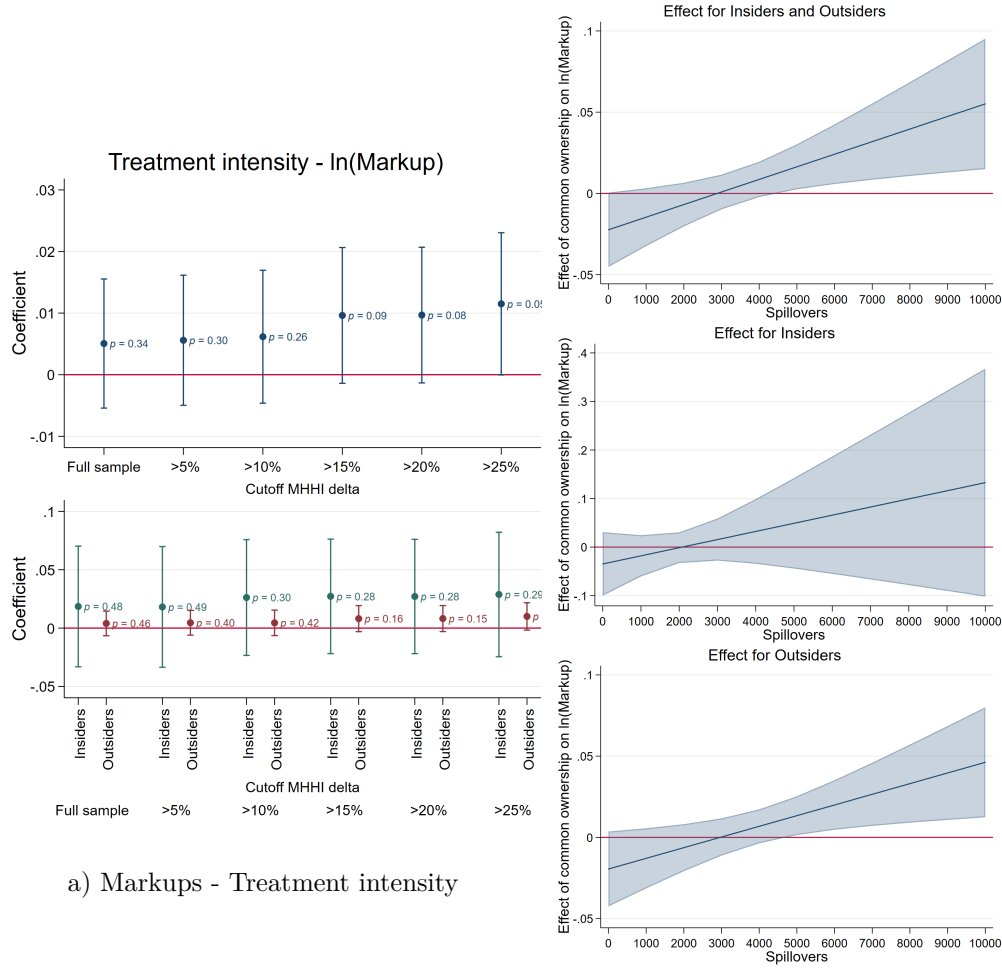
## Alternative Production Function Specifications

Figure 1.19: Reweighting estimator: Markups - Translog production function



*Note:* The graph on the left plots the estimated coefficients of the treatment indicator and respective confidence intervals and p-values. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. The graph on the right plots the treatment effect for varying degrees of spillovers. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, share of institutional holdings, firm and year-fixed effects and cluster standard error at the three-digit industry-country level. The red line indicates zero.

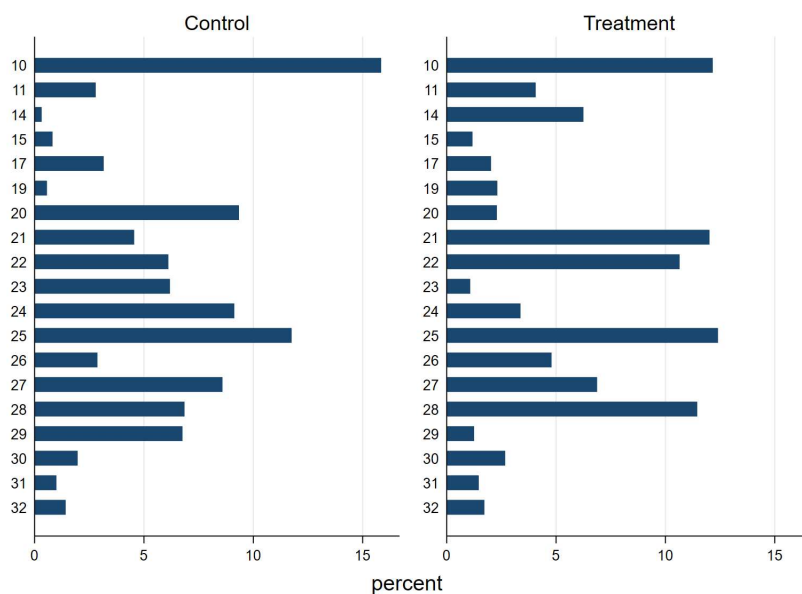
Figure 1.20: Reweighting estimator: Markups - Wages in control function



*Note:* The graph on the left plots the estimated coefficients of the treatment indicator and respective confidence intervals and p-values. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. The graph on the right plots the treatment effect for varying degrees of spillovers. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, share of institutional holdings, firm and year-fixed effects and cluster standard error at the three-digit industry-country level. The red line indicates zero.

## Industry Balancing

Figure 1.21: Distribution of industries for treatment and control group



*Note:* This graph shows the sample probabilities of NACE two-digit industries for the reweighted regression sample using propensity score weights. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta.

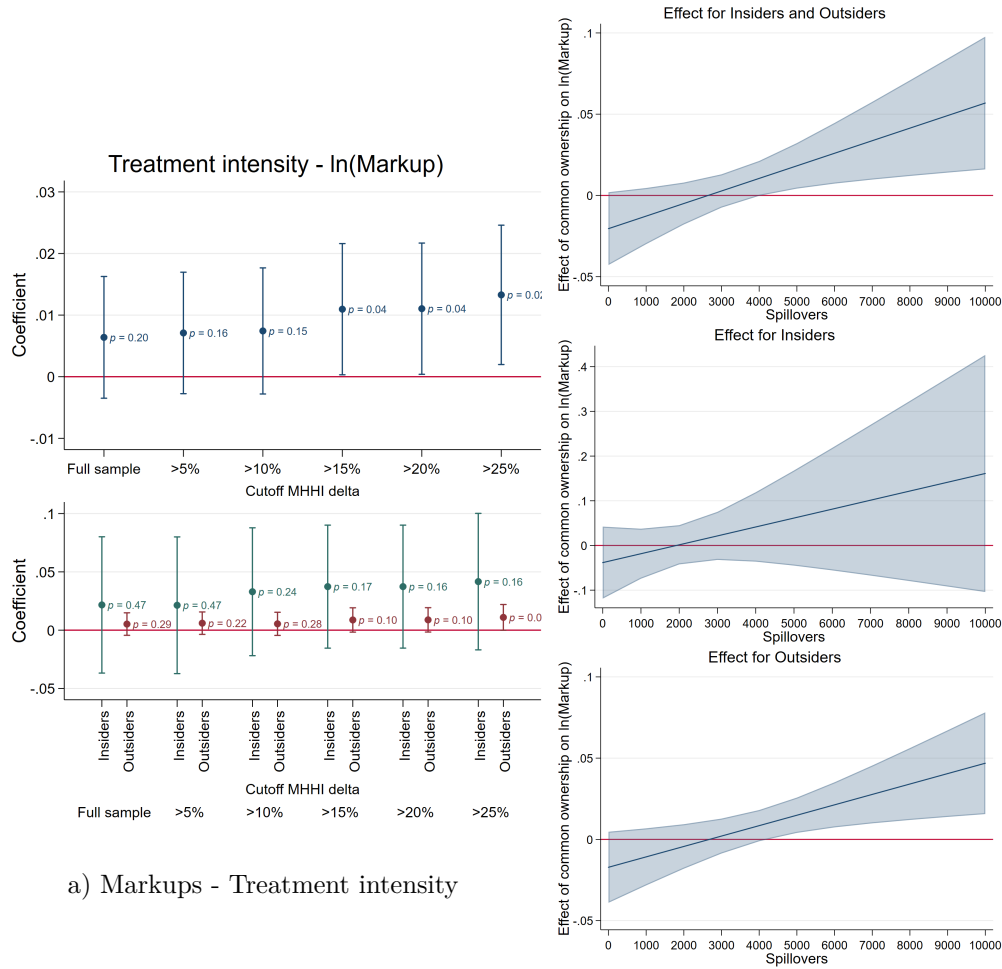


Table 1.23: Balancing: Weighted sample - NACE two-digit industries

| NACE two-digit |                      |
|----------------|----------------------|
| NACE 10        | -0.032<br>(0.079)    |
| NACE 11        | -0.012<br>(0.020)    |
| NACE 14        | 0.070<br>(0.048)     |
| NACE 15        | 0.011<br>(0.019)     |
| NACE 17        | -0.012<br>(0.020)    |
| NACE 19        | 0.018<br>(0.024)     |
| NACE 20        | -0.083***<br>(0.026) |
| NACE 21        | 0.079<br>(0.087)     |
| NACE 22        | 0.015<br>(0.068)     |
| NACE 23        | -0.050***<br>(0.019) |
| NACE 24        | -0.057<br>(0.037)    |
| NACE 25        | 0.052<br>(0.140)     |
| NACE 26        | 0.003<br>(0.022)     |
| NACE 27        | -0.016<br>(0.064)    |
| NACE 28        | 0.050<br>(0.056)     |
| NACE 29        | -0.053**<br>(0.024)  |
| NACE 30        | 0.008<br>(0.017)     |
| NACE 31        | 0.004<br>(0.013)     |
| NACE 32        | 0.005<br>(0.016)     |

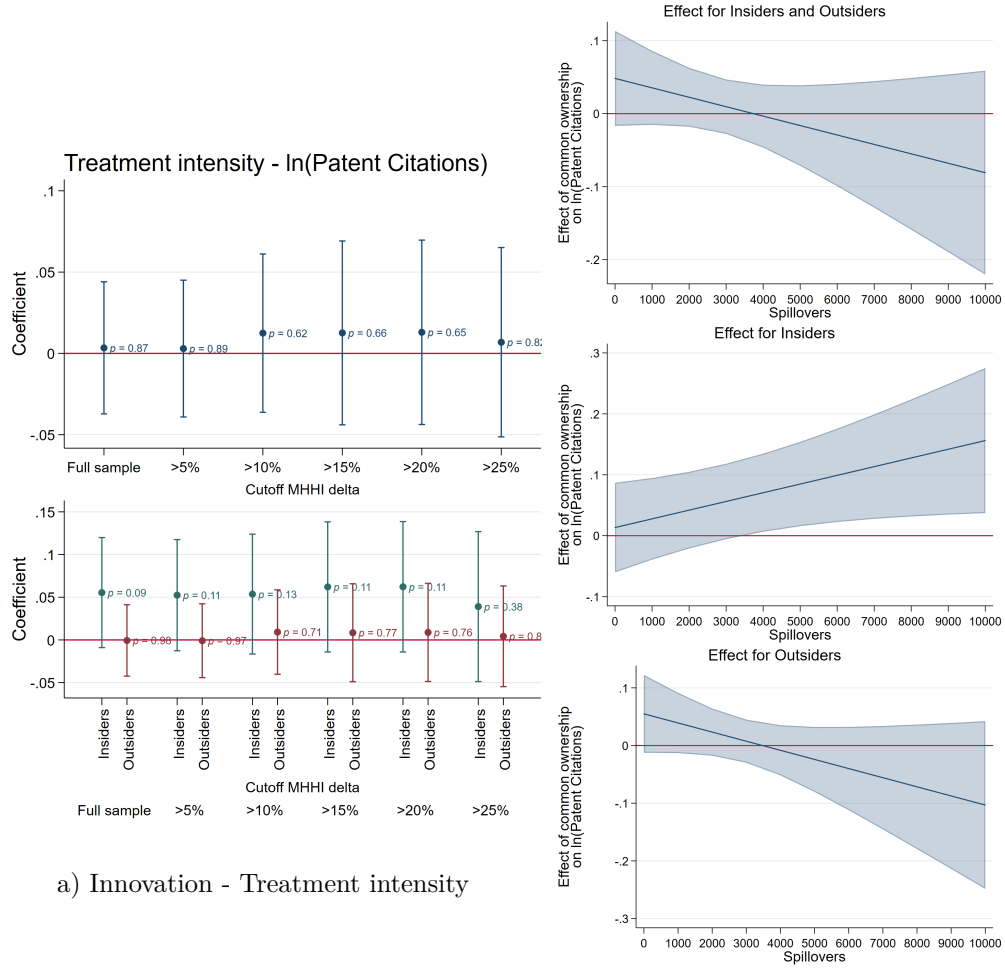
*Note:* Standard errors in parentheses and clustered at the market level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . The table shows the differences in pre-treatment means of the weighted sample between treatment and control group after controlling for year fixed effects.

Figure 1.22: Reweighting estimator: Markups - Without unbalanced NACE two-digit industries



*Note:* The graph on the left plots the estimated coefficients of the treatment indicator and respective confidence intervals and p-values. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. The graph on the right plots the treatment effect for varying degrees of spillovers. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, share of institutional holdings, firm and year-fixed effects and cluster standard error at the three-digit industry-country level. The red line indicates zero.

Figure 1.23: Reweighting estimator: Innovation - Without unbalanced NACE two-digit industries



*Note:* The graph on the left plots the estimated coefficients of the treatment indicator and respective confidence intervals and p-values. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. The graph on the right plots the treatment effect for varying degrees of spillovers. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, share of institutional holdings, firm and year-fixed effects and cluster standard error at the three-digit industry-country level. The red line indicates zero.

## Difference-in-Differences

The basic idea of matching is to find an adequate control group that can approximate the counterfactual outcome of the treatment group absent treatment. Propensity score matching consists of a two-stage procedure. In the first step, a probit model is estimated to determine the treatment probabilities, or balancing score, from covariates for all observations. In the second step, pair matching on the balancing score is performed, such that the distribution of covariates is similar in treatment and control group (Rosenbaum and Rubin, 1983).

We perform the matching procedure for each year individually with separate probit regressions. The outcome variable is one if the market experiences entry of common ownership in the next year, and zero otherwise. We use the same pre-treatment variables for matching as in the propensity score reweighting approach<sup>22</sup> and include a dummy for high-tech industries. By including the latter, we can construct the control group on the full sample while ensuring that the matched controls also operate in industries of the same technological capacities as the treated firm.

$$y_{jt} = \delta_1 \text{Treat}_p \times \text{Post}_{pt} + \delta_2 \text{Post}_{pt} + \tau_t + \nu_j + \epsilon_{jt}. \quad (1.6)$$

The outcome variable  $y_{jmt}$  is either the logarithm of markups or the logarithm of patent citations. In addition to the difference-in-differences coefficient  $\text{Treat}_p \times \text{Post}_{pt}$  and the post period with  $\text{Post}_{pt}$ , we control for firm and year-fixed effects  $\nu_j$  and  $\tau_t$ , as time of treatment varies across markets and therefore individual firms. The indicator variable  $\text{Treat}_p$  for the treatment group is subsumed by the firm-fixed effects. We cluster standard errors at the market level.

---

<sup>22</sup>We use the following pre-treatment firm-level variables: markups, log TFP, age, number of patent citations, labour, capital, and output in logarithms, and share of institutional holdings. As treatment varies at the market-level (defined by three digit-industry code and country combinations), we do not match on industries and countries directly, but rather on market and industry-level variables such as the HHI, technological spillovers, the technological gap between firms, and the high-tech industry dummy. For some years, we use additional functional forms of the firm-level variables TFP, age, and capital to ensure balancing of the samples.

Table 1.24: Difference-in-differences: Markups and Innovation

| Dep. Variable:                                | ln(Markup)        |                   | ln(Patent Citations) |                      |
|-----------------------------------------------|-------------------|-------------------|----------------------|----------------------|
|                                               | (1)               | (2)               | (3)                  | (4)                  |
| $1_{(MHHI\delta > 0)}$                        | 0.019*<br>(0.010) |                   | -0.103**<br>(0.041)  |                      |
| $1_{(MHHI\delta > 0)} \times \text{Insider}$  |                   | 0.017<br>(0.022)  |                      | 0.036<br>(0.041)     |
| $1_{(MHHI\delta > 0)} \times \text{Outsider}$ |                   | 0.019*<br>(0.010) |                      | -0.112***<br>(0.042) |
| Post                                          | -0.011<br>(0.008) | -0.011<br>(0.008) | 0.088***<br>(0.030)  | 0.088***<br>(0.030)  |
| Firm FE                                       | Yes               | Yes               | Yes                  | Yes                  |
| Year FE                                       | Yes               | Yes               | Yes                  | Yes                  |
| Adj. $R^2$                                    | 0.95              | 0.95              | 0.71                 | 0.71                 |
| N                                             | 5935              | 5935              | 5935                 | 5935                 |
| Market clusters                               | 258               | 258               | 258                  | 258                  |

*Note:* Standard errors in parentheses and clustered at the three-digit industry-country level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market.

Table 1.25: Difference-in-differences: Markups - Median split spillovers

| ln(Markup)                                    | Average effect   |                    | Direct & indirect effect |                    |
|-----------------------------------------------|------------------|--------------------|--------------------------|--------------------|
|                                               | (1)              | (2)                | (3)                      | (4)                |
| Spillovers                                    | <50%             | >50%               | <50%                     | >50%               |
| $1_{(MHHI\delta > 0)}$                        | 0.009<br>(0.013) | 0.031**<br>(0.014) |                          |                    |
| $1_{(MHHI\delta > 0)} \times \text{Insider}$  |                  |                    | -0.001<br>(0.021)        | 0.031<br>(0.041)   |
| $1_{(MHHI\delta > 0)} \times \text{Outsider}$ |                  |                    | 0.009<br>(0.013)         | 0.031**<br>(0.014) |
| Post                                          | 0.001<br>(0.012) | -0.024*<br>(0.012) | 0.001<br>(0.012)         | -0.024*<br>(0.012) |
| Firm FE                                       | Yes              | Yes                | Yes                      | Yes                |
| Year FE                                       | Yes              | Yes                | Yes                      | Yes                |
| Adj. $R^2$                                    | 0.96             | 0.93               | 0.96                     | 0.93               |
| N                                             | 3041             | 2894               | 3041                     | 2894               |
| Market clusters                               | 150              | 132                | 150                      | 132                |

*Note:* Standard errors in parentheses and clustered at the three-digit industry-country level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market.

Table 1.26: Difference-in-differences: Innovation - Median split spillovers

| ln(Patent Citations)                        | Average effect      |                   | Direct & indirect effect |                   |
|---------------------------------------------|---------------------|-------------------|--------------------------|-------------------|
|                                             | (1)                 | (2)               | (3)                      | (4)               |
| Spillovers                                  | <50%                | >50%              | <50%                     | >50%              |
| $1_{(MHHI\delta>0)}$                        | -0.133**<br>(0.057) | -0.063<br>(0.061) |                          |                   |
| $1_{(MHHI\delta>0)} \times \text{Insider}$  |                     |                   | -0.016<br>(0.054)        | 0.085<br>(0.058)  |
| $1_{(MHHI\delta>0)} \times \text{Outsider}$ |                     |                   | -0.140**<br>(0.058)      | -0.074<br>(0.063) |
| Post                                        | 0.143***<br>(0.048) | 0.038<br>(0.038)  | 0.143***<br>(0.048)      | 0.038<br>(0.037)  |
| Firm FE                                     | Yes                 | Yes               | Yes                      | Yes               |
| Year FE                                     | Yes                 | Yes               | Yes                      | Yes               |
| Adj. $R^2$                                  | 0.62                | 0.77              | 0.62                     | 0.77              |
| N                                           | 3041                | 2894              | 3041                     | 2894              |
| Market clusters                             | 150                 | 132               | 150                      | 132               |

*Note:* Standard errors in parentheses and clustered at the three-digit industry-country level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market.

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# Declaration of Contribution

Hereby I, Alexandra Jennifer Gibbon, declare that the chapter “Rising Markups, Common Ownership, and Technological Capacities” is coauthored with Jan Philip Schain. All authors contributed equally to the chapter.

Signature of coauthor (Jan Philip Schain): \_\_\_\_\_

Dr. Jan Philip Schain



## Chapter 2

# Falling Markups, Rising Costs: German Manufacturing During the 2008 Financial Crisis

## 2.1 Introduction

In recent years, both the US and Europe have seen a rise in firms’ market power and a reallocation of market shares towards firms with the highest markups (De Loecker et al., 2020; De Loecker and Eeckhout, 2021; Ganapati, 2021; Döpper et al., 2025). This shift has been accompanied by a growing concentration of sales among the most productive firms. These firms tend to have high markups and a low share of labour in value added, which contributes to increasingly concentrated markets (Autor et al., 2020). Although these trends are well documented, their drivers remain partially unclear. Simultaneously, the years after the Great Recession of 2008 have been marked by a slowdown in globalisation, coined *slowbalisation*, with trade flows and global value chain expansion decelerating (The Economist, 2019; Antràs, 2020; Goldberg and Reed, 2023). Again, drivers are not fully understood. Together, these developments raise concerns about their broader implications for industry dynamics.

This study investigates the role of a large-scale demand shock in the context of rising market power and the onset of slowbalisation. The 2008 financial crisis is a salient example, widely viewed as a demand shock that spilled into global trade patterns (Bems et al., 2010; Bricongne et al., 2012; Chor and Manova, 2012). Between the third quarter of 2008 and the first quarter of 2009, worldwide GDP contracted by about 3 percent, while total world trade suffered a much stronger decline of 30 percent (Levchenko et al., 2010; Amiti and Weinstein, 2011; Bricongne et al., 2012; Eaton et al., 2016). Such downturns can substantially change firms’ pricing strategies, production decisions, and investment plans. I study how demand shocks affect product-market outcomes and firm performance by examining German manufacturing firms’ responses to the 2008 financial crisis. This setting is particularly relevant for studying micro-level adjustments to crisis conditions: the manufacturing sector accounted for the majority of global trade in 2007 (Eaton et al., 2016), and Germany has long been a leading export-oriented economy and key player in global manufacturing.

I use a comprehensive administrative dataset on the German manufacturing sector to study the impact of the financial crisis. The *Amtliche Firmendaten für Deutschland* (AFiD) database spans the full universe of German manufacturing firms with more than 20 employees and provides annual company and product data for the period 2003 to 2016. The rich price and quantity information at the eight-digit product level allows me to apply the method by De Loecker et al. (2016) to recover estimates of firm-product-level markups, marginal costs, and firm-level total factor productivity (TFP) under the assumption of cost minimisation. Specifically, I estimate a translog production function for single-product firms. After recovering input allocation shares for multi-product firms, I calculate product-level price-cost markups for all firms as the wedge between the output elasticity and the revenue share of a variable input. Firm-product-level marginal costs are defined as the ratio of observed prices to markups. The procedure relies on a quantity-based production function and addresses several common issues in production function estimation, including selection bias, simultaneity bias, input price bias, and unobserved input



allocation.

To construct the primary variable of interest, I combine the production data with information on global trade flows. I adopt the measure proposed by Aghion et al. (2021), which uses changes in actual trade patterns as a proxy for the short-term demand shock from the 2008 financial crisis. Using UN Comtrade data on German exports at the six-digit product level, I calculate crisis exposure as the log difference between average export quantities in 2008 and 2009 (during the crisis period) and in 2006 and 2007 (during the pre-crisis period).

Based on the distribution of these export changes, I construct a binary treatment variable at the firm and product-category level. Product categories in the bottom quarter of the export change distribution, those with the largest export declines, are classified as treated. A whole firm is considered treated if it produced at least one such product in either 2006 or 2007. The control group consists of firms that never produced any items in the treated six-digit categories from 2006 onwards. As the baseline specification, I estimate a dynamic difference-in-differences model by interacting the treatment indicator with year-fixed effects. For administrative reasons, part of the information in the AFiD database is only reported for a rotating subsample of 40 percent of firms. I account for the sampling design by weighting observations with their inverse sampling probability.

The treated firms' products show persistent micro-level effects of the financial crisis: markups decline, while marginal costs increase and prices remain flat. Exposed products display a gradual, ongoing decline in markups relative to the control group's products. The largest drop occurred in 2013 at 18.3 percent. Upon examining the two components of the price-cost markup, I find that prices remain largely unchanged, while marginal costs increase significantly. Analogously to the effect on markups, the largest increase in marginal costs also materialised in 2013 at 22.1 percent. Average effects from canonical two-way difference-in-differences regressions using all years after 2007 as the post period are -10.2 percent for markups and 12.4 percent for marginal costs.

I consider three channels to investigate potential mechanisms behind rising marginal costs: changes in output, TFP, and factor prices (Stiebale and Vencappa, 2018, with theoretical foundations by Hallak and Sivadasan, 2013, and Antoniadou, 2015). I observe output quantities and TFP directly, and use data on employment and average wages to examine labour as an input. All four regressions show negative effects following the financial crisis. Decreasing wages, therefore, do not seem to be driving the increase in marginal costs, while a decrease in TFP is generally consistent with higher costs (Syverson, 2019). An average negative effect of -11.9% on quantities is consistent with a substantial negative demand shock and the globally observed output decline. Still, further analysis of scale economies does not unambiguously identify them as the sole driver: I explore industry-level sunk costs as a proxy (Davies and Lyons, 1996), but find no evidence of effect heterogeneity. Taken together, the results indicate that the rise in marginal costs reflects a combination of several contributing factors rather than a single

underlying cause.

I further examine the within-firm dynamics of treated firms' additional products that do not face large export declines. These indirectly affected products also exhibit falling markups and rising marginal costs. The pattern suggests within-firm spillovers of the negative impact and a loss of economies of scope. Additionally, I study several other margins of heterogeneity. The effects on markups and marginal costs are stronger for products that rely strongly on intermediate inputs and for those that enter as inputs in the production of many sectors, as measured by Acemoglu et al. (2012). I do not find statistically significant differences for firms' non-core products (Eckel et al., 2016) or for multi-product firms.

The key identification assumption in the analysis above is that, after controlling for fixed effects, the financial crisis measure is uncorrelated with unobservables that affect within-firm-product variation in outcome variables. The plausibility is supported by the unexpected rise and sharp fall in housing prices, which led to the collapse of the US subprime mortgage industry in 2007 and ultimately the failure of major financial institutions in 2008. The housing boom and the subsequent, unusually severe financial crisis were generally unforeseen, even by managers in securitised finance (Cheng et al., 2014); default risks of subprime mortgages were under-predicted by statistical models (Rajan et al., 2015). According to Aghion et al. (2021), the export-based measure likely reflects global demand fluctuations rather than country or industry-specific supply conditions. The authors argue that firms engaged in exporting prior to the crisis were directly exposed to the collapse in international demand. Consistent with this interpretation, estimated effects are more pronounced for these firms, supporting the measure's validity in capturing exposure to the crisis.

I conduct several additional robustness checks that all further support my strategy. The specifications include alternative ways to calculate the outcomes and the treatment variable. I use multiple approaches to estimate markups: using a Cobb-Douglas specification to recover intermediate input elasticities, alternative input shares to allocate inputs to the product level, and firm-level markup estimation with a corresponding firm-level treatment variable based on a weighted average export shock. To assess the robustness of the treatment variable, I adjust the treatment status cutoff to the 20th or 30th percentile and also construct an analogous export change measure using monetary values in Euros. Further successful checks include placebo timing of the crisis, fixed effects of different granularity, clustering standard errors at a higher level of aggregation, and omitting sampling weights. I also apply propensity score weighting and matching on pre-crisis characteristics.

By linking a large-scale demand shock to firm-product markups and marginal costs, this paper contributes to the literature in three ways. First, using detailed production and trade data, I document that micro-level effects did not fade quickly but persisted for more than five years after the crisis. Second, I decompose marginal cost changes into quantity, productivity, and input price components to analyse how economic shocks materialise in individual firms.

Third, I uncover within-firm spillovers and stronger effects for products more embedded in vertical production networks, providing new evidence on the propagation of global demand shocks. By treating multi-product firms explicitly, the study provides granular evidence on how these micro patterns connect to aggregate outcomes, such as markup cyclicity.

**Related Literature** This paper is closely related to a large literature on the causes, mechanisms, and consequences of the Great Recession. Existing research recognises the critical role of financial crises for firm performance and competition. García-Perea et al. (2021) show that markups rose during the financial crisis, driven by small and less productive firms with rising average costs. Gilchrist et al. (2017) find a countercyclical increase in US markups for financially constrained firms, while financially strong firms lowered markups. Evidence for Germany is mixed: aggregate firm-level markups rise in Meinen and Soares (2020), whereas Weche and Wambach (2021) and Ganglmair et al. (2020) find a small negative impact of the financial crisis on German markups. For Austria, Gugler et al. (2015) find a decrease of average markups in auction markets.

A separate strand studies the international transmission of the crisis. Levchenko et al. (2010) show that sectors used intensely as intermediate inputs experience larger reductions in imports and exports during the trade collapse. In Antràs and Foley (2015), the authors discuss how the financial crisis, as a liquidity shock and demand decline, interacts with the terms of international trade financing. Alfaro and Chen (2012) find that foreign ownership helped international subsidiaries stay more resilient. Further work on firm resilience by Aghion et al. (2021) develops a measure of crisis exposure based on global export data, which forms the basis for the treatment variable I use in this study. The authors study firms' internal organisation and resulting resilience during the crisis. Gupta (2026) uses the same shock measure and provides evidence that firms investing in R&D outperformed non-innovative firms following the financial crisis.

Another body of work focuses on productivity effects and finds a broadly consistent pattern. Duval et al. (2020) study the post-crisis productivity slowdown and show that firms with greater financial frictions exhibit lower total factor productivity because of reduced investment in intangible capital. Similar declines in TFP are found by Christiano et al. (2015). Foster et al. (2016) document that the Great Recession had unusually low levels of reallocation, which did not generate the typical productivity gains seen in earlier downturns. Moreover, Giroud and Mueller (2017) identify highly levered firms as less productive. Dieppe et al. (2021) find that demand-driven, non-technological shocks account for the majority of the decline in productivity growth since the financial crisis. Related evidence in Manaresi and Pierri (2024) shows that productivity declined persistently because of credit supply shocks. My findings of persistent TFP declines align with this general pattern.

A broader debate concerns the cyclical behaviour of markups throughout the business cycle

(Bils, 1987; Rotemberg and Woodford, 1991, 1999; Chevalier and Scharfstein, 1995, 1996; Wilson and Reynolds, 2005; Hall, 2010; Nekarda and Ramey, 2020; Anderson et al., 2025). My paper adds to the discussion by showing that markups respond in a cyclical way, as the markups of most affected product categories decline in response to the financial crisis as a negative economic shock.

This paper is also closely related to the literature on rising market power. A growing body of empirical work documents this global phenomenon and investigates its potential causes. The seminal study by De Loecker et al. (2020) shows rising aggregate markups from 1980 to recent years, characterised by stronger growth in the upper percentiles of the markup distribution and a reallocation of market shares towards high-markup firms. Within the US, consistent findings of rising markups appear across datasets and methods, including the production approach using financial report data (De Loecker and Eeckhout, 2021; Conlon et al., 2023) and the demand-side approach using household scanner data (Döppler et al., 2025; Atalay et al., 2025).

Across Europe, average markups appear relatively stable over time, although the upper percentiles still exhibit sharper increases (De Loecker et al., 2018; Gradzewicz and Mućk, 2024; Cavalleri et al., 2020; Gibbon and Schain, 2023). German evidence is limited, with Wambach and Weche (2020) and Weche and Wagner (2021) reporting steady average markup estimates but substantial heterogeneity across industries. A small group of studies uses the present German administrative firm data to estimate labour market power and firm-level markups (Mertens, 2020, 2022; Weche and Wagner, 2021) as well as aggregate revenue productivity and industry concentration (Mertens and Müller, 2022; Bighelli et al., 2023). To my knowledge, no study recovers markups at the firm-product level for Germany.

Several drivers of rising markups have been investigated, for example, changes in marginal cost and less elastic consumer demand (Döppler et al., 2025; Brand, 2021; Atalay et al., 2025), economies of scale and distribution network expansion (Ganapati, 2025), technological innovation (Miller et al., 2023), and common ownership (Gibbon and Schain, 2023). With the exception of Grieco et al. (2024), who show that US automobile markups declined over time in the US, most studies focus on forces behind the observed increase. Conversely, my paper characterises firms and products that do not contribute to the lasting rise in markups—those hit severely by the 2008 financial crisis.

This paper also specifically relates to the literature on markups of multi-product firms, drawing on methodological insights and complementing applied studies. I use the estimation procedure for physical TFP and firm-product-level markups developed by De Loecker et al. (2016), which has motivated further methodological work on multi-product firms' productivity and markups (Orr, 2022; Dhyne et al., 2026; Cairncross et al., 2025). In their original application, De Loecker et al. (2016) examine the impact of trade liberalisation in India. Later studies focus, for example, on exchange rate fluctuations in Mexico (Caselli et al., 2017), acquisitions also on Indian manufacturing data (Stiebale and Vencappa, 2018), or export entry in Chile,

Colombia, and Mexico (Garcia-Marin and Voigtländer, 2019). In contrast, I study the 2008 financial crisis as a large demand shock on firm-product-level markups in a major German sector.

The remainder of this article is organised in the following way. Section 2.2 gives an overview of the data sources as well as the production function and markup estimation. In Section 2.3, I describe the empirical strategy. The empirical results are presented in Section 2.4. Section 2.5 explores potential mechanisms and robustness checks follow in Section 2.6. Section 2.7 concludes.

## 2.2 Data and Markup Estimation

This section describes the data and the construction of firm-product markups. Section 2.2.1 introduces the two data sources used in the analysis: administrative data on German manufacturing firms and German export data from Comtrade. In Section 2.2.2, I describe the De Loecker et al. (2016) production function and markup estimation procedure.

### 2.2.1 Data

**Administrative firm and product data.** As my main data source, I use the Amtliche Firmendaten für Deutschland (AFiD). The administrative data on German manufacturing firms are supplied by Research Data Centre of the Federal Statistical Office and Statistical Offices of the Federal States of Germany (2025). Given Germany’s status as a world-leading, export-oriented economy and key player in manufacturing, the annual panel is a valuable source for researchers. It consists of two linked modules: one with firm-level information, similar to financial reports, and another with a firm-product-level production survey.<sup>1</sup>

The first module provides annual information from 2003 to 2016 on the main industry, sales, employment, wages and salaries, cost structures, and investment of manufacturing firms with at least 20 employees. These variables are essential for estimating productivity and markups (De Loecker and Warzynski, 2012; Akerberg et al., 2015). The information is reported by owners or management and covers the entire legally independent enterprise, including producing and non-producing units, but excluding branches abroad. Some variables, such as expenditures on intermediate inputs and full-time equivalent employment, are only recorded for a rotating subsample to reduce administrative burden. The subsample alternates periodically and includes approximately 40% of surveyed firms. The stratification by industry and size can be reconstructed following Mertens (2020), which allows me to use inverse probability weighting in the

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<sup>1</sup>The sources for the raw datasets are: Research Data Centre (RDC) of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0; 10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0; 10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0. All results presented in this study are based on my own calculations.

regression analysis.

The second module is a firm-product panel with quarterly production sales values and quantities produced for sales and for further processing. The production sales value is determined by the firm and, regardless of whether a sale took place, reflects the attainable or realised price at the time of the sale. I calculate the average price per product, or unit value, by dividing production sales values by the quantities produced. Products, or rather product groups, are classified using the eight-digit Product Classification for Production Statistics (GP, *Güterverzeichnis für Produktionsstatistiken*) in combination with a unit of measurement. The module is a full census of all manufacturing firms with more than 20 employees. Among other purposes, the production data is used in the official calculations of German national accounts and input-output tables. It is ideal for the approach by De Loecker et al. (2016) for estimating markups of multi-product firms, as described in Section 2.2.2 below.

Most of the data preparation follows the approach in Mertens (2020). The detailed eight-digit product codes are based on the 2002, 2009, or 2012 version of the GP classification. The reclassification from GP09 to GP09V2 affects observations from 2012 to 2016 and is unambiguous; therefore, it is straightforward to reverse these codes to GP09 using concordance tables. The conversion from GP02 to GP09 for the years 2003 to 2008 is more complex. Some product codes map directly to a single new code, while others are split or consolidated. Following Mertens (2020), I consider the most plausible GP09 code to be the one that remains in the firm’s product portfolio after the classification change. When multiple GP09 codes correspond to the same GP02 code within a firm, there is no exact eight-digit match. If all candidate GP09 codes share the same first part, however, I can still determine the new four, three, or two-digit industry code. As each product is labelled with up to three measurement units, consolidated product codes may still have different measurement units. I select the unit most frequently assigned for each product code. Although only a small share of products is affected by inexact matches, this ambiguity prevents the analysis of changes in a firm’s product mix, as product exit may or may not stem from reclassification.

I deflate monetary values with two-digit industry deflators from the German Federal Statistical Office. The AFiD data contain firms’ investment values but no information on capital stock. I approximate capital stock using a perpetual inventory method (Mueller, 2008; Bräuer et al., 2023; Mertens, 2020). I also construct a firm-specific price index as in Mertens (2020), to remove price-driven variation from firms’ revenues, which I use in firm-level production function estimation. The index is the product of individual product price growth, weighted by each product’s sales shares in the current and previous year.

**Export data.** I complement the main firm-product panel with trade flow data from the United Nations Commodity Trade Statistics Database (UN Comtrade, United Nations Statistics Division 2025). UN Comtrade provides standardised official trade statistics, including

international bilateral import and export data at the six-digit product level based on the Harmonized Commodity Description and Coding System of tariff nomenclature (HS). I use data on the values and quantities of goods traded between Germany and the rest of the world, covering around 5,000 HS product codes.

The Harmonised System classification was revised from HS2 (2002) to HS3 (2007) between 2006 and 2009, affecting the data used in my analysis. Using a concordance by Pierce and Schott (2012b), I map HS2 into HS3. Because some product categories are split, while others are consolidated, the unit of quantity is not always consistent across product categories. In such cases, I use the additional UN Comtrade variable reporting quantities in net weight kilograms, provided the unit is available for most observations within a six-digit class. If kilograms are not the most common unit, I use the predominant alternative unit.

Merging the UN Comtrade data with the AFiD dataset on firm-product codes requires converting the six-digit HS 2007 codes to six-digit GP codes. After linking the datasets, I use the annual world export quantities from Germany to construct a six-digit product-level measure of the 2008 financial crisis demand shock. The degree of exposure to export changes is the foundation for my main variable of interest, as described in detail in Section 2.3.1.

## 2.2.2 Production Function and Markup Estimation

In the following section, I describe the construction of my main outcome variable, the firm-product-specific price-cost markup. I use the procedure for production function estimation by De Loecker et al. (2016), which is particularly suitable for multi-product firms and the detailed production data at hand. The approach builds on the standard literature on the estimation of production functions that addresses the endogeneity of inputs (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Akerberg et al., 2015).

Firm  $f$  produces a discrete number  $J_{ft}$  of products in period  $t$ . A production technology is the same for single-product and multi-product firms, such that the production function  $F(\cdot)$  varies by product  $j$ , but not by firm. The firm-product level production function is

$$Q_{fjt} = F_j(K_{fjt}, L_{fjt}, M_{fjt})\Omega_{ft},$$

with physical output  $Q_{fjt}$ , capital stock  $K_{fjt}$ , labour inputs  $L_{fjt}$  and intermediate inputs  $M_{fjt}$ . Log-additive Hicks-neutral total factor productivity  $\Omega_{ft}$  is inherent to the firm and does not vary across products for multi-product firms.

Following De Loecker and Warzynski (2012), it is possible to recover a firm-level average multiplicative markup  $\mu = \frac{P}{MC}$ . The measure is derived from the first-order condition of the firm's cost-minimisation problem and from estimated output elasticities, assuming that at least one static input exists for which firms are price-takers. De Loecker et al. (2016) define the

analogue for firm-product markups under product-by-product cost minimisation as

$$\mu_{fjt} = \left( \frac{P_{fjt} Q_{fjt}}{W_{fjt}^M M_{fjt}} \right) \frac{\partial Q_{fjt}(\cdot)}{\partial M_{fjt}} \frac{M_{fjt}}{Q_{fjt}} = \frac{\theta_{fjt}^M}{\alpha_{fjt}^M}, \quad (2.1)$$

where  $P_{fjt}$  is the output price,  $W_{fjt}^M$  is the price of flexible input  $M_{fjt}$ ,  $\theta_{fjt}^M$  is the output elasticity with respect to  $M_{fjt}$  from the production function estimation.  $\alpha_{fjt}^M$  is the share of firm-level input expenditure on  $M_{fjt}$  allocated to product  $j$  relative to the product's revenue.

Consider the production function in logarithms with log-additive error  $\epsilon_{fjt}$ ,

$$q_{fjt} = f_j(\mathbf{x}_{fjt}; \beta) + \omega_{ft} + \epsilon_{fjt}, \quad (2.2)$$

which relies on logged physical inputs  $\mathbf{x}_{fjt}$  (capital  $k_{fjt}$ , labour  $l_{fjt}$ , and intermediate inputs  $m_{fjt}$ ). Concretely, I assume a translog production function, because it provides flexible output elasticities over time and across firms:

$$\begin{aligned} f_j(\mathbf{x}_{fjt}; \beta) = & \beta_l l_{fjt} + \beta_m m_{fjt} + \beta_k k_{fjt} + \beta_{lm} l_{fjt} m_{fjt} + \beta_{lk} l_{fjt} k_{fjt} + \beta_{mk} m_{fjt} k_{fjt} \\ & + \beta_{ll} l_{fjt}^2 + \beta_{mm} m_{fjt}^2 + \beta_{kk} k_{fjt}^2 + \beta_{lmk} l_{fjt} m_{fjt} k_{fjt}, \end{aligned}$$

with the translog output elasticity for intermediate inputs

$$\theta_{fjt}^M = \beta_m + \beta_{lm} l_{fjt} + \beta_{mk} k_{fjt} + 2\beta_{mm} m_{fjt} + \beta_{lmk} l_{fjt} k_{fjt}.$$

The markup is calculated as the wedge between the output elasticity of intermediate inputs and its revenue share. The wedge is equal to one only under perfect competition. Otherwise, it reflects the extent of market power that the firm can exert by setting prices above marginal costs. The empirical counterpart to the markup formula in Equation (2.1) is

$$\hat{\mu}_{fjt} = \hat{\theta}_{fjt}^M \frac{P_{fjt} Q_{fjt}}{\exp(\hat{\rho}_{fjt}) \tilde{X}_{ft}^M} \quad (2.3)$$

where  $\hat{\theta}_{fjt}^M$  is the estimated output elasticity with respect to intermediate inputs,  $\exp(\hat{\rho}_{fjt})$  is firm  $f$ 's estimated input allocation share for product  $j$ ,  $\tilde{X}_{ft}^M$  represents the observed intermediate input expenditures of the firm, and  $P_{fjt}$  and  $Q_{fjt}$  are observed prices and quantities. Firm-product-level marginal costs are the ratio of the price  $P_{fjt}$  to the estimated markup  $\hat{\mu}_{fjt}$ . I describe the necessary steps to estimate  $\hat{\beta}$  and  $\exp(\hat{\rho}_{fjt})$  further below.

To infer output elasticities, I estimate the De Loecker et al. (2016) model using the one-step GMM estimator by Wooldridge (2009). I estimate production functions separately for groups of two-digit industries<sup>2</sup> to allow for industry-specific technologies and input prices, using firms

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<sup>2</sup>I group the following NACE two-digit industries together: 10, 11, 12 Food, beverages, tobacco; 13, 14, 15 Textiles, wearing apparel, leather; 16, 17 Wood, paper; 19, 21 Coke, chemicals, pharmaceuticals; 22, 23 Rubber,



observed for at least three consecutive years. The resulting markup and marginal cost estimates vary by firm, eight-digit product, and year combination.

The procedure by De Loecker et al. (2016) addresses several biases that arise in production function estimation. Price, simultaneity, and selection biases are well-known challenges when estimating production functions on firm-level data. Most datasets contain firm-level input expenditures, which are commonly deflated using industry-specific indices. Multi-product firm data introduces two additional sources of bias: unknown input allocations across products and unknown input prices. Concretely, the two biases enter the production function in Equation (2.2) as additional terms  $A(\cdot)$  and  $B(\cdot)$ , such that

$$q_{fjt} = f_j(\tilde{\mathbf{x}}_{ft}; \boldsymbol{\beta}) + A(\rho_{fjt}, \tilde{\mathbf{x}}_{ft}, \boldsymbol{\beta}) + B(\mathbf{w}_{fjt}, \rho_{fjt}, \tilde{\mathbf{x}}_{ft}, \boldsymbol{\beta}) + \omega_{ft} + \epsilon_{fjt}, \quad (2.4)$$

where  $\tilde{\mathbf{x}}_{ft}$  are observed deflated input expenditures,  $\rho_{fjt}$  are input allocation shares, and  $\mathbf{w}_{ft}$  are unobserved firm-product-specific input prices. I discuss the treatment of the biases and the underlying assumptions in detail below.

**Output price bias.** Physical output quantities  $q_{fjt}$  mitigate the output price bias, which commonly arises in firm-level studies when output values are obtained by deflating revenues with an industry-level price index (Foster et al., 2008; De Loecker, 2011; Bond et al., 2021).

**Unobserved input allocation.** The bias from unobserved input allocations within multi-product firms is the term  $A(\cdot)$  in Equation (2.4). I restrict the estimation sample to single-product firms as in De Loecker et al. (2016). The approach removes the allocation-bias term  $A(\cdot)$  when estimating the production function parameters  $\boldsymbol{\beta}$  by assuming that such firms use the same technology as a single-product firm producing the same product. The same assumption is implicitly made in firm-level estimation approaches. I recover the input shares for multi-product firms later using parameters  $\boldsymbol{\beta}$ . For single-product firms,  $\rho_{fjt} = 1$  because the inputs are fully allocated to one product; therefore,  $A(\cdot) = 0$ . Equation (2.4) then becomes

$$q_{ft} = f(\tilde{\mathbf{x}}_{ft}; \boldsymbol{\beta}) + B(\mathbf{w}_{ft}, \tilde{\mathbf{x}}_{ft}, \boldsymbol{\beta}) + \omega_{ft} + \epsilon_{ft}. \quad (2.5)$$

**Selection bias.** Restricting the estimation sample to single-product firms may introduce selection bias if the productivity threshold influencing a firm's decision to produce multiple products correlates with capital or labour. Therefore, I follow De Loecker et al. (2016) and apply a selection correction procedure in two steps. First, I predict  $SP_{ft}$ , the probability of remaining a single-product firm in period  $t$ , using variables from period  $t-1$ . I estimate a Probit model and include inputs and their higher-order and interaction terms, output prices, market

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plastic, minerals; 24, 25 Basic and fabricated metals; 26, 27 Computer, electronic, electrical equipment; 28, 29, 30 Machinery, motor, transport; 31, 32 Furniture, other manufacturing.

shares, export status and R&D status as well as year, state, and industry dummies. Second, I include the probability of remaining a single-product firm in the productivity law of motion described in Equation (2.8) below. The selection correction assumes that the introduction of an additional product is determined in the preceding time period.

**Input price bias.** Inputs are typically reported as deflated expenditures, while input prices are unobserved. I flexibly model input prices for each product category using a control function as proposed by De Loecker et al. (2016). Input prices may vary across firms for several reasons. First, based on assumptions by Khandelwal (2010), high-quality products require high-quality inputs, which are associated with higher prices.<sup>3</sup> I include output prices, market shares and product and unit dummies to proxy for output quality. Controlling for unobserved input quality allows for both horizontal and vertical product differentiation. The control function approach accommodates a broad range of demand models and is consistent with any degree of pass-through. Second, firm location, captured by federal state dummies, accounts for geographic variation in input prices. Finally, I include the firms' export status to reflect different demand conditions among trade partners and the general positive relationship between exporting and product quality (Hallak and Sivadasan, 2013; Bas and Strauss-Kahn, 2015; Fan et al., 2015). The input control function then enters the production function as the expression for  $\mathbf{w}_{ft}$  in term  $B(\mathbf{w}_{ft}, \tilde{\mathbf{x}}_{ft}, \beta)$  in Equation (2.5), such that

$$B(\mathbf{w}_{ft}, \tilde{\mathbf{x}}_{ft}, \beta) = B((p_{ft}, \mathbf{ms}_{ft}, \mathbf{D}_f, \mathbf{G}_f, EXP_{ft}) \times \tilde{\mathbf{x}}_{ft}; \beta, \delta), \quad (2.6)$$

with output prices  $p_{ft}$ , market shares  $\mathbf{ms}_{ft}$ , product dummies  $\mathbf{D}_f$ , firm location  $\mathbf{G}_f$ , and export status  $EXP_{ft}$ . The De Loecker et al. (2016) procedure jointly identifies both sets of coefficients  $\delta$ , of the input price control function, and  $\beta$ , of the production function.

**Simultaneity bias.** The simultaneity problem from the correlation between unobserved TFP and the production inputs is well known (see, e.g., Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Akerberg et al., 2015). The most common solution involves inverting an input demand equation for materials or intermediate inputs to proxy for productivity. Intermediate input demand depends on labour, capital, TFP, and other state variables,

$$\tilde{m}_{ft} = m_t(\omega_{ft}, \tilde{k}_{ft}, \tilde{l}_{ft}, \underbrace{p_{ft}, \mathbf{ms}_{ft}, \mathbf{D}_f, \mathbf{G}_f, EXP_{ft}}_{\mathbf{c}_{ft}}), \quad (2.7)$$

where  $\omega_{ft}$  is unobserved productivity,  $\tilde{k}_{ft}$  and  $\tilde{l}_{ft}$  are deflated capital and labour expenditures, and  $\mathbf{c}_{ft}$  includes output prices  $p_{ft}$ , market shares  $\mathbf{ms}_{ft}$ , product dummies  $\mathbf{D}_f$ , firm location

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<sup>3</sup>This relationship is well documented in the trade literature, see, e.g., Verhoogen (2008); Kugler and Verhoogen (2012); Manova and Zhang (2012).

$\mathbf{G}_f$ , and export status  $EXP_{ft}$ . Inverting the intermediate input demand function yields the control function for firm  $f$ 's productivity at time  $t$ , such that productivity can be represented as a function of inputs and the other state variables.

Following standard practice (e.g. Akerberg et al., 2015; De Loecker et al., 2016), I model the serial correlation of productivity as a controlled first-order Markov process. I include treatment dummies for products directly ( $Treat_m \times Post_t$ ) and indirectly ( $Indirect_{fm} \times Post_t$ ) affected by the financial crisis as well as the the strength ( $ExportChange_m \times Post_t$ ; see Section 2.3.1 for details on these variables) in the productivity law of motion, allowing the financial crisis to influence productivity endogenously:

$$\omega_{ft} = g(\omega_{ft-1}, Treat_m \times Post_t, Indirect_{fm} \times Post_t, ExportChange_m \times Post_t, EXP_{ft-1}, SP_{ft}) + \xi_{ft}. \quad (2.8)$$

Including a firm's export status  $EXP_{ft-1}$  accounts for potential learning-by-exporting effects (De Loecker, 2013).  $SP_{ft}$  denotes the selection correction for the propensity to remain a single-product firm, as described above, and  $\xi_{ft}$  is the innovation in productivity. I then substitute the input price control function and the inverted intermediate input demand function into Equation (2.5), such that

$$q_{ft} = \phi_t(\tilde{\mathbf{x}}_{ft}, \mathbf{c}_{ft}) + \epsilon_{ft}, \quad (2.9)$$

where  $\mathbf{c}_{ft}$  contains all variables that influence intermediate input demand besides input expenditures and unobserved productivity.  $\phi_t = f(\tilde{\mathbf{x}}_{ft}; \beta) + B(\mathbf{w}_{ft}, \tilde{\mathbf{x}}_{ft}, \beta) + \omega_{ft}$  reflects output net of noise. I obtain productivity as the difference between predicted output from the first stage estimation of Equation (2.9) and the production function and input price function:

$$\omega_{ft}(\beta, \delta) = \hat{\phi}_{ft} - f(\tilde{\mathbf{x}}_{ft}; \beta) - B((p_{ft}, \mathbf{ms}_{ft}, \mathbf{D}_f, \mathbf{G}_f, EXP_{ft}) \times \tilde{\mathbf{x}}_{ft}; \beta, \delta). \quad (2.10)$$

I construct moment conditions to identify the production function parameters  $\beta$  and input price parameters  $\delta$  based on the innovation in productivity,  $\xi_{ft}$  in Equation (2.8), where

$$\begin{aligned} \xi_{ft}(\beta, \delta) = & \omega_{ft}(\beta, \delta) \\ & - E(\omega_{ft}(\beta, \delta) | \omega_{ft-1}(\beta, \delta), Treat_{mt-1}, Indirect_{ft-1}, EXP_{ft-1}, SP_{ft}). \end{aligned} \quad (2.11)$$

The moment conditions are  $E(\xi_{ft}(\beta, \delta) Z_{ft}) = 0$ . To identify production function parameters  $\beta$  for German firms, I treat capital and labour as dynamic inputs that face adjustment costs, and consider intermediate inputs as flexible and freely adjustable.  $Z_{ft}$  therefore contains current values of capital and labour, lagged values of intermediate inputs, their higher orders and interactions as in the production function and the instruments for the joint identification of the production function and input price parameters. These include lagged output prices, lagged

market shares, their interactions with inputs, and the treatment variables.

**Input shares.** With the production function coefficients  $\hat{\beta}$  in hand, I recover input allocation shares  $\exp(\rho_{fjt})$  as the final step before constructing markups (see Equation (2.3)). Following De Loecker et al. (2016), I assume inputs are allocated exclusively and exhaustively across products in non-joint production, and multi-product firms are equally productive across all products. These assumptions allow recovering input allocations across products without restricting productivity differences between single- and multi-product firms, only within-firm differences. Even in highly detailed product-level datasets, information on input distribution across products is typically unavailable. Using  $\hat{\beta}$ , I compute firm-level productivity  $\hat{\omega}_{ft}$  and input allocation shares  $\hat{\rho}_{fjt}$  for multi-product firms: the procedure numerically solves a system of equations for all products a firm produces in a year, with input allocation parameters constrained to sum to one per firm-year. As recent studies highlight that weighting choices matter and that the approach can yield many small shares (Cairncross et al., 2025), I conduct a robustness check that incorporates revenue shares as an alternative allocation under the assumption of CES demand, which I further describe in Section 2.6.

Given the production data for eight-digit product categories, the supply-side approach to estimating markups is a natural choice. The quantity and price information permits the estimation of product-level markups using the De Loecker et al. (2016) method for a broad range of industries. The data allows me to disentangle the markup estimate into observed prices and the marginal cost and study possible within-firm mechanisms of markup reallocation in more detail. The production approach by De Loecker et al. (2016) does not require information on consumer behaviour or impose assumptions about the demand system or market conduct, as is necessary for demand-based approaches that rely on, for example, retail scanner data. These approaches allow even finer product definitions, but are far more demanding to estimate for a large number of product categories and require information on product sales or transactions (see e.g. Döpper et al., 2025).

In two consistency checks, I find evidence of increasing returns to scale and core competencies similar to De Loecker et al. (2016). First, the results from correlational regressions that include a set of product-unit-year fixed effects show an inverse relationship between marginal costs and quantities and a positive association between markups and quantities. This is in line with firms producing more output having higher markups because of lower marginal costs. Second, I regress markups and marginal costs on the sales share and fixed effects. Again, the correlation is positive for markups and negative for marginal costs. This is consistent with predictions in the multi-product trade literature: in these models, a firm’s core product has the highest markup and the lowest marginal cost (Eckel and Neary, 2010; Melitz and Ottaviano, 2008; Mayer et al., 2014). Empirical studies commonly characterise the product with the highest sales share as

the core competency (Goldberg et al., 2010; Bernard et al., 2010; Manova and Yu, 2017; Eckel et al., 2015, 2016).

## 2.3 Empirical Strategy

The following section describes the empirical strategy. In Section 2.3.1, I introduce the treatment variable for strong exposure to the financial crisis and the construction of the treatment and control groups. Section 2.3.2 describes the event study methodology for estimating product market effects and Section 2.3.3 briefly discusses the identifying assumptions.

### 2.3.1 Construction of Financial Crisis Treatment Variable

With the main variable of interest, I aim to capture the impact of the 2008 financial crisis on product markets  $m$ . I construct a proxy measure developed by Aghion et al. (2021) that uses actual changes in trade patterns. I rely on the same database as Aghion et al. (2021), Comtrade (United Nations Statistics Division, 2025), which provides import and export volume data at the HS six-digit product code level. I assume the degree of exposure is the same across all eight-digit products in the same six-digit category. For each category, I calculate the average export quantity for 2008 and 2009 (the crisis period) and for 2006 and 2007 (the pre-crisis period). I take the log difference between the two periods' averages to construct the change in exports. A positive value reflects export growth, while a negative value reflects export declines:

$$\text{ExportChange}_m = \ln(\bar{X}_{m,08-09}) - \ln(\bar{X}_{m,06-07}), \quad (2.12)$$

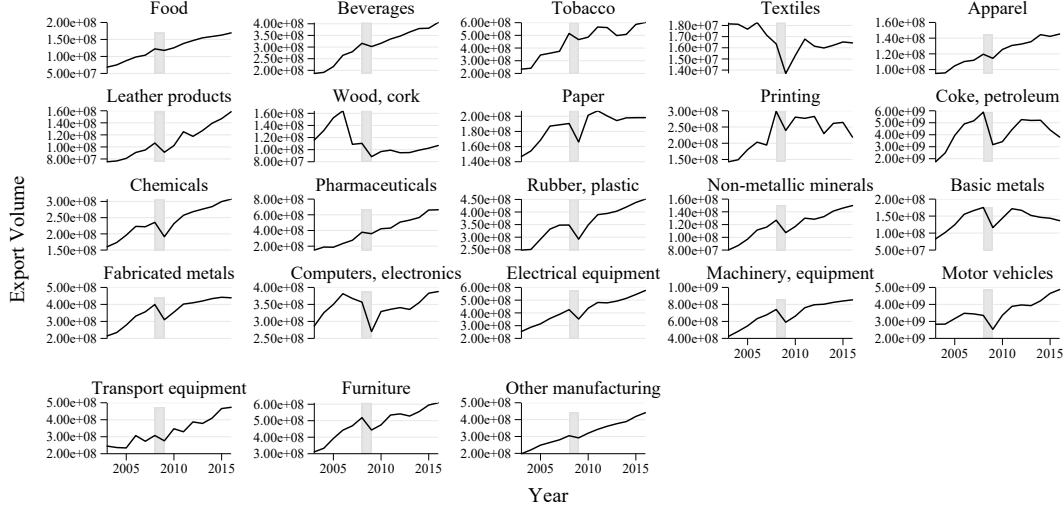
where  $\bar{X}_{mt}$  is the average export volume in six-digit product category  $m$  during period  $t$ . For a discussion on the exogeneity of the measure, see Section 2.3.3.

From September 2008 to January 2009, total world trade declined by around 30 percent, much more severely than the 3 percent decline in global GDP (Amiti and Weinstein, 2011; Bricongne et al., 2012; Eaton et al., 2016). For Germany, manufacturing exports dropped by around 32 percent in the same period (own calculations based on UN Comtrade), while GDP decreased by only around 7 percent from the third quarter of 2008 to the first quarter of 2009 (own calculations based on German GDP data by the Federal Reserve Bank of St. Louis, 2025).<sup>4</sup> Figure 2.1 shows world export volumes of Germany's manufacturing sector from 2003 to 2016 in thousands of Euros. The largest declines were in wood/cork, textiles, computers, and motor vehicles, likely because purchases of durables can be delayed. In contrast, essential consumer goods are the least affected, including food, beverages, tobacco, and apparel. This pattern is consistent with King and Rebelo (1999), who show that recessions typically affect durable

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<sup>4</sup>The year-on-year GDP decline is 6.6 percent in the first quarter of 2009 (Eaton et al., 2016).

Figure 2.1: Annual Export Volumes by Two-Digit Industry



*Note:* Exports from Germany to the world in thousands of Euros. The grey shading marks the years 2008 and 2009 of the financial crisis. Source: UN Comtrade.

goods more than non-durables, and with Levchenko et al. (2010) and Eaton et al. (2016), who document the same for the 2008 financial crisis.

The change in export volumes compares pre-crisis averages from 2006-07 with those during the crisis from 2008-09 to indicate product markets most severely affected. Based on the distribution of export changes, I consider product categories in the bottom 25 percent—those with the largest export declines—as treated. If a firm produced at least one such product in either 2006 or 2007, it is part of the treated group. The post-treatment period began in 2008. In the baseline regressions, I exclude the other products of treated multi-product firms that did not experience large declines.

I construct a binary variable that equals one if exports in a given product category declined significantly during the crisis and fall within the bottom 25 percent of the export change distribution, and zero if exports experienced smaller absolute changes or increased:

$$\text{Treat}_m = \mathbb{1}[\text{ExportChange}_m < P25(\text{ExportChange}_m)] \quad (2.13)$$

Firms that never produced items from the treated six-digit categories in or after 2006 serve as the control group. I exclude products in the top 25 percent of export changes from the main sample to ensure the results are not driven by export gains. When including these observations with an analogous export increase indicator in additional regressions, I find no evidence of symmetric effects.

Multi-product firms might react strategically through their other products or experience within-firm spillovers. Therefore, I also account for indirect effects in an additional specifica-

tion. As in the baseline specification, a firm is treated if it produced at least one product before the crisis that later experienced an export decline. I distinguish between directly treated observations, which are the treated firm-products as before, and indirectly treated observations, which are other products in the treated firm’s portfolio. For these, I include the indicator variable  $\text{Indirect}_{fm}$ . Lastly, I construct a firm-level aggregate treatment variable. For each firm, I weight its products by their sales values and take the average export change. Similarly to the firm-product-specific measure, firms with a sales-weighted export change in the bottom 25 percent of the aggregated export change distribution are considered the treatment group. Firms with aggregate values between the 25th and 75th percentiles serve as the control group. The next section describes the event study design.

### 2.3.2 Event Study Design

In this section, I present the empirical strategy for estimating the direct effect of the financial crisis, as described in Section 2.3.1, on firms’ outcome variables. I use a dynamic difference-in-differences approach and estimate the following econometric specification.

The regression model includes the interaction of treatment dummies with year-fixed effects and weights observations by the inverse sampling probability:

$$y_{fjt} = \sum_{\substack{t=2003 \\ t \neq 2007}}^{2016} \beta_t \text{Treat}_m \times \mathbb{1}[\text{Year} = t] + \nu_{fj} + \nu_{it} + \nu_{gt} + \epsilon_{fjt}, \quad (2.14)$$

where  $y_{fjt}$  denotes the logarithm of the outcome of eight-digit product  $j$  in six-digit category  $m$  and four-digit industry  $i$ , produced by firm  $f$  at time  $t$ .  $\text{Treat}_m$  is the indicator for large declines in German world exports in the six-digit category during the financial crisis.  $\mathbb{1}[\text{Year} = t]$  are year dummies from 2003 until 2016, excluding 2007 as the reference year.

I include fixed effects at the firm-product-unit  $\nu_{fj}$ , four-digit industry-unit-year  $\nu_{it}$ , and NUTS2 geographical area-year (government regions, *Regierungsbezirke*)  $\nu_{gt}$  level. The same eight-digit product measured in a different unit is assigned a separate fixed effect, so  $j$  effectively refers to a product-unit combination. For notational simplicity, I omit the unit subscript. A product’s industry is fully nested in its product category membership. Firm-product-unit fixed effects, therefore, capture time-invariant characteristics inherent to the firm’s product in its specific unit, such as pre-recession market share, quality, or brand reputation. The time-heterogeneous fixed effects control for shocks or trends common to all products within a specific unit in a four-digit category, such as demand or cost shocks. Similarly, the geographical fixed effects capture local economic conditions, labour market shocks, or regional policies that affect all products in the same region in a given year. I cluster standard errors at the six-digit product level according to treatment assignment.

Further, I estimate supporting difference-in-differences specifications of the form

$$y_{fjt} = \alpha \text{Treat}_m \times \text{Post}_t + \nu_{fj} + \nu_{it} + \nu_{gt} + \epsilon_{fjt}, \quad (2.15)$$

where  $\text{Post}_t$  is an indicator variable for all years including and after 2008, capturing the during-crisis and post-crisis period. The fixed effects are analogous to Equation (2.14). For heterogeneity analysis, I interact dummy variables for different subgroups with  $\text{Treat}_m \times \text{Post}_t$ , as described in further detail in Section 2.5.4.

Moreover, I explore indirect effects of the financial crisis. I consider products to be indirectly treated if they were part of the treated firms' portfolios in 2006 or 2007 but did not experience a large export decline themselves. These products were excluded from the previous analysis. To capture indirect exposure, I reintroduce these firm-product-year observations into the sample and extend the difference-in-differences model above by adding a treatment indicator for indirectly treated products. I interact the indicator with the post-crisis period dummy in the same way as the direct treatment indicator in Equation (2.15). The indicator variables  $\text{Treat}_m$  and  $\text{Indirect}_{fj}$  are mutually exclusive, such that each coefficient measures its separate effect without additive interpretation. All other elements of the specification remain unchanged:

$$y_{fjt} = \alpha_1 \text{Treat}_m \times \text{Post}_t + \alpha_2 \text{Indirect}_{fj} \times \text{Post}_t + \nu_{fj} + \nu_{it} + \nu_{gt} + \epsilon_{fjt}. \quad (2.16)$$

As a robustness check, I estimate regressions at the firm level. For each firm, I compute a sales-weighted average of export changes across all its products. I adapt the econometric specification to reflect the aggregate firm-level treatment as follows:

$$y_{ft} = \sum_{\substack{t=2004 \\ t \neq 2007}}^{2016} \beta_t \text{Treat}_f \times \mathbb{1}[\text{Year} = t] + \eta_f + \eta_{ct} + \eta_{gt} + \epsilon_{ft}, \quad (2.17)$$

where  $y_{ft}$  characterises firm  $f$ 's outcome in logarithms at time  $t$ .  $\text{Treat}_f$  is an aggregated indicator that equals one if the firm's sales-weighted export decline exceeds the treatment threshold. As before,  $\mathbb{1}[\text{Year} = t]$  denotes a set of year indicator variables with the reference year 2007. Fixed effects now control for time-invariant unobserved heterogeneity at the firm level ( $\eta_f$ ), for industry-specific time trends at the two-digit NACE level ( $\eta_{ct}$ ) and NUTS2 geographical region-year variation ( $\eta_{gt}$ ). I reweight the regression using sample weights as before and cluster standard errors at the firm level, since the treatment is now defined for the whole firm rather than at the product level.

### 2.3.3 Identification

To estimate the effect of the 2008 financial crisis on product-market outcomes, the econometric specification relies on the fixed effects described in Section 2.3.2, which account for unobserved



heterogeneity from firm-product characteristics or regional and industry trends. Following Aghion et al. (2021), I use export changes as a proxy for exposure to the crisis across product markets. To measure the causal effect of the financial crisis, the export shock must be uncorrelated with unobservables that influence the remaining within-firm-product variation in outcomes after controlling for the fixed effects.

The housing boom and the subsequent financial crisis were not widely anticipated: studies of personal housing transactions by mid-level finance managers in the mortgage securitisation industry neither showed caution nor superior market timing before the crash, suggesting limited awareness of the bubble among industry insiders (Cheng et al., 2014). Statistical default models used by market participants to assess default risk of subprime mortgages also performed poorly in the years before the crisis, helping explain why risks were under-predicted (Rajan et al., 2015). Additionally, as I show in Section 2.4, pre-crisis period estimates from the event study regressions do not exhibit divergent trends, as all coefficients are small and insignificant. I therefore treat the export declines as a plausibly exogenous, demand-driven shock rather than a response to prior firm-level decisions or unobserved characteristics.

Aghion et al. (2021) also argue that such export-based measures are more likely to reflect global demand fluctuations than country or industry-specific supply characteristics. The financial crisis of 2008–2009 is commonly characterised as a demand shock, which spilled over into international trade patterns (Bems et al., 2010). As shown in Figure 2.1, exports of German manufacturing goods indeed declined rapidly. According to Bricongne et al. (2012), most of the trade collapse can be attributed to the exceptional demand shock, which I aim to exploit, and product characteristics, which I control for with fixed effects.

To validate exports as a proxy of demand in world markets, I estimate the model separately for exporters and non-exporters as in Aghion et al. (2021). The effects should be concentrated among exporting firms, which, by definition, are directly exposed to changes in international demand. In fact, I find that the results are driven primarily by exporting firms. Additional robustness checks described in Section 2.6, such as placebo tests on timing and treatment thresholds in the pre-crisis period or changing the cutoff for large export shocks, lend further credibility to the identification strategy.

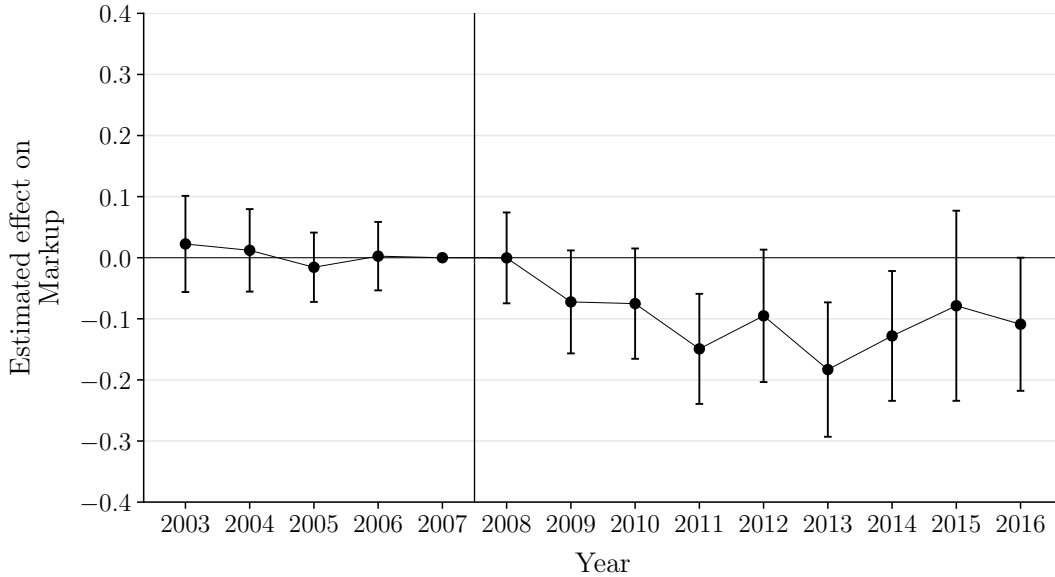
## 2.4 Empirical Results

I now turn to the event study estimates of the impact of the 2008 financial crisis on severely affected product markets. Section 2.4.1 discusses the empirical results on markups, while Section 2.4.2 presents results on prices and marginal costs to shed light on the drivers behind the markup effects.

### 2.4.1 Effect on Markups

Empirical markup estimates provide valuable insights into firms' market power and cost pass-through. Firm-product-level markups are particularly well suited for analysing product market effects of the financial crisis, with export shocks serving as a proxy for crisis exposure. I use the event study specification for markups in logarithms introduced in Equation (2.14). By estimating dynamic treatment effects over time, I also assess the validity of the parallel trends assumption and capture the timing and persistence of any crisis-related effects. Figure 2.2 presents the main results graphically. The plot shows the estimated coefficients for each year along with 95% percent confidence intervals. The absence of statistically significant pre-crisis trends supports the credibility of my identification strategy.

Figure 2.2: The Effect of the Financial Crisis on Firm-Product Markups



*Note:* This figure presents event study point estimates with 95% confidence intervals from Equation (2.14). The coefficients represent the estimated effect of the treatment variable, as described in Section 2.3.1, on the outcome, using 2007 as the reference year. The dependent variable is the estimated firm-product-year-level markup in logarithmic form. The estimation of markups is detailed in Section 2.2.2. The regression includes firm-product-unit, four-digit industry-unit-year, and NUTS2 region-year fixed effects. Standard errors are clustered at the six-digit product level. Coefficients are reported in Appendix Table 2.4.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0; 10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0; 10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

The event study reveals a statistically significant decline in markups for exposed products relative to the control group. The coefficients indicate a gradual and persistent decline following the crisis, with the largest drop of 18.3 percent occurring around 2013. The event study coefficients are reported in Appendix Table 2.4. In the two-period difference-in-difference anal-

ysis (see Equation (2.15)), exposure to treatment is associated with an average decrease of 10.2 percent in markups over all post-crisis time periods, significant at the 5 percent level (see Appendix Table 2.3). The decrease suggests that products in markets with large export declines incurred lasting markup reductions, possibly driven by price decreases or cost increases. To understand the drivers behind the decline, I follow De Loecker et al. (2016) to calculate firm-product-specific marginal costs from estimated markups and available price data. In the next section, I repeat the event study analysis using prices and marginal costs as outcomes to separate pricing behaviour from cost pressures as potential drivers.

## 2.4.2 Effect on Prices and Marginal Costs

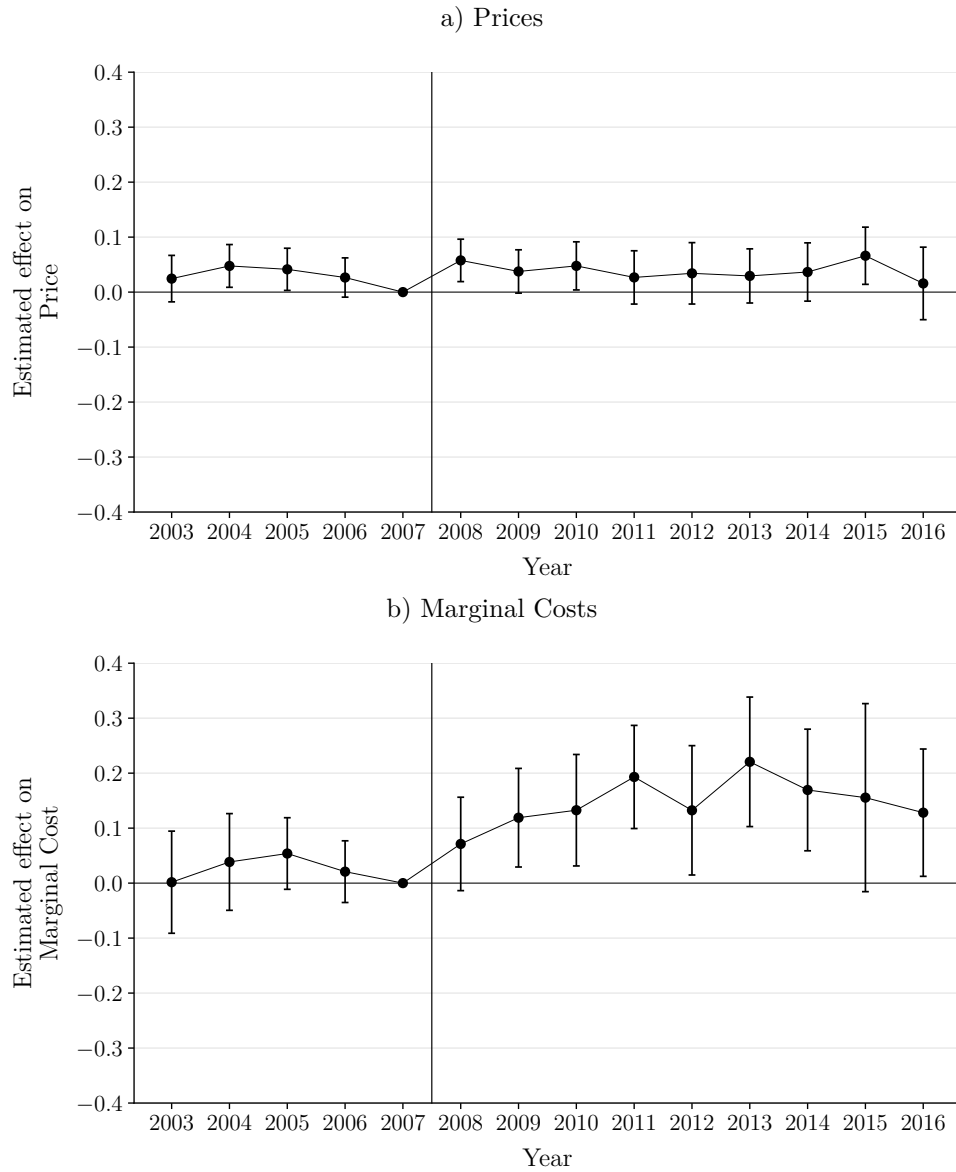
The previous section presented the results for markups of products that were strongly exposed to export declines during the financial crisis. Having established their pronounced decrease, I now turn to the two components that determine price-cost markups: output prices and marginal costs.

Figure 2.3a) shows the estimated coefficients with 95 percent confidence intervals for prices. The event study reveals that prices increase slightly but remain largely unchanged in the post-treatment period. The effects are economically small and only occasionally significant. In a standard two-period difference-in-differences setup using yearly average factory-gate prices in logarithms as the outcome, the coefficient of 1.3 percent (reported in Appendix Table 2.3) is positive but not statistically significant. The results suggest that firms did not strongly adjust prices in response to declining demand or rising costs. Relatedly, Gopinath et al. (2012) show that US import and export prices barely declined for differentiated manufacturing, both in durables and non-durables, only for undifferentiated goods.

Instead, the decline in markups appears to be primarily driven by rising marginal costs, as shown in Figure 2.3b). The coefficients indicate a significant and persistent increase after the crisis, mainly at the 1 or 5 percent significance level. Mirroring the pattern of decreasing markups, the largest effect occurs in 2013 with marginal costs rising by 22.1 percent. After 2014, the effect becomes smaller but persists. On average, the difference-in-differences estimate after exposure to the financial crisis indicates a 12.4 percent marginal cost increase in the post-treatment period, significant at the 1 percent level; see Appendix Table 2.3. The event study results for both prices and marginal costs are reported in Appendix Table 2.4.

In the following sections, I provide a closer examination of potential marginal cost drivers. There are three main channels through which marginal costs may increase: firms might either produce less and consequently lose scale economies, become less productive, or face higher input prices (Stiebale and Vencappa, 2018). I investigate these potential mechanisms behind rising marginal costs in Section 2.5.

Figure 2.3: The Effect of the Financial Crisis on Firm-Product Prices and Marginal Costs



*Note:* This figure presents event study point estimates with 95% confidence intervals from Equation (2.14). The coefficients represent the estimated effect of the treatment variable, as described in Section 2.3.1, on the outcome, using 2007 as the reference year. In Panel a), the dependent variable is the average firm-product-year-level factory-gate product price in logarithms, while Panel b) shows the effect on the estimated firm-product-year-level marginal cost in logarithms. The calculation of marginal costs is detailed in Section 2.2.2. The regression includes firm-product-unit, four-digit industry-unit-year, and NUTS2 region-year fixed effects. Standard errors are clustered at the six-digit product level. Coefficients are reported in Appendix Table 2.4.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0; 10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0; 10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

## 2.5 Mechanisms and Heterogeneity

The analysis in Section 2.4 revealed that firms adjusted product markups downwards following the financial crisis. The shift is primarily driven by rising marginal costs, while prices remain largely unchanged, except for slight increases in some periods. In this section, I explore potential mechanisms behind the increase in costs. Based on trade theoretical models with heterogeneous firms (Hallak and Sivadasan, 2013; Antoniadou, 2015), Stiebale and Vencappa (2018) derive three potential drivers for shifts in marginal costs: changes in output quantities in the presence of non-constant returns to scale, changes in total factor productivity, or changes in factor prices. I investigate the first two channels directly in Sections 2.5.1 and 2.5.2 using the firm-level event study framework. Information on input costs is not available in the production data, but I explore two dimensions of the input labour, average wages and employment, in Section 2.5.3. Further heterogeneity analysis follows in Section 2.5.4.

### 2.5.1 Scale Economies

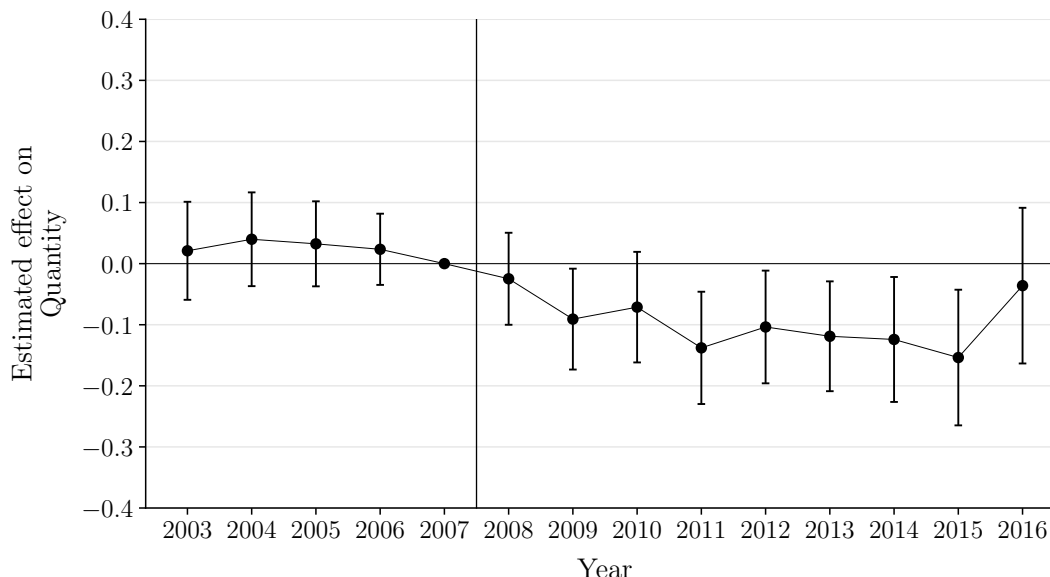
As the first channel through which marginal costs may change, I investigate two dimensions of economies of scale: quantities produced and heterogeneity arising from scale economies, using a classification of industries by Davies and Lyons (1996). I include related results on within-firm indirect effects, reflecting possible economies of scope.

**Quantities** The financial crisis led to a contraction in aggregate output, a pattern well documented in the empirical literature (see, e.g., Levchenko et al., 2010). To examine the consistency of my results and explore the role of potential scale economies in the increase in marginal costs observed in Section 2.4.2, I estimate the same event study regressions as in Equation (2.14) with the log of output quantities as the outcome variable.

Figure 2.4 plots the event study coefficients for produced quantities. Quantities decrease after the crisis, in line with the empirically observed output contraction. Again, the pre-trends of the treated products are not statistically significantly different from those of the control group. After the onset of the financial crisis, the estimates show a sharp decline for exposed products. The significant drop remains persistently low for several years, with an average decrease of 9.6 percent; see Appendix Table 2.3. In the presence of increasing returns to scale, a decline in output could therefore help explain the rising marginal costs after exposure to the financial crisis. I examine this mechanism in more detail below.

**Sunk Costs** To further assess the relevance of scale economies, I estimate heterogeneous treatment effects. I use the classification by Davies and Lyons (1996), who group industries by their expected magnitude of sunk costs. Fixed irrecoverable costs proxy for economies of scale, as they imply cost structures in which costs decline with higher output and are spread over

Figure 2.4: The Effect of the Financial Crisis on Firm-Product Quantities



*Note:* This figure presents event study point estimates with 95% confidence intervals from Equation (2.14) with 2007 as the reference year. The coefficients represent the estimated effect of the treatment variable, as described in Section 2.3.1, on the outcome. The dependent variable is the firm-product-year-level produced quantity in logarithmic form. The regression includes firm-product-unit, four-digit industry-unit-year, and NUTS2 region-year fixed effects. Standard errors are clustered at the six-digit product level. Coefficients are reported in Appendix Table 2.4.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0; 10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0; 10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

many units. Similar to Stiebale (2011) and Gupta and Stiebale (2024), I assign firm-products to two groups: those in three-digit industries identified as exhibiting scale economies and those that do not. I interact the two mutually exclusive indicator variables with the difference-in-differences treatment dummy. A significant difference in treatment effects between the two groups could indicate the loss of scale economies as a driver of increasing marginal costs.

Results are shown in column (1) of Table 2.1 Panel A for markups and Panel B for marginal costs. I test for equality between the coefficients of industries with and without scale economies. The two treatment effects do not differ significantly for marginal costs or markups; however, the point estimates for high-sunk-cost industries are slightly larger for markups. Although quantities decrease, the observed rise in marginal costs cannot be entirely attributed to the loss of scale economies and is likely driven by other factors as well.

**Indirect Effects** The main advantage of the German administrative data is the product-level information, which allows me to examine within-firm responses of multi-product producers. As defined in Section 2.3.1, treated firms experience a sharp drop in demand for one or more

Table 2.1: Estimation Results - Heterogeneity

## Panel A. Markup

|                                                    | Markup               |                      |                      |                        |                      |                           |
|----------------------------------------------------|----------------------|----------------------|----------------------|------------------------|----------------------|---------------------------|
|                                                    | Scale<br>(1)         | Indegrees<br>(2)     | Outdegrees<br>(3)    | Differentiation<br>(4) | Core Products<br>(5) | Multiproduct Firms<br>(6) |
| Low/0                                              | -0.078<br>(0.050)    | 0.010<br>(0.063)     | -0.015<br>(0.074)    | -0.144***<br>(0.051)   | -0.099*<br>(0.054)   | -0.054<br>(0.041)         |
| High/1                                             | -0.156***<br>(0.057) | -0.195***<br>(0.045) | -0.162***<br>(0.042) | -0.071<br>(0.058)      | -0.070*<br>(0.039)   | -0.098**<br>(0.043)       |
| Firm-Product-Unit FE                               | ✓                    | ✓                    | ✓                    | ✓                      | ✓                    | ✓                         |
| 4 Digit-Unit-Year FE                               | ✓                    | ✓                    | ✓                    | ✓                      | ✓                    | ✓                         |
| NUTS2-Year FE                                      | ✓                    | ✓                    | ✓                    | ✓                      | ✓                    | ✓                         |
| N                                                  | 169,654              | 169,654              | 169,654              | 169,654                | 169,654              | 169,654                   |
| Adj. $R^2$                                         | 0.000                | 0.000                | 0.000                | 0.000                  | 0.000                | 0.000                     |
| <b>Wald-Test, <math>H_0</math>: Low/0 = High/1</b> |                      |                      |                      |                        |                      |                           |
| F-statistic                                        | 1.06                 | 7.86***              | 3.09*                | 0.87                   | 0.28                 | 1.01                      |

## Panel B. Marginal Cost

|                                                    | Marginal Cost      |                     |                     |                        |                      |                           |
|----------------------------------------------------|--------------------|---------------------|---------------------|------------------------|----------------------|---------------------------|
|                                                    | Scale<br>(1)       | Indegrees<br>(2)    | Outdegrees<br>(3)   | Differentiation<br>(4) | Core Products<br>(5) | Multiproduct Firms<br>(6) |
| Low/0                                              | 0.123**<br>(0.052) | -0.006<br>(0.065)   | 0.054<br>(0.077)    | 0.132**<br>(0.053)     | 0.121**<br>(0.055)   | 0.095*<br>(0.051)         |
| High/1                                             | 0.126*<br>(0.065)  | 0.228***<br>(0.048) | 0.171***<br>(0.045) | 0.118*<br>(0.061)      | 0.086*<br>(0.045)    | 0.116***<br>(0.045)       |
| Firm-Product-Unit FE                               | ✓                  | ✓                   | ✓                   | ✓                      | ✓                    | ✓                         |
| 4 Digit-Unit-Year FE                               | ✓                  | ✓                   | ✓                   | ✓                      | ✓                    | ✓                         |
| NUTS2-Year FE                                      | ✓                  | ✓                   | ✓                   | ✓                      | ✓                    | ✓                         |
| N                                                  | 169,654            | 169,654             | 169,654             | 169,654                | 169,654              | 169,654                   |
| Adj. $R^2$                                         | 0.000              | 0.000               | 0.000               | 0.000                  | 0.000                | 0.000                     |
| <b>Wald-Test, <math>H_0</math>: Low/0 = High/1</b> |                    |                     |                     |                        |                      |                           |
| F-statistic                                        | 0.00               | 9.31***             | 1.73                | 0.03                   | 0.33                 | 0.17                      |

*Notes:* This table reports heterogeneous treatment effects from interactions of the difference-in-differences dummy, as described in Section 2.3.1, with mutually exclusive group indicators. The specification implies a non-additive interpretation of the coefficients. The dependent variables in Panels A and B are the estimated firm-product-year-level markups and marginal costs, in logarithmic form. The estimation of markups and marginal costs is detailed in Section 2.2.2. Column (1) distinguishes firms operating in industries expected to have low and high sunk costs, following Davies and Lyons (1996), as a proxy for scale economies. Columns (2) and (3) divide the industries by indegrees and outdegrees of production networks, based on Acemoglu et al. (2012), using the median as the cutoff. Column (4) uses the classification by Rauch (1999) of homogeneous and differentiated goods. Column (5) estimates separate treatment effects for firms' core and non-core products, defined as the product with the highest pre-crisis revenue share, following Eckel et al. (2016). Column (6) compares the effects for firms producing a single product with those producing multiple products. All regressions include firm-product-unit, four-digit industry-unit-year, and NUTS2 region-year fixed effects. Standard errors are clustered at the six-digit product level and reported in parentheses.

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0; 10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0; 10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

product lines following the financial crisis. Many of them also produce goods that were less severely affected by the crisis. While I previously discarded the other products in the treated firms' portfolios in the main specifications, I now include them in the regression sample to assess potential indirect treatment effects.

Although these remaining products are not directly exposed to the export shock, they may still be affected through within-firm mechanisms. Firms typically share inputs and costs across product lines. When the firm produces less because of more expensive inputs or reduced demand, these disruptions may affect the entire firm and spill over to other products.

Table 2.2: Estimation Results - Indirect Effects Product-Level Outcomes

|                                                            | Markup               |                      | Marginal Cost       |                     | Price             |                   |
|------------------------------------------------------------|----------------------|----------------------|---------------------|---------------------|-------------------|-------------------|
|                                                            | Average              | Early v Late         | Average             | Early v Late        | Average           | Early v Late      |
|                                                            | (1)                  | (2)                  | (3)                 | (4)                 | (5)               | (6)               |
| <i>Treat</i> $\times$ <i>Post</i>                          | -0.132***<br>(0.039) |                      | 0.131***<br>(0.040) |                     | -0.008<br>(0.018) |                   |
| <i>Indirect</i> $\times$ <i>Post</i>                       | -0.122***<br>(0.042) |                      | 0.146***<br>(0.044) |                     | 0.005<br>(0.021)  |                   |
| <i>Treat</i> $\times$ <i>Post</i> $\times$ <i>Early</i>    |                      | -0.058<br>(0.038)    |                     | 0.077*<br>(0.040)   |                   | 0.010<br>(0.014)  |
| <i>Treat</i> $\times$ <i>Post</i> $\times$ <i>Late</i>     |                      | -0.169***<br>(0.046) |                     | 0.158***<br>(0.045) |                   | -0.017<br>(0.023) |
| <i>Indirect</i> $\times$ <i>Post</i> $\times$ <i>Early</i> |                      | -0.073<br>(0.046)    |                     | 0.098**<br>(0.050)  |                   | 0.005<br>(0.015)  |
| <i>Indirect</i> $\times$ <i>Post</i> $\times$ <i>Late</i>  |                      | -0.148***<br>(0.050) |                     | 0.174***<br>(0.049) |                   | 0.007<br>(0.028)  |
| Firm-Product-Unit FE                                       | ✓                    | ✓                    | ✓                   | ✓                   | ✓                 | ✓                 |
| 4 Digit-Unit-Year FE                                       | ✓                    | ✓                    | ✓                   | ✓                   | ✓                 | ✓                 |
| NUTS2-Year FE                                              | ✓                    | ✓                    | ✓                   | ✓                   | ✓                 | ✓                 |
| N                                                          | 183,798              | 183,798              | 183,798             | 183,798             | 183,798           | 183,798           |
| Adj. $R^2$                                                 | 0.000                | 0.000                | 0.000               | 0.000               | -0.000            | 0.000             |

*Notes:* This table reports treatment effects from interactions between the firm-product-level treatment indicators and the post-crisis period indicators. The direct and indirect treatment variables are described in Section 2.3.1. Columns (1), (3), and (5) interact the treatment variables with the post-crisis dummy (2008 to 2016). The specifications in columns (2), (4), and (6) estimate separate effects for early (2008 to 2010) and later periods (2011 to 2016) after the crisis. The dependent variables are the estimated firm-product-year-level markups in columns (1)-(2), estimated firm-product-year-level marginal costs in columns (3)-(4), and observed firm-product-year-level prices in columns (5)-(6), all in logarithmic form. The estimation of markups and marginal costs is detailed in Section 2.2.2. All regressions include firm-product-unit, four-digit industry-unit-year, and NUTS2 region-year fixed effects. Standard errors are clustered at the six-digit product level and reported in parentheses.

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0; 10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0; 10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

Table 2.2 presents the results of the within-firm spillover analysis. I do not conduct an event study analysis for the sake of model parsimony, but report separate coefficients for the early



(2008 to 2010) and later periods (2011 to 2016) after the crisis. Indirectly treated products also show declining markups and rising marginal costs in columns (1) to (4), with effects similar in magnitude to those of directly treated products. The prices of indirectly affected products show no significant effects in columns (5) and (6), mirroring the pattern of their directly affected counterparts. While the financial crisis had a substantial impact on directly exposed goods, the shock also appears to have spread within firms, as their other products also experienced adverse effects as well. A loss of economies of scope from joint production and shared inputs or costs may have contributed to the severity of the financial crisis. Next, I turn to TFP as a second determinant of marginal costs.

### 2.5.2 Total Factor Productivity

Another potential contributor to the significant rise in marginal costs is total factor productivity. Because the product-level approach to production function estimation by De Loecker et al. (2016) yields only one firm-specific measure of TFP, I estimate a more parsimonious firm-level aggregate production function using the method by Akerberg et al. (2015). I follow Mertens (2020) for the exact specification and deflate revenues using a firm-specific price index to mitigate potential biases from using revenues as a proxy for output quantities. The instruments for firm-level inputs to mitigate the simultaneity bias remain the same as in Section 2.2.2. The procedure allows me to recover TFP, which I then use as an outcome in a firm-level event-study regression on the weighted-average export shock, as in Equation (2.17).

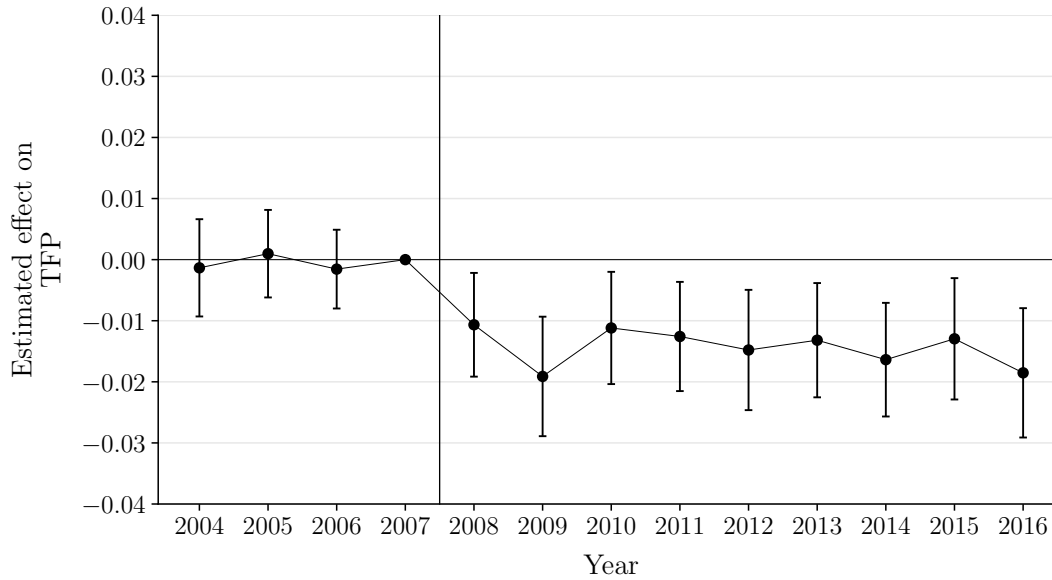
Figure 2.5 presents the resulting estimates. Before the crisis, coefficients fluctuate narrowly around zero, in favour of the parallel pre-treatment trends assumption. Almost immediately following the crisis, TFP reaches its most significant decrease of 1.9 percent in 2009. The effects remain persistently negative afterwards. The pattern suggests a lasting impact of the financial crisis on firm-level productivity: firms do not appear to recover to pre-crisis levels. Considering the observed increase in marginal costs in Section 2.4.2, the adverse and persistent effect in TFP is intuitive, as it is inversely associated with costs (Syverson, 2019). The general pattern is also consistent with the literature on the productivity slowdown after the Great Recession shown by, e.g., Hall (2015), Duval et al. (2020), and Manaresi and Pierri (2024). The authors name reduced intangible capital investment by financially constrained firms due to tightened credit access as a potential channel for reduced TFP growth.<sup>5</sup>

The relatively small effect size suggests that declining TFP was not the primary driver of the increase in marginal costs. As noted by Stiebale and Vencappa (2018), differences in effect sizes between average TFP and marginal cost may stem from, e.g., changes in fixed costs, economies of scale, or measurement error in TFP. Moreover, the product-level effects on marginal costs capture surviving products sold before and after the crisis, while the smaller effect on firm-level TFP may partly reflect that firms discontinue their least productive products. As shown by

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<sup>5</sup>For a discussion of the cyclicity of productivity, see, e.g., Basu (1996).

Figure 2.5: The Effect of the Financial Crisis on Firm TFP



*Note:* This figure presents event study point estimates with 95% confidence intervals from Equation (2.17) with 2007 as the reference year. The coefficients represent the estimated effect of the treatment variable, as described in Section 2.3.1, on the outcome. The dependent variable is the firm-year-level total factor productivity in logarithmic form. The regression includes firm, two-digit industry-year, and NUTS2 region-year fixed effects. Standard errors are clustered at the firm level. Coefficients are reported in Appendix Table 2.5.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0; 10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0; 10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

Bernard and Okubo (2016), recessions are a peak time for product switching. Unfortunately, I cannot directly track changes in firms' product mix because the 2009 GP reclassification lacks a 1:1 mapping for some categories, preventing a clear distinction between true product attrition and reclassification (see Section 2.2.1).

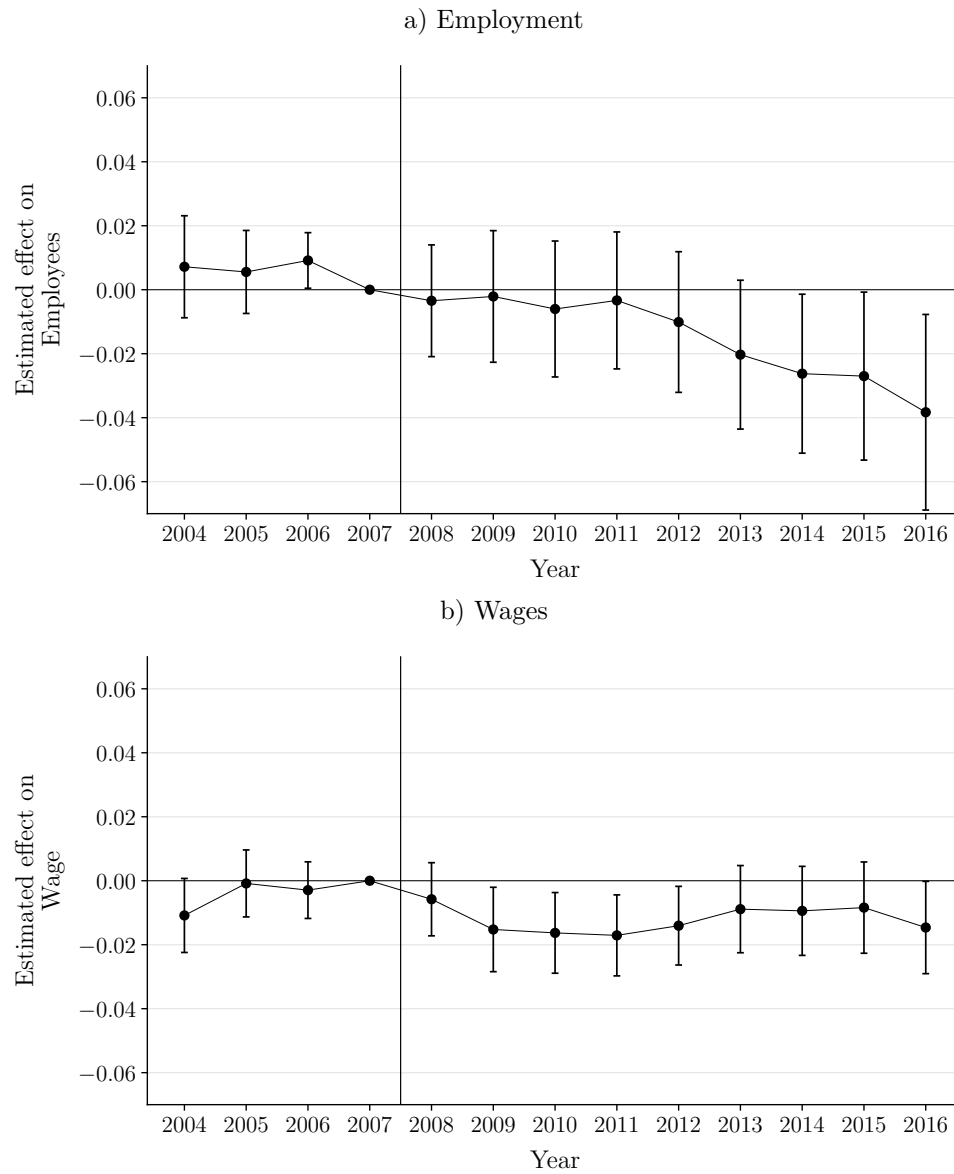
### 2.5.3 Input Costs

Finally, I examine factor prices as a determinant of marginal costs. I use data on labour, the one input I directly observe. Unfortunately, I do not observe input costs for capital and materials. Only the total expenditures are available, which do not allow statements on whether changes stem from quantities or input prices.

The AFiD panel reports both full-time equivalents and the wage bill, allowing me to calculate the firms' deflated average wages. I re-estimate the event study from Equation (2.17) and plot the results in Figure 2.6a) for employment and Figure 2.6b) for wages.

For employment, the event study reveals no immediate average short-run effect after the financial crisis, but a gradual decline after 2013. The pattern seems to align with Germany's

Figure 2.6: The Effect of the Financial Crisis on Firm Employment and Average Wages



*Note:* This figure presents event study point estimates with 95% confidence intervals from Equation (2.17). The coefficients represent the estimated effect of the treatment variable, as described in Section 2.3.1, on the outcome, using 2007 as the reference year. In Panel a), the dependent variable is the firm-year-level number of full-time equivalents in logarithms, while Panel b) shows the effect on the firm-year-level average wage in logarithms. Both regressions include firm, two-digit industry-year, and NUTS2 region-year fixed effects. Standard errors are clustered at the firm level. Coefficients are reported in Appendix Table 2.5.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0;  
10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0;  
10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

labour hoarding practices, such as the prominent initiative of short-time work (*Kurzarbeit*). Short-time employees count as an FTE in the data, as confirmed by the German Federal Statistical Office. Subsidised by the Federal Employment Agency, many German firms opted for reductions in hours rather than layoffs and paid the actual hours as well as a percentage of the lost income (Giroud and Mueller, 2017). Additionally, employees reduced their surplus in working time accounts from previously accumulated overtime hours (Möller, 2010). Several other German studies also find minimal declines in employment (Dietz et al., 2010; Möller, 2010; Burda and Hunt, 2011; Dustmann et al., 2014; Hoffmann and Lemieux, 2016).

The mild initial employment effect contrasts sharply with other countries: For example, Giroud and Mueller (2017) find substantial declines in US employment in response to falling housing prices during the financial crisis, especially among highly levered establishments. Likewise, Benmelech et al. (2021) show that financial constraints worsen negative employment effects. Figure 2.6a suggests that also in Germany, firms still suffered employment losses in the longer run, potentially through the decline in short-term employment observed in late 2010 (Münstermann et al., 2012) and its reversal by 2011 (Hoffmann and Lemieux, 2016).

I find that the average wage for the treated firms decreases after 2007. The strongest and highly significant effects of around -1.6 percent materialise in the years from 2009 to 2011. After 2012, the effects revert back and are no longer statistically significant. Because short-term employees are counted as FTE even though they work fewer hours, this may explain the reduction in the average wage. A moderate decline in wages during the financial crisis in Germany is also observed by Burda and Hunt (2011). Similarly, Elsby et al. (2016) find sluggish but procyclical wages in the UK and the US. As marginal costs are usually positively related to input costs, decreasing labour costs do not seem to be a main driver of rising marginal costs. As for capital, numerous studies have shown that the cost of financing or renting rose sharply, heavily affecting financially constrained firms' investments, production, and exports (see, e.g., Chor and Manova, 2012; De Ridder, 2016). Data on firms' capital costs and financial constraints are unavailable, although they are likely crucial.

#### 2.5.4 Heterogeneity

To explore heterogeneity in the direct effects of the financial crisis on German manufacturing firms, I examine several margins of variation. I estimate heterogeneous treatment effects by including interactions of mutually exclusive group indicators with the crisis difference-in-differences indicator. First, I investigate whether industries with higher indegrees and outdegrees in industry networks exhibit different reactions. Second, I examine industry-level product differentiation using Rauch (1999) as another dimension of heterogeneity. Third, I compare responses of the highest-revenue core products with those of the remaining non-core products. Fourth, I estimate separate effects for multi-product and single-product firms.

**Indegrees and outdegrees** To capture vertical industry networks at the industry level, I follow Acemoglu et al. (2012) and calculate the weighted indegrees and outdegrees of products. I use 2007 data from the US Bureau of Economic Analysis (BEA) commodity-by-commodity Total Requirements Table. This table quantifies how intensely sectors use one another as intermediate inputs in production. The BEA data, defining commodities at the NAICS four-digit industry level, provide the most granular input-output data available and report the amount of each commodity required to produce one dollar of each of the other commodities for final use. I use the US table as an approximation to German input-output tables, assuming similar production technologies across advanced manufacturing economies. *Weighted* refers to the input shares in the sector-by-sector matrix. The weighted indegree of a sector is calculated as the total intermediate input share of a sector across all commodities. The weighted outdegree of a sector is the share of its output in the input supply of the entire economy. It is calculated as the sum of all input shares of other sectors that take the focal sector as input (Acemoglu et al., 2012). Using the concordance by Pierce and Schott (2012a), I map the average indegrees and outdegrees to the German product classification.

Column (2) of Table 2.1 shows the heterogeneity analysis for indegrees for markups in Panel A and marginal costs in Panel B. I interact indicators for industries with high and low levels with the difference-in-difference term from Equation (2.15). The effects seem to be driven entirely by products highly dependent on inputs: markups decline by 19.5 percent and marginal costs increase by 22.8 percent. Estimates for low indegrees are insignificant, and the coefficients are significantly different at the 1 percent level for both outcomes. The literature highlights the role of vertical linkages in the propagation of shocks during crises: Blanchard and Kremer (1997)’s disorganisation hypothesis shows that after the fall of the Soviet Union as a shock to intermediate inputs, output in industries that used more intermediates fell more than in less vertically connected industries. Given that the trade collapse was largest in intermediates (Gopinath et al., 2012), similar findings by Levchenko et al. (2010) also support that this principle applies to the 2008 financial crisis.

Moreover, I find concentrated effects in industries with higher outdegrees. Table 2.1 column (3) shows a larger decline in markups in Panel A and a larger increase in marginal costs in Panel B, with a statistically significant difference in coefficients for markups. Above-median outdegrees indicate that these products are inputs to the production of more sectors. Again, the extent of network linkages seems to matter in the case of the financial crisis. Similarly, Levchenko et al. (2010) find that sectors used primarily as intermediate inputs were particularly marked by substantial trade declines in the financial crisis: with a drop in final demand and production, intermediate input demand falls, exacerbating the shock along the value chain. These transmissions can happen within the same country, but also across countries through international trade (di Giovanni and Levchenko, 2010).

Finally, I assess the relevance of indegrees and outdegrees for prices and quantities. I find

no evidence for heterogeneity along these dimensions, see Appendix Table 2.6.

**Further Heterogeneity** Another potential source of heterogeneity at the industry level is the degree of product differentiation. I merge the product-level data with a classification of internationally traded commodities at the four-digit SITC2 industry level from Rauch (1999)<sup>6</sup> using UN Comtrade correspondence tables<sup>7</sup>. This classification systematically groups products into differentiated and homogeneous goods. Homogeneous goods include either reference-priced or organised-exchange goods. Interacting the difference-in-differences dummy with indicators for differentiated and homogeneous goods does not show significant differences in Table 2.1 column (4) for markups in Panel A nor or marginal costs in Panel B.

I explore whether more pronounced effects occur for products that are farther from the firm’s core competency. Increasing costs could stem from weaker supply relationships or less efficient production (De Loecker et al., 2016), and firms may focus on their core business during downturns to prevent large margin reductions. The core product accounts for the highest revenue share within the firm prior to the crisis.<sup>8</sup> Comparing non-core and core products, I do not find a statistically significant difference; however, estimated effects on markups and marginal costs are slightly larger for non-core products (see Table 2.1, column (5) for markups in Panel A and marginal costs in Panel B). Again, the 2009 GP reclassification prevents reliable measurement of changes in product composition (see Section 2.2.1).

Finally, I differentiate between firms with single-product and multi-product status in the period before the crisis. Table 2.1 column (6) shows the results for markups in Panel A and marginal costs in Panel B. The effects are not statistically different from each other.

## 2.6 Robustness Checks

This section describes several robustness checks for the baseline results on markups and marginal costs in Section 2.4. My findings hold under all of the following specifications.

- (1) **Production function specification.** For markups from a translog production function, potential biases in production function coefficients might differ systematically between treated and control firms. I address potential issues by calculating markups and marginal costs from a Cobb-Douglas production function. In this functional form, biases in the coefficients affect all firms in the same industry equally. The fixed effects in the event

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<sup>6</sup>[https://econweb.ucsd.edu/~jrauch/rauch\\_classification.html](https://econweb.ucsd.edu/~jrauch/rauch_classification.html), date accessed 13.07.2021.

<sup>7</sup>United Nations Statistics Division (2021), <https://unstats.un.org/unsd/trade/classifications/correspondence-tables.asp>, date accessed 13.07.2021.

<sup>8</sup>This definition follows the literature on core competencies, where empirical studies typically define the core product as the main revenue source (e.g., Eckel and Neary, 2010; Goldberg et al., 2010; Bernard et al., 2010; Manova and Yu, 2017; Mayer et al., 2014; Eckel et al., 2015, 2016).

study control for two types of heterogeneity in elasticities: time-invariant, at the firm-product-category-level, and time-varying, at the industry or NUTS2 level. Any remaining bias may be due to firm-product-year-level changes relative to the group-specific average changes. The results are similar to the translog specification.

- (2) **Markup calculation.** The De Loecker et al. (2016) method requires estimation of each product’s share in the firm’s input expenditures. As shown by Cairncross et al. (2025), these estimates may not always be reliable. The results are robust to alternative markup construction using observed sales shares for input allocation, and the approach proposed by Cairncross et al. (2025). According to the authors, firm-level estimates are a weighted average of product markups with ideal aggregation weights and are more reliable than firm-product figures. I estimate a firm-level translog production function using revenues and include a price correction. I calculate firm-level markups without determining individual products’ input contributions, and compute sales-weighted average export changes per firm. I consider firms below the 25th percentile as treated, (see Section 2.3.1), and estimate Equation (2.17). The results are qualitatively similar to my main findings, but have a smaller effect size since they capture an aggregate firm-level effect that includes both directly and indirectly treated products.
- (3) **Export change measure.** To test the sensitivity towards the measurement of export changes, I construct a different version of the shock measure using real export values at the six-digit product level from UN Comtrade instead of export volumes. I convert export flows from nominal US Dollars to constant 2015 Euros using the currency exchange rate provided by UN Comtrade, and deflate with the year-specific German consumer price index (CPI) from the German Federal Statistical Office<sup>9</sup> with base year 2015. The construction of the alternative shock measure is analogous to Equations (2.12) and (2.13) as described in Section 2.3.1. The results remain similar.
- (4) **Treatment variable cutoff.** I probe the construction of the treatment and control groups to verify the findings are not driven by the specific choice of cutoff. In the baseline analysis, I define products below the 25th percentile of the export change distribution as treated. Adjusting the threshold in Equation (2.13) to the 20th or 30th percentile, I find that results remain similar. The only difference is that using the 30th-percentile cutoff yields slightly less significant results, likely reflecting dilution of the treatment effect as more unaffected products enter the treated group.
- (5) **Placebo timing.** I conduct placebo tests on the timing of the crisis. I restrict the sample to the pre-crisis period from 2003 to 2007 and estimate three difference-in-differences specifications, where I reassign the treatment date to each intermediate year before the

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<sup>9</sup><https://www-genesis.destatis.de/genesis/online>, code 61111-0001

crisis, i.e. 2004, 2005, and 2006. The definition of treated observations remains the same. As expected, placebo treatment dates in pre-crisis years produces statistically insignificant estimates. This supports the validity of the parallel trends assumption, suggesting no significant differences in markups and marginal costs between the treated and control observations prior to the crisis.

- (6) **Removal of 2008/2009.** The crisis years 2008 and 2009 were characterised by unusually high volatility in macroeconomic conditions and firm performance as well as by multiple overlapping shocks that could bias estimates of specific effects. As a further robustness check, I exclude the years 2008 and 2009 from the estimation sample. For both markups and marginal costs, the coefficients for the remaining years closely align with the main event study results.
- (7) **Export status.** Following the validation exercise proposed in Aghion et al. (2021), I re-estimate the main specification and split the sample by firms' exporting status as described in Section 2.3.3. If the export shock indeed captures exposure to the financial crisis, the effects should be more pronounced with firms that were exporters before the crisis, as they were directly affected by the collapse in international demand. This is exactly what the results confirm.
- (8) **Fixed effects.** I test the sensitivity of my findings to the inclusion of NUTS3-year fixed effects capturing finer regional trends. NUTS3 categories represent districts (Kreise). The results remain unchanged. Including more detailed product-category-time fixed effects is not feasible, as they would fully absorb the treatment variation.
- (9) **Clustering.** In the main analysis, I cluster standard errors at the six-digit product level. Following Angrist and Pischke (2009), I cluster at a higher level of aggregation, the four-digit product category, to account for potential within-group correlation in unobservables. The results are also robust to clustering at the firm level.
- (10) **Omission of sampling weights.** The data provided by the German Statistical Offices records some variables that are relevant for production function and markup estimation—specifically intermediate inputs—only for a rotating subsample of 40%, as described in Section 2.2. To account for the sampling design, I weight all main regressions by each firm's inverse sampling probability. The results from a regression without sample weights are similar, indicating that the weighting does not drive the findings.
- (11) **Balancing.** Finally, I conduct propensity score weighting and matching on pre-crisis characteristics to improve the balance between treated and control firms. Balance tests confirm that covariate differences between groups are substantially reduced afterwards. The resulting difference-in-differences regressions yield consistent results, reinforcing the credibility of the parallel trends assumption underlying the baseline approach.



## 2.7 Conclusion

This paper studies the impact of the 2008 financial crisis as a large-scale demand shock on product market outcomes. It contributes to a better understanding of how economic shocks translate into microeconomic firm-level responses and fits into ongoing debates of the causes of rising market power, a slowdown of productivity, and slowbalisation.

I provide evidence for the whole manufacturing sector in Germany, a world-leading exporting economy. A comprehensive administrative dataset with rich price and quantity information at the eight-digit product level allows me to estimate firm-product-level markups, marginal costs, and firm-level TFP according to the method by De Loecker et al. (2016). I construct a measure of exposure to the financial crisis as product-level export declines using detailed world trade data, following Aghion et al. (2021). Based on the bottom quarter of the distribution of these export changes, I classify products with the largest export declines as treated products. Firms that never produced any items in the treated six-digit categories serve as the control group. I use a dynamic difference-in-differences approach in which I interact the treatment indicator with year-fixed effects.

The analysis reveals persistent micro-level effects in the most affected product categories: markups decline, marginal costs increase, and prices stay mainly unchanged. Markups decrease on average by 10.2 percent over the periods following the financial crisis, while marginal costs increase by 12.4 percent. The largest effects materialise in 2013 for markups at -18.3 percent, and marginal costs at 22.1 percent. I investigate potential channels and find several driving forces behind the increase in marginal cost rather than a single cause: output, TFP, and employment outcomes all decrease. These results point to a combination of reasons contributing to the strong economic impact of the financial crisis. Exploring further mechanisms and heterogeneity, I find evidence of within-firm spillovers, in which indirectly affected products of treated firms also face higher marginal costs. Additionally, I find that the effects are stronger for products that are more embedded in production networks. In summary, I provide new evidence on how a global crisis affects granular firm-product outcomes and how these micro-adjustments connect to aggregate market trends.

## 2.A Additional Results

Table 2.3: Estimation Results - Difference-in-Differences

| Panel A. Product-Level Outcomes           |                     |                      |                     |                     |                  |                  |                      |                      |
|-------------------------------------------|---------------------|----------------------|---------------------|---------------------|------------------|------------------|----------------------|----------------------|
|                                           | Markup              |                      | Marginal Cost       |                     | Price            |                  | Quantity             |                      |
|                                           | Average             | Early v Late         | Average             | Early v Late        | Average          | Early v Late     | Average              | Early v Late         |
|                                           | (1)                 | (2)                  | (3)                 | (4)                 | (5)              | (6)              | (7)                  | (8)                  |
| <i>Treat</i> × <i>Post</i>                | −0.102**<br>(0.040) |                      | 0.124***<br>(0.041) |                     | 0.013<br>(0.019) |                  | −0.119***<br>(0.039) |                      |
| <i>Treat</i> × <i>Post</i> × <i>Early</i> |                     | −0.048<br>(0.038)    |                     | 0.082**<br>(0.041)  |                  | 0.023<br>(0.015) |                      | −0.084**<br>(0.034)  |
| <i>Treat</i> × <i>Post</i> × <i>Late</i>  |                     | −0.126***<br>(0.045) |                     | 0.143***<br>(0.046) |                  | 0.008<br>(0.023) |                      | −0.135***<br>(0.045) |
| Firm-Product-Unit FE                      | ✓                   | ✓                    | ✓                   | ✓                   | ✓                | ✓                | ✓                    | ✓                    |
| 4 Digit-Unit-Year FE                      | ✓                   | ✓                    | ✓                   | ✓                   | ✓                | ✓                | ✓                    | ✓                    |
| NUTS2-Year FE                             | ✓                   | ✓                    | ✓                   | ✓                   | ✓                | ✓                | ✓                    | ✓                    |
| N                                         | 169,654             | 169,654              | 169,654             | 169,654             | 169,654          | 169,654          | 169,654              | 169,654              |
| Adj. $R^2$                                | 0.000               | 0.000                | 0.000               | 0.000               | 0.000            | 0.000            | 0.000                | 0.000                |

| Panel B. Firm-Level Outcomes              |                      |                      |                     |                     |                   |                   |
|-------------------------------------------|----------------------|----------------------|---------------------|---------------------|-------------------|-------------------|
|                                           | TFP                  |                      | Employees           |                     | Wage              |                   |
|                                           | Average              | Early v Late         | Average             | Early v Late        | Average           | Early v Late      |
|                                           | (1)                  | (2)                  | (3)                 | (4)                 | (5)               | (6)               |
| <i>Treat</i> × <i>Post</i>                | −0.014***<br>(0.003) |                      | −0.023**<br>(0.010) |                     | −0.007<br>(0.005) |                   |
| <i>Treat</i> × <i>Post</i> × <i>Early</i> |                      | −0.014***<br>(0.003) |                     | −0.016*<br>(0.009)  |                   | −0.008<br>(0.005) |
| <i>Treat</i> × <i>Post</i> × <i>Late</i>  |                      | −0.013***<br>(0.003) |                     | −0.025**<br>(0.011) |                   | −0.007<br>(0.005) |
| Firm FE                                   | ✓                    | ✓                    | ✓                   | ✓                   | ✓                 | ✓                 |
| 2 Digit-Year FE                           | ✓                    | ✓                    | ✓                   | ✓                   | ✓                 | ✓                 |
| NUTS2-Year FE                             | ✓                    | ✓                    | ✓                   | ✓                   | ✓                 | ✓                 |
| N                                         | 62,200               | 62,200               | 62,200              | 62,200              | 62,200            | 62,200            |
| Adj. $R^2$                                | 0.001                | 0.001                | 0.001               | 0.001               | 0.000             | 0.000             |

*Notes:* This table reports difference-in-differences estimates. In Panel A, the dependent variables are firm-product-year-level markups, marginal costs, prices, and quantities in logarithmic form. The regressions include firm-product-unit, four-digit industry-unit-year, and NUTS2 region-year fixed effects. Standard errors are clustered at the six-digit product level and reported in parentheses. Panel B shows results for firm-year-level TFP, employees, and wages in logarithms. These regressions include firm, two-digit industry-year, and NUTS2 region-year fixed effects. Standard errors in parentheses, clustered at the firm level.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0; 10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0; 10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

Table 2.4: Estimation Results - Event Studies Product-Level Outcomes

|                      | Markup<br>(1)        | Marginal Cost<br>(2) | Price<br>(3)        | Quantity<br>(4)      |
|----------------------|----------------------|----------------------|---------------------|----------------------|
|                      | Fig. 2.2             | Fig. 2.3b            | Fig. 2.3a           | Fig. 2.4             |
| 2003                 | 0.023<br>(0.040)     | 0.002<br>(0.047)     | 0.025<br>(0.022)    | 0.021<br>(0.041)     |
| 2004                 | 0.012<br>(0.034)     | 0.038<br>(0.045)     | 0.048**<br>(0.020)  | 0.040<br>(0.039)     |
| 2005                 | -0.016<br>(0.029)    | 0.054<br>(0.033)     | 0.041**<br>(0.020)  | 0.032<br>(0.035)     |
| 2006                 | 0.003<br>(0.029)     | 0.021<br>(0.029)     | 0.027<br>(0.018)    | 0.023<br>(0.030)     |
| 2008                 | -0.000<br>(0.038)    | 0.071*<br>(0.043)    | 0.058***<br>(0.020) | -0.025<br>(0.038)    |
| 2009                 | -0.072*<br>(0.043)   | 0.119***<br>(0.046)  | 0.038*<br>(0.020)   | -0.091**<br>(0.042)  |
| 2010                 | -0.075<br>(0.046)    | 0.133**<br>(0.052)   | 0.048**<br>(0.022)  | -0.071<br>(0.046)    |
| 2011                 | -0.149***<br>(0.046) | 0.193***<br>(0.048)  | 0.027<br>(0.025)    | -0.138***<br>(0.047) |
| 2012                 | -0.095*<br>(0.055)   | 0.132**<br>(0.060)   | 0.034<br>(0.028)    | -0.104**<br>(0.047)  |
| 2013                 | -0.183***<br>(0.056) | 0.221***<br>(0.060)  | 0.029<br>(0.025)    | -0.119***<br>(0.046) |
| 2014                 | -0.128**<br>(0.054)  | 0.169***<br>(0.056)  | 0.037<br>(0.027)    | -0.124**<br>(0.052)  |
| 2015                 | -0.079<br>(0.079)    | 0.155*<br>(0.087)    | 0.066**<br>(0.027)  | -0.154***<br>(0.057) |
| 2016                 | -0.109*<br>(0.056)   | 0.128**<br>(0.059)   | 0.016<br>(0.034)    | -0.036<br>(0.065)    |
| Firm-Product-Unit FE | ✓                    | ✓                    | ✓                   | ✓                    |
| 4 Digit-Unit-Year FE | ✓                    | ✓                    | ✓                   | ✓                    |
| NUTS2-Year FE        | ✓                    | ✓                    | ✓                   | ✓                    |
| N                    | 169,654              | 169,654              | 169,654             | 169,654              |
| Adj. $R^2$           | 0.000                | 0.000                | 0.000               | 0.000                |

*Notes:* This table reports the event study coefficients from Figures 2.2, 2.3b, 2.3a, and 2.4 in the main text. For the full specification details, see the respective figure notes. Standard errors in parentheses, clustered at the six-digit product level.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0; 10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0; 10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

Table 2.5: Estimation Results - Event Studies Firm-Level Outcomes

|                 | TFP<br>(1)           | Employees<br>(2)    | Wage<br>(3)          |
|-----------------|----------------------|---------------------|----------------------|
|                 | Fig. 2.5             | Fig. 2.6a           | Fig. 2.6b            |
| 2004            | -0.001<br>(0.004)    | 0.007<br>(0.008)    | -0.011*<br>(0.006)   |
| 2005            | 0.001<br>(0.004)     | 0.006<br>(0.007)    | -0.001<br>(0.005)    |
| 2006            | -0.002<br>(0.003)    | 0.009**<br>(0.004)  | -0.003<br>(0.005)    |
| 2008            | -0.011**<br>(0.004)  | -0.003<br>(0.009)   | -0.006<br>(0.006)    |
| 2009            | -0.019***<br>(0.005) | -0.002<br>(0.010)   | -0.015**<br>(0.007)  |
| 2010            | -0.011**<br>(0.005)  | -0.006<br>(0.011)   | -0.016**<br>(0.006)  |
| 2011            | -0.013***<br>(0.005) | -0.003<br>(0.011)   | -0.017***<br>(0.006) |
| 2012            | -0.015***<br>(0.005) | -0.010<br>(0.011)   | -0.014**<br>(0.006)  |
| 2013            | -0.013***<br>(0.005) | -0.020*<br>(0.012)  | -0.009<br>(0.007)    |
| 2014            | -0.016***<br>(0.005) | -0.026**<br>(0.013) | -0.009<br>(0.007)    |
| 2015            | -0.013**<br>(0.005)  | -0.027**<br>(0.013) | -0.008<br>(0.007)    |
| 2016            | -0.019***<br>(0.005) | -0.038**<br>(0.016) | -0.015**<br>(0.007)  |
| Firm FE         | ✓                    | ✓                   | ✓                    |
| 2 Digit-Year FE | ✓                    | ✓                   | ✓                    |
| NUTS2-Year FE   | ✓                    | ✓                   | ✓                    |
| N               | 62,200               | 62,200              | 62,200               |
| Adj. $R^2$      | 0.001                | 0.001               | 0.000                |

*Notes:* This table reports the event study coefficients from Figures 2.5, 2.6a, and 2.6b in the main text. For the full specification details, see the respective figure notes. Standard errors in parentheses, clustered at the firm level.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0; 10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0; 10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

Table 2.6: Estimation Results - Heterogeneity: Price and Quantity

| Panel A. Price                                     |                   |                   |                  |                  |                  |                    |
|----------------------------------------------------|-------------------|-------------------|------------------|------------------|------------------|--------------------|
|                                                    | Price             |                   |                  |                  |                  |                    |
|                                                    | Scale             | Indegrees         | Outdegrees       | Differentiation  | Core Products    | Multiproduct Firms |
|                                                    | (1)               | (2)               | (3)              | (4)              | (5)              | (6)                |
| Low/0                                              | 0.033<br>(0.022)  | -0.008<br>(0.029) | 0.024<br>(0.032) | 0.002<br>(0.025) | 0.008<br>(0.022) | 0.036<br>(0.035)   |
| High/1                                             | -0.034<br>(0.029) | 0.028<br>(0.022)  | 0.005<br>(0.023) | 0.021<br>(0.027) | 0.013<br>(0.023) | 0.009<br>(0.020)   |
| Firm-Product-Unit FE                               | ✓                 | ✓                 | ✓                | ✓                | ✓                | ✓                  |
| 4 Digit-Unit-Year FE                               | ✓                 | ✓                 | ✓                | ✓                | ✓                | ✓                  |
| NUTS2-Year FE                                      | ✓                 | ✓                 | ✓                | ✓                | ✓                | ✓                  |
| N                                                  | 169,654           | 169,654           | 169,654          | 169,654          | 169,654          | 169,654            |
| Adj. $R^2$                                         | 0.000             | 0.000             | 0.000            | 0.000            | -0.000           | 0.000              |
| <b>Wald-Test, <math>H_0</math>: Low/0 = High/1</b> |                   |                   |                  |                  |                  |                    |
| F-statistic                                        | 3.25*             | 1.08              | 0.24             | 0.27             | 0.05             | 0.55               |

| Panel B. Quantity                                  |                     |                      |                      |                     |                     |                     |
|----------------------------------------------------|---------------------|----------------------|----------------------|---------------------|---------------------|---------------------|
|                                                    | Quantity            |                      |                      |                     |                     |                     |
|                                                    | Scale               | Indegrees            | Outdegrees           | Differentiation     | Core Products       | Multiproduct Firms  |
|                                                    | (1)                 | (2)                  | (3)                  | (4)                 | (5)                 | (6)                 |
| Low/0                                              | -0.126**<br>(0.051) | -0.055<br>(0.060)    | -0.073<br>(0.065)    | -0.145**<br>(0.057) | -0.102**<br>(0.045) | -0.113*<br>(0.062)  |
| High/1                                             | -0.102**<br>(0.048) | -0.168***<br>(0.047) | -0.154***<br>(0.049) | -0.099**<br>(0.050) | -0.099**<br>(0.050) | -0.106**<br>(0.041) |
| Firm-Product-Unit FE                               | ✓                   | ✓                    | ✓                    | ✓                   | ✓                   | ✓                   |
| 4 Digit-Unit-Year FE                               | ✓                   | ✓                    | ✓                    | ✓                   | ✓                   | ✓                   |
| NUTS2-Year FE                                      | ✓                   | ✓                    | ✓                    | ✓                   | ✓                   | ✓                   |
| N                                                  | 169,654             | 169,654              | 169,654              | 169,654             | 169,654             | 169,654             |
| Adj. $R^2$                                         | 0.000               | 0.000                | 0.000                | 0.000               | 0.000               | 0.000               |
| <b>Wald-Test, <math>H_0</math>: Low/0 = High/1</b> |                     |                      |                      |                     |                     |                     |
| F-statistic                                        | 0.12                | 2.41                 | 0.98                 | 0.37                | 0.00                | 0.01                |

*Notes:* This table reports heterogeneous treatment effects from interactions of the difference-in-differences dummy, as described in Section 2.3.1, with mutually exclusive group indicators. The specification implies a non-additive interpretation of the coefficients. The dependent variables in Panels A and B, are the observed firm-product-year level prices and quantities in logarithmic form. Column (1) distinguishes firms operating in industries expected to have low and high sunk costs, following Davies and Lyons (1996), as a proxy for scale economies. Columns (2) and (3) divide the industries by indegrees and outdegrees of production networks, based on Acemoglu et al. (2012), using the median as the cutoff. Column (4) uses the classification by Rauch (1999) of homogeneous and differentiated goods. Column (5) estimates separate treatment effects for firms' core and non-core products, defined as the product with the highest pre-crisis revenue share, following Eckel et al. (2016). Column (6) compares effects for firms producing a single product and with those producing multiple products. All regressions include firm-product-unit, four-digit industry-unit-year, and NUTS2 region-year fixed effects. Standard errors are clustered at the six-digit product level and reported in parentheses.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0; 10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0; 10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

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## Chapter 3

# The Impact of Profit Taxation on Prices, Product Quality, Investment, and Productivity

### 3.1 Introduction

Corporate tax cuts have become a popular tool for policymakers to stimulate the economy. The global average corporate tax rate has decreased from more than 40 percent in the 1980s to less than 25 percent (Tax Foundation, 2024). In the US, for instance, recent corporate tax reforms, such as the Tax Cuts and Jobs Act, aimed at boosting domestic competitiveness by sharply reducing the federal corporate tax rate. These policy changes have prompted a fierce debate among policymakers and scholars, questioning whether tax cuts actually promote economic growth by enhancing firm investments and productivity, or primarily serve firm interests by boosting their net-of-tax revenues.

In this paper, we study the impact of corporate taxation on product prices and quality, investigating its direct effects on consumers. Whereas prior research has examined the impact of corporate taxation on firm-level investment decisions, innovation, employment, and wages, much less is known about the consequences for consumers through changes in product prices and quality: are increases in profit taxes passed on to consumers, and—if so—to what extent? Or do tax-induced reductions in firm-level (R&D) investments eventually result in lower product quality and lower prices?

We study these questions by linking administrative firm-product data on prices and quality for Germany’s entire manufacturing sector to variation in the burden of profit taxation across German municipalities over time. To estimate the effects of profit taxation on firm-level behavior, we use an event-study design with staggered treatment using variation in local tax rates from 1998—2020. Our empirical strategy leverages more than 28,000 changes in municipalities’ local business tax rates, as well as multiple federal tax reforms with locally varying impact for identification. Municipalities in Germany possess notable self-government rights and determine the tax multiplier (*Hebesatz*) for the local business tax rate (*Gewerbesteuer*) annually. Moreover, federal reforms of the corporate and personal income tax induced indirect municipal variation through tax deduction possibilities, as they jointly determine firms’ effective tax liabilities.

The production data stem from the administrative *Amtliche Firmendaten für Deutschland* (AFiD) database and cover the period from 2003 to 2016. We derive firm-product quality from Khandelwal et al. (2013). In addition to firm-product-level prices, quantities, and quality, we examine various outcomes at the firm level—previously analyzed in the literature in the context of Germany as well as in other countries—namely, productivity, employment, average wages, investment, and R&D spending.

As the first of three main insights, we uncover statistically significant and economically meaningful negative effects of corporate taxation on product prices. The result is surprising at first glance, as economic theory suggests that firms would partially pass the additional tax burden on to consumers by raising prices. The estimated price changes, however, are not accompanied by meaningful changes in produced quantities. The findings suggest a more



complex relationship between profit taxation and pricing dynamics: Decreasing prices seem to reflect product quality adjustments rather than tax pass-through. Given a pre-trend in the event study for quantities, we interpret our findings cautiously. We estimate that in response to a one percent increase in the total statutory tax rate, on average, product prices decrease by 0.32 percent and product quality decreases by 0.41 percent.

Second, we show that—in line with previous evidence—increases in corporate tax rates reduce firm-level employment and investment in capital and R&D by sizable magnitudes. We find that a one percent increase in the total statutory tax rate is associated with a 0.31 percent reduction in employment and a 1.11 percent reduction in total investment, on average. Thus, firms appear to respond to higher profit taxation by contracting, which leads to lower product quality and warrants lower prices. Consistent with tax-induced cost and investment reductions as mechanisms behind the observed negative effects on product prices and quality, we further find a negative effect on firms’ total factor productivity (TFP). On average, TFP decreases by around 0.26 percent in response to a one percent tax hike.

Lastly, although more than 90 percent of the underlying tax changes in our sample are tax increases, we also provide evidence that the effect on quality is symmetric. We estimate an additional event study specification with separate treatment variables for tax hikes and cuts. We find that product quality increases following a cut in the statutory total tax rate.

Our findings contribute to the literature by providing evidence on product market effects of corporate tax changes beyond well-studied firm-level outcomes. Using detailed administrative product-level data from German manufacturing firms, we show that tax-induced quality adjustments translate into changes in output prices, introducing a new channel through which tax policy affects consumers. Existing research on corporate taxes has largely focused on distributional effects and firm or plant-level outcomes, such as investment (Chodorow-Reich et al., 2024a,b), innovation activities (Akcigit et al., 2022; Lichter et al., 2024), or retail prices (Baker et al., 2020; Dedola et al., 2023). There is limited evidence connecting profit taxation explicitly with price-quality trade-offs. We aim to address this gap and offer new insights by jointly investigating investment, TFP, product quality, and factory-gate prices. Demonstrating that tax reductions can enhance quality, we highlight potential consumer gains often overlooked in tax incidence debates. Unlike many studies exploiting cross-country variation, we use across-region within-country tax variation, following Fuest et al. (2018) and Lichter et al. (2024), who study the effects of local business tax rates on wages and R&D in the context of Germany.

**Related Literature** The results of our paper relate to two distinct strands of the literature. Foremost, our analysis contributes to recent studies on the effects of corporate taxation on retail prices, which find partial pass-through of higher corporate tax rates into prices of consumer-packaged goods. Baker et al. (2020) estimate the impact of increases in state corporate and personal income tax rates on retail prices using US scanner data. The authors find a net-of-

tax elasticity of 0.24, implying a 0.24 increase in retail prices in response to a one percentage point increase in taxes. A related study using German retail data by Dedola et al. (2023) reports a net-of-tax retail price elasticity of 0.4. Unlike these studies, which focus on consumer-packaged goods representing only a small subset of all manufacturing goods, we cover the full sector in Germany and examine a distinct mechanism linking taxation to producer behavior. By examining factory-gate prices net of retail margins and product quality, we focus on firms' production-side adjustments to tax policy. To our knowledge, we are the first to document that prices adjust in tandem with quality following corporate tax changes. While our results point to declining prices following tax increases, Mertens and Ravn (2013) find that federal tax cuts in the United States have disinflationary effects. Together, the studies suggest that tax policy can influence price dynamics, although the direction and underlying mechanisms may differ across contexts.

Moreover, our study is related to a growing set of papers investigating the impact of corporate taxation on total investment, specifically R&D investment. Several studies have demonstrated a robust negative relationship between corporate tax rates and firm-level investment and innovation activities. For example, two recent papers by Chodorow-Reich et al. (2024a) and Chodorow-Reich et al. (2024b) find that US firms' total investment increased by around 8–14 percent in response to the 40 percent tax decrease mandated by the 2017 Tax Cuts and Jobs Act, the largest business tax cut in the history of the United States. Similar evidence is provided by Moon (2022) for the Republic of Korea, who shows that firms (and in particular cash-constrained ones) increased their investments in response to a significant reduction in the capital gains tax. On the other hand, Giroud and Rauh (2019) show for the US that increases in corporate taxation significantly reduce firm-level investment activities and lead to the reallocation of business activities across US states. Relatedly, increases in corporate taxation have been shown to significantly reduce the extent of firm-level R&D spending as well as innovation output (Akcigit et al., 2022; Lichter et al., 2024; Bournakis and Romero-Jordán, 2024), suggesting real effects on firms' growth and productivity. Further evidence for tax-induced firm contraction is provided by Cornelissen et al. (2022) for German firms and by Suárez Serrato and Zidar (2016) as well as Cloyne et al. (2023) for US firms. All three studies show that increases in corporate taxation reduce firms' employment.

The rest of this article proceeds as follows. Section 3.2 introduces the data sources and institutional background. Section 3.3 presents the empirical strategy, including the construction of the outcome variables and identification. Empirical results, robustness checks, and an exploration of potential mechanisms follow in Section 3.4. Section 3.5 concludes.

## 3.2 Data and Institutional Background

The following section provides an overview of the institutional background of profit taxation in Germany and presents the data sources used in our event study analysis. Section 3.2.1 introduces the institutional background and essential features of the profit taxation system. Section 3.2.2 briefly describes the administrative production data for German manufacturing firms and the municipal business tax rate data. In this context, we also illustrate the variation in profit taxes across municipalities in Germany throughout our analysis period.

### 3.2.1 Institutional Background

Business profits of German companies are subject to federal and municipal taxes, with operating profits serving as the common tax base. The federal government levies the corporate income tax (CIT, *Körperschaftsteuer*) on incorporated firms and the personal income tax (PIT, *Einkommenssteuer*) on non-corporate businesses. Regardless of legal form, nearly all firms are liable for the local business tax (LBT, *Gewerbesteuer*) imposed by municipalities.

In Germany, the CIT is raised at a uniform rate and has been gradually reduced from 46 percent in the 1980s to 15 percent in 2008. In contrast, the PIT follows a progressive schedule, with marginal tax rates rising before flattening at higher income levels. Most non-corporate businesses are subject to the top marginal rate, which decreased over time from 56 percent in the 1980s to 42 percent in 2005 and has remained at that level since. Additionally, a solidarity surcharge (*Solidaritätszuschlag*) of about 5.5 percent is added to both corporate and personal income taxes throughout our sampling period. The surcharge was originally introduced to help finance the fiscal costs of German reunification.

The LBT is a significant revenue source for local governments and consists of two multiplicative components. The first is the base rate (*Steuermesszahl*), which was set at 5 percent until 2007 and reduced to 3.5 percent from 2008 onward for all municipalities. Second, the city councils vote on the local scaling factor (*Hebesatz*) at the end of the year, for which we provide descriptive values in the following Section 3.2.2. Notably, the municipalities have full autonomy in setting the scaling factor, although a minimum factor of 200 was imposed in 2004 to avoid tax havens.

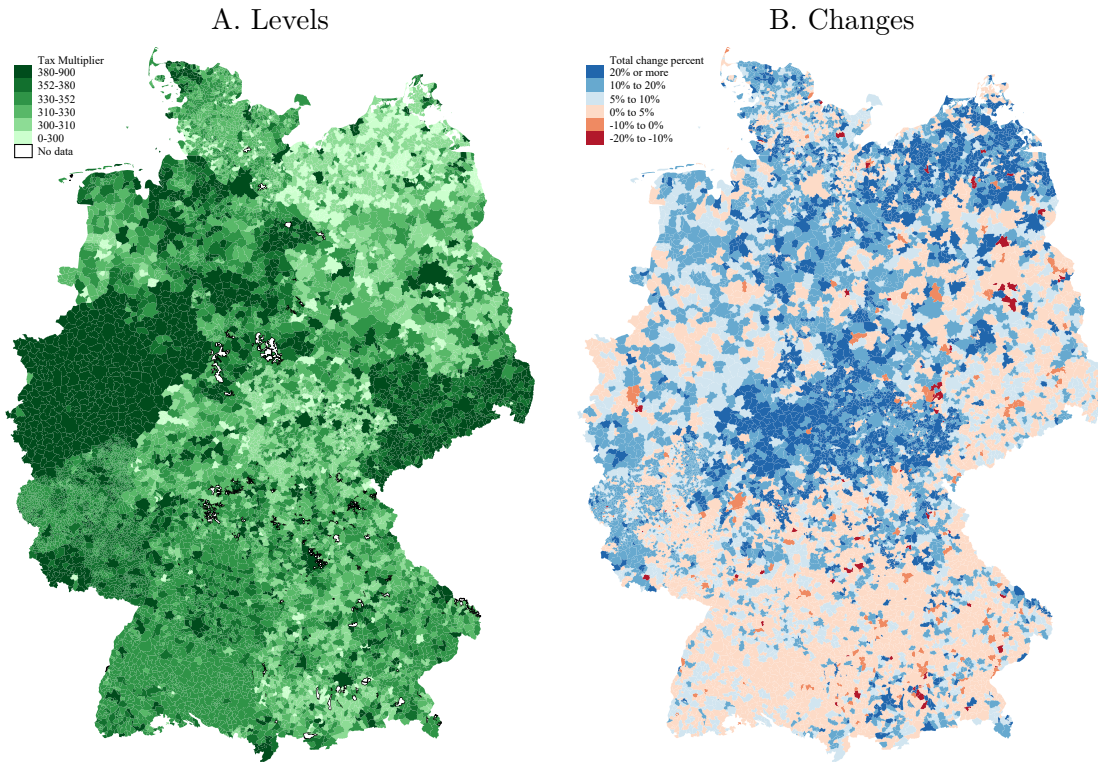
For a rotating subsample of approximately 40 percent of firms (see Section 3.2.2), we observe the legal form as one of three distinct categories: sole proprietorship (*Einzelunternehmen*), corporate firm (*Kapitalgesellschaft*), and other form. Given that only a few firms change legal form in our sample, we impute the legal form for the preceding and following missing years from the observed year. Based on the legal form, we assign corporate firms the CIT and non-corporate firms the PIT. For corporations, we compute the statutory total tax rate (STTR), which aggregates the CIT, the solidarity surcharge, and the local business tax (LBT) to capture the full tax burden. The composite tax reflects all relevant federal and municipal profit taxes

and is, therefore, our preferred measure for analyzing firm behavior. We construct an analogous measure for non-corporate firms taxed under the PIT regime. Moreover, prior to 2008, firms were allowed to deduct LBT payments from their federal taxable income as business expenses. This provision was eliminated with the 2008 tax reform, effectively increasing the statutory tax burden for many firms.

### 3.2.2 Data

**Municipal tax data** We use annual data on local business tax rates at the municipality level from 1999 to 2020 provided by Lichter et al. (2024). The tax data stem from information supplied by the German Federal Statistical Office and the Statistical Offices of the German States (Destatis Statistisches Bundesamt, 2024). Figure 3.1 shows the cross-sectional variation in the scaling factor of the local business tax for each German municipality in 2009. The local scaling factors range from 200 to 900, with an average of 340. Multiplying by the base rate yields effective local business tax rates ranging from 7 to 32 percent, averaging 12 percent in 2009. As national reforms interact with local business tax multipliers, they also result in geographically varying tax burdens.

Figure 3.1: Local Scaling Factors in 2009



*Note:* This figure presents the cross-sectional variation in the local scaling factor of the local business tax by municipality for German corporate firms in 2009. Darker coloring corresponds to higher levels and greater changes in the scaling factor.

**Administrative firm and product data** The *Amtliche Firmendaten für Deutschland* (AFiD) database, available in the Research Data Centre of the Federal Statistical Office and Statistical Offices of the Federal States of Germany (2025), provides rich annual administrative data on German manufacturing firms. The database consists of two panel modules: the first covers company-specific information, while the second contains production data at the firm-product level.<sup>1</sup>

The first module includes key company statistics for the years 2003 to 2016, including industry classification, sales, employment, average wages, costs, and total investment for manufacturing firms with at least 20 employees. The figures are usually reported by the firms' management and reflect the entire enterprise, including both producing and non-producing segments, but excluding international branches. Due to administrative constraints, information on intermediate input costs and R&D spending is collected from only about 40 percent of firms each year on a rotating basis. We reconstruct the sampling stratification by industry and size and use inverse probability weighting in the corresponding regressions following Mertens (2020).

Our baseline sample excludes firms that move between municipalities during the sample period and those located in Bavaria.<sup>2</sup> The regression sample for firm-level outcomes is unbalanced and includes 162,493 firm-year observations. The exceptions are regressions using TFP (59,172 observations) and R&D spending (31,581 observations) as outcomes. Both are available only for the 40 percent subsample of firms. Intermediate inputs are necessary to estimate TFP, but are only reported by the subsample. For R&D spending, we use a logarithmic specification to align with Lichter et al. (2024), thereby further limiting the analysis to firms in the subsample that report positive R&D expenditures. We also discard implausible growth rates in outcomes and the one percent top and bottom outliers in the respective outcomes' distributions.

The second module contains firm-product level data, including sales values and production quantities for direct sales and further processing. We derive the annual average price per product by dividing sales values by quantities. The production dataset covers the universe of manufacturing firms with more than 20 employees and contributes to the official calculations of German national accounts and input-output tables. The resulting unbalanced regression sample contains 422,747 firm-product-year observations. Products are categorized by the eight-digit Product Classification for Production Statistics (GP). Mertens (2020) guides our approach to data preparation and cleaning of the AFiD modules, in particular concerning the harmonization of product codes across several revisions during the observation period.

For each firm, we observe the municipality code (Amtlicher Gemeindeschlüssel) of its head-

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<sup>1</sup>The dataset sources are: Research Data Centre (RDC) of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0; 10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0; 10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0. All results are based on our own calculations.

<sup>2</sup>We exclude Bavaria because of additional data protection provisions by the German Statistical Offices.

quarters. The municipal directory records the official regional boundaries of Germany with municipality codes for specific reference dates. To ensure consistency, we harmonize all annual codes to a consistent definition using 2021 as the reference year. We assign annual business tax rates based on firms' headquarters. This approach differs from other studies that use plant-level information (Fuest et al., 2018; Lichter et al., 2024) and introduces a caveat: although approximately 90 percent of our sample are single-plant firms, the remaining 10 percent are likely large firms and contribute to a significant share of the market. In practice, firms operating establishments across multiple municipalities are subject to tax apportionment according to the German LBT law (*Gewerbesteuer*gesetz, §29-30). The local business tax liabilities are allocated in proportion to each establishment's payroll share.

### 3.3 Empirical Strategy

Our analysis focuses on several firm-level and firm-product-level outcomes. The construction of firm-product quality is detailed in Section 3.3.1. We describe our measure of TFP in 3.3.2. Section 3.3.3 describes the generalized event study design following Lichter et al. (2024). The approach uses multiple tax changes per municipality at different points in time to estimate the effect of changes in the effective statutory total tax rate. A discussion of assumptions and limitations of our identification strategy follows in Section 3.3.4.

#### 3.3.1 Quality

We examine the effect of corporate tax changes on product quality as an important adjustment margin beyond firm-level outcomes. To proxy for unobserved product quality, we adopt a method used in several studies in the international trade literature, such as Amiti and Khandelwal (2013); Khandelwal et al. (2013); Manova and Yu (2017) and Stiebale and Vencappa (2018). The method relies on the assumption of constant elasticity of substitution (CES) demand. In this framework, products with higher perceived quality are expected to sell larger quantities than other products in the same category produced by other firms, conditional on price and other market conditions.

The structural equation for quality follows directly from the log-linearised CES demand function. Under CES preferences, demand for variety  $j$  by firm  $f$  in period  $t$  is

$$Q_{fj,t} = \lambda_{fj,t}^{\sigma-1} P_{fj,t}^{-\sigma} P_{jt}^{\sigma-1} Y_{jt}, \quad (3.1)$$

where  $Q_{fj,t}$  is the demanded quantity,  $\lambda_{fj,t}$  denotes product quality,  $p_{fj,t}$  is the price of product  $j$ ,  $P_{jt}$  is the overall price index,  $Y_{jt}$  is the expenditure, and  $\sigma$  is the elasticity of substitution across products in the same market. Taking logs and collecting time and product fixed effects

to capture  $P_{jt}$  and  $Y_{jt}$  yields

$$q_{fj,t} = -\sigma p_{fj,t} + (\sigma - 1)\lambda_{fj,t} + \alpha_j + \alpha_t + u_{fj,t}. \quad (3.2)$$

After rearranging, our measure of quality at the firm-product-year level can be obtained from the residual from the following OLS regression,

$$q_{fj,t} + \sigma p_{fj,t} = \alpha_j + \alpha_t + \zeta_{fj,t}, \quad (3.3)$$

where  $\zeta_{fj,t} = (\sigma - 1)\lambda_{fj,t} + u_{fj,t}$ . Conditional on the fixed effects, the residual term is interpreted as demand shifters or product characteristics that consumers are willing to pay a premium for. Quality in logarithms can then be backed out as

$$\hat{\lambda}_{fj,t} = \hat{\zeta}_{fj,t}/(\sigma - 1). \quad (3.4)$$

We set  $\sigma$  to industry-specific values for Germany provided by Broda and Weinstein (2006). The fixed effects  $\alpha_j$  account for time-invariant price and quantity differences across eight-digit product categories. Time-fixed effects  $\alpha_t$  explain differences in demand from price-level developments over time. We also construct quality-adjusted prices as  $p_{fj,t} - \lambda_{fj,t}$ .

### 3.3.2 Total Factor Productivity

Next, we obtain firm-level total factor productivity from the estimation of a translog production function,

$$y_{f,t} = \phi'_{f,t}\boldsymbol{\beta} + \omega_{f,t} + \varepsilon_{f,t}, \quad (3.5)$$

where  $y_{f,t}$  is firm  $f$ 's revenue deflated with a firm-specific output price index in year  $t$  in logarithms,  $\phi_{f,t}$  is a vector of production inputs in logarithms and their polynomials as well as interactions,  $\omega_{f,t}$  captures Hicks-neutral firm-level productivity, and  $\varepsilon_{f,t}$  is an i.i.d. error term. We use capital stock  $k_{f,t}$ , full-time equivalents of labor  $l_{f,t}$ , and material expenditures  $m_{f,t}$  as production inputs in logarithms. For translog,  $\phi'_{f,t}\boldsymbol{\beta}$  then corresponds to

$$\begin{aligned} \phi'_{f,t}\boldsymbol{\beta} = & \beta_k k_{f,t} + \beta_l l_{f,t} + \beta_m m_{f,t} + \beta_{kk} k_{f,t}^2 + \beta_{ll} l_{f,t}^2 + \beta_{mm} m_{f,t}^2 \\ & + \beta_{kl} k_{f,t} l_{f,t} + \beta_{km} k_{f,t} m_{f,t} + \beta_{lm} l_{f,t} m_{f,t} + \beta_{lkm} l_{f,t} k_{f,t} m_{f,t}. \end{aligned}$$

We follow Mertens (2022) and implement the one-step approach of Wooldridge (2009) to estimate the production functions separately for groups of two-digit industries.<sup>3</sup> The method

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<sup>3</sup>We group the following NACE two-digit industries together: 10, 11, 12 Food, beverages, tobacco; 13, 14, 15 Textiles, wearing apparel, leather; 16, 17 Wood, paper; 19, 21 Coke, chemicals, pharmaceuticals; 22, 23 Rubber, plastic, minerals; 24, 25 Basic and fabricated metals; 26, 27 Computer, electronic, electrical equipment; 28, 29,

uses lagged values of flexible inputs as instruments to address the endogeneity of contemporaneous inputs and builds on the work by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Akerberg et al. (2015), addressing three key identification issues.

- (1) **Unobserved productivity shocks and simultaneity** Firm productivity, denoted by  $\omega_{f,t}$ , is unobserved by the econometrician but known to the firm, and may therefore be correlated with flexible input choices once productivity innovations are realised. To address this simultaneity problem, we invert the firm’s intermediate input demand function, following the approach of Akerberg et al. (2015). We model the productivity law of motion as a first-order Markov process, allowing lags of changes in tax rates to enter (De Loecker, 2013; Braguinsky et al., 2015), and construct moment conditions to identify the production function parameters. We assume that firms flexibly adjust intermediate inputs, whereas capital and labor are static inputs. This timing assumption is consistent with Germany’s strict labor protection laws. Accordingly, we treat capital and labor as uncorrelated with the innovation in productivity. The set of instruments contains current values of pre-determined inputs, labor and capital, and their polynomial terms, and lagged values of intermediate inputs and their polynomials. We also include indicator variables for exporting status and R&D activity, and the log number of products of the firm, as these may influence intermediate input demand. Finally, we control for log average wages, following De Loecker and Scott (2022), to mitigate identification issues in gross output functions highlighted by Gandhi et al. (2020).
- (2) **Product aggregation and measurement of quantities** Not all product categories are reported in a consistent unit; therefore, we cannot aggregate physical quantities for multi-product firms. Instead, we construct firm-specific price indices from observed product-level prices to deflate firm-level revenues following Mertens (2020).
- (3) **Unobserved input prices** To account for unobserved variation in input prices, we incorporate a price control function based on firm-product price information following Mertens (2020), who adapts the product-level approach by De Loecker et al. (2016). The price control function includes the firm-specific output price index interacted with production inputs, a weighted average of its product market revenue share, fixed effects for the firm’s federal state, and the main four-digit industry. These factors capture geographical variation in input prices and differences in product quality, assuming that higher-quality products require higher-quality inputs associated with higher prices; a relationship well documented in the trade literature (see, e.g., Verhoogen, 2008; Kugler and Verhoogen, 2012; Manova and Zhang, 2012).

We recover firm-level total factor productivity as the residual from estimating the production

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30 Machinery, motor, transport; 31, 32 Furniture, other manufacturing.



function. As intermediate input data is available only for the 40 percent subsample, we correct for the sampling design with inverse probability weighting in the event study following Mertens (2020).

### 3.3.3 Event Study Design

We study how changes in corporate taxes affect various firm-product-level and firm-level outcomes to provide a comprehensive view of firms' responses. In the baseline specification, we measure profit taxation by the statutory total tax rate. First, we examine firm-product-level outcomes to capture more granular effects than the existing literature. Second, we turn to firm-level variables, using the same identification strategy to both validate our approach by reproducing earlier findings from the literature with a new dataset and explore potential mechanisms behind our primary results. We present the two estimation specifications and then describe the construction of the treatment variable common to both below.

For our main analysis, we use a firm-product level adaptation of the generalized event study model design with staggered treatment typically used for plant-level outcomes (see, e.g., Suárez Serrato and Zidar, 2016; Fuest et al., 2018; Akcigit et al., 2022; Lichter et al., 2024). Our dataset allows us to gain new insights by exploiting variation within firms and their product mix. We use the following specification to estimate the effect of profit taxation on firm-product-level outcomes with five leads and four lags:

$$y_{fj,t} = \sum_{\substack{s=-5 \\ s \neq -1}}^4 \beta_s T_{g\ell,t}^s + \delta_{fj} + \alpha_{c\ell,t} + \alpha_{z\ell,t} + \epsilon_{fj,t}, \quad (3.6)$$

where  $y_{fj,t}$  is the outcome of interest in logarithms for firm  $f$ 's eight-digit product category  $j$ , part of six-digit product category  $c$ , in year  $t$ . Within an eight-digit category, we further distinguish products reported in different units, so that  $j$  represents a unique product code-unit combination. We denote a firm's municipality of residence by  $g$ , its legal status, which determines the effective tax rate, by  $\ell$ , and its NUTS2 region by  $z$ . The time period relative to treatment timing is indexed by  $s$  and we include five leads and four lags of our treatment variable  $T_{g\ell,t}^s$ . Firm-product-unit fixed effects  $\delta_{fj}$  control for unobserved time-invariant heterogeneity inherent to the product produced by the particular firm, i.e., permanent differences in technology and product characteristics. Because we exclude relocating firms from the baseline sample, any time-invariant municipality characteristic is also absorbed by the firm-product fixed effects. We further account for time-varying common shocks at both the six-digit product and NUTS2 level that differ between corporate and non-corporate firms. We denote these by  $\alpha_{c\ell,t}$  and  $\alpha_{z\ell,t}$ . We cluster standard errors at the municipality level.

We then aim at replicating established findings to confirm that our data and design yield comparable results to those in the literature. We estimate effects for labor and innovation

outcomes and compare them to results in Fuest et al. (2018), Cornelissen et al. (2022) and Lichter et al. (2024). Note that all three studies rely on plant-level outcomes, while we use firm-level outcomes. Our estimating equation again includes five leads and four lags:

$$y_{f,t} = \sum_{\substack{s=-5 \\ s \neq -1}}^4 \beta_s T_{g\ell,t}^s + \delta_f + \alpha_{i\ell,t} + \alpha_{z\ell,t} + \epsilon_{f,t}. \quad (3.7)$$

Here, term  $y_{f,t}$  refers to firm  $f$ 's outcome in logarithms for four-digit industry  $i$  in year  $t$ . We include firm fixed effects  $\delta_f$ , which again absorb all municipality-level time-invariant heterogeneity, four-digit industry-legal form and NUTS2 region-legal form time dummies,  $\alpha_{i\ell,t}$  and  $\alpha_{z\ell,t}$ .

In both equations,  $T_{g\ell,t}^s$  is a continuous treatment variable reflecting the adoption of tax reforms, scaled by the exact size of the change. This specification exploits the full extent of tax variation available in the data. It captures leads and lags of changes in the effective statutory total tax rate  $\tau_{g\ell,t}$  for corporate and non-corporate firms, distinguished by their legal form indicator  $\ell$ , and is defined as

$$T_{g\ell,t}^s = \begin{cases} \tau_{g\ell,2020} - \tau_{g\ell,t-s-1} & \text{if } s = -5 \\ \tau_{g\ell,t-s} - \tau_{g\ell,t-s-1} & \text{if } -5 < s < 4 \\ \tau_{g\ell,t-s} - \tau_{g\ell,1998} & \text{if } s = 4. \end{cases} \quad (3.8)$$

This measure of treatment intensity assumes that effects are linear in the magnitude of the tax change (Schmidheiny and Siegloch, 2023). The parameters  $\hat{\beta}_s$  capture the dynamic treatment effects in the  $s$ th period after treatment when  $s \geq 0$ . If  $s < 0$ , estimated pre-trend coefficients may provide corroborating evidence for the assumption of common trends. We use the year before the tax change as the reference period, so that all coefficients are interpreted relative to year -1. As municipalities can experience multiple treatments, we bin all tax changes before and after our observation period, assuming that effects remain constant beyond the endpoints of the event window (McCrary, 2007; Schmidheiny and Siegloch, 2023).

### 3.3.4 Identification

Conceptually, our approach boils down to a generalized event study approach with staggered treatment. Identification relies on comparing changes in firms' outcomes in municipalities affected by a tax change at  $t = 0$  to changes in firms located in municipalities that do not experience a tax change in the event window period or have not yet been affected. We control for regional and market-specific time-varying shocks by legal form.

Our event study results, reported below in Section 3.4.1, mainly reveal flat pre-trends. For prices, quality, and quality-adjusted prices, the estimated pre-treatment effects  $\hat{\beta}_s$  for  $s < 0$

show no significant deviations, supporting the parallel trends assumption and suggesting no systematic differences in firms’ outcomes prior to tax changes. For quantities, however, we do observe a pre-trend, which calls for a more cautious interpretation of these estimates. Further support for the identification strategy comes from Fuest et al. (2018) and Lichter et al. (2024). The authors show that tax changes cannot be predicted by population movements, deteriorating tax revenues, or increasing expenses in Germany. Last, in addition to the variation in local business tax rates, we use national tax reforms and their locally varying impact for identification, further limiting endogeneity concerns.

We conduct additional robustness checks as detailed in Section 3.4.2. These include (i) using the variation solely from changes in the local business tax, (ii) using an alternate value for  $\sigma$  in the construction of our quality measure, (iii) clustering standard errors at the coarser NUTS3 level, (iv) incorporating more disaggregated geographical, time-varying fixed effects, (v) including firms that relocate, (vi) excluding firms from East Germany, (vii) using a balanced panel of firms, and (viii) considering event windows of five leads/five lags and four leads/four lags.

## 3.4 Empirical Results

We first assess the effects of profit tax changes on firms’ product market outcomes. Section 3.4.1 summarizes our main empirical findings for product prices, quantities, quality, and quality-adjusted prices. We explore the robustness of our results in Section 3.4.2. In Section 3.4.3, we investigate potential mechanisms underlying our main results, focusing on effect symmetry with regard to tax increases and decreases as well as effects on firm-level outcomes such as employment, investment, and TFP.

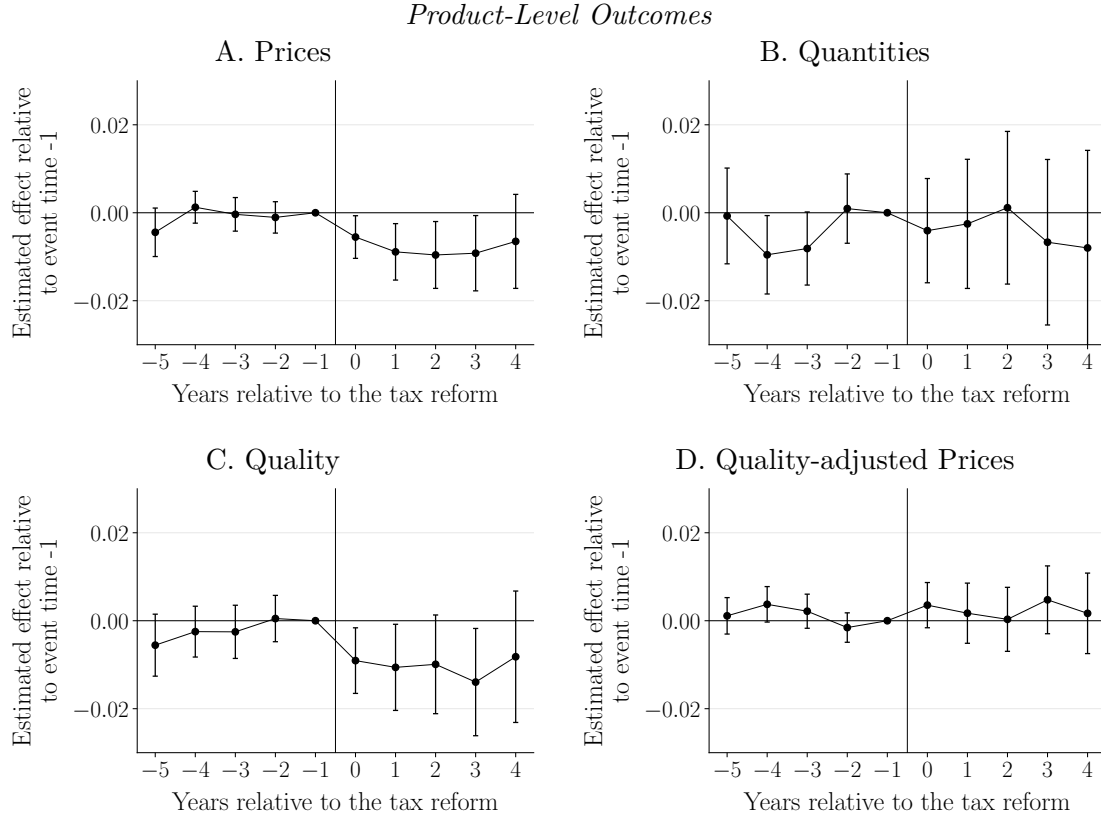
### 3.4.1 Main Results

**Prices** Firms may respond to tax increases by adjusting their pricing strategies. We study the dynamic effects of a tax change on firm-product-level factory gate prices and the extent to which higher taxes are passed through to consumers. Figure 3.2 Panel A shows the estimated effect of an increase in the STTR on prices. The estimates show statistically insignificant and flat pre-treatment trends.

After a tax increase, prices fall rather than increase, as one would expect in the case of pass-through. This suggests that firms absorb tax changes or adjust along other margins. In quantitative terms, a one percentage point increase in the tax is associated with a 0.82 percent long-run decrease in prices. Expressing this effect as an elasticity, we take the average over all post-treatment coefficients and evaluate at the average tax rate of 39.95 percent. This yields an implied elasticity of -0.32 with a standard error of 0.14. A one percent increase in the tax rate, therefore, corresponds to a 0.32 percent decrease in prices on average.

**Quantities** Next, we examine whether firms' produced quantities change alongside their prices. For this outcome variable, we do find pre-trends. Our findings should therefore be interpreted with caution. Moreover, the results of the event study in Figure 3.2 Panel B show insignificant and noisy estimates following a tax change, with an implied elasticity of -0.16 (SE: 0.30). This suggests that firms did not cut production in response to a tax increase. Instead, the adjustment may have been reflected in product quality, which we explore next.

Figure 3.2: The Effect of Profit Taxes on Price, Quantity, Quality, and Quality-adjusted Price



*Note:* This figure presents event study point estimates with 95% confidence intervals. The coefficients represent the estimated effect on the outcome of a one percentage point increase in the statutory total tax rate. In Panel A, the dependent variable is output price. Panel B shows the effect on quantities produced. In Panel C, we use the estimated product quality as described in Section 3.3.1. Finally, quality-adjusted prices serve as the outcome in Panel D. All outcomes vary at the firm-product-year level and are transformed into logarithms. All models include firm  $\times$  product, six-digit product  $\times$  legal form  $\times$  year, and NUTS2  $\times$  legal form  $\times$  year fixed effects based on the specification in Equation 3.6. Standard errors are clustered at the municipality level. We report regression coefficients in Appendix Table 3.2.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0; 10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0; 10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

**Quality** We now investigate quality downgrading as a potential explanation for the negative price effect. As shown in Figure 3.2 Panel C, the analysis reveals a significant decline in product quality over time in response to an increase in the STTR. A one percentage point tax increase lowers quality by approximately 1.04 percent in the long run. The implied elasticity is -0.41 (SE: 0.20). This is consistent with firms reducing costly product attributes to offset the tax burden rather than raising prices.

**Quality-adjusted Prices** Lastly, we focus on quality-adjusted prices in Figure 3.2 Panel D. Under CES demand, we can calculate quality-adjusted prices as log prices minus log quality. This outcome isolates the change in price holding quality constant. Once quality is taken into account, the effect on prices becomes flat and insignificant, with an implied elasticity of 0.10 (SE: 0.13). The negative effect of STTR increases on prices appears to be attributable to a decrease in quality, consistent with the quality downgrading hypothesis. Since the negative effect on quality (-0.41) is larger than the negative effect on price (-0.32), the effect on log price minus log quality should be positive, which is what we find (0.10).

Our findings suggest that firms adjust their production in response to STTR increases, leading to reduced quality and lower prices. Limited ability to pass on tax changes, whether because of competitive pressure or demand sensitivity, appears to constrain price adjustments. Instead, firms seem to rely on other strategies to maintain their market share or customer base. Consequently, consumers bear part of the adjustment to higher profit taxes, paying lower prices but for goods of inferior quality.

### 3.4.2 Robustness Checks

We assess the robustness of our findings in several ways. First, we isolate variation stemming solely from changes in the local business tax, excluding local variation from the federal tax reforms (Appendix Figure 3.8 Panel A for quality and Panel C for prices). The resulting dynamic patterns closely mirror our baseline findings, although the estimated effect sizes are smaller in magnitude. Second, we use the industry median elasticity of substitution from Khandelwal et al. (2013), as an alternative value in constructing our quality measure in Equation 3.3 (Appendix Figure 3.8 Panel B). Third, we cluster standard errors at the NUTS3 level as a coarser level of geographical aggregation than the municipality, following Angrist and Pischke (2009). Standard errors are barely affected. Fourth, we include geographically finer, time-varying group-fixed effects that capture unobserved heterogeneity at the NUTS3-legal form-year level. Fifth, we include firms that relocate during the analysis period while controlling for additional municipality fixed effects. We also re-estimate the models excluding East German municipalities affected by structural reforms that merged several jurisdictions. Furthermore, we validate our findings using a balanced panel of firms observed for at least six periods. Lastly, we consider

two alternative event windows: five leads and five lags, and four leads and four lags. Our main results remain robust across all specifications.

### 3.4.3 Mechanisms

Our primary analysis revealed that firms respond to higher profit taxes by reducing product prices and quality, rather than passing the increase on to consumers. We now explore several aspects that help to clarify the mechanisms behind these findings. First, we examine whether firms respond symmetrically to tax increases and decreases. We then extend the analysis to several firm-level aggregate outcomes related to employment and investment. Lastly, we turn to firm-level productivity as a proxy for production efficiency, explaining the construction of the measure and presenting the results of the event study.

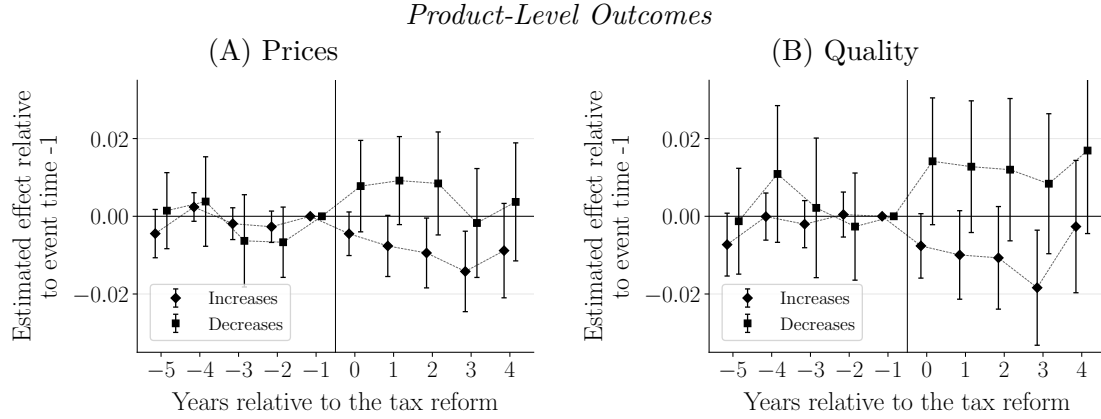
**Symmetry** The information on annual tax rates allows us to explore potential asymmetries in firms' responses to increases versus decreases in the STTR. To do so, we apply the same event study specification as in Equation 3.6, but now include distinct treatment indicators scaled by tax increases and decreases. Most tax reductions originate from federal reforms, whereas the observed increases mainly result from higher municipal business tax rates. We examine whether the separate effects for the two directions differ in strength and report the results in Figure 3.3 Panel A for prices and Panel B for quality. Again, pre-treatment trends estimated by our model are flat in both cases.

Panel A displays event-study estimates for price responses to tax changes. Prices decline following tax increases and rise slightly after tax decreases. Only the implied elasticity for tax increases of -0.36 (SE 0.16) is statistically significant at the 5 percent level. Panel B shows that quality declines after tax hikes and slightly improves after tax decreases. The estimated elasticities of -0.39 (0.23) and 0.51 (SE 0.30) are both statistically significant at the 10 percent level. The result suggests that firms adjust similarly in both directions. This would, in turn, imply that tax cuts may benefit not only firms through increased investment incentives, as shown, e.g., by Lichter et al. (2024), but also consumers through higher product quality, potentially accompanied by price adjustments that reflect improved value.

**Employment and Wages** We now turn to firm-level outcomes to explore potential mechanisms and validate our approach by replicating established findings. For all these analyses, we rely on the firm-level event study model as specified in Equation 3.7. We begin by replicating effects on two employment outcomes: full-time equivalents (FTE) and average wages.

We find that higher taxes incentivize firms to contract by reducing employment. Figure 3.4 Panel A shows a significant decrease in FTE following STTR increases. The effect is statistically significant immediately after treatment and grows in magnitude until year three before slightly reverting back. In the long run, a one percentage point increase in the tax rate is associated

Figure 3.3: Symmetric Effects of Profit Taxes on Prices and Quality



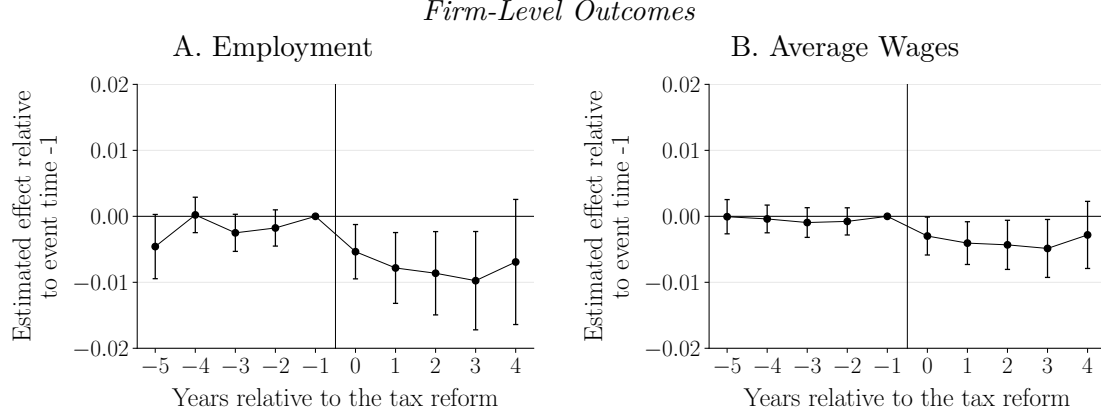
*Note:* This figure presents event study point estimates with 95% confidence intervals. The coefficients represent the estimated effect on the outcome of a one percentage point change in the statutory total tax rate. The estimation relies on the same model as in Figure 3.2 but includes distinct treatment indicators scaled by tax increases and decreases to allow for asymmetric effects. Panel A shows the effect on firm-product-level output prices. In Panel B, the dependent variable is the estimated firm-product-level product quality as described in Section 3.3.1. All outcomes vary at the firm-product-year level and are transformed into logarithms. Both models include firm  $\times$  product, six-digit product  $\times$  legal form  $\times$  year, and NUTS2  $\times$  legal form  $\times$  year fixed effects based on the specification in Equation 3.6. Standard errors are clustered at the municipality level. We report regression coefficients in Appendix Table 3.2.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0; 10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0; 10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

with a 0.78 percent decrease in employment. The pre-treatment coefficients are small and insignificant. We calculate the implied elasticity from the average post-treatment coefficients evaluated at the average statutory total tax rate of 39.79 percent in the firm regression sample. The implied elasticity of employment is -0.31 (SE: 0.12), suggesting that higher profit taxes reduce firms' demand for labor. The estimated elasticity is rather close to the estimated one in Cornelissen et al. (2022) of -0.17, supporting the credibility of our approach when analyzing new product-level outcomes such as quality and prices.

In Panel B, we show that average wages also decrease following the tax increase, though less sharply than FTE. The average post-treatment effect is -0.38, implying an elasticity of wages with respect to the STTR of -0.15 (SE: 0.07). The estimate lies between existing findings: Fuest et al. (2018) report a larger elasticity of -0.39, while Cornelissen et al. (2022) find a smaller one of -0.07. Together, the results point to moderate but consistent wage adjustments. The pattern remains in line with the interpretation of partial cost absorption through labor market adjustments, affecting both employment levels and wages.

Figure 3.4: The Effect of Profit Taxes on Employment and Wages



*Note:* This figure presents event study point estimates with 95% confidence intervals. The coefficients represent the estimated effect on the outcome of a one percentage point increase in the statutory total tax rate. In Panel A, the dependent variable is the total number of full-time equivalents in logs. Panel B shows the effect on the firm-level average wage. All outcomes vary at the firm-year level and are transformed into logarithms. All models include firm, four-digit industry  $\times$  legal form  $\times$  year, and NUTS2  $\times$  legal form  $\times$  year fixed effects based on the specification in Equation 3.7. Standard errors are clustered at the municipality level. We report regression coefficients in Appendix Table 3.3.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0;

10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0;

10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

**Investment and R&D** Motivated by recent findings of reduced investment and innovation incentives following tax increases (Lichter et al., 2024), we further examine effects on firms' investment decisions: total investment, investment in equipment, and R&D expenditures.

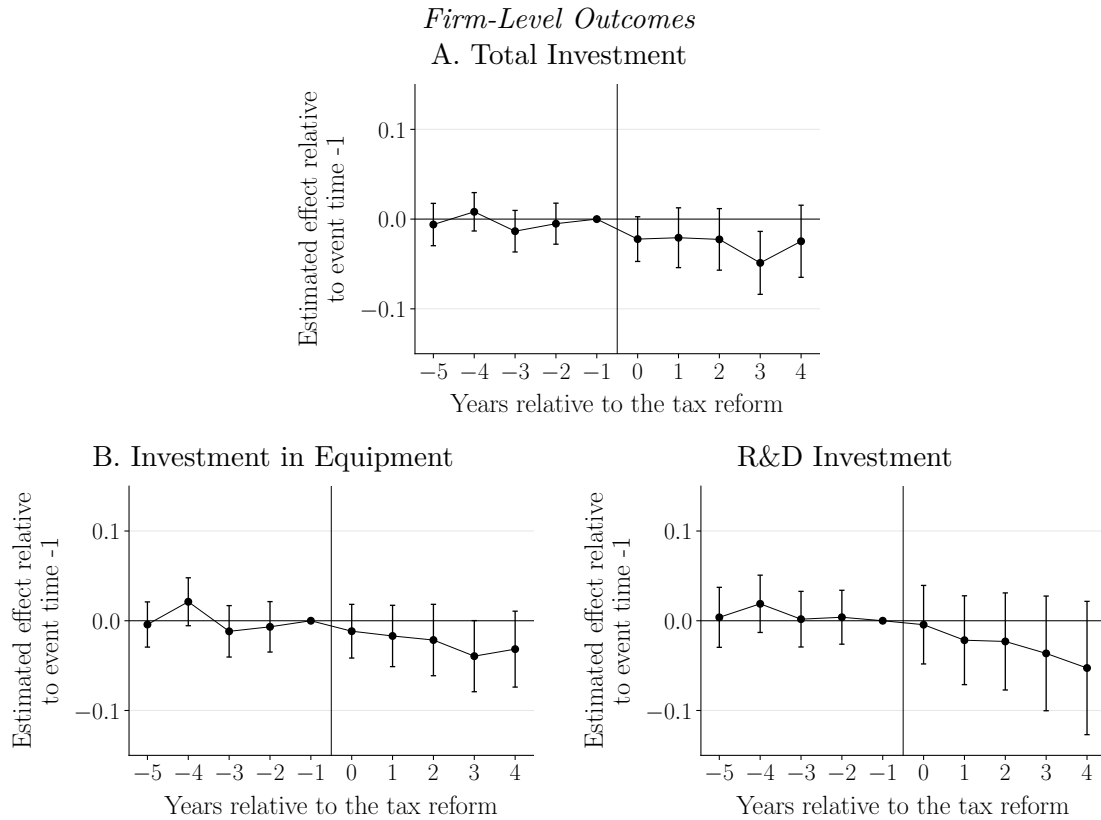
Figure 3.5 illustrates the event study results for changes in the STTR. Panel A shows a negative, statistically significant effect of tax increases on firms' total investment in the third year after the tax change, with no evidence of pre-trends. A one percentage point increase in the statutory total tax rate is associated with an average post-treatment effect of -2.8 percent. The results imply an elasticity of -1.11 (SE: 0.55) evaluated at the average tax rate.

We further investigate effects on two components of total investment: investment in equipment and machinery, and R&D spending. Both components decline following an increase in the STTR. Panel B displays a similar downward pattern for investment in equipment, though smaller in magnitude and less precisely estimated, with an average post-treatment effect of -2.42 percent and an implied elasticity of -0.96 (SE: 0.59). Panel C shows insignificant event study results and average effect of -2.76 for R&D investment, with an elasticity of -1.11 (SE: 0.98). This R&D response is smaller than the one reported by Lichter et al. (2024), who find an elasticity of -2.4.

Our results, while somewhat weaker, align with existing evidence and suggest that firms may respond to higher profit taxes by adjusting their cost structures, particularly by reducing



Figure 3.5: The Effect of Profit Taxes on Investment



*Note:* This figure presents event study point estimates with 95% confidence intervals. The coefficients represent the estimated effect on the outcome of a one percentage point increase in the statutory total tax rate. In Panel A, the dependent variable is total investment expenditure. Panel B shows the effect on the firm-level investment in equipment, while Panel C reports estimates for a subsample reporting R&D expenditures. All outcomes vary at the firm-year level and are transformed into logarithms. All models include firm, four-digit industry  $\times$  legal form  $\times$  year, and NUTS2  $\times$  legal form  $\times$  year fixed effects based on the specification in Equation 3.7. Standard errors are clustered at the municipality level. We report regression coefficients in Appendix Table 3.3.

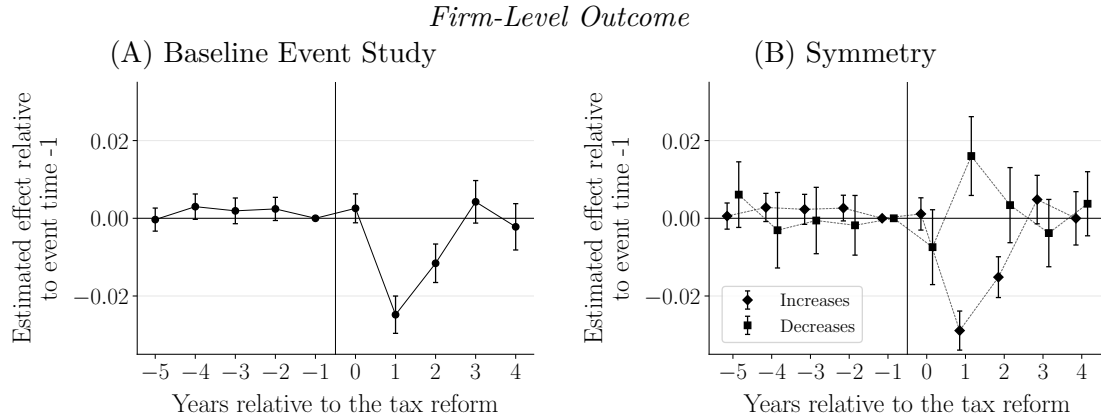
Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0; 10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0; 10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

employment and investment. The observed declines in investment and R&D point to a potential mechanism by which tax increases shift firms' focus from long-term innovation toward short-term cost savings, consistent with the observed reduction in product quality.

**Total Factor Productivity** To examine further within-firm adjustments, we last investigate the effect of corporate taxation on firms' total factor productivity as a proxy for production efficiency.

Figure 3.6 presents the dynamic effects of profit taxation on firm-level TFP. Consistent with

Figure 3.6: Effects of Profit Taxes on TFP



*Note:* This figure presents event study point estimates with 95% confidence intervals. The coefficients in Panel A represent the estimated effect on firm-level total factor productivity of a one percentage point increase in the statutory total tax rate. Panel B relies on the same model but includes distinct treatment indicators scaled by tax increases and decreases to allow for asymmetric effects. The estimation of TFP is described in Section 3.3.2. The outcome varies at the firm-year level and is transformed into logarithms. All models include firm, four-digit industry  $\times$  legal form  $\times$  year, and NUTS2  $\times$  legal form  $\times$  year fixed effects based on the specification in Equation 3.7. Standard errors are clustered at the municipality level. We report regression coefficients in Appendix Table 3.3.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of

Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0;

10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0;

10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

cost-cutting and reduced investment, we find a significant decline in TFP following increases in the STTR, as shown in Panel A. Unlike the other outcomes above, this effect is not persistent over time. Productivity declines are most pronounced in the first year after the tax reform and revert back after two years, suggesting short-lived changes in productivity.

Panel B distinguishes between increases and decreases in the STTR. Tax increases have negative and statistically significant effects in years one and two. A one percentage point increase in the tax rate is, on average, associated with a 0.76 percent decline in TFP. Tax decreases, by contrast, have a positive but even more temporary response: the effect is significant only after one year and reverses more quickly in the second year. These results remain robust when using a Cobb-Douglas production function instead of the translog model.

Rather than capturing isolated effects, the results on investment, quality, and productivity reveal a coherent pattern: profit taxation appears to induce firms to trade off long-term value creation with short-term cost reductions. At the same time, the observed symmetric quality effects suggest that corporate tax cuts can potentially benefit consumers. Together, the findings provide a more comprehensive understanding of how firms respond to tax policy and how such responses may impact both firm performance and consumer outcomes.

### 3.5 Conclusion

This paper investigates the impact of profit taxes on product market outcomes using a rich panel of administrative production data from German manufacturing firms. We employ an event-study design to estimate the effect of changes in corporate tax rates on product-level quality and factory-gate prices. The analysis leverages more than 28,000 municipality-level changes in the local business tax and approximately 14 federal tax reforms. These national reforms interact with local business tax multipliers and translate into geographically varying tax burdens.

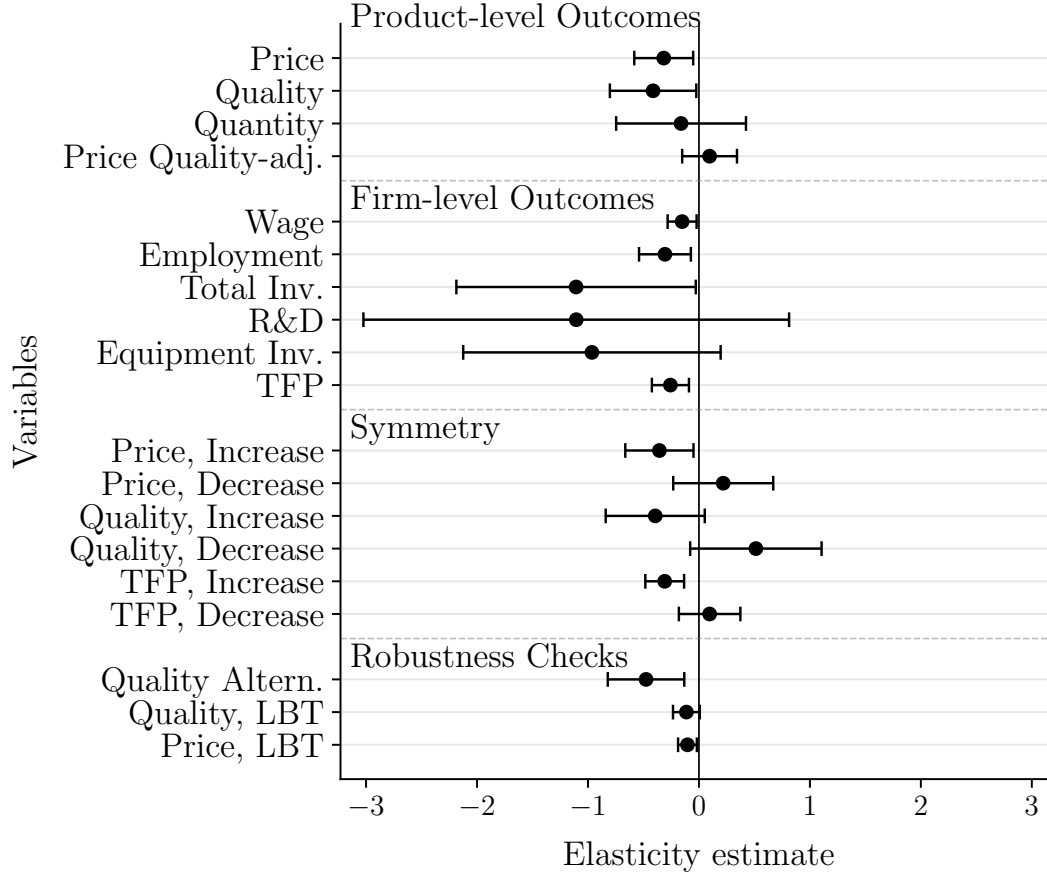
Granular production data enables us to move beyond traditional firm-level analysis and examine how profit taxation directly affects product-market outcomes. We provide the first evidence on product-level responses in quality to changes in profit taxes. Our findings suggest that firms reduce product quality after tax increases. Furthermore, we find no evidence of tax pass-through in factory gate prices. Instead, prices tend to fall after tax increases, a pattern consistent with quality downgrading. Once we control for quality, the price effect disappears, indicating that consumers obtain lower-quality products for the same expenditure. Given a pre-trend in quantities, we interpret the results with caution but view them, along with observed declines in employment and investment, as indicative of a broader pattern of firm contraction. Notably, we find symmetric responses to tax cuts: firms increase product quality when tax rates fall, addressing often overlooked gains for consumers. We also find that prices increase slightly after tax decreases, and although the implied elasticity is not statistically significant, the effect size is comparable to that for tax increases.

Our findings highlight the broader product-market consequences of profit taxation. We document that tax increases may lead to declines in product quality and prices, suggesting that firms may respond by shifting towards lower-cost products of lower quality. The observed declines in investment, employment, and TFP support this hypothesis and point to a trade-off between long-term innovation and short-term cost savings.

## 3.A Supplemental Results

### 3.A.1 Elasticities

Figure 3.7: Implied Elasticities of Profit Taxes



*Note:* This figure presents implied elasticities with respect to the statutory total tax rate and 95% confidence intervals calculated from event-study regressions in Figure 3.2. Models with dependent variables prices, quality, quantity, and quality-adjusted prices are estimated at the firm-product level and include firm  $\times$  product and six-digit product  $\times$  legal form  $\times$  year fixed effects. Models with dependent variables average wages, employment, total investment, R&D, investment in equipment, and total factor productivity, are estimated at the firm level and include firm and four-digit industry  $\times$  legal form  $\times$  year fixed effects. All models include additional NUTS2  $\times$  legal form  $\times$  year fixed effects. Estimation of product quality is described in Section 3.3.1. Estimation of total factor productivity is described in Section 3.3.2. All outcome variables are in logarithms. Standard errors are clustered at the municipality level.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0; 10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0; 10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

Table 3.1: Estimation Results - Baseline Event Study

| Variable                               | Tax rate | N       | Elasticity | SE   | CI               | p-value |
|----------------------------------------|----------|---------|------------|------|------------------|---------|
| <b>Panel A. Product-level Outcomes</b> |          |         |            |      |                  |         |
| Price                                  | 39.95    | 422,747 | -0.32**    | 0.14 | [-0.583, -0.052] | 0.02    |
| Quality                                | 39.95    | 422,747 | -0.41**    | 0.20 | [-0.803, -0.024] | 0.04    |
| Quantity                               | 39.95    | 422,747 | -0.16      | 0.30 | [-0.746, 0.424]  | 0.59    |
| Price Quality-adj.                     | 39.95    | 422,747 | 0.10       | 0.13 | [-0.151, 0.343]  | 0.45    |
| <b>Panel B. Firm-level Outcomes</b>    |          |         |            |      |                  |         |
| Wage                                   | 39.79    | 162,493 | -0.15**    | 0.07 | [-0.282, -0.021] | 0.02    |
| Employment                             | 39.79    | 162,493 | -0.31**    | 0.12 | [-0.540, -0.073] | 0.01    |
| Total Inv.                             | 39.79    | 162,493 | -1.11**    | 0.55 | [-2.186, -0.028] | 0.04    |
| R&D                                    | 40.01    | 31,581  | -1.11      | 0.98 | [-3.024, 0.812]  | 0.26    |
| Equipment Inv.                         | 39.79    | 162,493 | -0.96      | 0.59 | [-2.125, 0.196]  | 0.10    |
| TFP                                    | 40.45    | 59,172  | -0.26***   | 0.09 | [-0.424, -0.090] | 0.00    |
| <b>Panel C. Symmetry</b>               |          |         |            |      |                  |         |
| Price, Increase                        | 39.95    | 422,747 | -0.36**    | 0.16 | [-0.664, -0.049] | 0.02    |
| Price, Decrease                        | 39.95    | 422,747 | 0.22       | 0.23 | [-0.232, 0.669]  | 0.34    |
| Quality, Increase                      | 39.95    | 422,747 | -0.39*     | 0.23 | [-0.840, 0.053]  | 0.08    |
| Quality, Decrease                      | 39.95    | 422,747 | 0.51*      | 0.30 | [-0.079, 1.105]  | 0.09    |
| TFP, Increase                          | 40.45    | 59,172  | -0.31***   | 0.09 | [-0.483, -0.134] | 0.00    |
| TFP, Decrease                          | 40.45    | 59,172  | 0.10       | 0.14 | [-0.181, 0.373]  | 0.50    |
| <b>Panel D. Robustness Checks</b>      |          |         |            |      |                  |         |
| Quality Altern.                        | 39.95    | 422,747 | -0.48***   | 0.18 | [-0.822, -0.132] | 0.01    |
| Quality, LBT                           | 13.25    | 422,747 | -0.11*     | 0.06 | [-0.234, 0.008]  | 0.07    |
| Price, LBT                             | 13.25    | 422,747 | -0.10**    | 0.04 | [-0.188, -0.019] | 0.02    |

*Notes:* This table reports the implied elasticities from Appendix Figure 3.7, calculated from event-study regressions in Figure 3.2 in the main text. For the full specification details, see the respective figure notes. Standard errors in parentheses, clustered at the municipality level.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0; 10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0; 10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

### 3.A.2 Event Studies

Table 3.2: Estimation Results - Event Studies with Firm-Product-Level Outcomes

|                                 | Price                |                   |                      |                   | Quantity            | Quality             |                     |                   |
|---------------------------------|----------------------|-------------------|----------------------|-------------------|---------------------|---------------------|---------------------|-------------------|
|                                 | Base                 | Q-adj             | Increases            | Decreases         | Base                | Base                | Increases           | Decreases         |
|                                 | (1)                  | (2)               | (3)                  | (4)               | (5)                 | (6)                 | (7)                 | (8)               |
|                                 | Fig. 3.2             |                   | Fig. 3.3             |                   | Fig. 3.2            | Fig. 3.2            | Fig. 3.3            |                   |
| $t - 5$                         | -0.004<br>(0.003)    | 0.001<br>(0.002)  | -0.004<br>(0.003)    | 0.001<br>(0.005)  | -0.001<br>(0.006)   | -0.006<br>(0.004)   | -0.007*<br>(0.004)  | -0.001<br>(0.007) |
| $t - 4$                         | 0.001<br>(0.002)     | 0.004*<br>(0.002) | 0.002<br>(0.002)     | 0.004<br>(0.006)  | -0.010**<br>(0.005) | -0.002<br>(0.003)   | -0.000<br>(0.003)   | 0.011<br>(0.009)  |
| $t - 3$                         | -0.000<br>(0.002)    | 0.002<br>(0.002)  | -0.002<br>(0.002)    | -0.006<br>(0.006) | -0.008*<br>(0.004)  | -0.003<br>(0.003)   | -0.002<br>(0.003)   | 0.002<br>(0.009)  |
| $t - 2$                         | -0.001<br>(0.002)    | -0.002<br>(0.002) | -0.003<br>(0.002)    | -0.007<br>(0.005) | 0.001<br>(0.004)    | 0.000<br>(0.003)    | 0.000<br>(0.003)    | -0.003<br>(0.007) |
| $t$                             | -0.006**<br>(0.002)  | 0.004<br>(0.003)  | -0.004<br>(0.003)    | 0.008<br>(0.006)  | -0.004<br>(0.006)   | -0.009**<br>(0.004) | -0.008*<br>(0.004)  | 0.014*<br>(0.008) |
| $t + 1$                         | -0.009***<br>(0.003) | 0.002<br>(0.003)  | -0.008*<br>(0.004)   | 0.009<br>(0.006)  | -0.003<br>(0.007)   | -0.011**<br>(0.005) | -0.010*<br>(0.006)  | 0.013<br>(0.009)  |
| $t + 2$                         | -0.010**<br>(0.004)  | 0.000<br>(0.004)  | -0.009**<br>(0.005)  | 0.008<br>(0.007)  | 0.001<br>(0.009)    | -0.010*<br>(0.006)  | -0.011<br>(0.007)   | 0.012<br>(0.009)  |
| $t + 3$                         | -0.009**<br>(0.004)  | 0.005<br>(0.004)  | -0.014***<br>(0.005) | -0.002<br>(0.007) | -0.007<br>(0.010)   | -0.014**<br>(0.006) | -0.018**<br>(0.008) | 0.008<br>(0.009)  |
| $t + 4$                         | -0.007<br>(0.005)    | 0.002<br>(0.005)  | -0.009<br>(0.006)    | 0.004<br>(0.008)  | -0.008<br>(0.011)   | -0.008<br>(0.008)   | -0.003<br>(0.009)   | 0.017<br>(0.011)  |
| Firm-Product-Unit FE            | ✓                    | ✓                 | ✓                    | ✓                 | ✓                   | ✓                   | ✓                   | ✓                 |
| 6 Digit-Unit-Legal Form-Year FE | ✓                    | ✓                 | ✓                    | ✓                 | ✓                   | ✓                   | ✓                   | ✓                 |
| NUTS2-Legal Form-Year FE        | ✓                    | ✓                 | ✓                    | ✓                 | ✓                   | ✓                   | ✓                   | ✓                 |
| N                               | 422,747              | 422,747           | 422,747              | 422,747           | 422,747             | 422,747             | 422,747             | 422,747           |
| Adj. $R^2$                      | 0.000                | 0.000             | 0.000                | 0.000             | 0.000               | 0.000               | 0.000               | 0.000             |

*Notes:* This table reports the event study coefficients from Figures 3.2 and 3.3 in the main text. For the full specification details, see the respective figure notes. Standard errors in parentheses, clustered at the municipality level.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0; 10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0; 10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

Table 3.3: Estimation Results - Event Studies with Firm-Level Outcomes

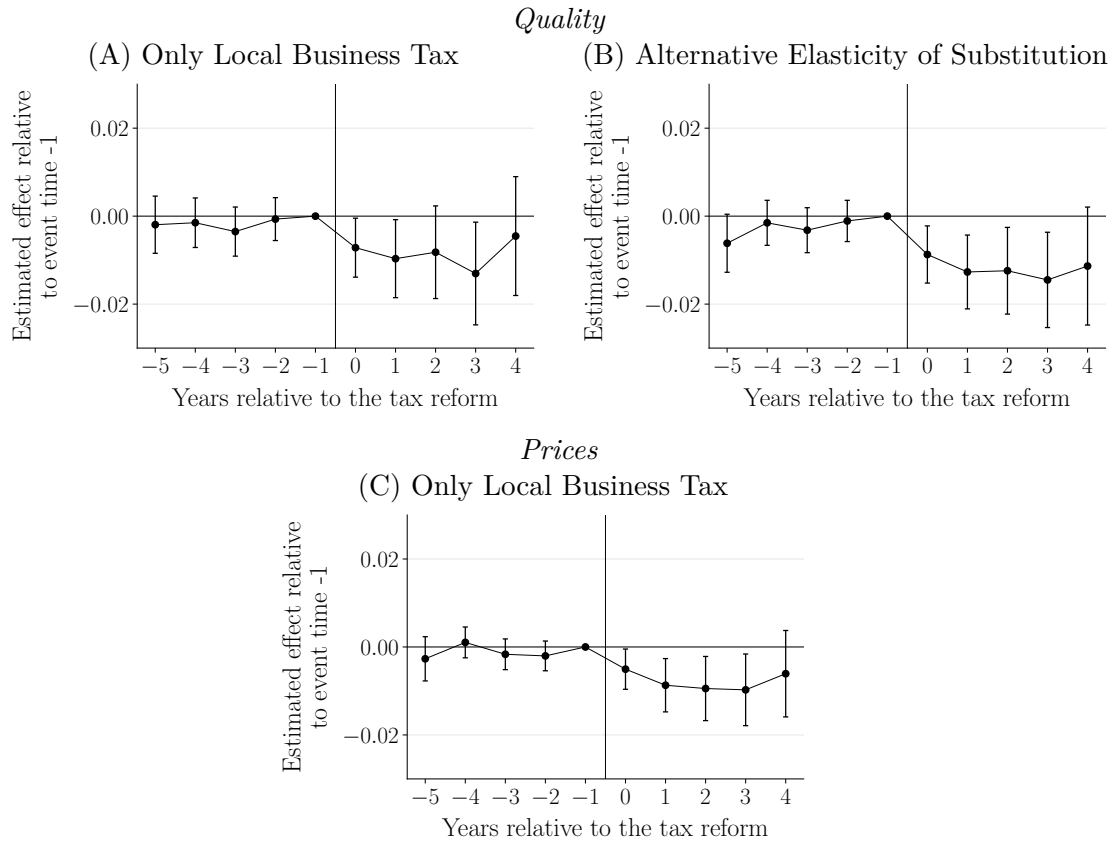
|                            | Employment           | Wage                | Investment           |                   |                    | TFP                  |                      |                     |
|----------------------------|----------------------|---------------------|----------------------|-------------------|--------------------|----------------------|----------------------|---------------------|
|                            | Base                 | Base                | Total                | R&D               | Equipment          | Base                 | Increases            | Decreases           |
|                            | (1)                  | (2)                 | (3)                  | (4)               | (5)                | (6)                  | (7)                  | (8)                 |
|                            | Fig. 3.4             |                     | Fig. 3.5             |                   |                    | Fig. 3.6             |                      |                     |
| $t - 5$                    | -0.005*<br>(0.002)   | -0.000<br>(0.001)   | -0.006<br>(0.012)    | 0.004<br>(0.017)  | -0.004<br>(0.013)  | -0.000<br>(0.002)    | 0.001<br>(0.002)     | 0.006<br>(0.004)    |
| $t - 4$                    | 0.000<br>(0.001)     | -0.000<br>(0.001)   | 0.008<br>(0.011)     | 0.019<br>(0.016)  | 0.021<br>(0.014)   | 0.003*<br>(0.002)    | 0.003<br>(0.002)     | -0.003<br>(0.005)   |
| $t - 3$                    | -0.003*<br>(0.001)   | -0.001<br>(0.001)   | -0.013<br>(0.012)    | 0.002<br>(0.016)  | -0.012<br>(0.015)  | 0.002<br>(0.002)     | 0.002<br>(0.002)     | -0.001<br>(0.004)   |
| $t - 2$                    | -0.002<br>(0.001)    | -0.001<br>(0.001)   | -0.005<br>(0.012)    | 0.004<br>(0.015)  | -0.007<br>(0.014)  | 0.002<br>(0.002)     | 0.003<br>(0.002)     | -0.002<br>(0.004)   |
| $t$                        | -0.005**<br>(0.002)  | -0.003**<br>(0.001) | -0.022*<br>(0.013)   | -0.004<br>(0.022) | -0.012<br>(0.015)  | 0.003<br>(0.002)     | 0.001<br>(0.002)     | -0.007<br>(0.005)   |
| $t + 1$                    | -0.008***<br>(0.003) | -0.004**<br>(0.002) | -0.021<br>(0.017)    | -0.022<br>(0.025) | -0.017<br>(0.017)  | -0.025***<br>(0.002) | -0.029***<br>(0.003) | 0.016***<br>(0.005) |
| $t + 2$                    | -0.009***<br>(0.003) | -0.004**<br>(0.002) | -0.023<br>(0.017)    | -0.023<br>(0.028) | -0.021<br>(0.020)  | -0.012***<br>(0.003) | -0.015***<br>(0.003) | 0.003<br>(0.005)    |
| $t + 3$                    | -0.010**<br>(0.004)  | -0.005**<br>(0.002) | -0.049***<br>(0.018) | -0.036<br>(0.033) | -0.039*<br>(0.020) | 0.004<br>(0.003)     | 0.005<br>(0.003)     | -0.004<br>(0.004)   |
| $t + 4$                    | -0.007<br>(0.005)    | -0.003<br>(0.003)   | -0.025<br>(0.020)    | -0.053<br>(0.038) | -0.032<br>(0.022)  | -0.002<br>(0.003)    | -0.000<br>(0.004)    | 0.004<br>(0.004)    |
| Firm FE                    | ✓                    | ✓                   | ✓                    | ✓                 | ✓                  | ✓                    | ✓                    | ✓                   |
| 4 Digit-Legal Form-Year FE | ✓                    | ✓                   | ✓                    | ✓                 | ✓                  | ✓                    | ✓                    | ✓                   |
| NUTS2-Legal Form-Year FE   | ✓                    | ✓                   | ✓                    | ✓                 | ✓                  | ✓                    | ✓                    | ✓                   |
| N                          | 162,493              | 162,493             | 162,493              | 31,581            | 162,493            | 59,172               | 59,172               | 59,172              |
| Adj. $R^2$                 | 0.000                | 0.000               | 0.000                | -0.000            | 0.000              | 0.010                | 0.011                | 0.011               |

*Notes:* This table reports the event study coefficients from Figures 3.4, 3.5, and 3.6 in the main text. For the full specification details, see the respective figure notes. Standard errors in parentheses, clustered at the municipality level.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0; 10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0; 10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

### 3.A.3 Robustness Checks

Figure 3.8: The Effect of Profit Taxes on Quality and Prices: Robustness Checks



*Note:* This figure provides robustness checks for the baseline event study estimates in Figure 3.2 with 95% confidence intervals. Panels A and B present results for product quality, while Panel C below shows results for prices. In Panel A (top left), we restrict the variation to changes in the local business tax only. Panel B (top right) uses an alternative elasticity of substitution to compute product quality. The lower panel C shows estimates for prices when restricting the variation to changes in local business taxes. For the full specification details, see the respective figure notes of the main results in Figure 3.2. Standard errors in parentheses, clustered at the municipality level. We report regression coefficients in Appendix Table 3.4.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0;  
10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0;  
10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.



Table 3.4: Estimation Results - Robustness Checks

|                                 | Quality             |                      | Price                |
|---------------------------------|---------------------|----------------------|----------------------|
|                                 | Only LBT            | Alt. Elasticity      | Only LBT             |
|                                 | (1)                 | (2)                  | (3)                  |
|                                 | Fig. 3.8            |                      |                      |
| $t - 5$                         | -0.002<br>(0.003)   | -0.006*<br>(0.003)   | -0.003<br>(0.003)    |
| $t - 4$                         | -0.001<br>(0.003)   | -0.002<br>(0.003)    | 0.001<br>(0.002)     |
| $t - 3$                         | -0.004<br>(0.003)   | -0.003<br>(0.003)    | -0.002<br>(0.002)    |
| $t - 2$                         | -0.001<br>(0.002)   | -0.001<br>(0.002)    | -0.002<br>(0.002)    |
| $t$                             | -0.007**<br>(0.003) | -0.009***<br>(0.003) | -0.005**<br>(0.002)  |
| $t + 1$                         | -0.010**<br>(0.005) | -0.013***<br>(0.004) | -0.009***<br>(0.003) |
| $t + 2$                         | -0.008<br>(0.005)   | -0.012**<br>(0.005)  | -0.009**<br>(0.004)  |
| $t + 3$                         | -0.013**<br>(0.006) | -0.014***<br>(0.006) | -0.010**<br>(0.004)  |
| $t + 4$                         | -0.005<br>(0.007)   | -0.011*<br>(0.007)   | -0.006<br>(0.005)    |
| Firm-Product-Unit FE            | ✓                   | ✓                    | ✓                    |
| 6 Digit-Unit-Legal Form-Year FE | ✓                   | ✓                    | ✓                    |
| NUTS2-Legal Form-Year FE        | ✓                   | ✓                    | ✓                    |
| N                               | 422,747             | 422,747              | 422,747              |
| Adj. $R^2$                      | 0.000               | 0.000                | 0.000                |

*Notes:* This table reports the event study coefficients from several robustness checks presented in Appendix Figure 3.8. For the full specification details, see the respective figure notes. Standard errors in parentheses, clustered at the municipality level if not specified otherwise.

Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, DOI: 10.21242/42221.2003.00.01.1.1.0 to 10.21242/42221.2016.00.01.1.1.0; 10.21242/42111.2003.00.01.1.1.0 to 10.21242/42111.2016.00.01.1.1.0; 10.21242/42131.2003.00.03.1.1.0 to 10.21242/42131.2016.00.03.1.1.0, own calculations.

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# Declaration of Contribution

Hereby I, Alexandra Jennifer Gibbon, declare that the chapter “Profit Taxation and Product Quality” is coauthored with Andreas Lichter and Joel Stiebale. All authors contributed equally to the chapter.

Signature of coauthor (Andreas Lichter): \_\_\_\_\_

Prof. Dr. Andreas Lichter

Signature of coauthor (Joel Stiebale): \_\_\_\_\_

Prof. Dr. Joel Stiebale



# Eidesstattliche Versicherung

Ich, Frau Alexandra Jennifer Gibbon, 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.

Bielefeld, der 18.02.2026

Unterschrift: \_\_\_\_\_