Economic Cyclicality, Board Structure and Firm Innovation

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Introduction

Innovation drives technical progress and human development. As an important source of innovation, private Research and Development (R&D) fosters the productivity and new products/technology development. Nowadays, firms, facing cutthroat competition pressure, engage more and more into R&D projects. According to the statistical summary from UNESCO, R&D expenditure over GDP increased from 1.57 percent in 2007 to 1.7 percent in 2013 and the upward trend remains robust (UNESCO, 2015). However, innovation investment incurs disproportionately high risk of failure and tremendous financial burden, whereas the outcome is not always ready to be fully commercialized or has to be shared because of the spillover effects even with the protection of patent system. Identifying determinant factors of innovation decisions and exploring how they can be wielded to form optimal innovation strategies have been the focus of previous literature and still attract continuous attention among scholars and practitioners. This thesis contributes to the understanding of innovation determinants along both macro and micro (firm level) directions by showing that economic cycle distorts the innovation input in the first chapter and that firms' independent directors' presence and the related interlock networks exert great influence on innovation decisions in chapter two and three.

Business cycle is one of the most important characteristics of the economy. Operating under such condition, firms' decisions, including innovation investment, are strongly subjected to fluctuations of demand, interest rate, inflation, etc. According to Schumpeter's theory of economic development, the opportunity cost of long-term investments such as innovation is lower in economic downturns and higher in booming periods, compared to that of short-term investment (Bloom, 2007). As a result, R&D investment should be counter-cyclical. Despite the unambiguous theoretical prediction of counter-cyclical innovation expenditure, the empirical results are more controversial.

In chapter one, we try to compromise this discrepancy, both theoretically and empirically. Firstly, we set up a benchmark theoretical model of counter-cyclical R&D investment, based on which moderating effects of credit constraint and R&D subsidy have been established. Secondly, we empirically investigate hypotheses based on dataset of Mannheim innovation panel, which consists of a great number of German SMEs. SMEs are interesting objects to examine the hypothesis, given their tighter financial constraints on innovation input. Results confirm counter-cyclical R&D investment in Germany overall, as well as the persistent pro-cyclical moderating effects of credit constraints, which are counteracted by R&D subsidy. Finally, two natural experiments, namely EU enlargement in 2004 and economic crisis in 2008, are exploited to further provide supports to our main findings.

An important component of firm governance mechanism is the independent board, whose economic interests are presumably independent of hosting firms. Two functions of independent directors are identified in the theory, monitoring over managers and advisory functions. Managers, when under external monitoring from outsiders, are precluded from being distorted by agency problems and thus make innovation investments more aligning with the interest of shareholders (Adams et al., 2010). On the other hand, the valuable information from independent directors can be shared to better counsel the innovation decision makings (Adams and Ferreira, 2007). However, no access to internal information (Nowak and McCabe, 2003) or busyness (Ferris et al., 2003) hinders them from exerting positive influences. Therefore, the net effects of independent directors on innovation boil down to an empirical problem. Furthermore, by having the same independent director on boards, a special bond is created amongst multiple firms. Theoretically speaking, the direction of interdependency among decisions can be either positive ((Bikhchandani et al., 1992; Scharfstein and Stein, 1990)) or negative ((Joanne, 1997; Luis and Nandini, 2012)). Identifying the presence, the interacting direction, as well as the underlying mechanism, is a pure empirical task.

The context of China is interesting in many regards. First and foremost, detailed annual information on independent board of Chinese listed firms is available. Chinese listed firms disclose in regular financial reports detailed information on their independent boards, including name, personal information, attendance history of board meetings and even the archive of vote on major issues. More importantly, several external policy reform regulations in China allow us to perform causality investigation, which is more difficult if not impossible without such exogenous shocks. Thirdly, as a representative growing economy, empirical evidence from China can be generalized to other countries, meanwhile contributing some unique institutional angles.

In chapter two, using panel dataset of Chinese listed firms, we empirically investigate the effects of independent directors' presence on total factor productivity and innovation output. Total factor productivity is estimated by the nonparametric estimator developed by Ackerberg et al. (2015) and innovation output is captured by patent counts, specifically total applications (of invention, utility model and design) and invention grants. Exploiting the policy of increasing independent directors on the board to overcome the endogenous board composition, we show that TFP and patent counts increase in the independent director presence. Further heterogeneity investigations point to the asymmetric importance of advisory channel in innovation and monitoring in productivity in the Chinese context. Lastly, the effects of independent directors are more pronounced in firms with dominance of non-state ownership and with mild product market competition.

Chapter three aims at identifying the peer effects of R&D investment among interlocked firms. An anti-corruption policy expelled senior officers of the party out of their independent director positions in the listed companies, creating exogenous breaks to the interlock connection. Exploiting this structural shock to construct an instrumental variable, we identify the significant and positive peer effects in R&D investment. In addition, heterogeneity effects shed light on the driving mechanisms, pointing to learning as a more plausible underlying channel behind the nontrivial responsiveness of innovation strategies. Finally, extensions report similar findings when peers are limited to only inter-industry interlocks and generalized to indirect (second-degree) interlocks. While peers' successful invention applications positively spillover to the focal firm, their rejected invention applications exert negative influence on rejections of the focal firm. Significantly negative and weakly positive peer effects characterize the interdependency of innovation decisions among firms within industries and locations, respectively.

Bibliography

Ackerberg, Daniel A., Kevin Caves, and Garth Frazer, "Identification Properties of Recent Production Function Estimators," *Econometrica*, 2015, *83* (6), 2411–2451.

Adams, Rene B and Daniel Ferreira, "A Theory of Friendly Boards," *The Journal of Finance*, 2007, *62* (1), 217–250.

_ , **Benjamin E Hermalin, and Michael S Weisbach**, "The Role of Boards of Directors in Corporate Governance: A Conceptual Framework and Survey," *Journal of Economic Literature*, 2010, *48* (1), 58–107.

Bikhchandani, Sushil, David Hirshleifer, and Welch Ivo, "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades," *Journal of Political Economy*, 1992, *100* (5), 992–1026.

Bloom, Nick, "Uncertainty and the Dynamics of R&D," *American Economic Review*, 2007, *97* (2), 250–255.

Ferris, Stephen P., Murali Jagannathan, and A. C. Pritchard, "Too Busy to Mind the Business? Monitoring by Directors with Multiple Board Appointments," *The Journal of Finance*, 2003, *58* (3), 1087–1111.

Joanne, Oxley, "Appropriability Hazards and Governance in Strategic Alliances: A Transaction Cost Approach," *The Journal of Law, Economics, and Organization*, 10 1997, *13* (2), 387–409.

Luis, Diestre and Rajagopalan Nandini, "Are All Sharks Dangerous? New Biotechnology Ventures and Partner Selection in R&D Alliances," *Strategic Management Journal*, 2012, *33* (10), 1115–1134.

Nowak, M. J. and M. McCabe, "Information Costs and the Role of the Independent Corporate Director," *Corporate Governance: An International Review*, 2003, *11* (4), 300–307.

Scharfstein, David and Jeremy Stein, "Herd Behavior and Investment," *The American Economic Review*, 1990, *80* (3), 465–479.

UNESCO, "UNESCO Science Report: Towards 2030," 2015.

Chapter 1.

On the Cyclicality of R&D Investments in the Presence of Financial Constraints and R&D Subsidies

Co-authored with Hanna Hottenrott

Based on Schumpeter's view of the business cycle, it is argued that opportunity cost of long-term investments, like R&D, is lower compared with that of short-term investment during recessions. This should make long-term investments more attractive during downturns. Thus, R&D activities in the private sector should expand during recessions and shrink in booms. While there has been theoretical support for this argument (Hall, 1992; Aghion and Saint-Paul, 1998; Bloom, 2007), the empirical literature paints a different picture.

Studies find pro-cyclical or a-cyclical R&D investments in different countries and over different time periods. For instance, Geroski (1994) studies UK macro-level data over the period 1948-1983 and finds pro-cyclical patenting and innovation outcomes, in terms of both commercial success and technological breakthrough. Waelde and Woitek (2004) look at a broader country-level data sample from G7 between 1973 and 2000 and observe pro-cyclical R&D spending. Barlevy (2007) also shows that aggregate R&D investment in the U.S during 1987-2004 behaved pro-cyclically and develops a dynamic theoretical model which attributes this pattern to the short-sighed entrepreneurs. R&D investment may also be a-cyclical. For instance, Saint-Paul (1993) uses panel data of 22 OECD countries from 1950 to 1988 and finds insignificant correlation between firm-financed R&D and sales shocks.[1]

In order to explain why such mixed results arise, studies increasingly explore the role of firm heterogeneity, in particular their access to financial resources to sponsor long-term investments. One basic assumption of the simple business cycle model is that firms have no difficulty financing their R&D expansion in down-turns. Building on previous literature that shows that firms' R&D spending relies more on internal funding than other types of investment (Hall, 1992; Himmelberg and Petersen, 1994; Rafferty, 2003), Czarnitzki and Hottenrott (2011b) argue that because of this pecking order effect, R&D investment tends to be pro-cyclical given that firms prefer to finance their R&D internally. Aghion et al. (2012); Domadenik et al. (2008); Lopez-Garcia et al. (2012) argue that financial frictions prevent firms from investing optimally in long-term projects in rough times, thus biasing R&D investment upwards in credit constrained firms during booming periods. This phenomena is specially strong among small and medium-sized enterprises (hereafter, SMEs) who lack collateral to endorse loans for intangible investments, thus making them particularly dependent on internal financing (Czarnitzki and Hottenrott, 2011a). Evidence has shown that SMEs are more sensitive to recessions (Sharpe, 1994) and monetary policy changes (Gertler and Gilchrist, 1994).

To compensate for the capital market failure to finance R&D projects, govern-

[1] Gali and Hammour (1992), among others, examine U.S. data and find a negative correlation between productivity and sale shocks. This evidence implicitly implies that some productivity-boosting investments or "human capital" investments are counter-cyclical.

ments worldwide provide various forms of financial support, aiming at fostering innovation and economic sustainability. For instance, in OECD countries, direct grant-based subsidies and tax reduction for R&D investment are commonly applied. Despite their popularity in the practice, the real influences on smoothing firms' R&D investment over the business cycle remain largely unexplored.

This paper extends previous work in several regards. First, we set up a simple model which captures the basic characteristics of R&D activities by differentiating between short-term and long-term investments. More specifically, short-term investments are made for routine operations, whereas R&D activities benefit firms through improving efficiency of their short-term investments. Then, we follow empirical specifications from (Czarnitzki and Hottenrott, 2011a,b) and use firms' credit rating as a proxy for access to external financing. Third, we take grant-based subsidies into consideration both in the theoretical modeling and empirical investigation. Innovation grants are widely used in Germany given the absence of R&D tax reduction policies in Germany. Our results show that aggregate R&D investments of German companies do not show either pro- or counter-cyclical pattern (see Figure 1.2). Absence of clear evidence implies considerable firm heterogeneity. Further estimating fixed-effects and dynamic panel data models, we identify dominant counter-cyclical R&D investments in general. Moreover, heterogeneity effects do play a critical role. Specifically, credit constraints turn the pattern more pro-cyclical, while subsidies offset such moderating effects.

In addition, we exploit two natural experiments, the EU enlargement in 2004 and the economic crisis in 2008, to capture positive and negative external shocks on sales and examine how firms' R&D spending causally adjusted to these shocks. Applying a synthetic control group method proposed by (Abadie and Gardeazabal, 2003; Abadie et al., 2010), we provide more evidence on the counter-cyclical pattern in R&D investment, along with the countervailing effects of credit constraint, which accords with our main regression results.

The paper proceeds as follows. In the next section, we propose a simple model to capture the relationship between R&D investment and the economic cycle and the moderating effects of credit constraints and subsidy. Section 1.2 describes our data, measurements, descriptive statistics and finally presents the results. Discussion and conclusion follow in section 1.3.

1.1 Theoretical framework

1.1.1 Benchmark model

In the following, we consider one representative risk-neutral firm that maximizes its profits given the market demand. First, we set up a benchmark model where there are neither credit constraints nor R&D subsidies. Without credit constraints, the firm is always able to collect enough financing from capital markets (loans or equity) to support both its short and long-term investments.

The product demand is captured by a Markov process, which is widely used in the literature.[2] Assume that the firm faces exogenous demand shocks denoted by a_t. Then the demand shock in the next stage is given based on the current shock plus a random disturbance term with mean assumed to be zero. We can simply express this as follows:

$$Ea_{t+1} = a_t^{\rho} \tag{1.1}$$

where ρ represents the persistence of exogenous demand. Given ρ between 0 and 1, we design a recurrent economic cycle. This simply suggests that if the firm faces a large a_t at period t, the rational expectation of sales at t+1 period will be milder. This assumption is of importance to our future analysis and has its practical ground, since no normal economy can be always booming or always in recession.

The model has two stages and the net present value is simply the sum of profit generated both periods. At $t = 0$, the firm has to make its decision on how much to invest in both short-term (k_t) and R&D investment (z_t). Consider the short-term investment to be the establishment of a fixed production line or operational machinery and once this capital investment is done, the size or scale of it can not be adjusted in the following stage. Once the production line is set, it produces goods at the end of the first stage, following a neo-classic production function $p(k)$, which follows $p' > 0 > p''$. In order to render explicit solution, we assume $p(k)$ takes the form of $(k_t)^{\alpha}$, with $\alpha \in (0,1]$. However the firm's profit does not only rely on production, but also the economic prosperity, namely a_t. When the demand shock a_t is positive, the total demand for that product increases, which leads to higher profit, and vice versa.

The profit derived from the first stage is thus:

$$\pi_t = a_t p(k_t) \tag{1.2}$$

R&D investment, on the other hand, plays a complementary role as it does not

[2] Another common way to model sales uncertainty is to use Geometric Brownian motion with a shift and volatility term as in Barlevy (2007). However, we choose Markov process in order to get closed-form solution.

generate any profit alone under our assumption. This implies that the contribution of R&D to firm performance is restricted to gaining of incremental technology, which then needs to be applied in the production process of goods or services. In addition, we assume R&D projects facilitate the productivity only in the second stage. Put differently, the R&D decision does not interfere with sales until second stage. The efficiency improvement of R&D investment is captured by $q(z_t)$. Thus, the profit function from the second stage has three elements: expected demand shock Ea_{t+1}, production function $p(k_t)$ and the benefit from R&D investment $q(z_t)$,

$$\pi_{t+1} = Ea_{t+1}p(k_t)q(z_t) \tag{1.3}$$

For simplicity, we impose a functional form on q, that is $q(z_t) = e\sqrt{z_t}$. Here, e represents the exogenous efficiency of innovation activities. For R&D investment to be efficient, we impose another condition, $e\sqrt{z_t} > 1$. Using backward induction, our target is to pin down optimal R&D input which maximizes firms' total profits:

$$\Pi = a_t p(k_t) + Ea_{t+1}p(k_t)\sqrt{z_t} \tag{1.4}$$

subjected to all financing sources available to the firm.

$$k_t + z_t \leq \omega_t \tag{1.5}$$

The optimal R&D share therefore can be easily calculated, shown as follows:

$$R\&Dshare_{bk} = \frac{\omega(1+2\alpha)e^2a^{2\rho} + 2a^2\alpha^2 - 2a\alpha\sqrt{\omega(1+2\alpha)e^2\alpha^{2\rho} + a^2\alpha^2}}{a^{2\rho}e^2(1+2\alpha)^2\omega} \tag{1.6}$$

We are interested in the dynamics of R&D investment. Taking the derivative of the optimal R&D share with respect to demand shock a_t, we derive negative sign if innovation efficiency e is sufficiently large. Negative derivative suggests that optimal R&D investment share tends to be larger when $0<a_t<1$ than in states of nature where $a_t>1$, which leads to our first Hypothesis:

H1: In the benchmark setting, the share of R&D investment is counter-cyclical.

The intuition behind this is straightforward. When faced with an upturn, firms would be better off grasping profits at present and holding back the R&D investment until the economy is relative weak. On the contrary, when the economy is on the downward trend, firms' optimal strategy is to firstly invest heavily in R&D in the first stage and harvest more at the end of second stage.

In addition, It is straightforward to see that the budget constraint is always binding, i.e. firms will exhaust their budget since there is no available outside option. According to the traditional pecking order theory and transaction cost theory, because of the basic characteristics of R&D investment, internal funds are always preferred. When firms exhaust their internal funding, they alternatively choose borrowing. Since the sign of the first order condition of R&D share with respect to budget size ω is positive, we hence propose that

H2: More internal fund leads to higher R&D share.

1.1.2 In the presence of credit constraint

Based on the benchmark setting, we proceed to analyze the effect of credit constraints by introducing the parameter μ. Compared to credit unconstrained firms, constrained firms have only μ amount of budget at their disposal, where μ lies between 0 and 1. Using the same reasoning, we can derive the best R&D strategy in the presence of credit constraint.

Again, negative first order condition of R&D share with respect to demand shock remains. It suggests, in principal, credit constraint does not reverse the counter-cyclical pattern completely. However, we further show that when some conditions hold ($\frac{2a^2\alpha^2(1+\sqrt{2})}{e^2\omega(1+2\alpha)a^{2\rho}} > 1$), for any $\mu \in (0,1]$, $\frac{\partial^2 R\&Dshare}{\partial a_t \partial \mu} < 0$ holds. This conclusion simply suggests that with tighter credit constraint, i.e., smaller μ, $\frac{\partial R\&Dshare}{\partial a_t}$ is lager than in state of nature where financial slack prevails. Combined with overall negative F.O.C of R&D investment share with respect to demand shock, the effect of credit constraint is to make the R&D investment less counter-cyclical:

H3: Credit constraints render less counter-cyclical R&D investment.

The intuition behind this result is the following. Because of lower opportunity cost, it is efficient for a firm to invest more in R&D during recessions. However, credit constraint holds firms back from engaging in optimal R&D expansion, making R&D less counter-cyclical and efficient. When economy is at its peak, financial slack enables firms to be more generous with innovation projects even though their more efficient strategy is to curb R&D spending.

1.1.3 In the presence of R&D subsidies

In the same vein, we analyze the effect of R&D subsidy. We assume, besides $\mu\omega$, firms that are subsidized have now access to another s of their own budget.[3] Now, subsidized firms have $\mu\omega(1+s)$ in total at disposal. It can be proven that under some conditions, we have $\frac{\partial(\frac{\partial^2 R\&Dshare}{\partial a_t \partial \mu})}{\partial s} > 0$. This result suggests that R&D subsidies increase the value of derivative $\frac{\partial^2 R\&Dshare}{\partial a_t \partial \mu}$, making it less negative given Hypothesis 2, i.e., negative partial derivative prevails. The implication is that subsidies counteract pro-cyclical effects of credit constraints and reduces, to some extent, the efficiency loss caused by credit constraint. Thus, the fourth hypothesis is:

H4: R&D subsidy counteracts the pro-cyclical moderating effects of credit constraints.

1.2 Empirical approach

1.2.1 Data

The main data for the following analysis is from the Mannheim Innovation Panel (hereafter MIP), conducted by the Center for European Economic Research (ZEW). The MIP is retrieved from repeated cross-section data samples as part of the European Community Innovation Survey program. The survey is conducted annually and sets a low bar for its participants, namely firms with more than five employees in service and manufacturing sectors.[4] We complement the MIP data with the credit rating index from the Credit-reform database[5]. We remain only firms located in western Germany in the sample. Even though reunification happened prior to our sample period, the structural difference between western and eastern Germany exists, in terms of firm size, R&D investment, wages, etc. More importantly, there have been huge government programs to restructure and rebuild Eastern Germany. In other words, eastern German firms' innovation strategies are more likely to be immune to economic cycles. Therefore, we exclude eastern counterparts from the sample. After elimination of incomplete records and outliers, we have full information on 5,126 firm-year observations. Almost 60% percent of observations are from SMEs. Hence,

[3]This extra part of budget can be either multiplicative or additive. Both render qualitatively similar result.

[4]See Table A1 in the Appendix for details on the industry distribution.

[5]See Czarnitzki and Hottenrott (2011b) for a detailed description on the construction of the index.

our sample is more representative, compared to previous research whose samples are restricted to large firms.

1.2.2 Econometric specification

We estimate different types of panel models, taking into account unobserved heterogeneity and serial correlation. In particular, our estimation models can be written in its simplest form as such:

$$\begin{aligned} ratioRD_{i,t} = {} & \beta_1 \triangle Sales_{i,t} + \beta_2 CreditConstraint_{i,t} + \beta_3 \triangle Sales_{i,t} \times CreditConstraint_{i,t} \\ & + \beta_4 PCM_{i,t} + Year + Industry + \tau_i + \varepsilon_{i,t} \end{aligned} \tag{1.7}$$

The dependent variable, the R&D investment ratio, is the ratio of $R\&Dinv_{i,t}$ over total investment, namely $R\&Dinv_{i,t} + Capinv_{i,t}$ in period t. R&D investment is computed as total expenditure on innovation. Capital investments include physical, non-innovation related investment. This measure corresponds to the expression in our theoretical model and describes the composition change in investment portfolio. Following literature, economy cycle is proxied as the change of sales in log between two consecutive periods. The credit rating index ranges from 100 to 600, with 100 being the best and 600 the worst. This rating has the advantage in that (i) it is continuous and therefore contains more information than commonly used dichotomous measures and (ii) this score is calculated by taking the future into account and keeps updated on regular basis by rating institute. In fact, this index is used by banks, customers and suppliers when deciding whether to engage business. The subsidy receipt is measured by a dummy variable from MIP. It takes value one when a firm received subsidies from regional, national or supranational entities (e.g. the EU) and zero otherwise. We also control for internal funding. Since accounting data is unavailable for firms in our sample, we calculate the proxy, namely firms' price cost margins based on their sales, intermediate inputs and personnel costs with the available information from the MIP. To control for liquidity accrued in the last period, we take one year lag for $PCM_{i,t}$.

$$PCM_{i,t} = \frac{Sales_{i,t} - StaffCost_{i,t} - MaterialCost_{i,t} + \delta R\&D_{i,t}}{Sales_{i,t}} \tag{1.8}$$

Finally, we include year and industry dummy variables to control for time and sector fixed effects. It should be noted that we do observe cases where firms switched to different sectors over our sample period.

According to our theoretical predictions, the counter-cyclical R&D expenditure should be captured by the negative coefficient on sales shocks, namely $\beta_1 < 0$. The estimate of positive interaction term, $\beta_3 > 0$, represents the moderating effects of credit constraint on R&D cyclicality. Positive β_4 echoes with Hypothesis 2, i.e., the deeper firms' pockets are, the bigger share R&D investments claims.

The descriptive statistics of full sample, both large firms and small firms subsamples are provided in Table 1.1.[6] In line with the definition of the European Commission, we categorize firms that have less than 250 employees as SMEs. As can be seen from Table 1.1, these firms differ in key variables. From the t-tests in the last column, it can be concluded that, in general:

1. SMEs invest more in R&D relative to total investments than larger firms, although higher R&D-shares do not necessarily mean higher absolute number.

2. Contrary to our expectation, larger firms have more volatile sales than SMEs.

3. SMEs have higher, thus worse, credit ratings. This finding also conforms to the theory which suggests that the SMEs lack hard collateral and, because of asymmetric information problem, are more likely to be credit constrained.

4. Larger firms have better chance to receive a subsidy.

1.2.3 The results

Main regression results are displayed in Table 1.2. We first focus on the results from the fixed effects panel model. The Hausman test reports Chi^2 value of 123 (Prob>chi2=0.00), suggesting the presence of unobserved heterogeneity. For the full sample, the counter-cyclical pattern (i.e. the coefficient of $\Delta Sales_{i,t}$ and its lagged terms are always negative) confirms Hypothesis 1. The estimate is significant at smaller than 1% level. Though the credit constraint measure is insignificant, the interaction term $\Delta Sales_{i,t} * CreditConstraint_{i,t}$ is positive and significant. This suggests that the worse the credit rating is, the more pro-cyclical the R&D investment becomes, speaking in favor of Hypothesis 3.

Hypothesis 2 has been supported by the significantly positive coefficient of $PCM_{i,t}$, as shown in column (2). This positive correlation indicates that the more internal capital a firm has access to, the more it will be engaged in the R&D investment, which agrees with previous research implying the importance of internal financing to R&D investment. The coefficient size and statistical significance of $\Delta Sales$ and of interaction term change mildly after introducing PCM. It should be noted that these results are robust to the definition of the credit constraint proxy, meaning our results sustain when replacing continuous with an alternative dichotomous credit constraint

[6]See Table A2 for the cross-correlation matrix.

indicators, as in Aghion et al. (2012). We include the main results of Aghion et al. (2012) in Table A3 as well for the sake of comparison.

In the third column we perform panel Tobit model, taking into account the fact that our dependent variable is bounded between 0 and 1. We choose the random effects specification, which assumes the controls to be orthogonal to the error term. It turns out that the sign of sales shock, interaction term and price cost margin remains unchanged and the magnitude of all coefficients is also comparable. In particular, we follow Wooldridge (2010) who suggests testing the joint significance of within-firm means of all time-variant covariates to control for unobservable factors. We report the results at the bottom of column (3). The overall test of joint significance of all means, including mean of sale shock, credit constraint, interaction term, price cost margin and firm age, implies that these means are indeed jointly significant, hence the setting in column (3) can be justified.

In column (4), we account for the potential persistence of R&D ratio by conducting the dynamic Tobit model, namely specification in column (3) with additional lagged dependent variable. As expected, current R&D share relies strongly on previous values. While the dynamics have been introduced, the estimated coefficients, β_1, β_3 and β_4, are robust, in terms of both sign and coefficient size. Similarly, we perform the test of joint significance of the within means. As expected, the overall F-test is smaller.

Finally, in the last column, the results of a system GMM estimation are shown, following Arellano and Bond (1991). This model allows us to examine dynamic effect and control for endogenous variables with their own lagged terms as instruments. However, applying GMM method halves the observation number. We come up with a compromise solution, that is using total innovation expenditure as dependent variable for the GMM specification, instead of ratio. Total innovation expenditure is more broadly defined as input on both intangible assets, like patent maintenance and R&D projects. The post-estimation statistics reveal auto-correlation of order one. With only AR(1), we can use $y_{i,t-2}$ as our first instrument, tracing back to $y_{i,1}$. Our specification passes the Sargan-test, confirming the validity of our instruments, though, as suggested by Roodman (2009), the test should be interpreted with caution.

Column (5) shows that the hypotheses are also empirically supported by the dynamic GMM model. Both contemporaneous and previous Sales shocks are negative and statistically significant, which suggests that the counter-cyclical effects persist over time. All interactions terms are positive and significant, an indication that the pro-cyclical effect of credit constraint remains over time. More interestingly, the magnitude of these effects mentioned above is constant and does not shrink over time. As suggested by Hypothesis 2, current price cost margin increases firms' incentive to engage in R&D activities. However, remaining earnings in previous stages seem to play a rather negligible role.

To examine the heterogeneous effects on R&D cyclicality, we split the full sample into subsidized VS unsubsidized sub-samples. Fixed effects regressions are applied on each sub-sample and our aim is to compare the coefficients, mainly significance level. Detailed results are presented in Table 1.3.

Column (1) shows that, when subsidy is present, the pro-cyclical effects of credit constraint fades away, meaning that firms do indeed benefit greatly from acquisition of financial grants. Meanwhile, it seems that subsidy makes R&D investment immune from economic cycles, given insignificant estimate of sales shock. In contrast, unsubsidized firms behave less counter-cyclically because of the credit constraint. Two pieces of information together indicate that subsidy compensates for the credit constraint problem.

One uniqueness of our sample is the better representation of SMEs. To further investigate this question on SMEs, we further stratify the sample into SME with and without subsidy in column (3) and (4). The offsetting effects of subsidy among SMEs are also confirmed by the statistically more significant and economically stronger pro-cyclical effects of credit constraint in column (3) than in column (4). To summarize, not all SMEs counter-cyclically adjust their R&D investment. SMEs with access to subsidy act more like deep pocket firms in the sense that their R&D expenditures are stable along the economic cycle. Minor differences between column (1) and (3), column (2) and (4) reveal that the results above are essentially not driven by firm size, rather by whether they successfully obtained subsidies.

Moreover, the contribution of internal earnings on R&D investment has been recovered in all specifications, except for the third column. The plausible justification can be that unsubsidized firms are usually less competitive provided the strict scrutiny process of the application for such grants. This competitive disadvantage renders low level of internal earnings which are insufficient to exert positive influence on investment input.

Finally, it is important to point out that we do observe cases where count-cyclical investment turns into pro-cyclical, which partially differentiates our results from those of Aghion et al. (2012). Based on French data, they argue that credit constraint could, at most, weaken the counter-cyclical effects, but never reverse it. This may indicate that in Germany, credit constraints have a more severe consequence. When exposed to tight credit constraint, firms' investments conform to the cycle. While French firms benefit from not only direct grant but also R&D tax credits, their German counterparts have only access to subsidies.

1.2.4 Two natural experiments: EU enlargement and economic crisis

Two problems remain not addressed in previous empirical settings. First, causality remains unclear even though correlations have been established in previous investigations. It is equally likely that innovation activities lead to evolution of sales. Secondly, we did not distinguish between positive sales changes and negative ones. In the following, we exploit two external events that result in sales shocks. Specifically, the EU enlargement in 2004, embracing another 10 members, constituted a positive shock to German exporting companies because of the unexpected surge in market demand, provided that all barriers on trade activities among newly formed EU member states have been removed. As can be seen in figure 1.3, exporters increased sales following the enlargement, while domestic producers did not. On the contrary, the 2008 global economic crisis reduced exports tremendously, but affected domestic sales to a lesser extent. Both events can be considered as exogenous shocks to sales to exporting firms (treatment group), whereas domestic firms are qualitatively irrelevant (control groups).

Exploiting these quasi-natural experiments, We are able to explore how R&D investments causally responded to sales shocks of different directions. Additionally, dichotomize credit constraints are integrated to identify the moderating effects. To better measure causal effects, we employ a "synthetic control group method", which uses information of non-exporting firms to best synthesize appropriate control group. The basic idea of this method is to construct a weighted combination from non-exporters to match the treatment group (exporters) before the policy shock and then perform difference-in-difference investigation to identify the average treatment effect (ATE) by comparing two groups.

In Table A4, we report balancing tests to confirm that the "synthetic" group and the treatment group are comparable in measures including R&D ratio and main controls in our main specifications. Since this method requires strongly balanced panel structure, we fill missing values of continuous control variables with the sector-size mean values. In first panel, the treatment and synthetic group both have R&D ratio of 0.21. In contrast, before matching, the R&D ratio is 0.06, 15 percentage point lower than the treatment group. Put differently, there exist structural differences between exporters and domestic firms and the synthetic method succeeds in bringing them parallel. Same pattern appears among credit constraint exporters, as well as in 2008 recession periods. In summary, results show that no essential differences exist between synthetic and treatment groups in both dependent and explanatory variables after the matching.

To better visualize the results, we illustrate the ATE in figure 1.1. The graphs on the left show the results of the credit unconstrained firms and on the right hand side firms with credit constraint. The upper panel represents the positive demand shock in 2004 and the bottom panel the crisis in 2008.

Among the credit slack firms, we basically find results in line with our regressions. During economic boom in 2004, treatment group, i.e., exporters, reduced their R&D investment for pursuit of higher current profit. In constrained firms, similar counter-cyclical pattern dominates R&D investment. Comparison between upper left and upper right graphs renders conclusion that credit constraints do not play such significant role in booms.

During recession period in 2008, we observe almost slightly reduction in R&D investment among unconstrained firms. Furthermore, in comparison to increasing R&D expenditure within synthetic group, deep pockets exporters invested way less in innovation, Both pieces of information are at odds with our expectation. On the other hand, among credit disadvantaged firms, R&D spending suffered from a plunge. Controlling for the change of control group does not bring about positive R&D. This seems consistent with our observation in the main findings that credit constraints affected German firms so hard that counter-cyclicality can be converted into pro-cyclicality. One plausible explanation is that recession struck German firms a year later. If shock came into effect in 2009, positive ATE among financial slack firms and almost zero ATE among credit constrained firms point to both the overall counter-cyclical patterning and the positive moderating effects of credit constraints. To conclude, these Diff-in-Diff estimates seem to be in line with our theoretical prediction that credit constraints turn firms' R&D more pro-cyclical. However, negative sales shock in recession only lends little creditability to counter-cyclical pattern.

Finally, it is worth mentioning that in response to the 2004 enlargement, the non-exporting control group indeed behaved as expected, that is no violent reaction to the shock. However, when faced with the negative shock, domestic firms, regardless of credit constraint, hold back their innovation investment. It seems that high level of uncertainty from recession hit domestic firms just as hard as exporting firms.

1.3 Discussion and conclusion

The paper examines the cyclical R&D investment in the presence of credit constraints and R&D subsidies. We complement current literature both theoretically and empirically.

Firstly, we set up a simple theoretical model, based on which we argue that it is efficient for firms to invest R&D counter-cyclically. Nevertheless, this counter-cyclical pattern can be weakened by the presence of credit constraints, whereas subsidies counteract with such inefficiency effects from credit constraints. Secondly, results of empirical analysis based on firm-level panel data of German firms show that, R&D investment, in general, can be characterized as counter-cyclical. In addition, heterogeneous effects of credit constraints and subsidies are confirmed.

Furthermore, we studied two specific quasi-natural external events, the EU enlargement in 2004 and the economic crisis in 2008, representing positive and negative shocks to demand, respectively. Our aim is to test the causal effects of sales shocks on R&D investment to exogenous sales shocks. Employing a synthetic control group generating method by Abadie and Gardeazabal (2003); Abadie et al. (2010), we found that counter-cyclical pattern of R&D investment to sales shock holds in general, as well as the countervailing effects of credit constraint.

These results are interesting for policy makers. The results point to smoothing effects of R&D subsidies, avoiding firms to cut back R&D in recessions. While partially solving the problem of credit constraints, subsidy, on the other hand, renders more a-cyclical R&D investment. In this manner, the efficiency gain from following counter-cyclical path is lost. Policy makers have to trade off these effects when designing such supportive programs.

The access to more detailed and more accurate data on credit constraints and the particular policy environment in Germany (availability of R&D grant policy) allows us to go further in exploring how firm heterogeneity plays a role in shaping the interaction between R&D investment and the economic cycle. We encourage more research in this direction to better understand the innovation decision making.

Bibliography

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller, "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program," *Journal of the American Statistical Association*, 2010, *105* (490), 493–505.

_ **and Javier Gardeazabal**, "The Economic Costs of Conflict: A Case Study of the Basque Country," *The American Economic Review*, 2003, *93* (1), pp. 113–132.

Aghion, Philippe and Gilles Saint-Paul, "Virtues of Bad Times: Interaction Between Productivity Growth and Economic Fluctuations," *Macroeconomic Dynamics*, 1998, *2* (03), 322–344.

_ **, Philippe Askenazy, Nicolas Berman, Gilbert Cette, and Laurent Eymard**, "Credit Constraints and the Cyclicality of R&D Investment: Evidence from France," *Journal of the European Economic Association*, 2012, *10* (5), 1001–1024.

Arellano, Manuel and Stephen Bond, "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *The Review of Economic Studies*, 1991, *58* (2), 277–297.

Barlevy, Gadi, "On the Cyclicality of Research and Development," *The American Economic Review*, 2007, *97* (4), 1131–1164.

Bloom, Nick, "Uncertainty and the Dynamics of R&D," *American Economic Review*, 2007, *97* (2), 250–255.

Czarnitzki, Dirk and Hanna Hottenrott, "Financial Constraints: Routine Versus Cutting Edge R&D Investment," *Journal of Economics & Management Strategy*, 2011, *20* (1), 121–157.

_ **and** _ , "R&D investment and Financing Constraints of Small and Medium-sized Firms," *Small Business Economics*, 2011, *36* (1), 65–83.

Domadenik, Polona, Janez Prasnikar, and Jan Svejnar, "How to Increase R&D in Transition Economies? Evidence from Slovenia," *Review of Development Economics*, 2008, *12* (1), 193–208.

Gali, Jordi and JL Hammour, "Long-run Effects of Business Cycles," *Discussion Papers from Columbia University Department of Economics*, 1992.

Geroski, Paul, *Market Structure, Corporate Performance, and Innovative Activity*, Oxford: Oxford University Press, 1994.

Gertler, Mark and Simon Gilchrist, "Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms," *The Quarterly Journal of Economics*, May 1994, *109* (2), 309–340.

Hall, Bronwyn H, "Investment and Research and Development at the Firm level: Does the Source of Financing Matter?," *NBER Working Paper No.4096*, 1992, *1*.

Himmelberg, Charles P. and Bruce C. Petersen, "R & D and Internal Finance: A Panel Study of Small Firms in High-Tech Industries," *The Review of Economics and Statistics*, 1994, *76* (1), pp. 38–51.

Lopez-Garcia, Paloma, José Manuel Montero, and Enrique Moral-Benito, "Business Cycles and Investment in Intangibles: Evidence from Spanish Firms," *Banco de Espana Working Paper No. 1219*, 2012, *1*, 1–42.

Rafferty, Matthew C, "Do Business Cycles Influence Long-run Growth? The Effect of Aggregate Demand on Firm-financed R&D Expenditures," *Eastern Economic Journal*, 2003, *29* (4), 607–618.

Roodman, D., "How to do xtabond2: An Introduction to Difference and System GMM in Stata," *Stata Journal*, 2009, *9* (1), 86–136(51).

Saint-Paul, Gilles, "Productivity Growth and the Structure of the Business Cycle," *European Economic Review*, 1993, *37* (4), 861 – 883.

Sharpe, Steven A, "Financial Market Imperfections, Firm Leverage, and the Cyclicality of Employment," *The American Economic Review*, 1994, *84* (4), 1060–1074.

Waelde, Klaus and Ulrich Woitek, "R&D Expenditure in G7 Countries and the Implications for Endogenous Fluctuations and Growth," *Economics Letters*, 2004, *82* (1), 91–97.

Wooldridge, Jeffrey M, *Econometric Analysis of Cross-section and Panel Data*, MIT press, 2010.

Tables

Table 1.1: Descriptive statistics

Variable name	units	Mean	Std. Dev.	Min.	Max.	T-value
Overall sample (5,126 observations)						
$R\&Dintensity$	Ratio	0.284	0.32	0	1	
$\triangle Sales$	Log	0.031	0.35	-5.39	41734,00	
$CreditConstraint$	Index [100,600]	208.12	53.72	100	600	
$\triangle Sale * CreditConstraint$	multiply	5.58	79.21	-1300.8	1173.5	
$Subsidy$	dummy	0.284	0.45	0	1	
PCM	log	0.21	3.3	-165.62	1.35	
sme	dummy	0.57	0.5	0,00	1,00	
Small firms (2,917 observations)						
$R\&Dintensity$	Ratio	0.3	0.336	0	1	
$\triangle Sales$	Log	0.007	0.332	-5.4	2.48	
$CreditConstraint$	Index [100,600]	225.7	50.42	101	600	
$\triangle Sales * CreditConstraint$	multiply	1.54	80.8	-1300.8	589.1	
$Subsidy$	dummy	0.275	0.446	0	1	
PCM	log	0.17	4.36	-165.6	1.35	
Large firms (2,209 observations)						
$R\&Dintensity$	Ratio	0.255	0.282	0	1	-5.25***
$\triangle Sales$	Log	0.061	0.37	-4.0	5.4	5.39***
$CreditConstraint$	Index [100,600]	185,00	48.95	100	600	-29.03***
$\triangle Sales * CreditConstraint$	multiply	10.93	76.75	-1098.8	1173.5	4.21***
$Subsidy$	dummy	0.295	0.456	0	1	1.53*
PCM	log	0.264	0.32	-10.83	1.12	1.21

Table 1.2: Regression results on full sample

Variables	FE(Without PCM) (1)	FE(With PCM) (2)	Panel Tobit (RE) (3)	Dynamic panel Tobit(RE) (4)	Dynamic panel (5)
$DepVar_{i,t-1}$				0.561***	0.204***
				(0.034)	(0.04)
$DepVar_{i,t-2}$					0.038
					(0.056)
$\Delta Sales_{i,t}$	-0.096***	-0.11**	-0.15**	-0.233**	-0.345***
	(0.028)	(0.038)	(0.06)	(0.097)	(0.13)
$\Delta Sales_{i,t-1}$					-0.37***
					(0.124)
$\Delta Sales_{i,t-2}$					-0.3**
					(0.124)
$\Delta Sales_{i,t} * CreditConstraint_{i,t}$	0.0004***	0.0005**	0.0007***	0.0012***	0.0012**
	(0.0001)	(0.0002)	(0.0002)	(0.0004)	(0.0005)
$\Delta Sales_{i,t-1} * CreditConstraint_{i,t-1}$					0.0013**
					(0.0006)
$\Delta Sales_{i,t-2} * CreditConstraint_{i,t-2}$					0.0013**
					(0.006)
$PCM_{i,t}$		0.002***	0.0015	0.1***	0.115*
		(0.0005)	(0.0023)	(0.03)	(0.063)
$PCM_{i,t-1}$					-0.03
					(0.073)
$PCM_{i,t-2}$					-0.039
					(0.045)
$CreditConstraint_{i,t}$	-0.00013	-0.0002	-0.0001	-0.0002	-0.0000
	(0.000)	(0.0001)	(0.0002)	(0.0003)	(0.0004)
$ln(FirmAge)_{i,t}$			-0.14***	-0.134***	
			(0.04)	(0.046)	
$[ln(FirmAge)]^2_{i,t}$			0.025***	0.023***	
			(0.08)	(0.007)	
$MEAN[\Delta Sales]_i$			0.589***	0.397**	
			(0.21)	(0.2)	
$MEAN[CreditConstraint]_i$			-0.0003	-0.0003	
			(0.0002)	(0.003)	
$MEAN[\Delta Sales * CreditConstraint]_i$			-0.002**	-0.0014*	
			(0.001)	(0.0008)	
$MEAN[PCM]_i$			-0.0007	-0.01**	
			(0.004)	(0.004)	
$MEAN[ln(FirmAge)]_i$			-0.07***		
			(0.026)		
$Constant$	0.15	0.2***	0.587**	0.334*	
	(0.11)	(0.07)	(0.2)	(0.178)	—
Overall significance	3.46	3.36	1011.8	1481.82	301.9
Joint significance of time	7.01***	2.1***	160.5***	56.42***	
Joint significance of industry	1.22	42.7***	714.48***	423.04***	
Joint significance of means			17.17***	13.08**	
AR(1)					-4.6***
AR(2)					-0.126
Sargan-test (chi2)					330.1
Number of obs	8,492	5,126	3,479	5,191	1,943

Notes: ***,**,* indicate a significance level of 1%, 5%, 10%.
Standard errors are clustered at firm level and reported in parentheses.

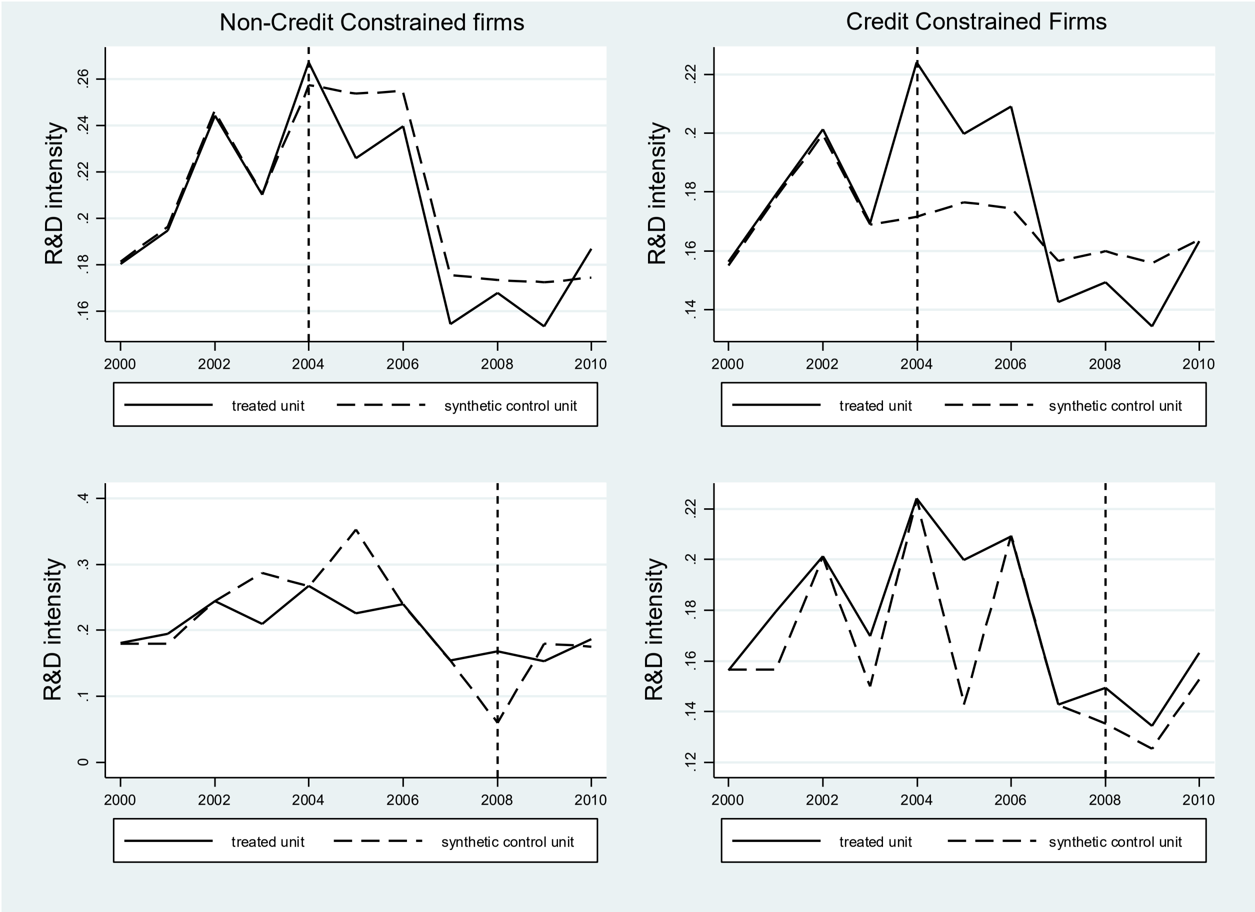
Table 1.3: Results of regressions on sub-samples

Variables	Subsidized (1)	Unsubsidized (2)	SME & Subsidized (3)	SME & Unsubsidized (4)
$\Delta Sales$	-0.1	-0.158**	-0.183	-0.196**
	(0.064)	(0.068)	(0.12)	(0.081)
$CreditConstraint$	-2.06 e-06	-0.0003	0.0001	-0.0004*
	(0.0003)	(0.0002)	(0.0006)	(0.0002)
$\triangle Sales * CreditConstraint$	0.0003	0.0008***	0.0007*	0.0009***
	(0.0003)	(0.0003)	(0.0004)	(0.0003)
PCM	0.12**	0.0013**	0.18*	0.0012
	(0.048)	(0.0005)	(0.09)	(0.0007)
$Constant$	0.54***	0.26***	0.55***	0.211**
	(0.12)	(0.06)	(0.17)	(0.086)
Overall significance	3.4***	12.31***	17.07***	
Joint significance of time	3.66***	5.14***	6.51***	3.88***
Number of obs	1,361	3,608	746	2,059

Notes: ***,**,* indicate a significance level of 1%, 5%, 10%.

Standard errors are clustered at firm level and reported in parentheses.

Figure 1.1: R&D cyclicality between credit slack and credit constrained in 2004 and 2008



1.4 Appendix

Table A1: Industry classification

Industry	NACE rev. 2008	Description	Number of firms	Percentage
1	1.1; 1.2; 1.4; 2; 3;	Agriculture/Forestry/Fishing	7	0.13
2	6-9;	Mining	59	1.1
3	11; 12;	Food/tobacco	168	3.13
4	13; 14; 15;	Textiles	167	3.11
5	16,17	Paper/wood	199	3.71
6	18	print	145	2.7
7	19	Coke/oil	39	0.73
8	20	Chemicals	271	5.05
9	21	Pharmacy	48	0.89
10	22,23	Plastics/Rubber/Non-metal	499	9.3
11	24	Basic Metal	147	2.74
12	25	Fabricated metal	380	7.08
13	26	Computers/Electronics	425	7.92
14	27	Electronic equipment	406	7.57
15	28	Machinery nec	667	12.43
16	29,3	Vehicles	79	1.47
17	31	Furniture	98	1.83
18	32	Other manufacturing	60	1.12
19	33,34	Repair of machinery s	140	2.61
20	35	Electricity/ Gas	116	2.16
21	36-40	Water/waste	37	0.69
22	41-43	Construction	95	1.77
23	45-47	Wholesale/Retail	134	2.5
24	49-55	Transport/Communication	123	2.29
25	59-63	Information/ Communication	227	4.23
26	64.3-69	Bank/Institutions/Real-state	145	2.7
27	70; 71; 72; 73.1-74.3; 75;	Prof/ Scientific/Tech-Services	343	6.39
28	74.9; 78-82	Admin/ Support services	50	0.93
29	77; 84-88; 90-99	Social/ Other services	90	1.68
Total			5,364	100

Table A2: Cross-correlation matrix

	$R\&Dintensity$	$\triangle Sale$	$CreditConstraint$	$\triangle Sale * CreditConstraint$	$Subsidy$	PCM	sme
$R\&Dintensity$	1						
$\triangle Sale$	-0.0012	1					
$CreditConstraint$	0.053*	-0.042*	1				
$\triangle Sale * CreditConstraint$	0.0053	0.964*	-0.0518*	1			
$Subsidy$	0.263*	0.0298	-0.008	0.0212	1		
PCM	0.0037	-0.0253	-0.0233*	-0.03	0.0166	1	
sme	0.073*	-0.075*	0.3758*	-0.0587*	-0.0213*	0.003	1

Note: * indicates a significance level of 1%.

Table A3: Comparison between our results of dichotomy credit constraint and Aghion et al. (2012) results with payment incident

Variables	Credit constraint as a dummy FE	Result from Aghion IVFE
$\Delta Sale$	-0.012	-0.018***
	(0.012)	(0.003)
$CreditConstraint$	0.012	0.003
	(0.024)	(0.002)
$\Delta Sale * CreditConstraint$	0.041*	0.029***
	(0.0224)	(0.01)
PCM	0.0017	
	(0.0017)	
$Constant$	0.157	
	(0.243)	
Overall significance	3.32***	
Joint significance of time	6.9***	
Joint significance of industry	1.32	
Number of obs	5,126	73,237

Note: the credit rating of a firm is higher than that of the 75th percentile, we set the value of credit constraint dummy to unity. Otherwise, it is zero.

Table A4: Comparison of mean value between treatment and synthetic group

Variables	Credit Unconstrained Exporters in 2004		Average of Credit Unconstrained exporters
	Real	Synthetic	
$R\&Dintensity$	0.21	0.21	0.06
$CreditConstraint$	211.9	218.8	195.2
PCM	-0.14	-0.39	0.27
$ln(FirmAge)$	3.24	3.37	3.44
$Capitalintensity$	0.08	0.21	0.27
	Credit Constrained Exporters in 2004		Average of Credit Constrained Non-exporters
	Real	Synthetic	
$R\&Dintensity$	0.17	0.17	0.07
$CreditConstraint$	199.9	214.45	268.32
PCM	0.284	-0.54	-0.03
$ln(FirmAge)$	3.35	3.21	3.06
$Capitalintensity$	0.127	0.132	0.16
	Credit Unconstrained Exporters in 2008		Average of Credit Unconstrained Non-Exporters
	Real	Synthetic	
$R\&Dintensity$	0.155	0.154	0.06
$CreditConstraint$	221.9	219	195.2
PCM	0.26	0.26	0.27
$ln(FirmAge)$	3.35	3.31	3.44
$Capitalintensity$	0.1	0.098	0.27
	Credit Constrained Exporters in 2008		Average of Credit Constrained Non-exporters
	Real	Synthetic	
$R\&Dintensity$	0.143	0.143	0.07
$CreditConstraint$	207.5	217.86	268.32
PCM	0.26	0.256	-0.03
$ln(FirmAge)$	3.4	3.37	3.06
$Capitalintensity$	0.145	0.104	0.16

Figure 1.2: Growth rate of GDP and R&D investments

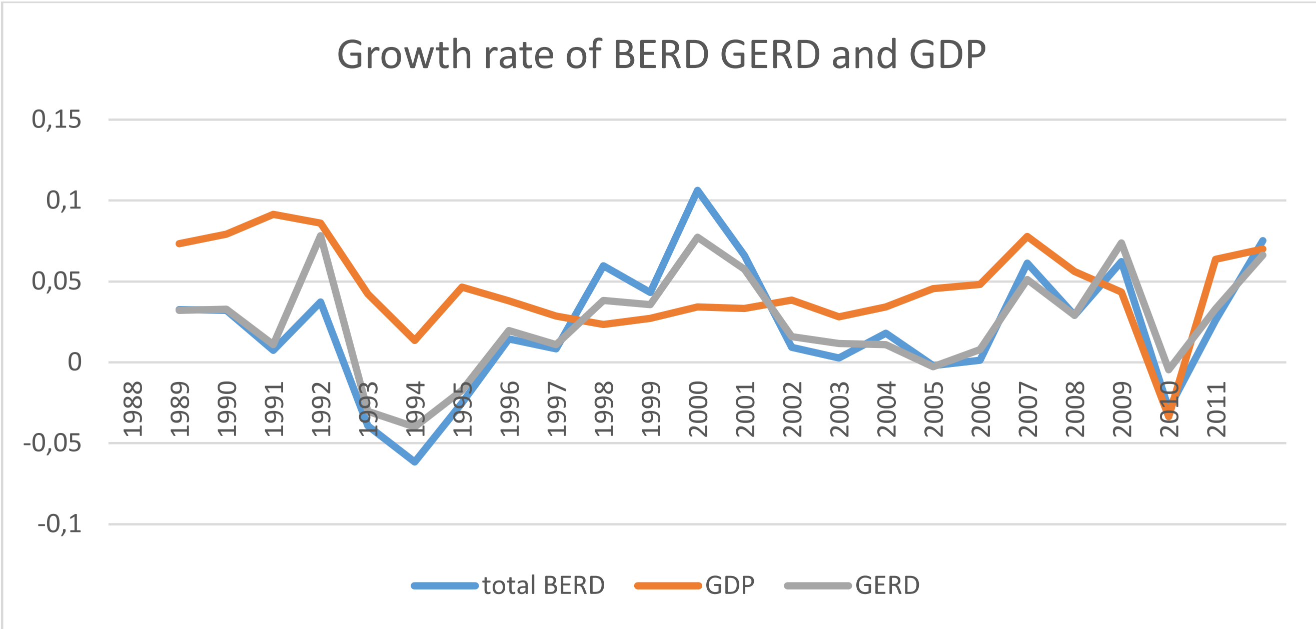
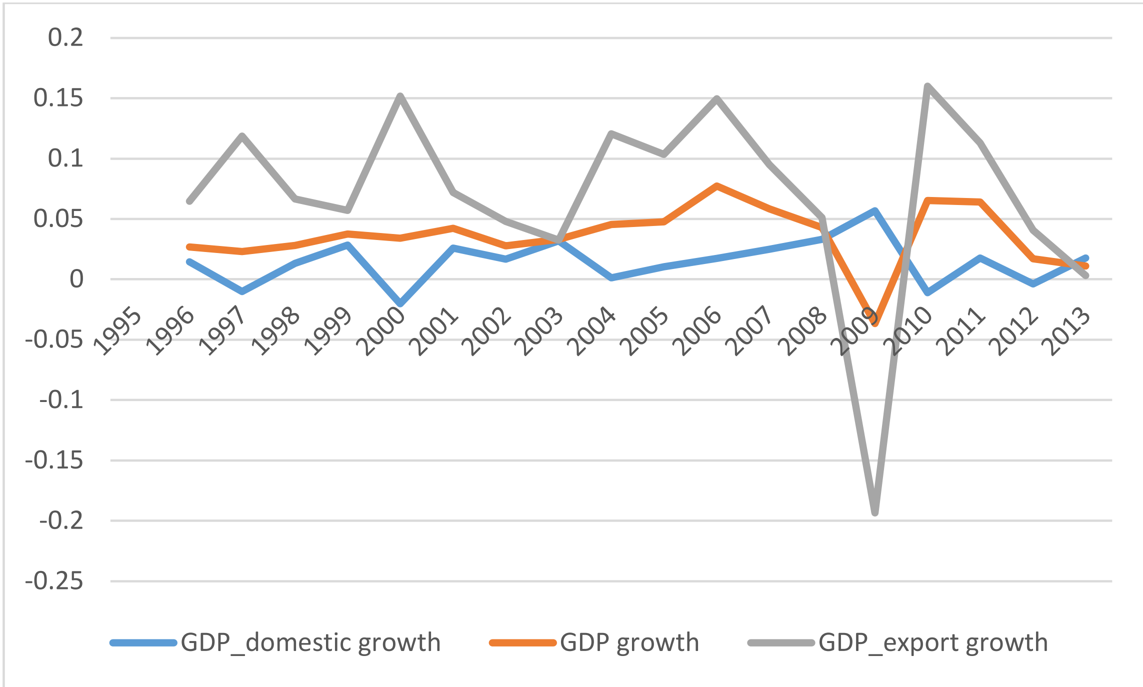


Figure 1.3: Growth rate of GDP: Domestic GDP versus export GDP



Chapter 2.

Efficiency Effects of Independent Boards: Evidence from China

Co-authored with Joel Stiebale

2.1 Introduction

The majority of large companies are characterized by a separation of ownership and control and are thus subject to agency problems between managers and shareholders. One of the responsibilities of boards is to monitor managers and to induce them to make decisions in the interest of shareholders. It is often argued that monitoring is more effectively performed by independent directors, i.e. those with no personal or business relationship with the firm besides their presence on the board (see the overview of related literature in Adams et al., 2010). In addition to the monitoring channel, independent directors also have an advisory function and can affect performance by sharing knowledge and experience (e.g. Adams and Ferreira, 2007). However, some characteristics of independent directors may prevent them from efficiently implementing their functions, such as lack of access to private information or insufficient amount of time devoted to advising and monitoring, which may in turn harm firms' performance (see, for instance, Ferris et al., 2003; Falato et al., 2014). Therefore, the investigation of net effects of independent directors on the efficiency of firms ultimately boils down to an empirical question.

Previous empirical research has studied the effects of independent (or outside) directors on stock market performance and accounting measures (e.g., Bhagat and Black, 2002; Byrd and Hickman, 1992; Chhaochharia and Grinstein, 2007; Duchin et al., 2010), hiring, dismissal and remuneration of CEOs (see, for instance, Core et al., 1999; Denis and Sarin, 1999; Weisbach, 1988) and innovation strategies (Balsmeier et al., 2014, 2017). However, little is known about the effects of independent directors on the productivity.

This paper investigates empirically how independent directors affect total factor productivity, as well as operating costs and other performance measures of Chinese listed firms. The concept of independent directors was introduced in China in 1997 as a response to financial scandals and the resulting regulations in developed western countries.[1] The case of China is particularly interesting for at least two reasons.

[1]The Chinese context distinguishes itself from those in developed western countries in some important regards. Firstly, though the current governance mechanism borrows the form of two-tier board system from continental countries, such as Germany and Japan. However, it belongs to, in essence, one-tier board system. The contradiction stems from the inability of the supervisory board to exercise the responsibility of monitoring over management. Awkwardly, supervisory board has not been given the legitimate right to vote against management or other board directors. Further, members are usually appointed because they are closely connected to the interest party. In addition, the definition of "independence" and the how related policy is enforced may also differ. According to the definition by the China Securities Regulatory Commission CSRC, independent directors (Duli-Dongshi) are those who (and whose relatives) have no business relationship with anyone else employed by the firm and can thus provide objective advise to the firm. CSRC explicitly states rules to determine whether a person can be classified as independent. In contrast, in the UK, there exist no such hard rules on independence and German corporate law even allows employee representatives to be on the supervisory

First, due to high market potential but relatively severe agency problem, independent directors are introduced in China to partially strengthen the weak corporate governance mechanism, especially dereliction of duty of the supervisory board. Further, most developing and transition countries have recently introduced requirements for more presence of independent directors on the board or plan to implement such regulations. However, little about the effects of independent directors in these countries is known. Our paper contributes to the literature by providing evidence on the efficiency effects of independent directors in an emerging market.

A major empirical challenge arises because of the endogenous board composition. To address this problem, we exploit a policy reform that affected the requisite minimal number of independent directors on the board. This policy, put forth by China Securities Regulatory Commission (CSRC) in August 2001, required all listed firms to have more than one third independent directors on the board by June 30, 2003. This allows us to compare performance change between firms that had to increase the independent directors share as a result of the regulation and firms that had already reached the goal.

Our results show that an increasing share of independent directors, induced by the policy change, is associated with higher productivity growth, more patent applications and granted inventions. These effects are both statistically significant and economically important. For instance, our results suggest that increasing the share of independent directors by 10 percentage points results in an increase in total factor productivity of around 7.5%. Independent directors also seem to induce lower operating costs and higher growth in free cash flow from operation, while they have negligible impact on the wage payments and cash flow from financing and investment activities. We show that these findings are unlikely to be explained by systematic characteristics of early adopters ex ante the policy. Our results are robust to various robustness checks including different measures of productivity and various control variables at firm and industry level.

In addition, our results indicate that advisory and monitoring functions have asymmetric impacts in different tasks. Put differently, among listed firms in China, advisory function is associated with higher innovation outcomes, while little positive influence of active monitoring on productivity has been revealed. Conversely, monitoring is shown to facilitate TFP but has no material contribution to the innovation efficiency.

We further demonstrate that positive effects are more likely to occur when the

board. We do not find any specifically written sanction that essentially follows if firms fail to comply with the regulation. However, as argued by Clarke (2006), CSRC may use its authority over company filings (for example by increasing the likelihood of rejecting the filing) to enforce the policy. Further, a firm's senior officers may fear that failure to obey the rule will ruin their reputation in the CEO market.

influence of independent directors is presumably higher, as in cases when firms are controlled by non-state owners and when product market competition is mild.

The rest of this paper is organized as follows. Section 2.2 discusses the related literature and section 2.3 provides a summary of the data and variables. Section 2.4 describes identification strategy and presents results. Section 2.5 finally concludes.

2.2 Related literature

A growing empirical literature analyzes how board characteristics and other aspects of corporate governance affect firm performance. Significant correlation between profitability/Tobin's Q and inside directors' holdings has been established (e.g, Demsetz and Villalonga, 2001; Kole, 1996; Kaserer and Moldenhauer, 2008; Kapopoulos and Lazaretou, 2007). It has also been found that various internal governance mechanisms such as the presence of block-holders (Koeke and Renneboog, 2005) and insider ownership (Palia and Lichtenberg, 1999; Martikainen et al., 2009) are associated with higher productivity. Recent research finds that measures of innovation, which may be an important determinant of productivity, are correlated with different aspects of corporate governance (see Belloc, 2012, for an overview). More generally speaking, our paper is also related to a growing literature that analyzes the determinants of productivity differences across firms within industries (Syverson, 2011).

A more recent focus of empirical studies has been the effects of independent directors, an important component of external governance mechanism. Previous literature has mainly studied effects on firms' profitability, Tobin's Q, and stock market returns and the results are mixed.[2] Studies have lately extended the scope to other outcome variables, for instance, Balsmeier et al. (2014), Balsmeier et al. (2017) and Helmers et al. (2017) discover that appointments of outside directors are associated with increased innovation input and change in innovation strategy. Our empirical analysis addresses the effects of independent directors on productivity-related measures and innovation outcome variables, namely patenting applications and grants.

Monitoring and advisory have been identified as two main channels via which independent directors contribute to firm performance (see, for instance, Clarke, 2006; Fama and Jensen, 1983; Weisbach, 1988). Starting from Fama and Jensen (1983), the monitoring function of boards and its effects have been discussed among researchers and practitioners. The monitoring channel tackles agency problems which mainly arise between managers and shareholders due to managers' entrenchment

[2] See the survey of related empirical literature in Balsmeier et al. (2014). Recent examples include Bhagat and Black (2002), Chhaochharia and Grinstein (2007) and Duchin et al. (2010).

by means of management-specific investment or managerial "empire building" (e.g., Jensen, 1986; Shleifer and Vishny, 1989).[3] Because of the greater objectivity (Mizruchi, 1983), independent (or outside) directors are able to curb agency problems by inducing more efforts from managers and strictly scrutinizing decisions made by managers. Further, current governance systems endow independent directors with sufficient power to challenge managers. For instance, it has been found that CEOs are more frequently replaced as a result of firms' bad performance when more outsiders are present (e.g. Weisbach, 1988). If independent directors are more effective in monitoring, this should affect firms' productivity positively. However, counter-arguments exist. Adams and Ferreira (2007) argue that monitoring by independent directors may work in a dual board system with a separate supervisory board, but not in a single board system due to managers' incentives to withhold information. Similarly, managers may take advantage of the informational asymmetry to persuade independent directors to make decisions in managers' interest or to monitor less effectively (Duchin et al., 2010).

The advisory channel is based on the information resource view (e.g. Dalton et al., 1999; Hillman and Dalziel, 2003), according to which human capital and relationship capital (social network) associated with board members improve firm performance. Through spillover effects, the appointing firm is able to acquire knowledge and resources from independent directors who possess experience from advising other firms on related activities. For instance, Kor and Sundaramurthy (2008); Kor and Misangyi (2008) argue that the advisory function of independent directors offsets the lack of experience amongst top management of young firms and helps them sustain high growth. Balsmeier et al. (2014, 2017); Helmers et al. (2017) provide empirical evidence that the advisory role of outside directors benefits the appointing firms' innovation through knowledge spillovers. Nevertheless, low access to private information can distort the advisory channel as well.

In spite of the two positive channels discussed above, some scholars question the function of independent directors in improving firm performance. For instance, it has been argued that outside board members benefit the sending firm more than the appointing firm (Fahlenbrach et al., 2010) and that outsiders can jeopardize firms' innovative activity due to limited ability to separate managerial ability from luck in innovation projects (Aghion et al., 2013). Furthermore, "busy directors" are unable to devote sufficient amount of time to each company they serve, which can be detrimental to firm performance (e.g., Fich and Shivdasani, 2006; Falato et al., 2014).

[3] Some scholars also argue that independent directors can address agency problems between large block-holders and minority shareholders. However, in our paper, we focus on the agency problem between management and all shareholders.

2.3 Data and variables

Our data set is constructed based on two widely used databases, RESSET and CSMAR which cover all Chinese listed firms. These two database have been used in several empirical studies on Chinese firms (see, for instance, Gul et al., 2013; Chen et al., 2013; Guo et al., 2014). CSMAR and RESSET contain information on a variety of financial indicators as well as detailed information on the composition of boards including the number of independent directors, board size, characteristics of board members and attendance at board meetings. Patent data mainly comes from the Chinese patent database constructed by He et al. (2018), which contains information on annual patent application counts for invention, utility model and design patents. Additional data on sales, number of employees and different types of assets, which we use to estimate total factor productivity, are also available. Since banks, insurance companies and consulting firms provide highly specialized services and thus have fundamentally different production function, we exclude observations of these niche markets from our main sample. Our unbalanced panel contains 2,447 firms over the time periods 2000 to 2012.

We employ mainly two measures of total factor productivity (TFP) based on the method proposed by Ackerberg et al. (2015) (hereafter, ACF) as indicators of productivity.[4]

2.3.1 Productivity estimation

Our starting point for the productivity measure is a Leontief production function, that is:

$$Y_{it} = \min\{\alpha L_{it}^{\beta_l} K_{it}^{\beta_k} \exp(\omega_{it}), \alpha_m M_{it}\} \exp(\varepsilon_{it}) \tag{2.1}$$

where Y_{it} is firm i's output at time period t, L_{it} denotes labor input, K_{it} stands for its capital stock. ω_{it} and ε_{it} denote TFP and measurement error in output, respectively. Under this functional form, we estimate a structural value added production function (Ackerberg et al., 2015; Gandhi et al., 2011), which can be expressed in logarithmic form as:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \varepsilon_{it} \tag{2.2}$$

where y_{it}, l_{it} and k_{it} denote the logarithm of firms' output, labour input and capital stock. Our measure of output is deflated sales and labour input and capital are

[4]The ACF method builds on estimation techniques developed by Olley and Pakes (1996) and Levinsohn and Petrin (2003) but accounts for potential collinearity problems that can affect these methods.

proxied by the total number of employees and fixed assets.

It is assumed that the capital stock evolves following $K_{it} = K_{i,t-1} - \delta_{it} + I_{i,t-1}$, where δ_{it} is firm-specific depreciation and $I_{i,t-1}$ is the amount invested at time period $t-1$, adjusted by the investment price index. The two error terms in equation (2.2) are an unobserved shock ε_{it} that is independent of firms' input choices and the unobservable productivity term ω_{it} which is observed by the firm but not by econometricians. ω_{it} is modeled as a first-order Markov process, $\omega_{it} = E[\omega_{it}|\omega_{i,t-1}] + \nu_{it}$, where ν_{it} denotes an independent shock to productivity at time period t, independent of firm's information set at $t-1$.

We assume that labor adjustment takes time, which is consistent with characteristics of the Chinese labor market. Therefore, we specify both capital and labor as state variables that are determined before the shock ν_{it} is realized. This yields two moment conditions: $E(\nu_{i,t}|k_{i,t}) = 0$ and $E(\nu_{i,t}|l_{i,t}) = 0$. The average of our estimated coefficients for capital and labor inputs across all industries are 0.4 and 0.55, respectively.[5] We use these coefficients to retrieve our first measure of total factor productivity, *TFP1*, from residual.

An alternative outcome variable can be valued added. Unfortunately, in both dataset reliable data on variable costs such as material/packaging expenditures is unavailable. However, we are able to approximate value added from operating costs[6]. Following De Loecker and Eeckhout (2017), we construct a proxy for costs of goods sold, namely operating costs deducted by fixed costs (mainly depreciation). What remains in the proxy should be variable costs including labor, raw material costs and energy expenditures.[7] This proxy is then deflated by the one-digit industry based Producer Price Index. Finally, total factor productivity is re-estimated from the Cobb-Douglas production function specified in equation (2.2), using replacement of labour input with deflated costs of goods sold. Using the ACF method, coefficients of inputs and capital are estimated to be 0.77 and 0.12 respectively. Based on these coefficients, we calculate the second productivity measure, *TFP2*.

[5]These inputs estimates are qualitatively similar to previous studies for Chinese firms, for instance Xiaodong and Yujun (2012).

[6]As in most firm-level data sets, we implicitly have to assume that firms are price takers in input and output markets since we do not have data on firm-specific output and material prices.

[7]Generally, operating costs are defined as the cost that can be attributed to producing a firms' core products or services. In the annual reports of Chinese firms, operating costs mainly consist of costs for intermediate inputs, labor costs including wages and bonuses paid to workers, energy consumption and manufacturing expenses (mainly depreciation).

2.3.2 Innovation output measures and control variables

In addition to productivity, effects of independent directors on innovation are examined. We proxy innovation performance by patent counts. In our application, it has two advantages over using research and development (R&D) expenditures. First, Chinese listed firms seldom disclosed R&D expenditures before 2007. Further, a measure of innovation output accounts for the efficiency of innovation activities, as opposed to the R&D level. Our patent data comes from the Chinese patent data research project, initiated by He et al. (2018).[8] Patent output variable takes value zero if we fail to map main-sample observations onto the patent data base. However, robustness checks displayed in Table B6 in Appendix show that our results are even more significant observations are restricted to only positive patent outcomes.

Our dataset contains detailed information on patents including counts of applications for each type (invention, utility model and design), at which entity level (headquarter, subsidiaries and joint ventures/associated enterprises), locations of assignees and whether a patent has been granted. One of our innovation indicators is the total number of patent application counts for all three types[9]. Unfortunately, total counts do not reveal much about the value of patent applications. Meanwhile, there is no information on citations in the Chinese patent system. Therefore, the other innovation output measure is constructed on invention grants. Compared to utility model and design, invention represents the highest level of novelty. We believe that passing the 2-3 years-long strict scrutiny by experts in specific areas and finally obtaining the patent strongly indicate high innovativeness. More specifically, the

[8]The authors construct the database based on several steps. Firstly, they search the directory of corporate affiliations (subsidiaries, sub-subsidiary companies, joint ventures and associated enterprises) of all Chinese publicly traded firms. Secondly, they extract raw patent data from the State Intellectual Property Office of China (SIPO) and match patent-by-patent to all identified directories according to the Levenshtein edit distance matching algorithm. Finally, they conduct a manual check to guarantee the accuracy of the match. The final database covers 1,426 firms that filed at least one patent from 1990 to 2010 and we merge this data with our main estimation sample covering the years 2000-2010 using a unique identifier of publicly traded firms. Research papers using this database include Hong and Su (2013); Zhou et al. (2017). The CSMAR database has its own patent sub database, containing aggregated counts of patent applications for invention, utility models and designs. However, no specific information on each patent is provided, which makes it difficult to verify the accuracy of these numbers. The average numbers, 22.3 patent applications and 7.89 invention applications, are generally larger than counts from database from (He et al., 2018). However, in a robustness check, we rerun our estimates based on patent applications from CSMAR and derive similar conclusions.

[9]Invention is defined by the Chinese patent law as new technological plan towards new products/materials/substances, methodologies (such as manufacturing/communication/measurement/analysis) or the improvement of existing products and methodologies, thus can be broadly categorized into product invention and methodology invention. Utility model patent refers to new technological plan concerning products' shape, configuration or mix of both. Design patent covers wide range of aesthetic alterations, from shape, color to pattern. Given the high value of novelty, Chinese patent law states that the protection duration for invention patents is 20 years compared to 10 years for utility model and design patents.

granted invention count measures how many patents were granted afterwards from all applications filed in a particular year period. Based on the previous literature, we control for important determinants of innovation including firm size (natural logarithm of total asset), tangibility of assets (total fixed asset over total assets), debt ratio (total debt over total asset) and number of employees.

2.3.3 Summary statistics

Summary statistics for main variables are listed in Table 2.1. Industry distribution, which we use to calculate TFP, are documented in Table B1 in appendix. There is considerable variation in TFP across and within industries in our sample.

Firms have, on average, filed 17.35 patent applications in total and 5.7 invention applications, out of which 2.67 inventions have been granted. Utility model applications (8.1) account for almost half of all applications, followed by invention and design patents (3.55). In our merged sample, 1,206 firms filed at least one patent application and 1,097 firms haven been granted at least one invention patent. Although patenting activities have become more important for Chinese firms over time, the number and quality of innovations is still relatively low compared to America and European countries.

Regarding control variables, Chinese listed firms are, on average, characterized by large asset scale (the logarithm of total assets is 21.5) and high leverage (46%). In addition, the average logarithm of the number of employees is 7.48 and fixed assets account for about 27% of the total asset. The means of control variables for the patent samples are very close to those of the productivity sample. Specifically, in the patent sample, the average size of firms, debt ratio, labor force and tangibility are 21.4, 49%, 7.53 and 29%, respectively. This suggests that sample selection bias for our patent investigation is not a major concern.

2.4 Identifying the effects of independent directors

2.4.1 Simple regressions

As a first attempt to establish the correlation between independent directors and productivity, we estimate fixed effects models using the whole sample. Particularly, we estimate the following equation:

$$Pr_{it} = \theta InddirShare_{i,t-1} + Z'_{i,t-1}\gamma + \alpha_i + d_t + u_{it} \tag{2.3}$$

Pr refers to our measure of productivity described in the previous section. $InddirShare$ denotes the share of independent directors on the board, Z is a vector of control variables, namely firms size, debt ratio, tangibility and labor. α_i represents firm fixed effects and d_t denotes year dummies. We lag the share of independent directors and all control variables by one year relative to the outcome to partially address simultaneity problems. However, as we report in robustness checks, this is not crucial for our results.

In column (1) through (2) of Table 2.2, we report results of fixed effects models for both TFP measures. In all specifications, the estimated coefficients are positive, implying that increasing the presence of independent directors is associated with higher productivity growth. The estimate under $TFP2$ is 0.10 and statistically significant at 5% level. Standard OLS models with two-digit industry dummies yield similar results. The estimates suggest that there is a significant positive correlation between the share of independent directors and productivity.

Estimates of control variables are mainly in line with expectations. The coefficients indicate that large firms are more productive and that more intangible assets are associated with high productivity. Negative coefficient on labour force suggests that Chinese listed firms tend to be overstaffed. Given the opposite signs, influences of $Debtratio$ are unclear.

Time lag between independent directors and patent outcomes is expected to be longer, since it usually takes several years till board members' monitoring and advice on innovation activities taking effects in patent outputs. According to our summary statistics, it takes on average 1151, 319 and 301 days (starting from filing) for an invention, utility and design patent to be approved, respectively. To be consistent with the existing literature and our summary statistics, we therefore allow for time lags of 2 to 3 years between independent directors ratio and patenting outcomes. To account for the integer nature of patent counts, we estimate the following equation:

$$Pat_{it} = \exp(\phi InddirShare_{i,t-k} + Z'_{i,t-k}\pi + \alpha_i + d_t) + u_{it} \tag{2.4}$$

where Pat_{it} denotes patents measures, k takes value of 2 or 3 and all other variables are defined as before.

In column (3) through (6) of Table 2.2, we show results of fixed effects Poisson model. Column (3) and (4) assume time lag of 2 years and column (5) and (6) 3 years. Positive associations between independent directors share and patent counts hold in all specifications. The correlation is stronger and more significant for invention grants. The estimated coefficients are also of economic importance and suggest that a 10 percentage points increase in the independent director share is associated with an increase of 11.6% in the expected number of patents and an increase in the number of 29.4% in granted inventions. As suggests by column (6), using controls lagged by three years yields similar estimates for invention patents regarding the magnitude and significance. However, as to *Patapp_total*, the coefficient becomes insignificant, possibly due to the unmatched shorter time lag for other two types (utility model and design), as indicated by the summary statistics.

To summarize, the results indicate that changes in the share of independent directors are strongly and positively correlated with productivity and patent outcomes.

2.4.2 Exogenous variation in the share of independent directors

Due to the endogenous nature of board structure, it is challenging to identify causal effects of independent directors (Adams et al., 2010). The positive correlation between board structure and firm performance documented in the previous section might arise because firms with higher productivity and more efficient innovation activity tend to employ more independent directors. In this section, we exploit a policy shock imposed by CSRC to identify the causal effect of independent board.

To show how this regulation affected board structure, we plot the average independent director share of all listed firms by year in figure 2.1. As can be seen, beginning from 2002, independent directors presence in noncomplying firms increased dramatically from 0.21 to 0.33. By contrast, those complying firms hardly reacted to the reform, remaining above 0.35. This bifurcation implies that the exogenous mandate exerted effect only on some firms while leaving others intact. By the end of 2003, the independent director share on average almost reached 0.33, the requisite quota. The share has been slightly but steadily rising after 2003.

Before exploiting this policy change to identify the causal effects of independent directors, we perform a balancing test to shed light on whether there were systematic differences between treatment and control group prior to the policy shock. Early complying firms are defined as those that had already complied with the quota in the pre-treatment period. These firms should form valid control group since the policy shock has no essential influence on their board structures, shown in the Figure 2.1. Our treatment group consists of those firms whose independent directors' share was below the quota before the policy was implemented. These firms had to restructure their board composition to conform to the regulation. We focus on the policy change in 2003 and therefore define the year 2002 as the pre-treatment period. Based on this setting, t-tests are applied for all control variables and dependent variables, productivity and patent counts, between treatment and control group.[10]

[10]We choose the year 2002 as the pre-treatment year to construct an adequate instrumental variable. The independent director ratio in 2001 is also a possible but considerably weaker predictor

Table 2.3 indicates that control firms and treated firms display no statistically significant difference in the trend before the policy took place. It indicates that we can cautiously infer that these two groups can be regarded as qualitatively similar. As we discuss in more detail in Table B18, lagged values of productivity do not explain compliance decisions during the sample period, which points to the random selection of treatment. Similarly, control variables, except for employees counts, do not vary systematically between complying and non-complying firms. Closely comparing upper with down panels, item by item, reveals that the productivity and innovation samples are qualitatively the same. To sum up, our balancing tests are consistent with the assumption that the treatment induced by the policy change should be orthogonal to firm performance and important characteristics.

We employ an instrumental variable (IV) strategy similar to Stevenson (2010); Ahern and Dittmar (2012); Matsa and Miller (2013), who exploit pre-treatment compliance. One advantage of this IV strategy is that it allows for exploitation of the panel structure and richer information to be elicited on long-run effects (Ahern and Dittmar, 2012), compared with standard difference-in-difference method. We argue that *InddirShare* ex ante is a valid instrument because it is related to the post-treatment *InddirShare* but is independent of other determinants of firm performance, as indicated by our balancing tests. Specifically, instruments are constructed by interacting *InddirShare* in 2002 with post-treatment year dummies. Given this specification, observations of firms that became listed after 2002 are omitted. In other words, our sample is limited to firms who have experienced the regulation enforcement. We implement the two stage least squares estimation with fixed effects. Controlling for firm fixed effects is potentially important in our analysis because unobserved firm heterogeneity might be correlated with both independent director share and firm performance. Nevertheless, pooled IV regressions with two-digit industry dummies yield similar results. Standard errors for all regressions are clustered by firm-level to allow for serial correlation. Similar to the previous setting, we regress our productivity measures on one year lagged *InddirShare* and patent application counts on two year lagged *InddirShare* and other control variables.

Results of IV regressions are depicted in Table 2.4. In all specifications, the Kleibergen-Paap rk Wald F statistics clearly exceed the Stock-Yogo weak ID test threshold values at 5 % level which leads to the rejection of the null hypothesis of weak instruments. First stage estimates show that post-treatment *InddirShare*, is strongly correlated with our instruments. Negative coefficients imply the ever growing presence of independent directors on the board, holding independent directors share in

of board independence post the shock. Further, using 2001 as the pre-treatment period results in a considerably low number of observations. Ahern and Dittmar (2012) choose the latest pre-treatment year for similar reasons.

2002 as benchmark. P-values of the Hansen-J test are all above conventional threshold significance, an indication that we cannot reject the null hypothesis, i.e., the exogeneity of our instruments holds. These two pieces of evidence combined suggest that our instruments are valid and strong.

Second stage results of our productivity measures indicate strong and significantly positive causal effects. Our point estimates suggest that a 10 percentage points increase in the share of independent directors ceteris paribus increases $TFP1$ by 7.5% (exp(0.0075)-1) and $TFP2$ by 3.9%.

Imposing standard production function might invite concerns over our productivity measures, provided huge technical differences across industries. Therefore, we tackle this concern by estimating the production function separately for each industry. Table B2 and Table B4 show estimated industry specific input elasticities. In Table B3 and Table B5, the corresponding results of standard fixed effects and instrumental fixed effects estimates based on $TFP3$ and $TFP4$ are reported. The results are qualitatively similar to specifications with $TFP1$ and $TFP2$. As another robustness check, we directly assume the effects of independent directors enter into the law of motion in the productivity estimation process. 500 bootstrap replications render the obtained estimate for the coefficient of *InddirShare* of 0.75, which is statistically significant at the 1% level with standard error of 0.24.

To shed light on the causal effects of independent directors on innovation, we apply similar IV methodology in patent application counts and invention grants as outcome variables. The results are reported in Table 2.5. To allow for i)applying instrumental estimator, ii)controlling for firm fixed effects and iii) accounting for Poisson distribution of patents, we perform log-transformation on original counts, that is the logarithm of original patent measures plus one. In Table 2.5, results of specifications with both two (column (1)-(4)) and three year lags (column (5)-(8)) are listed, along with corresponding first stage regressions. As before, the Kleibergen-Paap rk Wald F statistics indicate that the instruments are strong while the Hansen test statistics show that we cannot reject IVs' validity at conventional levels of significance.

Our estimated coefficients of *InddirShare* in column (1) and (3) are both positive and statistically significant. Estimates suggest that a 10 percentage points increase in the independent director share leads to a 8.2% increase in expected patent applications and to a 7.1% increase in the expected number of granted invention patents. Specifications with three years lag derive similar conclusions for both total patent applications and invention grants in column (5) and (7). From now on, for the sake of brevity, we only report results with two years lags for patent counts.

In an alternative specification, we drop all observations whose patent applications and grant counts are zeros and report the results in Table B6. While the number of our observations drops substantially, our instruments seem to remain valid. Positive-patent restricted sample yields even larger and statistically more significant estimated coefficients than the whole unrestricted sample.

More robustness checks are documented in the Appendix. Firstly, in order to preclude possible bias stemming from possible causal linkage between time-varying control variables and the regulation, we regress our control variables (*Size*, *Labor*, *Tangibility* and *Debtratio*) on instrumented independent director share, as suggested by Angrist and Pischke (2008). From Table B7, no significant effect has been established, suggesting that the control variables do not change as a result of the policy.

Secondly, dynamics in productivity and innovation activities are taken into account by introducing lagged dependent variables. Specifically, our choice of lag is one year earlier relative to that of the corresponding *InddirShare*, i.e. $TFP1_{t-1}$, $TFP1_{t-2}$, $TFP2_{t-1}$, $TFP2_{t-2}$ for productivity and $Patapp\_total_{t-2}$, $Patapp\_total_{t-3}$, $Patgrant\_invent_{t-2}$, $Patgrant\_invent_{t-3}$ for patent. Despite significant lagged dependent variables, estimates of *InddirShare* in Table B8 in the Appendix remain statistically significant and even increase in magnitude, except for column (1).

Thirdly, endogeneity problem may also arise if some unobservable factors are correlated with board independence level. We address this problem by two additional tests. First, we capture the individual ex ante trend by subtracting TFP/patent outputs by their ex ante values in 2002. Our results documented in Table B9 show that our main results are robust to controlling for individual prior trends. Second, the target is concerned with industry-wide heterogeneity effects. we perform Chi-tests to examine whether complying and non-complying firms can be deemed as randomly distributed across industries in the pre-treatment period. As Table B10 demonstrates, the assignment of treatment is likely to be evenly distributed across industries, confirming the validity of our instruments. In a word, both individual and industry heterogeneity does not interfere with the main results.

Lastly, we applied a test in the spirit of Altonji et al. (2005). The results documented in Table B11 indicate that fitted values of *InddirShare* based on observable regressors are not significantly correlated with our outcome variables of interest, indicating that unobservable heterogeneity does not drive our results.

2.4.3 Mechanisms: Advisory and monitoring channel

Given the strong positive causal effects of independent directors' presence on productivity and innovation performance, we further investigate underlying mechanisms.

Advisory channel

One potential explanation for the positive effects of these "outsiders" is the counsel from independent directors on major issues, closely related to both productivity and innovation output. The common sources of information, based on which advice is provided, consist of previous knowledge, private information and information transferred from interlocking firms. Due to data availability, we mainly focus on the third type. Following Helmers et al. (2017), the idea of interlock network is exploited to capture possible information sharing among firms. If the information transmission is the main driver of the results, firms interlocking with other firms are better off than their counterparts without such connections. For this purpose, we merge in information on annual composition of the board. The CSMAR database keeps track of names of all sitting board members, allowing us to construct the interlock network.

An adjacency matrix forms the basis for network analysis. This adjacency matrix is constructed such that each entry describes whether two firms, indexed by the column and the row respectively, are connected. If there is an interlock connection between two firms by one or more independent directors, value one is assigned to the entry, otherwise zero. Note that according to our definition, the connection between firm i and firm j is exactly the same as the connection between firm j and firm i. Summing all the entries in each row across columns, we collapse the adjacency matrix into a column vector. Each entry denotes the number of current interlocks. To analyze the moderating effect of interlocking, we stratify the full sample into two sub-samples, namely firms with interlocks (IntLock, whose corresponding entry takes positive values) and firms without any interlocks (Non-IntLock, whose corresponding entry takes value of zeros). Given that the police shock automatically changed the topology of interlock network, our sample splitting is conducted based on pre-shock value of interlock counts in 2002 to preclude potential endogenous stratification. Hereafter, we perform the sample splitting in the same manner. Sub-sample IV results are shown in Table 2.6.

Results of total factor productivity in Table 2.6 provide little supportive evidence for the advisory function. With $TFP1$, coefficients from column (1) and (2) are both insignificant and are of similar size, suggesting that interlocking and non-interlocking firms both benefit weakly from independent directors. In column (3) and (4) with $TFP2$ as dependent variable, the important difference in significance level and in size between the coefficients indicates that interlocks even hinder independent directors from contributing to firm productivity. This inconsistency echoes the argument of "busy independent directors". To sum up, little evidence supports the positive moderating effects of advisory function on independent directors' contribution to higher productivity.

On the contrary, results of innovation performance show consistent evidence that independent directors boost innovation output through counseling CEO with information from other sitting firms. Specifically, for counts of all patent applications (invention, utility model and design combined), the coefficient from positive interlocks sub-sample is not only economically more important but also statistically more significant than the coefficient derived from zero-interlock sub-sample. Similarly, invention grants seem to benefit greatly from independent directors who are sitting on more boards. The point estimate from the sub-sample labeled IntLock in column (7) is statistically significant at 1.4% level and the coefficient size is multiple times larger than the coefficient from the sub-sample with Non-IntLock in column (8). The evidence of positive moderating effects of advisory channel on innovation agrees with previous findings by Balsmeier et al. (2014) on German firms and Helmers et al. (2017) on Indian firms.

To summarize, our empirical results show that independent directors' information sharing channel can be of great value to innovation activities, but less so to total factor productivity.

Monitoring channel

Monitoring over management can be an alternative theoretical explanation for the positive effects of independent boards on firm performance. It is explicitly stated in the guidance from CSRC that it is independent directors' responsibility to offer their judgments on important decisions such as management appointment, dismissal, compensation package design, major investment and financing decisions. When independent directors believe that some decisions by the management are at odds with the interest of shareholders, they have right and responsibility to intervene. If the monitoring channel spurs the relationship between independent directors and productivity, the positive effects should be concentrated in firms that are ex-ante suffering more from severe agency problems.

Directly measuring agency cost is difficult. Instead, we follow the previous literature and use managerial equity holdings as the proxy of the severity of potential agency problems. According to Jensen and Meckling (1976); Fama and Jensen (1983), when managers hold a significant amount of a firm's stock, they are motivated by their own interest to act discreetly because they themselves are residual claimants of profit. In this case, the interest of managers and owners are aligned and the agency problem is minimized. In contrast, if managers hold a small or zero share of the firm's stock, agency problems are arguably severe. We construct a measure from stock holdings by managers and board of directors over total tradable shares (*Manshare*) and split the sample into two sub-samples, using *Manshare* ex ante in 2002. If firms had a smaller *Manshare* than the industry-year (industry by two-digit) median, they are categorized as "firms with potentially severe agency problems" (High_Agency). Firms with value of *Manshare* above the median are instead categorized as "firms with moderate agency problems" (Low_Agency). Exactly the same IV regressions are applied on both sub-samples.

The results are depicted in Table 2.7. The fact that economic importance and statistical significance of estimator *InddirShare* appear in column (4) but not in (3) points to nontrivial positive moderating effects of agency problem severity, an evidence consistent with monitoring hypothesis. Not only $TFP2$, coefficients based on $TFP1$ seem to support the monitoring function as well, since 10 percentage points increase in independent director share increases $TFP1$ by 13% when firms are facing severe agency problem (column (2)). In contrast, the coefficient is much smaller and of no significance when managers' interest is aligned with shareholders. Admittedly, Hansen test in column (2) is mildly higher, which might cast some doubt on our previous argument. However, the main message is clear, that is independent directors exert greater influence when agency problem is presumably more serious.

The opposing, albeit insignificant, pattern is observed with respect to innovation output. When agency problem is less severe (column (5)), coefficient is 1.09, larger than that derived from severe agency problem observations in column (6). Similarly, column (7) and (8) provide no decisive evidence that the monitoring over R&D projects induces more successful inventions. The monitoring over R&D activities might be undermined by lack of expertise knowledge about concrete innovation projects or the inability to obtain core information due to the interference from "empire building" oriented managers.

Overall, monitoring function is asymmetric in its contribution to productivity and innovation efficiency. Specifically, effective monitoring function boosts total factor productivity but not innovation outputs.

2.4.4 Further heterogeneous effects

State ownership

The institutional context of China is non-negligible, particularly regarding the role of state ownership. Though the direct relationship between ownership and firm performance has been extensively discussed in both western and Chinese context, no consensus has been yet reached. For example, Gupta (2005) provides empirical evidence from India that privatization induced higher sales, profits and labor productivity which, in turn, points to the inefficiency of state ownership. On the contrary, using data of Chinese listed companies, Sun et al. (2002); Mei (2013) argue that due to potential government support and political connections, state ownership sustains higher profitability. Innovation is also found to be positively correlated to state ownership (Choi et al., 2011). Different from these papers, our focus is how state ownership moderates the impact of independent directors on firm performance.

Ownership is defined based on the ultimate controller and we are mainly interested in comparing stated-owned against non-state owned firms. When the firm is essentially controlled by the Chinese government, its affiliated departments[11] or central/state owned enterprises, it is categorized as state owned. Non-state owned firms, on the other hand, include private firms, foreign-owned firms and collective firms, i.e. all firms that are essentially controlled by non-government owners. In our sample, the number of state-owned observations accounts for 67% of all observations, which is obviously overvalued. The reason is that Chinese capital market used to be dominated by state ownership in early periods, including year 2002 based on which the stratification is performed.

Results using split sample depending on state ownership are displayed in Table 2.8. Total factor productivity of non-state owned firms seems to benefit more from independent directors than that of state owned counterparts. In column (2) and (4), the estimated coefficients imply that a 10 percentage points increase in the independent directors ratio leads to increases of $TFP1$ and $TFP2$ by 13.2% and 7.3%, respectively. In contrast, in the state-owned subsample, the estimated effects are much smaller and statistically insignificant. In general, similar pattern is also found in innovation activities, though lack of significance. Estimates from non-state subsamples dominate state subsample in magnitude. To summarize, state ownership seems to prevent independent directors from playing an active role in stimulating productivity.

Product competition

How competition at the industry level interacts with the effectiveness of independent directors is examined. For instance, Tian and Twite (2011) argue that product market competition exerts pressure on managers and can therefore serve as an efficient governance mechanism. Their empirical results imply that governance mechanism is less effective when a firm faces fiercer competition in product markets which points to the substitutability between product competition and internal governance mechanisms. If substitutable relationship holds, stronger effects of independent directors on firm performance can be expected among less competitive industries, vice versa. We measure product market competition by Lerner Index proposed by Aghion et al. (2005).

Our estimates speak for the expected substitutability between product market competition and independent director mechanism. It is in less competitive product markets that independent directors boost $TFP1$ and $TFP2$ more substantially, as can be seen from estimates 0.88 and 0.46 in column (1) and (3). In contrast, independent directors from firms operating in more competitive product markets, tend to

[11]The Chinese government is a typical vertical hierarchical system, consists of central, province-level, city-level and county-level. Affiliated departments include SASAC (State-owned Assets Supervision and Administration Commission), Treasury department, NDRC (National Development and Reform Commission), Ministry of Education, Ministry of Transport and others.

affect productivity only weakly. Same pattern also applies to patent counts. To sum up, our data is consistent with substitutability rather than complementarity between independent directorship and product market competition.

2.4.5 Independent directors: Incumbent VS newly appointed

The policy introduced a great number of newly appointed independent directors to boards. Are these new comers essentially contributing to the process of efficiency improvement? Individual level analysis reveals richer and deeper understandings of the underlying structural changes behind the efficiency effects of independent directors. To this end, we perform t-tests on some important individual characteristics between previously and newly hired independent directors in Table 2.11.

Individual specific information on age, sex, education level and qualification is available in CSMAR database[12], which allows for t-tests between incumbent directors, i.e. those who already served on the board before the regulation was implemented in 2001 and new independent directors, i.e. those who never appeared on the independent director list before 2003 but entered the "game" afterwards. Since no more concrete information about reasons behind employment is available, we assume that policy enforcement is the main drive of this massive influx. In total, we have information on about 790 incumbent independent directors and 1,053 newly appointed directors.

T-tests in Table 2.10 indicate that new directors have significantly lower education level. It implies that the unexpected demand shock results in loose selection and lower standard, in terms of education level. However, notice that the absolute value (0.13) is only trivial, given that both means stay around 3.7-3.8, somewhere between bachelor and master. Meanwhile, new comers are more likely to possess a qualification/title than incumbent directors. The difference is conspicuous and statistically significant at less than 1% level. Qualifications highlight the ability to assume some specific responsibilities and to tackle complicated business problems. To summary, due to the restructuring, although theoretical knowledge slightly decreased, vocational education level rose.

Gender and age differ in an important manner between incumbent and new independent directors. According to first row, the policy change led to 5.6 percentage points more women directors on the board, from 7.34% to 13%.[13] In China, boards

[12]Qualification refers to whether a person is employed as a professor at university, is a certificated public accountant (CPA), or holds important positions such as CEO, CFO, chairman on the board. Education level 1 stands for technical secondary school and below; 2 indicates junior college; 3 to 5 denote undergraduate, master and Ph.D degree

[13]In many advanced western economies, laws have been formulated that require publicly traded firms to have a certain number of female members on the board.

are usually dominated by male directors, like many other countries. Carter et al. (2003); Levi et al. (2014); Liu et al. (2014) argue that firm value and size increase in representation and engagement of female members and minority groups on the board. Conditional on positive heterogeneity effects on the board composition, increasing diversity may contribute to productivity and innovation output. Additionally, new independent directors are, on average, almost five years younger than incumbent directors. It is acknowledged that younger directors are more ambitious and less constraint by time or energy, which makes them better match for this position. In short, t-tests on demographic characteristics shed light on possible microscopic channels at individual level.

2.4.6 Other outcome variables

In this subsection, we investigate the effects of independent directors on other outcome variables using the same empirical strategy. Regression results are reported in Table 2.11.

Firstly, we focus on cash flow, an alternative performance measure. In contrast to book profit, data on operating cash flow, investment cash flow and financing cash flow stresses firms' real income inflow, which matches better to the productivity argument. From column (1) through (3), positive and significant effects of board independence on only growth of operating cash flow have been established, but not on growth of investment and financing cash flow. This piece of evidence is in line with our main results of positive effects of independent board on productivity. Meanwhile, trivial effects on the investment and financing exclude other potential channels.

We show in column (4) that, firms' total operating costs over sales decrease by 2.4% when share of independent directors increases by 10 percentage points. Nevertheless, as shown in column (5), payable salary of employees (from cash flow report) seems to be irrelevant of the board independence. These findings narrow the plausible channel behind our main findings further down to efficiency effects of independent directors, since lower operation costs do not stem from cutting expanse on labor wage rather from higher productivity and more efficient capital utilization.

To summarize, our results indicate that independent directors boost operating cash flow but have no qualitative effects on labour costs, which corroborates the positive causal effects of board independence on productivity growth.

2.5 Conclusion

The external regulatory requests imposed on all Chinese listed firms to increase the share of independent directors create a natural experiment setting to study the causal effects of independent directors on total factor productivity, innovation and other outcomes. We exploit variation in the initial share of independent directors to compare changes in performance of firms affected by the reform with those belonging to control group, namely early adopters that did not have to restructure their board composition.

Our results indicate that a higher share of independent directors induced by the reform led to higher productivity growth and to better innovation performance in terms of quantity and quality. Further evidence shows that more independent directors result in higher growth in operating cash flow and lower operating costs. According to heterogeneous effects, more patent applications and more invention grants are mainly realized through information sharing by independent directors, i.e., advisory channel, whereas the monitoring channel is more relevant in facilitating productivity growth. In a word, depending on specific responsibilities, independent directors wield different functions, which contribute asymmetrically to different aspects of firm performance.

In addition, we find that the effectiveness of board independence exhibits great heterogeneity at both firm and industry level. Positive effects of independent directors seem to be more pronounced in non-state owned firms. Our findings also indicate substitutability between board independence and alternative governance mechanism, i.e., product market competition.

Our results have important implications for both firms and policy makers. Firstly, it can be inferred that the policy on introducing independent directors to Chinese governance mechanism was successful in improving the performance of listed firms. Our mechanism investigation highlights uneven importance of independent directors' functions to distinct responsibilities. Nevertheless, answering questions in the Chinese context, such as "which factors block the monitoring functions in scrutiny of innovation projects?" and "what can be done to undo the inefficiency factors of counseling to productivity?" is of great importance to better exploit independent director mechanism. Meanwhile, subjected to time and attention constraints, outsiders struggle to be excel at both. Therefore, how to arrive at more rational trade-off between the two functionalities deserves more attention for both policy makers and firms. Finally, firms should not be skeptical about independent directors and shall be more open to their advice. Given the significant heterogeneity effects both on the individual-firm level and the industry level, firms should adapt their own characteristics to create friendly environments in which independent directors are able to more efficiently monitor and better counsel the managers.

Bibliography

Ackerberg, Daniel A., Kevin Caves, and Garth Frazer, "Identification Properties of Recent Production Function Estimators," *Econometrica*, 2015, *83* (6), 2411–2451.

Adams, Rene B, Benjamin E Hermalin, and Michael S Weisbach, "The Role of Boards of Directors in Corporate Governance: A Conceptual Framework and Survey," *Journal of Economic Literature*, 2010, *48* (1), 58–107.

Adams, Renee B and Daniel Ferreira, "A Theory of Friendly Boards," *The Journal of Finance*, 2007, *62* (1), 217–250.

Adena, Maja, Ruben Enikolopov, Maria Petrova, Veronica Santarosa, and Ekaterina Zhuravskaya, " Radio and the Rise of The Nazis in Prewar Germany ," *The Quarterly Journal of Economics*, 07 2015, *130* (4), 1885–1939.

Aghion, Philippe, John Van Reenen, and Luigi Zingales, "Innovation and Institutional Ownership," *The American Economic Review*, 2013, *103* (1), 277–304.

_ , Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt, "Competition and Innovation: an Inverted-U Relationship*," *The Quarterly Journal of Economics*, 2005, *120* (2), 701–728.

Ahern, Kenneth R. and Amy K. Dittmar, "The Changing of the Boards: The Impact on Firm Valuation of Mandated Female Board Representation," *The Quarterly Journal of Economics*, 2012, *127* (1), 137–197.

Altonji, Joseph G, Todd E Elder, and Christopher R Taber, "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools," *Journal of Political Economy*, 2005, *113* (1).

Angrist, Joshua D and Joern-Steffen Pischke, *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton, NJ: Princeton university press, 2008.

Balsmeier, Benjamin, Achim Buchwald, and Joel Stiebale, "Outside Directors on the Board and Innovative Firm Performance," *Research Policy*, 2014, *43* (10), 1800–1815.

_ , Lee Fleming, and Gustavo Manso, "Independent Boards and Innovation," *Journal of Financial Economics*, 2017, *123* (3), 536 – 557.

Belloc, Filippo, "Corporate Governance and Innovation: A Survey," *Journal of Economic Surveys*, 2012, *26* (5), 835–864.

Bhagat, Sanjai and Bernard S Black, "The Non-correlation Between Board Independence and Long-term Firm Performance," *Journal of Corporation Law*, 2002, *27*, 231–273.

Byrd, John W and Kent A Hickman, "Do Outside Directors Monitor Managers?: Evidence From Tender Offer Bids," *Journal of financial Economics*, 1992, *32* (2), 195–221.

Carter, David A, Betty J Simkins, and W Gary Simpson, "Corporate Governance, Board Diversity, and Firm Value," *The Financial Review*, 2003, *38*, 33–53.

Chen, Haiqiang, Qian Han, Yingxing Li, and Kai Wu, "Does Index Futures Trading Reduce Volatility in the Chinese Stock Market? A Panel Data Evaluation Approach," *Journal of Futures Markets*, 2013, *33* (12), 1167–1190.

Chhaochharia, Vidhi and Yaniv Grinstein, "Corporate Governance and Firm Value: The Impact of the 2002 Governance Rules," *the Journal of Finance*, 2007, *62* (4), 1789–1825.

Choi, Suk Bong, Soo Hee Lee, and Christopher Williams, "Ownership and Firm Innovation in a Transition Economy: Evidence from China," *Research Policy*, 2011, *40* (3), 441 – 452.

Clarke, Donald C, "The Independent Director in Chinese Corporate Governance," *Delaware Journal of Corporate Law*, 2006, *31* (1), 125–228.

Core, John E., Robert W. Holthausen, and David F. Larcker, "Corporate Governance, Chief Executive Officer Compensation, and Firm Performance," *Journal of Financial Economics*, 1999, *51* (3), 371 – 406.

Dalton, Dan R, Catherine M Daily, Jonathan L Johnson, and Alan E Ellstrand, "Number of Directors and Financial Performance: A Meta-analysis," *Academy of Management journal*, 1999, *42* (6), 674–686.

Demsetz, Harold and Belen Villalonga, "Ownership Structure and Corporate Performance," *Journal of corporate finance*, 2001, *7* (3), 209–233.

Denis, David J and Atulya Sarin, "Ownership and Board Structures in Publicly Traded Corporations," *Journal of Financial Economics*, 1999, *52* (2), 187 – 223.

Du, Shenli and Jie Zhang, "Empirical Study on Determining Factors of Independnet Directors' Compensation (In Chinese)," *Accounting Research*, 2004, (9), 82–88.

Duchin, Ran, John G Matsusaka, and Oguzhan Ozbas, "When Are Outside Directors Effective?," *Journal of Financial Economics*, 2010, *96* (2), 195–214.

Fahlenbrach, Rudiger, Angie Low, and Rene M Stulz, "Why do Firms Appoint CEOs as Outside Directors?," *Journal of Financial Economics*, 2010, *97* (1), 12–32.

Falato, Antonio, Dalida Kadyrzhanova, and Ugur Lel, "Distracted Directors: Does Board Busyness Hurt Shareholder Value?," *Journal of Financial Economics*, 2014, *113* (3), 404 – 426.

Fama, Eugene F. and Michael C. Jensen, "Separation of Ownership and Control," *The Journal of Law and Economics*, 1983, *26* (2), 301–325.

Ferris, Stephen P, Murali Jagannathan, and Adam C Pritchard, "Too Busy to Mind the Business? Monitoring by Directors with Multiple Board Appointments," *The Journal of Finance*, 2003, *58* (3), 1087–1112.

Fich, Eliezer M and Anil Shivdasani, "Are Busy Boards Effective Monitors?," *The Journal of finance*, 2006, *61* (2), 689–724.

Gandhi, Amit, Salvador Navarro, and David A Rivers, "On the Identification of Production Functions: How Heterogeneous is Productivity?," 2011.

Gul, Ferdinand A, Donghui Wu, and Zhifeng Yang, "Do Individual Auditors Affect Audit Quality? Evidence from Archival Data," *The Accounting Review*, 2013, *88* (6), 1993–2023.

Guo, Biao, Xingguo Luo, and Ziding Zhang, "Sell in May and Go Away: Evidence from China," *Finance Research Letters*, 2014, *11* (4), 362–368.

Gupta, Nandini, "Partial Privatization and Firm Performance," *The Journal of Finance*, 2005, *60* (2), 987–1015.

He, Zi-Lin, Tony W. Tong, Yuchen Zhang, and Wenlong He, "Constructing a Chinese Patent Database of Listed Firms in China: Descriptions, Lessons, and Insights," *Journal of Economics & Management Strategy*, 2018, *27* (3), 579–606.

Helmers, Christian, Manasa Patnam, and P. Raghavendra Rau, "Do Board Interlocks Increase Innovation? Evidence from a Corporate Governance Reform in India," *Journal of Banking & Finance*, 2017, *80*, 51 – 70.

Hillman, Amy J and Thomas Dalziel, "Boards of Directors and Firm Performance: Integrating Agency and Resource Dependence Perspectives," *Academy of Management review*, 2003, *28* (3), 383–396.

Hong, Wei and Yu-Sung Su, "The Effect of Institutional Proximity in Non-local University-industry Collaborations: An Analysis based on Chinese Patent Data," *Research Policy*, 2013, *42* (2), 454 – 464.

Jensen, Michael C., "Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers," *The American Economic Review*, 1986, *76* (2), 323–329.

Jensen, Michael C and William H Meckling, "Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure," *Journal of Financial Economics*, 1976, *3* (4), 305–360.

Kapopoulos, Panayotis and Sophia Lazaretou, "Corporate Ownership Structure and Firm Performance: Evidence from Greek Firms," *Corporate Governance: An International Review*, 2007, *15* (2), 144–158.

Kaserer, Christoph and Benjamin Moldenhauer, "Insider Ownership and Corporate Performance: Evidence from Germany," *Review of Managerial Science*, 2008, *2* (1), 1–35.

Koeke, Jens and Luc Renneboog, "Do Corporate Control and Product Market Competition Lead to Stronger Productivity Growth? Evidence from Market-Oriented and Blockholder-Based Governance Regimes*," *Journal of Law and Economics*, 2005, *48* (2), 475–516.

Kole, Stacey R, "Managerial Ownership and Firm Performance: Incentives or Rewards?," *Advances in financial economics*, 1996.

Kor, Yasemin Y and Chamu Sundaramurthy, "Experience-based Human Capital and Social Capital of Outside Directors," *Journal of Management*, 2008.

_ **and Vilmos F Misangyi**, "Outside Directors' Industry-specific Experience and Firms' Liability of Newness," *Strategic Management Journal*, 2008, *29* (12), 1345–1355.

Levi, Maurice, Kai Li, and Feng Zhang, "Director Gender and Mergers and Acquisitions," *Journal of Corporate Finance*, 2014, *28*, 185–200.

Levinsohn, James and Amil Petrin, "Estimating Production Functions Using Inputs to Control for Unobservables," *The Review of Economic Studies*, 2003, *70* (2), 317–341.

Liu, Yu, Zuobao Wei, and Feixue Xie, "Do Women Directors Improve Firm Performance in China?," *Journal of Corporate Finance*, 2014, *28*, 169–184.

Loecker, Jan De and Jan Eeckhout, "The Rise of Market Power and the Macroeconomic Implications," Working Paper 23687, National Bureau of Economic Research August 2017.

Martikainen, Minna, Jussi Nikkinen, and Sami Vahamaa, "Production Functions and Productivity of Family Firms: Evidence from the S&P 500," *The Quarterly Review of Economics and Finance*, 2009, *49* (2), 295–307.

Matsa, David A. and Amalia R. Miller, "A Female Style in Corporate Leadership? Evidence from Quotas," *American Economic Journal: Applied Economics*, July 2013, *5* (3), 136–69.

Mei, Yu, "State Ownership and Firm Performance: Empirical Evidence from Chinese Listed Companies," *China Journal of Accounting Research*, 2013, *6* (2), 75–87.

Mizruchi, Mark S, "Who Controls Whom? An Examination of the Relation Between Management and Boards of Directors in Large American Corporations," *Academy of management Review*, 1983, *8* (3), 426–435.

Olley, G Steven and Ariel Pakes, "The Dynamics of Productivity in the Telecommunications Equipment," *Econometrica*, 1996, *64* (6), 1263–1297.

Palia, Darius and Frank Lichtenberg, "Managerial Ownership and Firm Performance: A Re-examination Using Productivity Measurement," *Journal of Corporate Finance*, 1999, *5* (4), 323 – 339.

Perry, Tod, "Incentive Compensation for Outside Directors and CEO Turnover," *SSRN Working paper*, 2000, pp. 1–36.

Sengupta, Partha and Suning Zhang, "Equity-Based Compensation of Outside Directors and Corporate Disclosure Quality," *Contemporary Accounting Research*, 2015, *32* (3), 1073–1098.

Shen, Yifeng and Xuan Chen, "The Determination of Non-performance Related Outside Director Compensation (in Chinese)," *Nankai Business Review*, 2016, (2), 4–18.

Shleifer, Andrei and Robert W. Vishny, "Management Entrenchment," *Journal of Financial Economics*, 1989, *25* (1), 123 – 139.

Stevenson, Betsey, "Beyond the Classroom: Using Title IX to Measure the Return to High School Sports," *The Review of Economics and Statistics*, 2010, *92* (2), 284–301.

Sun, Qian, Wilson HS Tong, and Jing Tong, "How does Government Ownership Affect Firm Performance? Evidence from China's Privatization Experience," *Journal of Business Finance & Accounting*, 2002, *29* (1-2), 1–27.

Sun, Zerui and Xiaomei Zhu, "The Theory Sutdy and Actuality Analysis on the Independent Directors' Compensation System in Chinese Public Corporations (in Chinese)," *Nankai Business Review*, 2005, (1), 21–29.

Syverson, Chad, "What Determines Productivity?," *Journal of Economic Literature*, 2011, *49* (2), 326–365.

Tian, Gloria Y and Garry Twite, "Corporate Governance, External Market Discipline and Firm Productivity," *Journal of Corporate Finance*, 2011, *17* (3), 403–417.

Weisbach, Michael S., "Outside Directors and CEO Turnover," *Journal of Financial Economics*, 1988, *20* (0), 431 – 460. The Distribution of Power Among Corporate Managers, Shareholders, and Directors.

Xiaodong, Lu and Lian Yujun, "Estimation of Total Factor Productivity of Industrial Enterprises in China: 1999-2007," *China Economic Quarterly*, 2012, *11* (2), 542–558.

YERMACK, DAVID, "Remuneration, Retention, and Reputation Incentives for Outside Directors," *The Journal of Finance*, 2004, *59* (5), 2281–2308.

Zheng, Zhigang, *Theory and Evidence of China's Corporate Governance (in Chinese)*, Peking University Press, 2016.

Zhou, Kevin Zheng, Gerald Yong Gao, and Hongxin Zhao, "State Ownership and Firm Innovation in China: An Integrated View of Institutional and Efficiency Logics," *Administrative Science Quarterly*, 2017, *62* (2), 375–404.

Tables

Table 2.1: Descriptive statistics

Variable	Description	Mean	Std. Dev	25th	75th	Obs
$TFP1$	Estimated TFP using labor force and capital	7.14	0.96	6.50	7.64	17,789
$TFP2$	Estimated TFP using variable inputs and capital (full-sample)	3.42	0.93	2.75	4.08	17,789
$Patapp\_total$	Total application counts of all three types of patents	17.35	97.09	0	6	12,329
$Patgrat\_invent$	Counts of invention patent granted	2.67	36.00	0	0	12,329
$InddirShare$	Independent directors over total board directors	0.32	0.12	0.33	0.36	17,759
$Size$	Total asset in absolute terms (RMB)	6.73e+09	3.93e+10	9.45e+8	3.94e+9	17,914
$Labor$	logarithm of employees	3,597	5,967.20	814	3,707	17,248
$Tangibility$	Fixed asset over total asset	0.27	0.18	0.13	0.38	17,911
$Debtratio$	Total liability(book value) over total asset	0.46	0.21	0.31	0.62	17,914
$Cashgrw\_oper$	Growth of cash flow from operation activities	-0.24	1.53	-0.97	0.43	14,628
$Cashgrw\_invest$	Growth of cash flow from investment activities	0.13	1.58	-0.73	0.69	14,695
$Cashgrw\_finan$	Growth of cash flow from financing activities	-0.60	2.02	-1.33	0.11	14,520
$Cost$	Total cost over Total sales	0.84	0.19	0.68	0.97	17,542
$Ln(Salary)$	logarithm of payable wages and welfare of employees	16.06	1.56	15.01	17.16	17,896

Table 2.2: The correlation between independent director ratio and performance measures based on standard fixed effects model

	*TFP*1 (1)	*TFP*2 (2)	*Patapp_total* (3)	*Patgrant_invent* (4)	*Patapp_total* (5)	*Patgrant_invent* (6)
InddirShare	0.13	0.10**	1.16**	2.94***	0.77	3.21***
	(0.11)	(0.05)	(0.49)	(0.98)	(0.50)	(0.92)
Size	0.14***	0.09***	0.54***	0.61***	0.49***	0.74***
	(0.02)	(0.01)	(0.10)	(0.14)	(0.08)	(0.20)
Tangibility	-1.26***	-0.14***	0.16	1.43**	0.63	0.93
	(0.09)	(0.04)	(0.44)	(0.71)	(0.45)	(0.61)
Labor	-0.20***	-0.02***	0.07	0.08	-0.05	-0.09
	(0.02)	(0.01)	(0.06)	(0.12)	(0.05)	(0.10)
Debtratio	0.31***	-0.07**	-0.41	-1.39**	-0.38	-0.55
	(0.08)	(0.03)	(0.36)	(0.64)	(0.31)	(0.66)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Obs	13,481	13,481	6,279	4,537	5,390	3,904

***,**,* indicates significance level of 1%, 5%, 10%.

Robust standard errors are reported in parentheses.

Dependent variables are listed at the table headers.

For productivity (Column 1-2), all control variables are lagged by one year.

For patents, in Column (3) and (4)/Column (5) and (6), two/three years lag is chosen.

Table 2.3: Balancing test of firm characteristics between complying and non-complying firms

Variables	Complying firms		Non-complying firms		Difference	
	Mean	Std.Err	Mean	Std.Err	Mean	t-value
$\Delta TFP1$	0.13	0.04	0.09	0.02	0.04	1.05
$\Delta TFP2$	-0.31	0.015	-0.31	0.01	0.003	0.14
Size	21.15	0.07	21.05	0.03	0.10	1.45
Tangibility	0.31	0.01	0.30	0.01	0.01	0.95
Debtratio	0.45	0.01	0.45	0.01	0.003	0.24
Labor	7.55	0.08	7.41	0.04	0.14*	1.69
Obs	207		823			
$\Delta Patapp\_total$	2.86	1.35	1.52	0.49	1.33	1.11
$\Delta Patgrant\_invent$	0.49	0.26	0.59	0.23	-0.10	-0.18
Size	21.14	0.07	21.04	0.03	0.11	1.52
Tangibility	0.31	0.01	0.30	0.01	0.014	1.03
Debtratio	0.45	0.01	0.45	0.01	-0.002	-0.16
Labor	7.56	0.08	7.40	0.038	0.15*	1.83
Obs	208		838			

***,**,* indicates significance level of 1%, 5%, 10%.

T-values in last column are two-sided t-tests.

Table 2.4: The causal effect of board independence on $TFP1$, and $TFP2$

	$TFP1$ (1)	First-stage (2)	$TFP2$ (3)	First-stage (4)
InddirShare	0.75* (0.41)		0.39** (0.17)	
Size	0.15*** (0.03)	0.001 (0.002)	0.08*** (0.01)	0.001 (0.002)
Tangibility	-1.26*** (0.11)	0.0004 (0.01)	-0.16*** (0.05)	0.0004 (0.007)
Labor	-0.20*** (0.03)	0.001 (0.001)	-0.02** (0.01)	0.0008 (0.001)
Debtratio	0.21** (0.11)	0.01 (0.01)	-0.09** (0.04)	0.007 (0.007)
$InddirShare\_2002 * Dummy\_2004$		-0.47*** (0.03)		-0.47*** (0.03)
$InddirShare\_2002 * Dummy\_2005$		-0.54*** (0.03)		-0.54*** (0.03)
$InddirShare\_2002 * Dummy\_2006$		-0.59*** (0.03)		-0.59*** (0.03)
$InddirShare\_2002 * Dummy\_2007$		-0.59*** (0.03)		-0.59*** (0.03)
$InddirShare\_2002 * Dummy\_2008$		-0.59*** (0.03)		-0.59*** (0.03)
$InddirShare\_2002 * Dummy\_2009$		-0.59*** (0.03)		-0.59*** (0.03)
$InddirShare\_2002 * Dummy\_2010$		-0.63*** (0.03)		-0.63*** (0.03)
$InddirShare\_2002 * Dummy\_2011$		-0.60*** (0.03)		-0.60*** (0.03)
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F	130.40		130.40	
Hansen test	8.75 (p-val=0.27)		3.16 (p-val=0.87)	
Obs	7,750	7,750	7,750	7,750

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

InddirShare, controls and corresponding instruments are lagged by one year.

Fixed effect instrumental regression model is applied.

Stock-Yogo weak ID test critical values:5% maximal IV relative bias:20.25, 10%:11.39, 20%:6.69, 30%:4.99.

Table 2.5: The causal effect of board independence on patent applications and invention grants

	$Ln(Patapp\_total+1)$ (1)	First-stage (2)	$Ln(Patgrant\_invent+1)$ (3)	First-stage (4)	$Ln(Patapp\_total+1)$ (5)	First-stage (6)	$Ln(Patgrant\_invent+1)$ (7)	First-stage (8)
InddirShare	0.82* (0.50)		0.71** (0.34)		1.06** (0.52)		0.94** (0.40)	
Size	0.39*** (0.07)	-0.001 (0.003)	0.14*** (0.04)	-0.0002 (0.003)	0.43*** (0.08)	-0.002 (0.003)	0.11** (0.05)	-0.002 (0.003)
Tangibility	0.48*** (0.18)	-0.008 (0.008)	0.06 (0.10)	-0.008 (0.008)	0.29 (0.19)	-0.014 (0.009)	-0.10 (0.12)	-0.014 (0.009)
Labor	0.20*** (0.04)	0.002 (0.001)	-0.01 (0.03)	0.002 (0.002)	0.17*** (0.05)	0.003 (0.002)	-0.09** (0.04)	0.003 (0.002)
Debtratio	-0.17 (0.19)	-0.002 (0.007)	0.02 (0.11)	-0.002 (0.008)	-0.54*** (0.20)	-0.006 (0.007)	-0.19 (0.13)	-0.006 (0.007)
$InddirShare\_2002*Dummy\_2004$		-0.73*** (0.03)		-0.73*** (0.03)		-0.75*** (0.03)		-0.75*** (0.03)
$InddirShare\_2002*Dummy\_2005$		-0.85*** (0.03)		-0.85*** (0.03)		-0.83*** (0.03)		-0.83*** (0.03)
$InddirShare\_2002*Dummy\_2006$		-0.87*** (0.03)		-0.87*** (0.03)		-0.87*** (0.03)		-0.87*** (0.03)
$InddirShare\_2002*Dummy\_2007$		-0.93*** (0.03)		-0.93*** (0.03)		-0.93*** (0.03)		-0.93*** (0.03)
$InddirShare\_2002*Dummy\_2008$		-0.94*** (0.03)		-0.94*** (0.03)		-0.92*** (0.03)		-0.92** (0.03)
$InddirShare\_2002*Dummy\_2009$		-0.94*** (0.03)		-0.94*** (0.03)				
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F	357.31		357.31		376.50		376.50	
Hansen test	1.97 (p-val=0.85)		4.18 (p-val=0.52)		3.22 (p-val=0.52)		3.66 (p-val=0.45)	
Obs	5,290		5,290		4,504		4,504	

***,**,* indicates significance level of 1%, 5%, 10%.
Standard errors are clustered by firms and are reported in parentheses.
In column (1) through (4), *InddirShare*, controls and corresponding instruments are lagged two years.
In column (5) through (8), *InddirShare*, controls and corresponding instruments are lagged three years. Last instrument is dropped because our patent data is bounded from 2000-2010.
Fixed effect instrumental regression model is applied.
Stock-Yogo weak ID test critical values:5% maximal IV relative bias:18.37, 10%:10.83, 20%:6.77, 30%:5.25.

Table 2.6: Investigation of the advisory function

	$TFP1$		$TFP2$		$Ln(Patapp\_total+1)$		$Ln(Patgran\_invent+1)$	
	Non-IntLock	IntLock	Non-IntLock	IntLock	Non-IntLock	IntLock	Non-IntLock	IntLock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
InddirShare	0.70	0.78	0.55**	0.19	0.44	1.38*	0.17	1.45**
	(0.62)	(0.52)	(0.26)	(0.20)	(0.61)	(0.79)	(0.37)	(0.59)
Other control vars	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F	58.20	94.24	58.20	94.24	198.51	215.00	198.51	215.00
Hansen test	10.57	10.41	6.34	3.99	6.32	7.92	1.89	5.37
	p=0.16	p=0.17	p=0.50	p=0.78	p=0.28	p=0.16	p=0.86	p=0.37
Obs	3,580	4,170	3,580	4,170	2,449	2,841	2,449	2,841

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

The results of first-stage regression are shown in table B12 in the appendix.

In patent sub-sample, *InddirShare* and controls are lagged by two years. For the rest, one year lag is applied.

Table 2.7: Investigation of the monitoring function

	$TFP1$		$TFP2$		$Ln(Patapp\_total+1)$		$Ln(Patgrant\_invent+1)$	
	Low_Agency	High_Agency	Low_Agency	High_Agency	Low_Agency	High_Agency	Low_Agency	High_Agency
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
InddirShare	0.18	1.30**	0.33	0.43*	1.09	0.62	0.87	0.59
	(0.50)	(0.63)	(0.22)	(0.24)	(0.74)	(0.65)	(0.56)	(0.38)
Kleibergen-Paap rk Wald F	79.13	64.76	79.13	64.76	190.30	210.01	190.30	210.01
Hasen test	8.25	12.5	10.71	1.89	0.82	6.26	1.09	9.39
	p-val=0.31	p-val=0.09	p-val=0.15	p-val=0.97	p-val=0.98	p-val=0.28	p-val=0.96	p-val=0.10
Other control vars	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	3,823	3,927	3,823	3,927	2,625	2,660	2,625	2,660

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

The results of first-stage regression are shown in table B13 in the appendix.

In patent sub-sample, *InddirShare* and controls are lagged by two years. For the rest, one year lag is applied.

Table 2.8: State-ownership and effectiveness of independent directors

	$TFP1$		$TFP2$		$Ln(Patapp\_total+1)$		$Ln(Patgrant\_invent+1)$	
	$State$	$Non-state$	$State$	$Non-state$	$State$	$Non-state$	$State$	$Non-state$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
InddirShare	0.44	1.32**	0.22	0.73**	0.37	1.06	0.54	0.78
	(0.54)	(0.65)	(0.19)	(0.30)	(0.66)	(0.73)	(0.42)	(0.58)
Kleibergen-Paap rk Wald F test	91.91	53.38	91.91	53.38	235.21	168.65	235.21	168.65
Hansen test	8.45	9.10	4.36	4.9	2.07	0.46	10.81	6.04
	p-val=0.29	p-val=0.25	p-val=0.74	p-val=0.67	p-val=0.84	p-val=0.99	p-val=0.06	p-val=0.30
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	5,224	2,526	5,224	2,526	3,640	1,650	3,640	1,650

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

We report the results of first stage in Table B15 in the appendix.

In patent sub-sample, *InddirShare* and controls are lagged by two years. For the rest, one year lag is applied.

Table 2.9: The moderate effect of product market competition on effectiveness of independent directors

	$TFP1$		$TFP2$		$Ln(Patapp\_total+1)$		$Ln(Patgrant_invent+1)$	
	Low_Comp	High_Comp	Low_Comp	High_Comp	Low_Comp	High_Comp	Low_Comp	High_Comp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
InddirShare	0.88**	0.64	0.46**	0.34	1.44*	0.19	1.81***	-0.26
	(0.44)	(0.68)	(0.20)	(0.25)	(0.74)	(0.63)	(0.54)	(0.39)
Kleibergen-Paap rk Wald F	85.42	55.37	85.42	55.37	235.99	192.41	235.99	192.41
Hansen test	4.69	7.54	4.39	2.00	2.39	1.13	9.89	1.04
	p-val=0.70	p-val=0.37	p-val=0.73	p-val=0.96	p-val=0.79	p-val=0.95	p-val=0.08	p-val=0.96
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	4,041	3,702	4,041	3,702	2,724	2,562	2,724	2,562

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

The results of first-stage regression are shown in Table B16 in the appendix.

In patent sub-sample, *InddirShare* and controls are lagged by two years. For the rest, one year lag is applied.

Table 2.10: T-test of individual characteristics between "entrants" and "incumbents" independent directors

	New-arrivals	Independent directors in office	Difference t-test
Gender	0.13	0.073	0.056***
Obs	1,053	790	(3.87)
Age	47.6	52.52	-4.92***
Obs	1,050	775	(-9.43)
Education	3.7	3.84	-0.13**
Obs	863	510	(-2.39)
Qualification	0.53	0.18	0.35***
Obs	1,053	790	(16.49)

**,* indicate the significance at level of 1%, 5% and t-values are reported in parentheses.
Education level 1 stands for technical secondary school and below;
2 represents junior college; 3 to 5 denote undergraduate, postgraduate (master and Ph.D).
Gender is 1 for female and 0 for male.
Age is normalized at year 2003.
T-values in the last column are two-sided t-tests.

Table 2.11: The causal effect of board independence on other firm performance measures

	Cashgrw_oper (1)	*Cashgrw_invest* (2)	*Cashgrw_finan* (3)	*Cost* (4)	*Ln(Salary)* (5)
InddirShare	2.01***	0.92	-0.61	-0.24***	0.63
	(0.88)	(1.01)	(1.32)	(0.09)	(0.80)
Kleibergen-Paap rk Wald F	103.46	122.76	137.90	129.85	134.00
Hansen-test	7.15	3.53	9.81	8.12	5.12
	p-val=0.41	p-val=0.83	p-val=0.20	p-val=0.32	p-val=0.65
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Obs	6,982	6,955	6,873	7,643	7,789

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by the firm and are reported in parentheses.

The results of first-stage regression are shown in Table B17 in the appendix.

InddirShare, instruments and controls are lagged by one year.

2.6 Appendix

Table B1: Two-digit Industry classification

Industry	CSRC Two-digit IND code	Industry name	Number of firms
1	1-5	Agriculture	45
2	6	Coal mining	25
3	7	Gasoline mining	6
4	8	Nonferrous metal mining	5
5	9	Ferrous metal mining	21
6	11	Mining supporting	11
7	13	Agriculture products	39
8	14	Food manufacturing	24
9	15	Alcohol/drinks manufacturing	30
10	17-19	Textile and clothing manufacturing	75
11	22-24	Paper manufacturing and printing	45
12	25	Petroleum processing	17
13	26	Chemical manufacturing	172
14	27	Medicine manufacturing	147
15	28	Chemical fiber manufacturing	24
16	29	Plastic manufacturing	48
17	30	Non-metallic mineral products	76
18	31	Metallurgy for nonferrous	33
19	32	Metallurgy for ferrous	58
20	33	Metallic products	43
21	34	General manufacturing	83
22	35	Special equipment manufacturing	143
23	36	Auto manufacturing	16
24	37	Transportation manufacturing	91
25	38	Electric manufacturing	136
26	39	Computer manufacturing	217
27	40-43	Instrument manufacturing and others	50
28	44	Electricity and heat supply	61
29	45	Gas supply	7
30	46	Water supply	10
31	47-50	Constructions	58
32	51	Wholesales	43
33	52	Retailing	99
34	53-60	Transportation	78
35	61,62	Lodging and catering	13
36	63,64	Telecommunication	24
37	65	Software/information tech	99
38	70	Real estate	124
39	71,72	Business service	28
40	73,74	Research and technological development	14
41	77-78	Environmental and public infrastructures	13
42	81-83	Civil service, education and hygiene	13
43	85-87	Media, sport and entertainment	27
44	90	Comprehensive service	43
	Total		

Robustness of productivity measures

Given that each industries might differ greatly in production factor intensities, assuming constant coefficients across industries might introduce measurement error. We try to address this problem by estimating production functions separately for each industry. In Table B2, we display the estimates of capital and variable inputs/labor using the same industry classification as in Table B1. In comparison with the full-sample estimates, coefficients across different industries do exhibit some, albeit minor, differences.

The resulting productivity measure, which we label $TFP3$ ($TFP4$) has mean of 2.01 and standard deviation of 0.81. In contrast, $TFP2$ has relative larger mean (2.81) and smaller standard deviation (0.32). This implies that estimating productivity based on full sample smooths out industry heterogeneity, as is expected.

We rerun our fixed effects OLS and IV models using $TFP3$ as the dependent variable. The results are listed in Table B3. Although the size of estimated coefficients for *InddirShare* is somewhat smaller, a positive and significant effect remains.

Similar industry specific production factor estimators are reported in Table B4 and the matching results of fixed effects and instrumental regression with $TFP4$ as dependent variables are displayed in Table B5. It is obvious to see that the coefficients are similar to the one in our main results, both in terms of size and statistical significance. Hence, our main results in Table 2.4 are robust to potential industry-specific heterogeneity in production factors.

Table B2: Productivity factors estimates for each Industry based on capital and variable input costs

$Two-digitINDcode$	$Industry$	$Estimate\_capital$	$Estimate\_variable\ inputs$
1-5	Agriculture	0.06	0.87
6	Coal mining	0.18	0.78
7	Gasoline mining	0.29	0.80
8	Nonferrous metal mining	0.04	0.88
9	Ferrous metal mining	0.11	0.84
11	Mining supporting	0.04	0.93
13	Agriculture products	0.14	0.85
14	Food manufacturing	0.14	0.78
15	Alcohol/drinks manufacturing	0.22	0.93
17-19	Textile and clothing manufacturing	0.08	0.86
22-24	Paper manufacturing and printing	0.10	0.85
25	Petroleum processing	0.09	0.90
26	Chemical manufacturing	0.11	0.80
27	Medicine manufacturing	0.13	0.77
28	Chemical fiber manufacturing	0.12	0.79
29	Plastic manufacturing	0.12	0.83
30	Non-metallic mineral products	0.06	0.87
31	Metallurgy for nonferrous	0.16	0.73
32	Metallurgy for ferrous	0.10	0.82
33	Metallic products	0.06	0.91
34	General manufacturing	0.09	0.84
35	Special equipment manufacturing	0.04	0.90
36	Auto manufacturing	0.03	0.90
37	Transportation manufacturing	0.12	0.86
38	Electric manufacturing	0.1	0.88
39	Computer manufacturing	0.07	0.85
40-43	Instrument manufacturing and others	0.06	0.85
44	Electricity and heat supply	0.14	0.77
45	Gas supply	0.29	0.74
46	Water supply	0.08	0.76
47-50	Constructions	0.07	0.90
51	Wholesales	0.05	0.86
52	Retailing	0.06	0.88
53-60	Transportation	0.17	0.74
61,62	Lodging and catering	0.38	0.50
63,64	Telecommunication	0.15	0.73
65	Software/information tech	0.13	0.73
70	Real estate	0.04	0.91
71,72	Business service	0.06	0.85
73,74	Research and technological development	0.21	0.92
77-78	Environmental and public infrastructures	0.11	0.72
81-83	Civil service, education and hygiene	0.16	0.74
85-87	Media, sport and entertainment	0.05	0.93
90	Comprehensive service	0.05	0.80
	Total		

Table B3: FE regression and IV regression with $TFP3$ as dependent variable

	$TFP3$ (1)	$TFP3$ (2)	$InddirShare$ (3)
$InddirShare$	0.074*	0.27*	
	(0.04)	(0.15)	
$Size$	0.03***	0.03***	0.001
	(0.01)	(0.01)	(0.002)
$Tangibility$	-0.06*	-0.06	0.0007
	(0.03)	(0.04)	(0.007)
$Labor$	-0.02***	-0.02*	0.001
	(0.01)	(0.01)	(0.001)
$Debtratio$	-0.10***	-0.13***	0.007
	(0.03)	(0.04)	(0.007)
$InddirShare\_2002 * Dummy\_2004$			-0.47***
			(0.03)
$InddirShare\_2002 * Dummy\_2005$			-0.54***
			(0.03)
$InddirShare\_2002 * Dummy\_2006$			-0.59***
			(0.03)
$InddirShare\_2002 * Dummy\_2007$			-0.59***
			(0.03)
$InddirShare\_2002 * Dummy\_2008$			-0.59***
			(0.03)
$InddirShare\_2002 * Dummy\_2009$			-0.59***
			(0.03)
$InddirShare\_2002 * Dummy\_2010$			-0.63***
			(0.03)
$InddirShare\_2002 * Dummy\_2011$			-0.60***
			(0.03)
Firm fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Kleibergen-Paap rk Wald F		130.22	
Hansen test		5.87 (p-val=0.55)	
Obs	13,426	7,726	7,726

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

Balancing test shows that $FTP3$ between complying and non-complying firms is similar (t-test=0.12) .

$InddirShare$ and all corresponding instruments are lagged by one year.

Table B4: Productivity factors estimates for each Industry based on capital and labor

$Two-digitINDcode$	$Industry$	$Estimate\_capital$	$Estimate\_labor$
1-5	Agriculture	0.44	0.42
6	Coal mining	0.68	0.24
7	Gasoline mining	0.73	0.31
8	Nonferrous metal mining	0.18	0.43
9	Ferrous metal mining	0.66	0.44
11	Mining supporting	0.22	1.02
13	Agriculture products	0.49	0.21
14	Food manufacturing	0.39	0.58
15	Alcohol/drinks manufacturing	0.54	0.30
17-19	Textile and clothing manufacturing	0.55	0.04
22-24	Paper manufacturing and printing	0.54	0.37
25	Petroleum processing	0.49	0.91
26	Chemical manufacturing	0.58	0.30
27	Medicine manufacturing	0.44	0.52
28	Chemical fiber manufacturing	0.97	0.05
29	Plastic manufacturing	0.81	0.25
30	Non-metallic mineral products	0.67	0.28
31	Metallurgy for nonferrous	0.61	0.15
32	Metallurgy for ferrous	0.54	0.46
33	Metallic products	0.70	0.20
34	General manufacturing	0.38	0.44
35	Special equipment manufacturing	0.38	0.68
36	Auto manufacturing	0.16	0.52
37	Transportation manufacturing	0.60	0.27
38	Electric manufacturing	0.60	0.43
39	Computer manufacturing	0.49	0.37
40-43	Instrument manufacturing and others	0.17	0.11
44	Electricity and heat supply	0.58	0.22
45	Gas supply	1.00	0.18
46	Water supply	0.38	0.34
47-50	Constructions	0.20	0.54
51	Wholesales	0.39	0.34
52	Retailing	0.25	0.18
53-60	Transportation	0.39	0.56
61,62	Lodging and catering	0.39	0.43
63,64	Telecommunication	0.28	0.42
65	Software/information tech	0.14	0.50
70	Real estate	0.09	0.37
71,72	Business service	0.13	0.37
73,74	Research and technological development	0.12	0.86
77-78	Environmental and public infrastructures	0.46	0.12
81-83	Civil service, education and hygiene	0.16	0.53
85-87	Media, sport and entertainment	0.76	0.15
90	Comprehensive service	0.24	0.30
	Total		

Table B5: FE regression and IV regression with $TFP4$ as dependent variable

	$TFP4$ (1)	$TFP4$ (2)	$InddirShare$ (3)
$InddirShare$	0.25**	0.78**	
	(0.11)	(0.39)	
$Size$	0.22***	0.22***	0.001
	(0.02)	(0.03)	(0.002)
$Tangibility$	-0.95***	-0.94***	0.001
	(0.08)	(0.10)	(0.007)
$Labor$	-0.10***	-0.10***	0.0006
	(0.02)	(0.03)	(0.001)
$Debtratio$	0.20**	0.12	0.007
	(0.08)	(0.11)	(0.007)
$InddirShare\_2002 * Dummy\_2004$			-0.47***
			(0.03)
$InddirShare\_2002 * Dummy\_2005$			-0.54***
			(0.03)
$InddirShare\_2002 * Dummy\_2006$			-0.58***
			(0.03)
$InddirShare\_2002 * Dummy\_2007$			-0.59***
			(0.03)
$InddirShare\_2002 * Dummy\_2008$			-0.59***
			(0.03)
$InddirShare\_2002 * Dummy\_2009$			-0.59***
			(0.03)
$InddirShare\_2002 * Dummy\_2010$			-0.62***
			(0.03)
$InddirShare\_2002 * Dummy\_2011$			-0.60***
			(0.03)
Firm fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Kleibergen-Paap rk Wald F		133.82	
Hansen test		9.43 (p-val=0.22)	
Obs	13,495	7,764	7,764

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

Balancing test shows that $FTP3$ between complying and non-complying firms is similar (t-test=0.74) .

InddirShare and all corresponding instruments are lagged by one year.

Table B6: The causal effect of board independence on positive total patent applications and positive invention grants

	$Ln(Patapp\_total+1)$ (1)	$InddirShare$ (2)	$Ln(Patgrant\_invent+1)$ (3)	$InddirShare$ (4)	$Ln(Patapp\_total+1)$ (5)	$InddirShare$ (6)	$Ln(Patgrant\_invent+1)$ (7)	$InddirShare$ (8)
InddirShare	1.82***		2.90***		2.63***		3.30***	
	(0.65)		(0.69)		(0.91)		(0.92)	
Size	0.41***	0.003	0.26**	0.005	0.42***	0.002	0.19*	0.004
	(0.08)	(0.003)	(0.12)	(0.005)	(0.09)	(0.004)	(0.11)	(0.006)
Tangibility	0.26	-0.01	-0.26	-0.03	-0.25	-0.02	-0.08	-0.02
	(0.28)	(0.01)	(0.34)	(0.02)	(0.29)	(0.01)	(0.36)	(0.02)
Labor	0.14**	-0.001	-0.01	0.001	0.15**	0.002	-0.15**	0.002
	(0.05)	(0.002)	(0.06)	(0.003)	(0.07)	(0.002)	(0.07)	(0.003)
Debtratio	-0.18	-0.01	-0.49	0.001	-0.39	-0.006	-0.17	-0.02
	(0.23)	(0.01)	(0.37)	(0.02)	(0.26)	(0.01)	(0.37)	(0.02)
$InddirShare\_2002 * Dummy\_2004$		-0.78***		-0.70***		-0.79***		-0.76***
		(0.05)		(0.08)		(0.06)		(0.09)
$InddirShare\_2002 * Dummy\_2005$		-0.83***		-0.82***		-0.82***		-0.77***
		(0.05)		(0.07)		(0.05)		(0.08)
$InddirShare\_2002 * Dummy\_2006$		-0.86***		-0.87***		-0.82***		-0.82***
		(0.04)		(0.07)		(0.05)		(0.07)
$InddirShare\_2002 * Dummy\_2007$		-0.91***		-0.91***		-0.92***		-0.84***
		(0.04)		(0.05)		(0.04)		(0.07)
$InddirShare\_2002 * Dummy\_2008$		-0.97***		-0.92***		-0.94***		-1.24***
		(0.04)		(0.07)		(0.05)		(0.15)
$InddirShare\_2002 * Dummy\_2009$		-0.95***		-1.25***				
		(0.05)		(0.16)				
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F	157.46		130.14		147.90		61.64	
Hansen test	13.21		12.98		7.41		5.89	
	p-val=0.02		p-val=0.02		p-val=0.12		p-val=0.21	
Obs	2,560		1,155		2,230		997	

***,**,* indicates significance level of 1%, 5%, 10%.
Standard errors are clustered by firms and are reported in parentheses.
In column (1) through (4), covariates including *InddirShare* and instruments are lagged two years.
In column (5) through (8), covariates including *InddirShare* and instruments are lagged three years.

Table B7: The causal effect of board independence on control variables

	Size (1)	*Tangibility* (2)	*Labor* (3)	*Debtratio* (4)
InddirShare	-0.17	0.07	-0.04	0.02
	(0.49)	(0.10)	(1.32)	(0.11)
Kleibergen-Paap rk Wald F	133.98	133.98	126.00	133.98
Hansen-test	11.90	4.60	4.23	4.40
	p-val=0.11	p-val=0.71	p-val=0.75	p-val=0.73
Other controls	No	No	No	No
Year fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Obs	8,164	8,164	7,799	8,164

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by the firm and are reported in parentheses.

InddirShare and controls are lagged by one year.

Table B8: The causal effect of board independence on firm performance with dynamic setting

	$TFP1$ (1)	First-stage (2)	$TFP2$ (3)	First-stage (4)	$Ln(Patapp\_total+1)$ (5)	First-stage (6)	$Ln(Patgrant\_invent+1)$ (7)	First-stage (8)
InddirShare	0.39		0.34**		0.90*		0.81**	
	(0.41)		(0.14)		(0.52)		(0.40)	
$DepVar_{t-1}$	0.57***	0.001	0.33***	0.007*	0.1***	0.0003	-0.04	0.003**
	(0.03)	(0.002)	(0.03)	(0.004)	(0.03)	(0.001)	(0.03)	(0.001)
$DepVar_{t-2}$	0.01	-0.002	0.04	-0.003	-0.07***	0.0004	-0.19***	0.001
	(0.02)	(0.001)	(0.03)	(0.004)	(0.02)	(0.001)	(0.03)	(0.001)
Size	-0.04**	0.001	0.02**	-0.0001	0.34***	0.001	0.19***	0.005
	(0.03)	(0.002)	(0.01)	(0.002)	(0.07)	(0.003)	(0.04)	(0.003)
Tangibility	-0.06	-0.005	-0.01	-0.003	0.47**	-0.012	0.13	-0.013
	(0.11)	(0.008)	(0.04)	(0.007)	(0.19)	(0.009)	(0.11)	(0.01)
Labor	-0.002	0.001	-0.03	0.001	0.19***	0.002	-0.01	0.002
	(0.02)	(0.002)	(0.01)	(0.002)	(0.04)	(0.002)	(0.03)	(0.002)
Debtratio	0.20**	0.01	0.01	0.01	-0.27	-0.006	-0.02	-0.006
	(0.08)	(0.008)	(0.03)	(0.008)	(0.19)	(0.009)	(0.11)	(0.01)
$InddirShare\_2002*Dummy\_2004$		-0.46***		-0.46***		-0.73***		-0.73***
		(0.02)		(0.02)		(0.03)		(0.03)
$InddirShare\_2002*Dummy\_2005$		-0.49***		-0.49***		-0.89***		-0.89***
		(0.03)		(0.03)		(0.03)		(0.03)
$InddirShare\_2002*Dummy\_2006$		-0.53***		-0.53***		-0.87***		-0.87***
		(0.03)		(0.03)		(0.04)		(0.04)
$InddirShare\_2002*Dummy\_2007$		-0.54***		-0.54***		-0.93***		-0.93***
		(0.03)		(0.03)		(0.03)		(0.03)
$InddirShare\_2002*Dummy\_2008$		-0.55***		-0.55***		-0.94***		-0.94***
		(0.03)		(0.03)		(0.03)		(0.03)
$InddirShare\_2002*Dummy\_2009$		-0.53***		-0.53***		-0.94***		-0.94***
		(0.03)		(0.03)		(0.03)		(0.03)
$InddirShare\_2002*Dummy\_2010$		-0.57***		-0.57***				
		(0.03)		(0.03)				
$InddirShare\_2002*Dummy\_2011$		-0.55***		-0.55***				
		(0.03)		(0.03)				
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald rk F	92.10		91.85		302.90		310.90	
Hansen test	8.93 (p-val=0.26)		7.03 (p-val=0.43)		1.23 (p-val=0.94)		2.81 (p-val=0.73)	
Obs	6,928	6,928	6,928	6,928	4,738	4,738	4,738	4,738

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

For productivity analysis, *InddirShare*, instruments and controls are lagged by one year.

Table B9: The causal effect of board independence on firm performance controlling ex ante trend

	$TFP1\_adj$ (1)	First-stage (2)	$TFP2\_adj$ (3)	First-stage (4)	$Ln(Patapp\_total+1)\_adj$ (5)	First-stage (6)	$Ln(Patgrant\_invent+1)\_adj$ (7)	First-stage (8)
InddirShare	0.77*		0.40**		2.11**		1.04**	
	(0.41)		(0.17)		(0.87)		(0.47)	
Size	0.15***	0.001	0.08***	0.001	0.40***	-0.0002	0.14***	-0.0002
	(0.03)	(0.002)	(0.01)	(0.002)	(0.09)	(0.003)	(0.05)	(0.003)
Tangibility	-1.27***	0.0003	-0.16***	0.0003	0.48**	-0.008	0.13	-0.008
	(0.11)	(0.007)	(0.05)	(0.007)	(0.23)	(0.008)	(0.12)	(0.008)
Labor	-0.20***	0.0005	-0.02**	0.0005	0.26***	0.002	-0.02	0.002
	(0.03)	(0.001)	(0.01)	(0.001)	(0.06)	(0.002)	(0.04)	(0.002)
Debtratio	0.20*	0.007	-0.09***	0.007	-0.27	-0.002	-0.07	-0.002
	(0.11)	(0.007)	(0.04)	(0.007)	(0.24)	(0.008)	(0.14)	(0.008)
$InddirShare\_2002 * Dummy\_2004$		-0.47***		-0.47***		-0.73***		-0.73***
		(0.03)		(0.03)		(0.03)		(0.03)
$InddirShare\_2002 * Dummy\_2005$		-0.54***		-0.54***		-0.85***		-0.85***
		(0.03)		(0.03)		(0.03)		(0.03)
$InddirShare\_2002 * Dummy\_2006$		-0.58***		-0.58***		-0.87***		-0.87***
		(0.03)		(0.03)		(0.03)		(0.03)
$InddirShare\_2002 * Dummy\_2007$		-0.58***		-0.58***		-0.93***		-0.93***
		(0.03)		(0.03)		(0.03)		(0.03)
$InddirShare\_2002 * Dummy\_2008$		-0.59***		-0.59***		-0.94***		-0.94***
		(0.03)		(0.03)		(0.03)		(0.03)
$InddirShare\_2002 * Dummy\_2009$		-0.59***		-0.59***		-0.94***		-0.94***
		(0.03)		(0.03)		(0.03)		(0.03)
$InddirShare\_2002 * Dummy\_2010$		-0.63***		-0.63***				
		(0.03)		(0.03)				
$InddirShare\_2002 * Dummy\_2011$		-0.60***		-0.60***				
		(0.03)		(0.03)				
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap Wald rk F	129.62		129.62		357.31		357.31	
Hansen test	8.10 (p-val=0.32)		4.41 (p-val=0.73)		5.45 (p-val=0.36)		4.73 (p-val=0.45)	
Obs	7,692	7,692	7,692	7,692	5,290	5,290	5,290	5,290

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

For productivity analysis, *InddirShare*, instruments and controls are lagged by one year.

For patent analysis, *InddirShare*, instruments and controls are lagged by two years

Distribution of complying and non-complying firms across industries.

In order to analyze whether industry heterogeneity might is correlated with the choice of hiring independent directors, we perform Pearson chi-square test and Likelihood Ratio Chi-Square test to compare the distribution of complying and non-complying firms across different sectors. It seems that there is no statistically significant relationship between industry and the distribution of complying and non-complying firms.

Table B10: Chi-tests of distribution of complying & non-complying firms across industries ex-ante shock

Variables	Complying firms	Non-complying firms	Total
Agriculture	1	15	16
Mining	10	25	35
Manufacturing	119	469	588
Power supply	7	46	53
Construction	1	15	16
Whole sales and retailing	19	73	92
Transportation	11	33	44
Hotel and catering	0	7	7
Information technology	9	15	24
Real estate	21	76	97
Leasing	2	11	13
Science and technology development	0	1	1
Infrastructure	1	5	6
Utility	0	1	1
Culture, sport and entertainment	3	9	12
Others	6	29	35
Total	210	830	
Pearson Chi2(15)	15.11	p-val=0.44	
likelihood-ratio chi2(15)	17.37	p-val=0.30	

Results of Altonji-Elder-Taber test

To further deal with unobservables that might lead to endogeneity problem and potential spurious correlation between independent director share and our productivity and patent measurements, additional Altonji-Elder-Taber robustness test is employed.

Our two-stage procedure to implement the Altonji-Elder-Taber test builds on (Altonji et al., 2005) and has been applied in similar form in recent research (e.g., Adena et al., 2015). The first stage is conducted on data before the policy shock in 2002, based on which the balancing test in Table 3.2 is performed. We regress *InddirShare* on contemporaneous values of our four baseline control variables, *ROA*, *Boardsize* and 2-digit industry dummies to compute a linear prediction of *InddirShare*, which we label *InddirSharehat*. In the second stage, the main outcome variables after the shock is regressed on fitted independent director share. If unobserved factors of independent director share is not important, the correlation between our outcome variables and *Inddirsharehat* should be small and statistically insignificant.

Based on results documented in Table B11, our main variables of interest, total factor productivity and patent counts are not statistically significantly correlated with linear fitted value of independent directors share. These results are robust to specifications without any controls, which have been included in the first stage. when instruments are reconstructed by interacting *Inddirsharehat* with year dummies, rerunning the instrumental regression renders all insignificant coefficients, another supporting signal that unobservable factors do not bias main findings. In conclusion, the Altonji-Elder-Taber test indicates that our main results are unlikely to be driven by unobserved heterogeneity across firms.

Table B11: Altonji-Elder-Taber robustness test

	$TFP1$ (1)	$TFP2$ (2)	$Ln(Patapp\_total+1)$ (3)	$Ln(Patgrant\_invent+1)$ (4)
InddirSharehat	-0.54 (0.84)	-0.02 (0.23)	1.39 (1.42)	-0.51 (0.86)
Basic controls	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Obs	6,700	6,700	5,408	5,408

***,** ,* indicates significance level of 1%, 5%, 10%.

Robust standard errors are reported in parentheses.

In column (1)-(2), all controls, except for *InddirSharehat* and industry dummies, are lagged one year.

In column (3)-(4), all controls, except for *InddirSharehat* and industry dummies, are lagged two years.

Table B12: First-stage of regression in Table 2.6

	$TFP1$		$FTP2$		$Ln(Patapp\_total+1)$		$Ln(Patgrant\_invent+1)$	
	IntLock	Non-IntLock	IntLock	Non-IntLock	IntLock	Non-IntLock	IntLock	Non-IntLock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$InddirShare\_2002*Dummy\_2004$	-0.51***	-0.44***	-0.51***	-0.44***	-0.66***	-0.79***	-0.66***	-0.79***
	(0.03)	(0.05)	(0.03)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)
$InddirShare\_2002*Dummy\_2005$	-0.56***	-0.52***	-0.56***	-0.52***	-0.87***	-0.83***	-0.87***	-0.83***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.05)	(0.03)	(0.05)
$InddirShare\_2002*Dummy\_2006$	-0.58***	-0.59***	-0.58***	-0.59***	-0.87***	-0.86***	-0.87***	-0.86***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
$InddirShare\_2002*Dummy\_2007$	-0.59***	-0.57***	-0.59***	-0.57***	-0.91***	-0.93***	-0.91***	-0.93***
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
$InddirShare\_2002*Dummy\_2008$	-0.60***	-0.57***	-0.60***	-0.57***	-0.93***	-0.95***	-0.93***	-0.95***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
$InddirShare\_2002*Dummy\_2009$	-0.56***	-0.60***	-0.56***	-0.60***	-0.93***	-0.93***	-0.93***	-0.93***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
$InddirShare\_2002*Dummy\_2010$	-0.60***	-0.65***	-0.60***	-0.65***				
	(0.04)	(0.04)	(0.04)	(0.04)				
$InddirShare\_2002*Dummy\_2011$	-0.60***	-0.59***	-0.60***	-0.59***				
	(0.04)	(0.04)	(0.04)	(0.04)				
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-value	94.24	58.19	94.24	58.19	215.00	198.51	215.00	198.51
Obs	4,170	3,580	4,170	3,580	2,841	2,449	2,841	2,449

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

Table B13: First-stage of regression in Table 2.7

	$TFP1$		$TFP2$		$Ln(Patapp\_total+1)$		$Ln(Patgrant\_invent+1)$	
	Low_Agency	High_Agency	Low_Agency	High_Agency	Low_Agency	High_Agency	Low_Agency	High_Agency
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$InddirShare\_2002 * Dummy\_2004$	-0.49***	-0.45***	-0.49***	-0.45***	-0.75***	-0.71***	-0.75***	-0.71***
	(0.03)	(0.06)	(0.03)	(0.06)	(0.05)	(0.04)	(0.05)	(0.04)
$InddirShare\_2002 * Dummy\_2005$	-0.53***	-0.55***	-0.53***	-0.55***	-0.89***	-0.82***	-0.89***	-0.82***
	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.06)	(0.04)	(0.06)
$InddirShare\_2002 * Dummy\_2006$	-0.60***	-0.57***	-0.60***	-0.57***	-0.84***	-0.91***	-0.84***	-0.91***
	(0.04)	(0.03)	(0.04)	(0.03)	(0.05)	(0.03)	(0.05)	(0.03)
$InddirShare\_2002 * Dummy\_2007$	-0.57***	-0.60***	-0.57***	-0.60***	-0.92***	-0.93***	-0.92***	-0.93***
	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
$InddirShare\_2002 * Dummy\_2008$	-0.55***	-0.63***	-0.55***	-0.63***	-0.91***	-0.98***	-0.91***	-0.98***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
$InddirShare\_2002 * Dummy\_2009$	-0.53***	-0.64***	-0.53***	-0.64***	-0.88***	-0.99***	-0.88***	-0.99***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
$InddirShare\_2002 * Dummy\_2010$	-0.55***	-0.70***	-0.55***	-0.70***				
	(0.03)	(0.04)	(0.03)	(0.04)				
$InddirShare\_2002 * Dummy\_2011$	-0.55***	-0.65***	-0.55***	-0.65***				
	(0.05)	(0.04)	(0.05)	(0.04)				
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-value	79.13	76.84	79.13	76.84	190.30	210.01	190.30	210.01
Obs	3,823	3,927	3,823	3,927	2,625	2,660	2,625	2,660

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

Table B14: The IV result of full partial sample with non-missing compensation information

	$TFP1$	$TFP2$	$Ln(Patapp\_total+1)$	$Ln(Patgrant\_invent+1)$
	(1)	(2)	(3)	(4)
InddirShare	0.72	0.46**	1.19*	0.97**
	(0.52)	(0.19)	(0.66)	(0.48)
Kleibergen-Paap rk Wald F	112.40	112.40	255.40	255.40
Hansen-test	13.31	8.07	3.73	6.15
	p-val=0.06	p-val=0.33	p-val=0.59	p-val=0.29
Year fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Obs	5,676	5,676	3,867	3,867

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by the firm and are reported in parentheses.

For *Pat*, *InddirShare* and controls are lagged by two years. while for the rest, one year lagged is applied.

Table B15: First-stage of regression in Table 2.8

	$TFP1$		$TFP2$		$Ln(Patapp\_total+1)$		$Ln(Patgrant\_invent+1)$	
	$State$	$Non-state$	$State$	$Non-state$	$State$	$Non-state$	$State$	$Non-state$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$InddirShare\_2002*Dummy\_2004$	-0.46***	-0.50***	-0.46***	-0.50***	-0.74***	-0.71***	-0.74***	-0.71***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
$InddirShare\_2002*Dummy\_2005$	-0.53***	-0.57***	-0.53***	-0.57***	-0.85***	-0.85***	-0.85***	-0.85***
	(0.03)	(0.05)	(0.03)	(0.05)	(0.04)	(0.06)	(0.04)	(0.06)
$InddirShare\_2002*Dummy\_2006$	-0.56***	-0.63***	-0.56***	-0.63***	-0.88***	-0.86***	-0.88***	-0.86***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.07)	(0.03)	(0.07)
$InddirShare\_2002*Dummy\_2007$	-0.56***	-0.64***	-0.56***	-0.64***	-0.92***	-0.94***	-0.92***	-0.94***
	(0.03)	(0.05)	(0.03)	(0.05)	(0.03)	(0.04)	(0.03)	(0.04)
$InddirShare\_2002*Dummy\_2008$	-0.60***	-0.59***	-0.60***	-0.59***	-0.94***	-0.96***	-0.94***	-0.96***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
$InddirShare\_2002*Dummy\_2009$	-0.59***	-0.59***	-0.59***	-0.59***	-0.95***	-0.93***	-0.95***	-0.93***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
$InddirShare\_2002*Dummy\_2010$	-0.64***	-0.56***	-0.64***	-0.56***				
	(0.03)	(0.04)	(0.03)	(0.04)				
$InddirShare\_2002*Dummy\_2011$	-0.64***	-0.56***	-0.64***	-0.56***				
	(0.04)	(0.05)	(0.04)	(0.05)				
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-value	91.91	53.38	91.91	53.38	235.21	168.65	235.21	168.65
Obs	5,224	2,526	5,224	2,526	3,640	1,650	3,640	1,650

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by the firm and are reported in parentheses.

For *Pat*, *InddirShare* and controls are lagged by two years. while for the rest, one year lagged is applied.

Table B16: First-stage of regression in Table 2.9

	$TFP1$		$TFP2$		$Ln(Patapp\_total+1)$		$Ln(Patgrant_invent+1)$	
	Low Comp	High Comp	Low Comp	High Comp	Low Comp	High Comp	Low Comp	High Comp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$InddirShare\_2002*Dummy\_2004$	-0.50***	-0.44***	-0.50***	-0.44***	-0.70***	-0.77***	-0.70***	-0.77***
	(0.03)	(0.05)	(0.03)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
$InddirShare\_2002*Dummy\_2005$	-0.49***	-0.58***	-0.49***	-0.58***	-0.85***	-0.85***	-0.85***	-0.85***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.05)	(0.03)	(0.05)
$InddirShare\_2002*Dummy\_2006$	-0.59***	-0.59***	-0.58***	-0.59***	-0.84***	-0.89***	-0.84***	-0.89***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
$InddirShare\_2002*Dummy\_2007$	-0.60***	-0.58***	-0.60***	-0.58***	-0.93***	-0.92***	-0.93***	-0.92***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
$InddirShare\_2002*Dummy\_2008$	-0.57***	-0.61***	-0.57***	-0.61***	-0.94***	-0.93***	-0.94***	-0.93***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
$InddirShare\_2002*Dummy\_2009$	-0.57***	-0.60***	-0.57***	-0.60***	-0.91***	-0.96***	-0.91***	-0.96***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
$InddirShare\_2002*Dummy\_2010$	-0.62***	-0.64***	-0.62***	-0.64***				
	(0.04)	(0.04)	(0.04)	(0.04)				
$InddirShare\_2002*Dummy\_2011$	-0.59***	-0.60***	-0.59***	-0.60***				
	(0.04)	(0.04)	(0.04)	(0.04)				
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-value	85.42	55.37	85.42	55.37	235.99	192.41	235.99	192.41
Obs	4,041	3,702	4,041	3,702	2,724	2,562	2,724	2,562

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by the firm and are reported in parentheses.

Table B17: First-stage of regression in Table 2.11

	Cashgrw_oper (1)	*Cashgrw_invest* (2)	*Cashgrw_finan* (3)	*Cost* (4)	*Ln(Salary)* (5)
*InddirShare*_2002 ∗ *Dummy*_2004	-0.48***	-0.50***	-0.50***	-0.48***	-0.47***
	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
*InddirShare*_2002 ∗ *Dummy*_2005	-0.54***	-0.51***	-0.53***	-0.54***	-0.54***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
*InddirShare*_2002 ∗ *Dummy*_2006	-0.59***	-0.57***	-0.57***	-0.58***	-0.58***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
*InddirShare*_2002 ∗ *Dummy*_2007	-0.59***	-0.57***	-0.58***	-0.58***	-0.59***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
*InddirShare*_2002 ∗ *Dummy*_2008	-0.60***	-0.58***	-0.58***	-0.60***	-0.59***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
*InddirShare*_2002 ∗ *Dummy*_2009	-0.58***	-0.56***	-0.58***	-0.58***	-0.59***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
*InddirShare*_2002 ∗ *Dummy*_2010	-0.63***	-0.61***	-0.62***	-0.61***	-0.62***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
*InddirShare*_2002 ∗ *Dummy*_2011	-0.60***	-0.59***	-0.59***	-0.59***	-0.60***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
F-values	103.46	122.75	137.89	129.85	134.00
Obs	6,982	6,955	6,873	7,643	7,789

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by the firm and are reported in parentheses.

Empirical investigation on determinants of early, non-compliance and timely compliance

As we discussed in the main text, the policy does not state explicitly what kind of penalty follows if firms choose not to comply with the regulation. Although the majority of firms managed to reach the quota, we also noticed that 220 firms failed to do so by the year 2003. This number dropped to 124 in 2004 and further to 67 in 2005. In addition to the decision whether to abide by the mandate, firms choose to which degree they increase board independence and at what time. In this section, we investigate heterogeneous response to the policy and explore whether there are specific characteristics that motivate firms to act early, what factors prevent firms from following the regulation and what characterizes firms choosing to hire the exact number of independent directors required.

In column (1) and (2), we analyze the determinants of early compliance in 2001 and 2002, respectively. Accordingly, we define early compliance firms as those who had less than one third of independent directors in 2000/2001 but increased the ratio to at least one third in 2001/2002. The dummy variable equals one if firms met the previous demand. Otherwise, the dummy takes on value zero if firms failed to elevate the ratio over one third in 2002. Hence, we drop observations whose independent directors was larger than the threshold prior to 2001. In our sample, 29 and 135 firms decided to lead the trend in 2001 and 2002. Standard Logit model with industry dummies is employed. Beside *size*, *tangibility*, *debt* and *labor*, *ROA* and *boardsize* are also included as control variables.

The result in column (1) indicate that firms with higher return on assets are more likely to be early adopters in 2001. Except for *ROA*, all other firm characteristics are statistically insignificant, even the *InddirShare* in the year 2000. It implies profitability tends to push firms to act in advance. In column (2), we find that the probability of adjusting the board structure in 2002 increase in the value of previous *InddirShare*. the implication is that if firms are already not far away from achieving the quota, they tend to act earlier than they have to.

In the third and fourth column, we focus on firms who refused to have conform to the rule by the end of 2003 and 2004. In column (3), the significant negative coefficients on *ROA* and *Debtratio* suggest that the less profitable the firm is and the higher financial risk it bears, the more likely it fails to stick to the policy. Positive estimate of *Boardsize* points to the fear of dilution of power and thus the difficulty of having more outsiders when larger board is concerned. In column (4), no covariates display statistical significance, suggesting the failure of common indicators to explain firms' decision. Some deeper organizational reasons might be hidden under the surface.

Surprisingly, estimated coefficients of *Inddirpct* in both settings are insignificant. In other words, when firms failed to achieve the goal, "how far am I away from the destination" matters no more, as opposed to the positive encouragement in column (2).

Column (5) identifies the underlying force behind the decision of "barely reaching" the threshold. In fact, it is commonly observed in our sample, since dots of independent director ratio are clustered around the threshold, one third. The sample is restricted to firms who managed to increased the share above the quota. The dependent variables takes value one if the share lies between 0.33 and 0.35. If firms set the independence level higher than 0.35, value 0 is assigned. Estimates show that there is no particular reasoning behind the choice. It seems that the decision is more about following the rule than strategically choosing the ratio.

Table B18: Determinants of early compliance in 2001 and 2002, no compliance in 2003 and 2004 and Just-compliance

	Dummy_Earlycomp_2001 (1)	Dummy_Earlycomp_2002 (2)	Dummy_Noncomp_2003 (3)	Dummy_Noncomp_2004 (4)	Dummy_Onlythreshold (5)
InddirShare	-3.19	3.22***	-2.01	3.24	-1.23
	(6.10)	(1.09)	(1.74)	(3.4)	(2.18)
TFP2	-0.98	0.19	-0.21	-1.15	0.01
	(0.98)	(0.46)	(0.35)	(0.92)	(0.38)
Size	-0.14	0.10	-0.008	0.45	-0.12
	(0.33)	(0.18)	(0.17)	(0.31)	(0.18)
ROA	9.66**	0.63	-3.42**	2.80	-1.05
	(4.44)	(2.38)	(1.51)	(2.18)	(1.96)
Debtratio	-1.43	0.55	-1.14*	-0.55	-1.08
	(1.41)	(0.68)	(0.59)	(1.02)	(0.67)
Boardsize	-0.10	-0.07	0.10**	-0.09	-0.09*
	(0.10)	(0.05)	(0.04)	(0.08)	(0.05)
Labor	0.18	0.20	0.07	-0.24	0.03
	(0.30)	(0.14)	(0.12)	(0.22)	(0.13)
Tangibility	1.54	1.19*	-0.57	0.91	-0.71
	(1.51)	(0.67)	(0.64)	(1.13)	(0.73)
Industry fixed effect	Yes	Yes	Yes	Yes	Yes
Wald-overall test	57.55	48.22	58.6	26.21	37.49
Obs	452	725	701	191	493

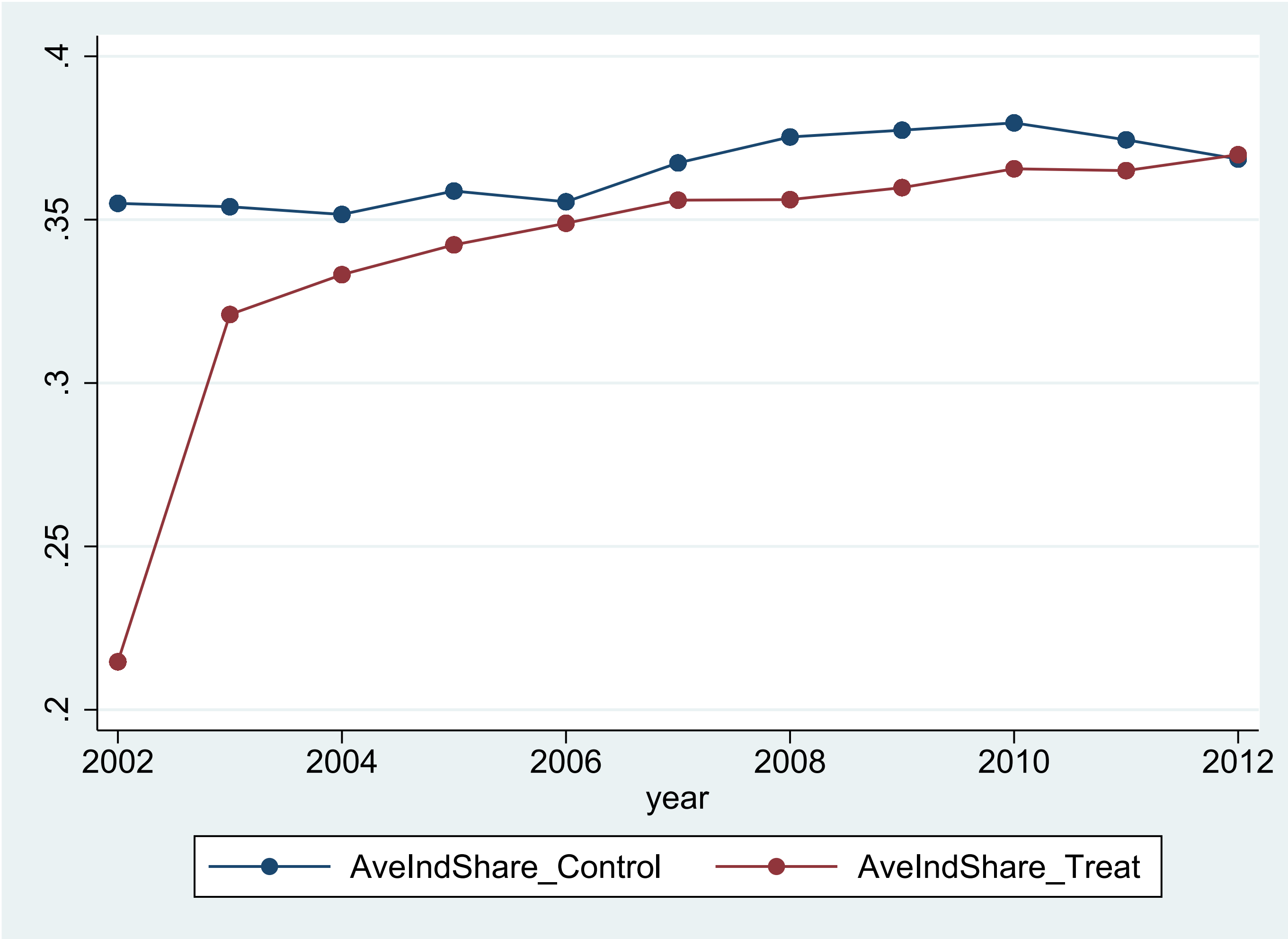
***,**,* indicates significance level of 1%, 5%, 10%.

Robust standard errors reported in parentheses.

All controls are lagged by one year compared to the dependent variable.

Standard logit model with industry fixed effect is used. Switch to probit model renders qualitatively identical results.

Figure 2.1: Plot of average independent director share over years between control group and treatment group



Chapter 3.

Peer Effects of R&D Investment based on Interlock Network: Evidence from China

3.1 Introduction

It is widely acknowledged that in addition to more objective monitoring over CEOs, independent directors (who, according to China Securities Regulatory Commission, are those directors having neither direct nor indirect economic interests in the firm and thus being able to objectively fulfill their responsibilities and excise their rights) counsel firms with their individual past experience, knowledge and information they have heard, observed and learned in other sitting firms (Adams and Ferreira, 2007). Informational resources are spilled over across firms through advisory channel. Interlock, a phenomena of particular independent directors serving boards of multiple firms, creates a special type of inter-firm connections. Vast majority of literature regards interlock as exogenously given and relates it to firm performance, decisions and strategic arrangement such as alliances formation (see review by e.g. Geoffrey et al., 2013).

However, not only the "edge" (whether a firm is interlocked) matters, the features of "nodes" to which the firm is connected also play a key role. When actions or characteristics of nodes are taken into consideration, the mutual interaction among decisions arises, which aligns with the concept of peer effects. Peer effects are defined as how focal unit's decision is influenced by actions or characteristics of peer units within reference groups[1] (Manski, 1993). The most fundamental nature of peer effects lies in the endogenous relationship among decision makers. Starting from Cournot and Bertrand model, the "responsiveness" has been long established as the core of the decision theory, while it is relative foreign in empirical studies.

To understand peer effects empirically is important in many regards. First and foremost, despite the extensive theoretical literature on corporate decision interaction, do firms' decisions respond to their competitors, strategic alliances or other stakeholders? Why does the interplay take place in the first place? Are these peer effects beneficial or harmful? Investigating peer effects provides the chance to peek at how decisions are rationalized and finalized, especially for such sophisticated and risky decisions as innovation. Furthermore, were positive spillover effects present, "social multiplier effects" lead to augmentation of small vibrations at individual level into violent variations at aggregate level (Glaeser et al., 2003; Graham, 2008), which can be exploited by the policy makers to achieve certain regulation goals.

Though some progress from experiments in the laboratory has been made[2], em-

[1]A reference group is defined such that for unit i, reference group consists of all other units, whose decisions, utilities or expectations are relevant to the decision making process of unit i (Banerjee et al., 2007).

[2]Through random selection and careful design, experiments have been used to detect peer effects in the context of academic outcome (Sacerdote, 2001; Zimmerman, 2003), productivity in the work place(Mas and Moretti, 2009) and financial decision making (Bursztyn et al., 2014).

pirical evidence on the interdependency of decisions in the real economic context remains limited until recently. There is emerging literature with special focus on the influence of industry peers and geographic neighbors on corporate decisions such as investment, financing and dividend payout, etc. (Leary and Roberts, 2013; Billett et al., 2017; Grennan, 2019; Dougal et al., 2014). In contrast, peer effects based on naturally formed social networks are under-explored. To the best of our knowledge, Helmers et al. (2017) and Fracassi (2017) are among the pioneering works which examine the influence of interlocked peers using Linear-in-means and dyadic model in conjunction with instruments constructed on exogenous events.

Our paper contributes to the literature in several aspects. Firstly, we provide more empirical evidence to the peer effects stemming from informal inter-firm relationships. This paper concentrates on interlock network based peer effects, whereas Fracassi (2017) reports mixed evidence from four types of social relationships. Unlike Helmers et al. (2017), our instrument originates from an exogenous innovation-irrelevant policy shock and does not hinge on the assumption that "more innovative interlocks" are added to the board due to the policy demands[3]. Robustness tests with one-on-one dyadic data structure reinforce our main findings. Secondly, by providing multidimensional heterogeneity evidence, we deepen understandings of underlying mechanisms. Lastly, extensions to different network structure, i.e., exclusive inter-industry network, global network examine the generality of peer effects. Extended analysis on output provides insights on efficiency effects of peer effects. Extension to industry/location peers complement the extant work on other reference group-based peer effects.

Identifying peer effects based on interlock network is difficult due to various identification problems (Manski, 1993). The main challenge lies in the self-selection problem, i.e., the characteristics or motivations that drive the formation of interlocks simultaneously determine the decision of interest. Without the artificial creation of randomness, the lack of counter-factual evidence in field data prevents econometricians from accurately pinning down the peer effects. Besides, unobservable common effects from institutional backgrounds or reference-group external environment might render similar R&D investments, which in form resemble but in essence differentiate from "peer effects".

Exploiting a policy change in China to overcome self-selection problem, this paper identifies peer effects using data from Chinese listed companies. This particular policy demands the exit of all independent directors who hold senior positions in

[3]Helmers et al. (2017) focuses more on the effects of policy-induced increase in interlocks on the innovation decisions and peer effects are introduced only as a possible explanation and the positive sign in the first stage, which implicit implies that firms tend to form interlocks with more innovative firms, automatically points to the positive peer effects in the second stage.

the party (on all levels), public service institutions (including universities, research institutes, public administration institute and hygiene providers) and stated-owned enterprises, etc, thus exogenously disrupting interlocks. Apart from the policy shock, studying this topic in the context of China is particularly interesting for two reasons. First, different from western culture, Chinese attach unparalleled weight to social relationships, or "Guanxi" in Chinese, which might complement extant framework with new research angle. Secondly, the respect of mentors is deeply rooted in thinking and behavior of Chinese. Put differently, the counsel of independent directors are especially appreciated and valued, which nurtures strong information exchange through the interlock channel.

Based on this quasi-experiment setting, we identify the presence of positive peer effects in R&D investment. The estimated coefficient suggests that focal firms increase its own R&D spending by, on average, 0.36-0.39 % as a respond to one percent increase of peers' R&D input. This finding is robust to various specifications. Performing Difference-in-Difference estimation on pairwise data, we show that the exogenous break of interlocks leads to higher degree of divergence in R&D investment strategy among formerly interlocked firms, which corroborates the existence of positive peer effects.

In addition, we investigate underlying theoretical mechanisms through which peers' decisions exert influence. Firms who locate more centrally, facing tougher competition, with more interlocks and with wider breadth of interlocked industries (i.e., in how many industries are peers operating, excluding the one of focal firms) are more strongly influenced by peers. Further heterogeneity investigations detect more sensitivity among firms that are financially slack and that are less prone to invest for the sake of CEO reputation building. All in all, evidence on heterogeneity speaks in favor of the learning theory as the driving mechanism.

Finally, extensions pertaining network structure, innovation output and reference group choices are examined. Strong interplay has been reported when interlocks are limited to inter-industries. In addition, peer effects remain of economic importance when direct peers are extended to second-degree peers (indirect interlock established via a common link to a third party), pointing to the spillover effects from local to global network. Positive peer effects in invention grants and negative peer effects in invention rejections highlight the efficiency improvement behind such learning behavior. With instrument based on interlocked inter-industry/inter-province peers to overcome reference-group-level common effects, we identify significant negative industry peer effects and weakly positive geographic peer effects, indicating the strategic substitutable nature of innovation strategies within industries and weakly positive spillover effects within provinces.

The rest of this paper is organized as follows. Section 3.2 discusses the related literature, followed by theoretical argument in section 3.3. Section 3.4 introduces the dataset, defines and summarizes variables. Section 3.5 describes our basic empirical model, the policy enforcement, instrumental variable construction and presents results of both reduced-form and instrumental variable estimations. Section 3.6 and 3.7 investigate the mechanism by examining heterogeneity effects and further extend the analysis to different topologies outcome dependent variable and reference groups. We conclude in section 3.8.

3.2 Related literature

The topic of "endogenous interaction of R&D among firms interlocked by independent directors" is mostly closely related to two strands of literature. One strand focuses on the effects of various board characteristics on firm innovation decisions, while the other strand centers on identifying peer effects in various corporate decisions within diverse reference groups.

3.2.1 Independent directors and innovation decisions

The separation of management from ownership leads to agency problems, which can be partially resolved by having good practices of corporate governance (Fama and Jensen, 1983). The keen search of the best possible board design motivates researchers to engage into empirically examining effects of board features on firm decisions and performance. Independent directors serve boards by more efficiently monitoring over and counseling CEOs (Clarke, 2006), both of which have been shown to be highly valuable (See the survey of related empirical literature in Balsmeier et al., 2014). Recently, a growing literature relates board independence to innovation strategies.

The board independence is the most extensively explored factor, though no consensus reached. Using data from multiple countries and various types of firms, most studies reach positive correlation between outsiders and R&D investment (E.g., Barry D et al., 1991; Chen and Hsu, 2009; Thomas et al., 2011). Based on patent outputs, Balsmeier et al. (2017) empirically verify the contribution of outside directors to patent applications. Further studies show that the degree of board independence additionally determines the composition of R&D expense. Highly independent board tends to emphasize more on external innovation (Hoskisson et al., 2002). However, counter-results have also been reported. For example, Kor (2006) finds no direct positive effects. On the contrary, board composition does play an indirect and beneficial role when interacting with top management team. Results by Deutsch (2005) demonstrate that independent directors seem to hold back R&D spending.

To get a more comprehensive sense of which factors underlie the above findings, scholars tackle the question at more micro function level, namely monitoring and advisory channel. On the one hand, information sharing, more specifically among interlocked firms, has been shown to be a stimuli of innovation activities. Using various measures of firm network connectedness, Chuluun et al. (2017) present significant positive correlation between board connections and innovation input and output. Mazzola et al. (2016) add another dimension, i.e., location in the network, and find that the more centrally a firm locates itself in the network, the more new products it introduces to the product market. The paper by Helmers et al. (2017) is the closes to ours. Their target is to capture the positive causal effects of increased interlocks on innovation measures relying on a policy shock. Further, peer effects have been proposed as an explanation.

On the other hand, monitoring channel plays an indirect role in shaping innovation decisions. Board friendliness, meaning less strict monitoring over managers, is under some circumstances a preferable quality in establishing trust between CEO and directors and sharing private information(Adams and Ferreira, 2007). Hence, more benefits to innovation activities can be reaped via more efficient advisory function at the cost of loose monitoring (Kang et al., 2018). In the similar vein but from another different viewpoint, board busyness matters in the sense that burdened by stressful monitoring duties, the precious time and attention allocated to counseling is greatly limited. When the value of advisory channel dominates the benefit of monitoring, highlighting the function of advising makes firms better off, especially pronounced in cases where long-term and decisive decisions such as M&A and innovation are involved (Faleye et al., 2011).

To sum up, this strand of literature highlights "edge", namely whether are there "edges" or how many "edges" do firms have. The focus of our paper is instead the actions of interlocked "notes", which are more concerned with the following strand of literature.

3.2.2 Peer effects in firm decisions

Peer effects originate from social studies, in which individuals are treated as mutually influencing decision making units within the boundary of reference group. So far, peer effects in education, teenage behavior (e.g alcohol assumption, pregnancy and drop-out), obesity, etc, have been identified (Evans et al., 1992; Sacerdote, 2001; Kremer and Levy, 2008; Trogdon et al., 2008). It is till recently that the concept of peer effects has been introduced into the analytical framework of empirical studies of firms' decisions, which traditionally assumes away other relevant firms' actions. As clearly pointed out by Manski (1993), peer effects essentially differ from industry/location oriented exogenous effects in that the former highlights the endogenous nature of mutual responses and the latter attributes similarity to facing similar external decision environment. We comb the literature on the basis of reference groups.

Industry/Product based peer effects

Because of well established industry classification system and the wild interest in understanding competition-driven decision interactions, majority work on peer effects relies on industry as reference group. With Linear-in-means model and an IV (instrumental variable), Leary and Roberts (2013) for the first time reveal positive peer effects in capital structure decision, i.e., one standard deviation change in industry peers' leverage causally leads to 10 percentage point change in the same direction. SEO (Seasoned Equity Offering) decision is partially explained by peer effects (Billett et al., 2017). Industry peers matter in investment strategies as well. Assuming that positive geographical spillover effects exist, Bustamante and Fresard (2018) employ orthogonal information from geography as IV to account for the industry-level common factors and report positive peer effects in capital investment. Based on the same IV from Leary and Roberts (2013), similar strategic complementarity among firms' capital investment in Chinese context has been uncovered (Chen and Ma, 2017). Other important strategic decisions, such as dividend payout(Grennan, 2019; Adhikari and Agrawal, 2018), stock splitting decisions (Kaustia and Rantala, 2015), tax paying and reporting behavior (Bird et al., 2018) and CEO compensation design (Chan et al., 2014) are also significantly shaped by industry peers.

Location based peer effects

Head-quartering in the same location forms another valid reference group. For instance, Dougal et al. (2014) present evidence that investment of one firm is very sensitive to investments of geographically adjacent firms, regardless of whether they are operating in the same or different industries. They interpret this finding as evidence of peer effects, rather than correlated effects stemming from facing the same geographic environment. Core et al. (2016) finds that in high-spillover areas, firms decisions are more similar and are of better quality. Using multiple identification methods, John and Kadyrzhanova (2008) conclude that the anti-takeover clauses are less likely to be taken when neighbors are not doing so either. Galbiati and Zanella (2012) regard the existence of social multiplier as the indirect evidence that tax avoidance practices can be spread out to adjacent firms.

Interlock based peer effects

Another source of bond connecting firms and their decisions is director interlocks. For Evidence shows that interlocked peers might be taken as benchmark in terms of compensation packaging design (Renneboog and Zhao, 2011; Wong et al., 2015) and in tax avoidance behavior (Brown and Drake, 2014). Based on deaths of interlocking directors, Patnam (2013) finds that there do exist strong peer effects in financial investment and compensation decisions. In the same vain but with pairwise data structure and network distance, Fan and Yang (2017) argue that the more closely firms are connected, the more differentiated they will position their products and technology.

Fracassi (2017) relates closely to our paper. However, he targets at not only interlocked peers, but also peers from other possible social bonds (including current/past employment experience, membership of clubs, affiliation to association/alumina) and integrates them into an overall Social Network Index. Additionally, he employs pair level information, as opposed to Linear-in-means model in our paper. Holding all else equal, being interlocked results in more similar R&D investment, capital investment and compensation design, but not debt and SG&A ratio decisions. Difference-in-Difference analysis based on exogenous tie break due to deaths of connecting persons points to the causality in peer effects [4].

Our research, one the one hand, converts the focus of current analysis of correlation between innovation and interlocks (as described in the first strand) from "edge" to "nodes", namely how individual's R&D responds endogenously to each other. On the other hand, second strand of literature on peer effects mainly focuses on industry/geographic peers, resulting in scarce evidence of peers effects pertaining director interlocks, especially in innovation strategy. Our findings with policy-based instrument complements extant literature with evidence in Chinese context.

3.3 Theories of peer effects based on interlock network

In this section, we propose several potential theoretical mechanisms to explain the presence of peer effects in R&D investment among interlocked firms, following two specific roles played by the interlock.

Firstly, interlock network provides an information sharing mechanism through which information is transmitted via interlocks from one decision maker to another. Each unit's information set is accordingly updated, posterior expectations are reformed and final decisions are modified. Under the assumption that peer effects represent essentially information, three specific models are relevant.

i) Learning theory

In order to "retain and improve competitiveness, productivity and innovativeness in uncertain technological and market circumstances" (Dodgson, 1993), firms

[4]Fracassi (2017) only reports the Difference-in-Difference analysis for capital investment.

actively engage in organizational learning. The essence of learning is the information exchange process through interaction with outside environment (Sinkula, 1994), including consumers, competitors, social network members, etc. Unlike externally accessible information such as financial reports or stock analytical reports, information acquired from interlocking independent directors tackles with specific questions, in greater detail and depth, and thus of greater value to innovation activities (Haunschild and Beckman, 1998). For instance, peers' opinion on prospects of particular new products or technologies can be conveyed. Firms who are not fully aware of the value or even the existence of these products or technologies are able to update their beliefs and make decisions more rationally, especially when the interlocked firm comes from other industries. In some extreme cases, known as informational cascade (Bikhchandani et al., 1992), focal firms will completely give up their private information and follow peers.

ii) Strategic predatory theory

Information acquired by word-of-mouth is in essence cheap talk and can be manipulated to achieve certain strategic goal. Strategic predatory theory contends that when firms are competing with each other, financially "deep-pocket" firms would, through manipulation of words, allure financially vulnerable peers to copy their aggressive R&D spending strategies, so that financial vulnerable peers drain their cash reservoirs and are forced out of the market (Bolton and Scharfstein, 1990). R&D spending especially fits in this argument because whether R&D input yields patents or how these patents can be applied, commercialized and finally turned into profits are of high uncertainty. Once R&D projects fail, they end up being sunken costs. Since financially weak peers are allured into investing R&D without strategic planning, it is highly likely that projects are in vain and that firms' financial state deteriorates.

iii) CEO reputation building theory

Different from previous two models where the agency problem between CEO and stockholders is absent, CEO reputation building theory posits that CEO's concern over his own prospects in the job market spurs them to imitate others (Scharfstein and Stein, 1990), causing positive peer effects. Nowadays, investment in R&D becomes a global trend. Those who do not engaged into innovation activities are negatively judged by not only the board but also private and institutional investors, even though holding back might be sometimes rational. This "keeping up with the Joneses" pressure motivates CEOs to turn to interlocked firms and refer to peers' R&D input as benchmark.

Secondly, establishing interlocks can also be deemed as symbol of cooperation, namely collusion among competitors or strategic alliances among non-competitive firms. Under both scenarios, peer actions directly enter the focal firms' response function of R&D investment. In other words, R&D investment, like price or quantity, is strategically chosen given peers' R&D decisions, such that profit is maximized.

iv) Innovation in collusion

The most fundamental purpose of forming collusion among competitors is to soften fierce R&D competition. Kamien et al. (1992) contend that competitive research joint ventures induce lower equilibrium of technological improvement and higher equilibrium product price. Martin (1996) further develops a theoretical model in which he demonstrates that all else equal, firms who form R&D joint ventures are more likely to sustain tacit product market price collusion. Following these arguments, if one firm abruptly decreases its external R&D contribution to the joint program, all other partners perceive it as the signal that the collusion has been breached and will retaliate by deviating from the prior compromised R&D level. In this logic, the positive peer effects would be observed, however only among collusion participants.

v) Innovation in strategic alliances

When interlocks serve the purpose of establishing strategic alliances with inter-industry firms, both positive and negative peer effects can arise. The underlying reasoning of positive peer effects is that more commitment to R&D spending can be perceived as a positive signal to the R&D collaboration by other allies, stimulating trust and more dedication to the alliance and yielding eventually positive peer effects. On the contrary, upon observing more dedication from peers, selfish focal firms might decide to free ride on them and reduce R&D expenditure, which results in negative peer effects. Furthermore, agency problems, such as strategic manipulation (Riitta et al., 2008) and knowledge/value appropriation problems (Luis and Nandini, 2012), further prevent firms from acting fully active in the R&D alliance, out of which negative peer effects appear.

To sum up, various mechanisms are available to explain peer effects in R&D investment. Positive or negative peer effects are equally likely to arise, depending on which mechanism or even which assumption (under one particular mechanism) is taken. Therefore, the investigation of peer effects ultimately boils down to an empirical question.

3.4 Data and variables

Our data set is constructed from two widely used databases, RESSET and CSMAR, which cover all Chinese listed firms. These two database have been used in several empirical studies on Chinese firms (see, for instance, Fan et al., 2007; Chan et al., 2012; Gul et al., 2013).

Most of our measurements are constructed based on CSMAR database. R&D expense comes from a sub-database named "firm-level analysis". This piece of information is collected from annual financial reports.[5] Note that before 2009 only very few firms disclosed R&D expenditures.[6] We drop observations with missing R&D information. Additional accounting data on total book asset, tangibility, capital structure, cash ratio, Tobin'Q, revenue and capital investment, et cetera are available. In addition, CSMAR offers multiple non-accounting information, ranging from the characteristics of external stock analysts, industry classification to head-quarter address. Finally, we winsorize all variables at 0.5 and 99.5 percentile levels to preclude the potential bias caused by outliers.

At the core of our analysis lies the interlock network, which is constructed on detailed annual information on board composition from CSMAR database, including the name/person ID[7], position (Chairman of the board, CEO, independent director, etc), tenure in office, age, education background, monetary compensation and so on. To ensure that the annual board member list is complete, we complement CSMAR database with RESSET database. Among all board members, we select only independent directors, based on which the interlock network is built.

Following the definition, when an outside director on the board of firm A is simultaneously assuming the position of outside director on the board of firm B, then one valid interlock is established between firm A and B. We match all firm-firm interlock connections based on all currently active outside directors (by their unique person identifier) listed in the board composition data. Note that this network is dynamically changing over time because of the exit and new appointment.[8] In this way, the annual interlock network structure is constructed. On average, the number of erected interlocks is on a upward trend, starting from around 2.26 in 2002 to 4.67 in 2015, especially pronounced in the manufacturing sector. In a word, firms tend to be more and more closely connected through independent director interlocks.

Matching the network with R&D expenditure and other accounting measures and then reducing the network structure to panel structure renders our final main dataset, which covers 2,169 firms from 2010 through 2015.

[5]Note that what we are interested in the total expense on R&D activities, both R&D expenses and capitalized R&D. Hereafter, we use the term R&D expenditure, R&D expense interchangeably. In financial reports, "R&D" expenditure is separately disclosed, rather than in standard financial reports like balance/income/cash flow sheets.

[6]In 2007, only 95, around 6.5% of all listed firms, reported the R&D expenditure. In 2008, the ratio rose to 11 % but was still not enough to construct the valid dataset.

[7]Since there are several directors with exact same Chinese names, we rely on the unique identification number provided by CSMAR database to construct the network.

[8]According to the official document named "Guide of establishing independent board system among listed firms", outside directors are allowed to serve the board for maximal two terms, three years each. But they have the right to leave the board at their will or when some special situations are applicable, for instance when they are no long "independent".

3.4.1 Variables definition

Our main dependent variable is R&D expenditure, which, compared with R&D intensity, excludes the source of spurious correlation from sales. To match the empirical specification, the sample consists of only non-missing observations. As routine, we perform log transformation onto R&D expenditure. Unlike patent counts with 2-3 years lag, R&D expense can be adjusted spontaneously to match peers decisions, which highlights the core concept of peer effects. Following the local network Linear-in-means model (Manski, 1993), peer R&D expenditure is defined as the average R&D expense of local peers, in our case all directly interlocked firms. Hence, each firm faces his own specific peer R&D expenditure, which changes accordingly when the topology of local network changes. To be consistent, the natural logarithm transformation has been also applied to peers' mean.

R&D investment is subject to asymmetric information problem and various agency problems. Therefore, we follow Fracassi (2017) and control for important determinants including firm size (natural logarithm of total book asset), tangibility of assets (total fixed asset over total book assets), debt ratio (total book liability over total book asset) and cash ratio (free cash over current liability). Similarly, peers' size, tangibility, leverage and liquidity are calculated in the similar manner and enter the equation as peer exogenous characteristics.

3.4.2 Summary statistics

We provide summary statistics for our main variables in Table 3.1. In general, Chinese listed firms invest 119 million Chinese Yuan (approximately 18.6 million US Dollar [9]) on innovation, accounting for approximately 5 % of sales. Positive mean of first difference points out the continuously uprising trend of R&D dedication, along with the strategic importance attached to innovation activities. Compared with focal firms, peers have larger means both in levels and in first differences, suggesting that firms with intense R&D spending tend to appear more frequently in the network and are preferred interlocking targets. The difference is significant at 0.017% level, according to the t-test. This empirical evidence lends support to the theoretical argument that interlock target are unlikely to be randomly chosen (Brian, 1990). The preference of interlocking with more innovation-oriented firms casts doubt on the validity of OLS estimates.

Regarding our control variables, Chinese listed firms are, on average, large in terms of total asset size (the book total assets value reaches 10.3 billion Chinese

[9]Average currency ratio is aggregated from annual ratio from 2009 through 2015, namely 1 US Dollar is equivalent to 6.42 Chinese Yuan.

Yuan, or 1.60 billion US dollar). High reliance on debt (40%) is another outstanding feature of Chinese firms, almost two times higher than American counterparts[10]. High leverage represents the financial risk and partially explains the low level of R&D investment. Fixed assets account for about 22% of the total book asset. Despite the large volume of book asset, the free cash flow is surprisingly small. Due to high uncertainty and the inherent agency problem of innovation activities, internal capital source is always preferred as the first choice to finance innovation projects. To sum up, summary statistics show that R&D input among Chinese listed firms is already comparable to western firms in levels and is still on a rising trend. The fundamentals seem to be not "friendly" to undertaking innovation activities.

3.5 Identifying causal peer effects

3.5.1 The basic empirical model and identification threats

The basic empirical model we employ is local network Linear-in-means model, proposed by (Manski, 1993), in which focal firms' decision is regressed upon local peers' decision, fundamentals of focal and peers and various fixed effects. Specifically, the following regression is estimated:

$$R\&D_{i,t} = \theta PeerR\&D_{i,t} + Z'_{i,t-1}\gamma + PeerZ'_{i,t-1}\delta + \alpha_i + d_t + u_{it} \tag{3.1}$$

where *R&D* refers to focal firm's logarithmic R&D spending. *PeerR&D* denotes the peers' R&D strategy, which, according to the Linear-in-means model, is measured as mean of all directly interlocked peers' R&D expenditure, i.e., $\frac{\sum_{j\in Net_{i,t}} R\&D_{j,t}}{n_{i,t}}$. Additionally, Z is a vector of control variables, including measures of firms size, debt ratio, tangibility and cash ratio. Based on these four controls, we further define and calculate peers' corresponding exogenous characteristics *PeerZ*. Focal firm's unobservable and time fixed effects are indexed by α_i and d_t, respectively.

Rationalized by Leary and Roberts (2013); Fracassi (2017), peer R&D action enters in contemporaneous term for two reasons, i) to preclude the confounding effects of other innovation relevant noises and ii) to limit the response time (which is assumed to be spontaneous). Meanwhile, we lag all control variables by one year relative to the outcome to address simultaneity problems.

Equation (1) can be rewritten into another more concise and clear matrix form, as follows:

[10]See for instance Leary and Roberts (2013), the average leverage ratio is 0.238.

$$\mathbf{R} = \theta \mathbf{GR} + \mathbf{Z}\gamma + \mathbf{GZ}\delta + \alpha + \mathbf{D} + u \tag{3.2}$$

where **R** is the vector whose entries are firms' *R&D*. All other capitals in bold are the corresponding matrix expressions for lower case letter in equation (1). The interlock connectedness is depicted by the normalized adjacency matrix **G**.[11].

The coefficient of our interest is θ. When θ is significant, peer effects exist. However, as pointed out by Manski (1993), direct estimating θ with Linear-in-means model is problematic because of identification problems. In fact, providing clean evidence of causal peer effects is the biggest challenge to this research question, insofar as some naturally networks are concerned, including strategically formed interlock network (Adams et al., 2010).

To estimate unbiased Θ, two endogenous problems must be properly addressed, self-selection and correlated effects Manski (1993). The former is well-grounded in the theory of "homophily". One important assumption of identifying θ using standard OLS is that interlocks are randomly generated or, at least, independent of any unobservable determinants of the outcome variable. However, suggested by theories, firms tend to strategically select peers in order to achieve certain goals, which in turn affects innovation activities. As our t-tests of R&D investment (both level and growth) reveal, peer firms invest more in innovation (18.00) than focal firms (17.50) and enjoy higher growth in the input (0.175) than the focal firms (0.14). The differences, being significant at less than 1% and 1.8 % level respectively, imply that firms prefer to establish interlock with more innovative firms. Put differently, the network structure is highly likely to be selective. The spurious correlation might in essence symbolizes the strategic planning driving both interlock selection and innovation strategy.

On the other hand, the correlated effects stand for some unknown institutional factors. Note that factors can reach beyond scope of network. For example, when economic cycles lead to similar adjustment of R&D investments for both focal and peers, co-movement arises. If those common factors drive R&D investment of both focal and peer firms in the same direction, we, as econometricians, only observe positive correlation between the two variables, which can be mistakenly interpreted as the evidence of positive peer effects.

To sum up, directly estimating θ in equation (1) might lead to serious bias when possible endogeneity is present. We attempt to deal with correlated effects by both

[11]To be more specific about adjacency matrix **G**, the element of row i column j describes the connectedness between firm i and j, which takes value 1 if one or more independent director are sitting on both boards and 0 otherwise. All entries are then normalized such that each row adds up to 1. Since the network is undirected, $g_{i,j}$=$g_{j,i}$

adding firm-level fixed effects and taking first order difference. Regarding self-selection problem, an instrument based on exogenously imposed policy shock is constructed, specifically aiming at solving this self-selection problem.[12]

3.5.2 Exogenous policy enforcement and IV construction

As mentioned before, our goal of applying instrumental method is to control for the self-selection problem. To this end, our instrumental variable should meet two requirements, on the one hand strong relevance to peer R&D, and on the other hand, independence of focal firms' characteristics that might contribute to interlocking and meanwhile innovation decisions.

In order to fight against corruption and put all possibilities of offering and receiving bribery to an end in the cradle, the organization department of CPC (Communist Party of China) Central Committee[13] put forth an official document named "On further regulating the problem of senior officers taking part time jobs in firms" (No.18) in October 2013, demanding all current and retired senior party officers quit their part-time jobs in firms. As follow-up policies, all other departments echoed the call from the central by proposing similar regulations, targeting at senior officers within each department. For example, in November 2015, the education department of CPC Central Committee explicitly demanded that all senior officers who are assuming important responsibilities in university/colleges/research institute should exit independent director positions. Ministry of finance of the CPC Central Committee has also released its own version. These policy shocks caused, according to *The times* newspaper and I quote here, "exodus of independent directors from Chinese listed companies"[14].

Among these resigned senior officers, many assumed independent directors positions in more than one firm. Their resignations directly led to exogenous disruptions to previous interlocks but had no specific implications on innovation activities, which satisfies the independence requirement, i.e., no correlation to the error term. On the other hand, the lost firms' R&D investments had mechanical correlation with peers'

[12]Two possible sources of exogenous shocks are available: one is the abrupt exit due to health concerns/deaths of independent directors (See for instance Fracassi, 2017; Falato et al., 2014) and the other is the policy shock. The former is more widely used when exogenous policy is absent. Luckily, the policy shock in China enables us to create orthogonality to network structure and we therefore go for the latter. Observations for the former event have also collected. It turns out that less than 100 such individual events occurred, which is statistically not enough to yield convincing estimates.

[13]The organization department is responsible for organizing and negotiating work among all other departments. More importantly, it has the authority to nominate, promote, demote and remove senior officers at all levels.

[14]See the link for the complete report: https://www.thetimes.co.uk/edition/news/beijing-gets-tough-on-party-officials-who-go-private-s9fpw0dw08r

innovation policy afterwards. Hence, relevant condition is also met. In a word, this exogenous event creates ideal exclusion restrictions to construct the instrument variable.

Given this background, we manually collect all resignation notices pertaining affected independent directors, released by listed firms from October 2013 to December 2014[15]. Two things worthy mentioning. Firstly, the way, in which resignations are formalized, differs from firm to firm and can be either explicit or implicit[16]. More specifically, some resignation notices explicitly attribute the exit to the policy enforcement, in loud and clear words such as: "According to the No.18 regulation from Central organization department, Mr/Ms X, who assumed independent director position, submitted the resignation." and "Due to the No.18 regulation, Mr/Ms X is no longer able to fulfill the responsibility of independent director.". In contrast, some firms phrase their notices in a more ambiguous and implicit manner, for instance "because of personal reasons/ work considerations". Following Lin et al. (2016), we believe this is an example of "framing effects" in the context of Chinese capital market, meaning one event with different disclosure preferences. Therefore, for the latter group, we manually search for the personal career information in CSMAR, Sohu finance, Juchao database and check whether the referred independent directors hold important position in the party (on all levels, including central, provincial, municipal and so on), universities and state-owned enterprises. If they do, we believe they left essentially because of the policy. Otherwise, the observation is excluded from the dataset. Secondly, most independent directors did not leave the position immediately upon the notice came out. According to the regulation on independent directors issued in 2003, resigned independent directors have to continuously serve the board until the vacancy is filled. This time lag varied across firms. We compare interlock list between 2013 and 2014, 2014 and 2015 to pin down the breaks. If by the end of 2015, the independent director was still on the board even though his/her resignation went public, we deem it as an invalid count to ensure that the "break" of interlocks is effective.

911 resignation notifications haven been manually collected. After deleting those who did not establish the interlock link and those who remained on the board and then matching the name list with prior interlock network, the final sample consists of 553 lost interlocks due to resignations from 222 officer independent directors. We plot the mean of affected firms' peers against that of unaffected firms. Averagely

[15]We collect data through JuChao database (http://www.cninfo.com.cn/cninfo-new/index), an information disclosure platform that integrates all relevant information about listed companies. It is affiliated to the Shenzhen stock market and is one of the four information platforms officially recognized by China Securities Regulatory Commission (CSRC).

[16]To the best of our knowledge, there are no clear reasons to justify why one firm chooses to organize the statement in explicit or implicit expressions.

speaking, affected firms lost, on average, 1.3 peers, in contrast to 0.3 increase among unaffected firms. Figure 3.1 indicates the policy indeed brought abrupt structural shock to the local network.

Lastly, we construct the instrumental variable in the same spirit like Waldinger (2012), who exploits a mandatory policy in 1933 expelling Jewish scientists from German universities to create exclusion conditions. Similarly, we construct an instrumental variable which captures average R&D spending of lost peers before the policy-led disruption took place. To be specific, it assumes value 0 before the interlock broke and thereafter the value of average R&D expense of lost peers ex ante the shock. This instrument satisfies two conditions of validity. Firstly, it is based on exogenous alteration to network structure, which is independent of self-selection driving factors. In fact, the event only exerts influence via the structure reform in network. Secondly, it mechanically correlates negatively to the peer decision in the next period[17].

One concern of our instrument is that firms hiring party members on boards might differ essentially from counterparts without party members in important aspects, such as resources allocation, access to inside information to policy updates, ect, which will be eventually reflected in innovation strategy. To address this concern, table 3.2 reports the balancing test. We show in the bottom panel that affected and unaffected firms in 2014 invest R&D projects in a similar trend, as suggested by both the trivial difference of 0.009 and the small t-statistics of 0.25. Peers also show no systematic difference in R&D spending. Other firm controls, including size, asset tangibility, debt ratio and cash ratio, are in parallel as well. As can be seen from upper panel, if the time point is moved a year ahead to 2013, same pattern applies to both R&D measures and controls. The balancing tests show us that policy-affected firms can be treated as exogenously chosen. Furthermore, some Chinese scholars provide supportive evidence, arguing that "independent directors with political background perform no better than their colleagues without party identity in terms of both monitoring and advisory functions" (Qing et al., 2016). To sum up, balancing tests and some second hand anecdotes all point to the treatment's independence of firm fundamentals.

Table C1 in appendix reports further regressions of instrument on both contemporaneous and one year lead measures of focal and peer firms (in levels and in first difference), following Leary and Roberts (2013). Results reveal that most of the estimates are of no economic importance. Furthermore, all estimates, except for *Debt*

[17]The logic is straightforward. If the lost peer invests heavily/marginally in innovation, the remaining interlocked peers' average R&D expenditure will drop/rise automatically. Same reasoning applies to the first difference, the more the lost peer invests, the more negative the change in peers' R&D will be.

in column (1) and *Cash* in column (4), do not show statistical significance. Hence, no information pertaining focal firms' current or future characteristics is contained in the instrument. In summary, evidence of multiple facet lends credit to the exogeneity of our instrument.

3.5.3 Reduced-form estimates results

Since the OLS results are not reliable due to the identification problems discussed previously, we proceed with reduced-form estimates. The results of various specifications are shown in Table 3.3. To control for the local network unobservables, from column (1) through (3), fixed effects model is applied on all level variables. From column (4) through (6) pooled OLS with year fixed effects is conducted on variables in first difference. All independent variables are lagged one year relative to the dependent variable.

Results of the specification with only the instrument, along with fixed effects are reported in column (1) and (4). It is noted that coefficients are negative and significant at less than 1% level. Column (2) and (5) complement with additional focal firms' individual exogenous observables. Economic magnitude of the estimates, as well as statistical significance, hardly changes. Same findings hold further conditioning on peer feature measures. Admittedly, the estimate here is the compound function of θ. Therefore, the economic meaning is difficult to interpret. Nevertheless, evidence in Table 3.3 points to the presence of peers' effects in R&D interactions.

Given the design of the instrument and our specification, the reduced form estimates describe essentially the difference-in-difference effects. The coefficient sign suggests how remaining interlocked firms adjusted R&D investment to the shock, compared against that of unaffected firms. The negative sign implies that the shock exerted negative effects on R&D investment of remaining firms. In conjunction with the negative mechanical correlation between the instrument variable and the endogenous peer R&D expenditures, positive peer effects follow automatically from the negative sign in reduced-form estimates.

We also notice that in column (3) and (6), all estimates of peer fundamentals are of relative small significance, except for *PeerSize*. This implies that peers' responsiveness mainly comes from the action rather than changes of peer characteristics, which resonates the similarities in coefficient estimate θ of specifications with and without peer measures (between column (2) and (3), (5) and (6)).

In conclusion, the reduced-form estimates results indicate that interlocked peers' actions do play a significant role in the determination of R&D investment input, both in level and in first difference.

3.5.4 Placebo tests

In this section, we perform placebo tests in order to address the potential concern that some unobservable common factors, arising from institution background, may attribute to our findings. To this end, treatment in the first placebo test is randomly selected, instead of induced by the policy. Specifically, the interlock network, as well as all variables, remains to take original values. Inflicted firms and their broken peers are counter-factual, selected by randomness. To match the number of observations in treatment group, we defined as many drop-outs as in the real case. The instrument is correspondingly recalculated. Because the mechanical negative correlation between R&D spending of "drop-outs" and "remaining firms" is still valid, so is our instrument in most scenarios. Reduce-form estimation results are listed parallel to the main results in Table 3.3, to highlight the difference brought by the randomness.

As shown in column (7), the coefficient from reduced form estimation is essentially close to zero (0.00008) in size when comparing with 0.006 in other columns. More importantly, significance does not hold. This information leads to the inference that, firms from fictitious "treatment" group do not respond to the counter-factually oriented peers' change of R&D spending. Conversely, the coefficients of other characteristics of both sides remain unchanged, ensuring the specification does not result in the structural change.

Second placebo test, on the other hand, fixes the network topology and the policy-forced dropouts but replaces the real values of R&D investment and other measures with the "counter-factual counterparts", i.e., data ex-ante the policy enforcement (namely, one year forward). In other words, we apply the same instrumental variable methodology as if the policy had happened one year earlier. Since firms acted as if they had not been informed of any counter-factual dropouts, no evidence of significant peer effects should be observed provided that the application of previous methodology and underlying assumptions does give rise to previous findings. This placebo test is reported in the Table C5 in Appendix.

In Column (1) and (4) state the results of reduced form estimates. The statistical insignificance and the negligible coefficients both suggest the indifference of focal firms to the interlocked dropouts under the counter-factual scenario, pointing to the fact that the previously identified significant peer effects reflect nothing but the real responses due to the exogenous policy. Unsurprisingly, the instrumental estimates in columns (2) and (5) are neither significant nor important, although the instruments seem still strong and valid.

The insignificance and small coefficient size from placebo tests, in sharp contrast to our main results, imply that the our finding is unlikely to be driven by unobserved or unknown common factors. It is the policy affected firms that contribute to the peer effects.

3.5.5 Instrumental variable estimates results

In this section, we perform instrumental variable estimates to explore the economic importance of peer effects, although more stringent assumptions have to be imposed compared with reduced-form estimates. Based on the instrument and the similar econometric specification, we conduct two stage least squares estimation on variables in level and in first-difference. Standard errors for all regressions are clustered by firms to allow for serial correlation. As mentioned before, except for peers' contemporaneous decision measures, all other covariates are lagged one year.

Results of IV regressions are depicted in Table 3.4. Firstly, as listed in even columns, the estimates of instrument in the first stage are always significant. The fact that Kleibergen-Paap rk Wald F statistics (which is essentially F-statistic of the first-stage regression) in all specifications exceed the Stock-Yogo weak ID test threshold value at 10 % level (8.96) at least further reinforces the explanatory power of our instrument. Moreover, the negative sign matches the mechanical relevance condition discussed before. Both significance and sign suggest that our instrument is valid and reasonable.

Second stage results show that the significant and positive peer effects exist in R&D decision. As before, in column (1) and (7), only peer R&D measure is included. The point estimates are positive and statistically significant at 5% level. Estimates of variables in levels and first difference do not differ much in magnitude, 0.40 versus 0.35. Coefficients imply that 1 percentage increase in the mean peer R&D expenditure ceteris paribus increases focal firms' R&D input by 0.40% (or 0.35%). Specifications with focal firms' controls (in column (3) and (9)) and further peers' controls (in column (5) and (11)) change neither coefficient magnitude nor statistical significance, suggesting the peer effects can not be explained away by the individual/peers observables.

Estimates of control variables are mainly in line with theories. The coefficients of *Size* are positive and of largest magnitude. It seems that larger firms have more resources at their disposal and are tempted to defend their market power by investing more in innovation. The positive albeit insignificant coefficients of *Tang* suggest the complementarity between R&D and tangible asset following asset complementarity theory. Additionally, the more leverage a firm bears, the less it will invest in R&D. The reason lies in agency problem between shareholders and creditors, i.e. the conflict of great uncertainty of R&D activities and the risk averse attitude of creditors. Similar to Fracassi (2017), we also find negative correlation between *Cash* and R&D spending, indicative of R&D smoothing behavior (Brown and Petersen, 2011).

Table C2 in appendix contains various robustness checks, all using the specification of column (11) in Table 3.4 as benchmark. For the sake of brevity, only results with first difference variables are reported, along with corresponding first-stage results. While the former three robustness checks focus on basic specification, the latter three center on the design of instrumental variables.

In column (1), we deal with the bias stemming from omission of other possible covariates which are relevant to the decision of interest, both on focal and peer firms' side. More R&D determinants, namely Tobin'Q, sales and profitability (ROA) are included. Newly added controls barely change results of both first stage and second stage.

Column (3) adds the past dependent variable in the regression to account for the dynamics of R&D investment. The negative and statistically strong coefficient of one-year-lagged R&D input, together with positive first difference in summary statistics, implies that Chinese listed firms are increasing R&D investment at a decelerated pace. The instrumental variable estimates point to 0.37% positive change in focal firms' R&D investment as response to 1 % change in peers' decision.

Given that possible time variant industry common factors might also drive the positive co-movement of R&D investments, we further include $IND \times Year$ fixed effects in column (5), on top of using variables in first difference. After controlling for possible industry-year common effects, the coefficient magnitude drops mildly from 0.39 to 0.30, but remains significant at 5% level.

In the specification of column (7), new instrument with same design is constructed using value of lost peers' R&D in the year t-2 (instead of year t-1 in the main regression) to further exclude the potential endogenous reaction to the policy change from the instrument. Result shows that the presumably more exogenous instrument is valid given the sufficiently high Kleibergen-Paap weak IV statistics. However, the coefficient changes only marginally.

In column (9), the disruption events are further narrowed down to only those laid-off independent directors whose resignation notices attribute explicitly the exit to the policy[18]. In other words, implicit statement events are excluded. Despite the lower Kleibergen-Paap statistics possibly due to the reduction in observation number, narrowly defined instrument does not bring qualitative shift to either first or second stage results.

Following Waldinger (2012), we augment our instrument with the number of lost peers in column (11). Weak IV test and Hansen test all imply that the multiple in-

[18]The explicit statements cases account for almost half of all breaks. Interestingly, in unreported regression whose instrumental variable is purely constructed on the implicit statement cases, the explanatory power of the instrument, as well as the coefficient estimates, is of similar scale to what we reported in column (9).

struments setting is acceptable. As suggested by the first-stage result in column (12), the number of lost peers is only marginally correlated to the endogenous variable, opposed to our main instrument. It seems that number of lost peers are weak in explaining peers' R&D ex post. What matters more is the "quality" measure of lost peers, rather than the number. With our main instrument still playing the dominant role in the first stage, it follows naturally that the estimate of peers' R&D remains qualitatively the same.

Another potential source of spurious correlation is the included controls, which is the focus of Table C3. The exclusion condition demands the instrument should be independent of other included controls. In other words, policy shock should have no qualitative influence on peers' fundamentals such that decision interactions are only realized through peer effects. This exogeneity assumption can be examined by applying the same IV methodology on controls, as proposed by Angrist and Pischke (2008). From Table C3, we notice that the reasoning of the instrument is still valid given the sufficiently high value of weak IV test. As opposed to R&D, all controls seem to be independent of strong peer effects given the insignificant coefficients in the second stage. This piece of evidence reassures the controls' exogeneity to policy shock and hence precludes the chance of introducing contaminated controls.

Finally, to relieve concerns over sample length and number of "broken interlocks", main sample is expanded to year 2017 and the instrument is extended to inclusion of resignation events in 2015. Results are listed in Table C4. First stage estimates indicate that sample expansion brings no change to the instrument's validity. The expectation that more information on interlock disruptions lead to stronger instrument is confirmed by the higher Kleibergen-Paap statistic. In column (1)/(3) and column (5)/(7), main instrument estimation is applied on the expanded sample, using previous and new instrument, respectively. Regardless of using level or first-difference variables, the presence of the strong peer effects has been reinforced in all specifications, despite relative smaller coefficients (0.26-0.29). In other words, our main findings are robust to the sample and instrument selection.

3.5.6 Alternative investigation on peer effects using pair model

In this section, we strengthen previous findings by resorting to pair model on the same policy shock setting. Different from local network Linear-in-means model, the pair model exploits more detailed information at firm-firm (pair) level. The basic concept of pair model is to regress dissimilarity of decision variables, proxy of how differently two firms behave from each other, on the variables of interest, in our case, a dummy indicator of whether interlock between two specific firms exists. Following Fracassi (2017), we proceed as follows.

First step is to extract the information on uniqueness of each firm's R&D decision from the error term. Error term can be calculated based on regression of R&D on firms' controls, namely *Size*, *Tang*, *Debt* and *Cash* (one year lagged), as in the following regression.

$$R\&D_{i,t} = Z'_{i,t-1}\gamma + \sum_{i \in I, t \in T} (\alpha_i \times d_t) + u_{it} \tag{3.3}$$

To accurately isolate industry and year exogenous shocks from firms' idiosyncratic component in R&D decision (denoted as $\varepsilon_{i,t}$), we further add $IND \times Year$ fixed effects. The estimates are reported in Table C6[19]. Next, the proxy of decisions difference is defined as the absolute value of the difference between two pairing firms' decision idiosyncratic components, following

$$PolicyDissmilarity = |\Delta\varepsilon_{i,j,t}| = abs(\varepsilon_{i,t} - \varepsilon_{j,t}) \tag{3.4}$$

According to Fracassi (2017), the final dependent variable is $ln(1 + |\Delta\varepsilon_{i,j,t}|)$, the log transformed absolute difference. In the similar way, how far two pairing firms' characteristics are away from each other can also be calculated and included as controls in the pair model.

Among millions of unrestricted combinations, data sample is restricted to pairs of firms who were interlocked at least once. We here focus on resigned independent directors who issued notice in 2014 and left the position before end of 2015. Year 2013 is thus defined as ante shock period and 2015 as post shock period. Firms who lost at least one of his interlocked peers because of the policy shock are firstly picked. Then all interlock pairs established in 2013 are pinned down as the sample of base period. Here arise two possible cases, interlocks either remained till 2015 (control group)[20] or broke in either 2014 or 2015 (treatment group). Our target is to detect how the dissimilarity measure in treatment group evolved compared to that of control group pairs. Provided the positive peer effects identified before, rational expectation is that firms' polices drifted apart once their bridging independent directors resigned. In other words, the treatment effects should be positive. Variables of pairwise interlocks used in the DiD investigation are summarized in Table C7.

Pairwise balancing test in panel A of Table 3.5 indicates that dissimilarity mea-

[19] In comparison to Table C6, the estimates in Table 3.4, except for *Size*, are both less significant and of weaker economic meaning. Interestingly, this distinction suggests that introducing peer measures might cause fundamental changes to our understanding of traditional controls.

[20] We choose stringent criteria to select control groups. The firms in control group remained interlocked from 2013 to 2015.

sures of R&D investment and control variables, except for cash ratio and asset tangibility, show no systematic difference between treatment and control groups in 2013. This more detailed alternative balancing test reinforces the validity of our instrument in main analysis.

In panel A of Table 3.6, Difference-in-Difference specification with only R&D dissimilarity measure estimates ATE (average treatment effects) to be 0.051, significant at the level of 0.022. The positive effects indicate that broken peers' R&D investments drifted away from focal firms to whom they used to be interlocked, relative to still remaining interlocked peers. Remember that when calculating heterogeneity in individual's R&D investment, focal firms' fundamentals have been controlled. Theoretically speaking, specification without any controls in panel is sufficient to induce causal effects. As a robustness, further including covariates brings only minor change to the results in panel B. The estimated ATE rises slightly to 0.057. To further account for the significant different trends between two groups in cash ratio and tangibility, we combine Difference-in-Difference estimation with matching. As in panel C of Table 3.5, after matching, all variables pass the balancing test. Based on the matched sample, we recalculate the ATE, which are estimated to be 0.066 and significant at 4% level. In summary, the established positive treatment effects in turn agree with positive peer effects.

Following Fracassi (2017), to reinforce previous positive ATE, we replicate Difference-in-Difference analysis using OLS regression, where the ATE is captured by the interaction term between $Dummy\_Treat$ (takes 1 if the interlock broke due to the policy and 0 otherwise) and dummy $Dummy\_Post$ (takes 1 for post period and 0 for base period). Similar dissimilarity measures of controls are included as well.

$$\begin{aligned} ln(1+|\Delta\varepsilon_{i,j,t}|) = \beta_0 + \beta_1 Dummy\_Post + \beta_2 Dummy\_Post \times Dummy\_Treat \\ + \beta_3 ln(1+|\Delta X_{i,j,t}|) + \eta_i, j, t \end{aligned} \tag{3.5}$$

Results are presented in Table 3.7. Despite various specifications (with pair fixed effects & without covariates in column (1), with covariates & firm fixed effects in column (2), with covariates & pair fixed effects in column (3) and (4)) and various choices of clustering for standard errors (S.E are clustered at pair level in column (1) through (3) and at both firms level in column (4), using the double-clustering algorithm from (Petersen, 2009).), interaction terms are always significantly positive. The coefficient magnitudes range from 0.05 to 0.06, which falls into the range of the standard Difference-in-Difference estimation in Table 3.6.

To sum up, by exploiting information of firms' idiosyncrasy in R&D decision at pair level, we provide supportive evidence that policy-induced-interlock breaks render more idiosyncratic innovation investments, which in turns corroborate the presence of positive peer effects.

3.6 Mechanism investigation: Heterogeneity in peer effects

Although peer effects have been identified as an important factor in determining R&D investment, the underlying economic mechanism remains to be unclear. The positive sign of peer effects helps at best preclude some hypotheses, such as free riding argument among R&D alliance members. To further discern mechanisms, our strategy is to firstly derive hypotheses of heteogeneity effects based on each theory, which can be confirmed or rejected by empirically estimating corresponding interaction terms (Duflo et al., 2011).

3.6.1 Learning mechanism

Heterogeneity effects from network centralities

Learning behavior is normally quoted as the main cause of mimicry in corporate decision making. If peer effects are driven by learning, or more essentially the information exchange, certain heterogeneity effects can be expected.

The first heterogeneity relates to the topology of the network structure, specifically the location. According to Friedkin (1991), details like how much information can be transmitted, via whom and to whom all depend on firms' centrality in the network. The more centrally a firm is located, the more information he collects and the more sensitive his decision is to others. If peer effects represent information acquisition, it is logical to expect that the magnitude of peer effects should be in accordance with the amount of incoming information and hence the centrality. Four common centrality measures are used, namely normalized degree, betweenness, closeness and eigenvector centrality. Degree centrality measures how many units are directly interlocked with the focal unit. Betweenness takes into account the global network and captures "how many times the shortest paths pass through the focal unit in order to link two certain units". Closeness depicts the sum of length of shortest connections between the focal unit and all other units in the global network. Eigenvector adds weight to interlocked units. Interlocking with more centrally located units gains extra weight than interlocking with periphery units, ceteris paribus.

The heterogeneity effects identification method is borrowed from Leary and Roberts (2013); Grennan (2019). We construct endogenous variables by interacting *PeerR&D*

with proxy variables, *GroupL* and *GroupH*, respectively. Accordingly, new instruments consist of two interaction terms of the previous instrument with proxy variables. Heterogeneity effects are identified by comparing estimated coefficients of two endogenous variables. To account for effects of the shock on network structure and firms' locations, the value of centrality measures before the shock, namely values in 2013, are used to construct proxy variables *GroupL* and *GroupH*. *GroupL* denotes focal firms with relatively lower centrality (lie in the smaller 50% percentile) and *GroupH* focal firms with higher centrality (lie in the upper half of the distribution). All variables are in first difference and all else remains the same. Table 3.8 display the results.

The first stage results in Table C9 show that the newly created instruments are significantly negatively correlated to the corresponding endogenous variables. Both economic magnitude and statistical significance are comparable to those from main results. As implied by the lower Kleibergen-Paap statistics, taking interaction terms does weaken instruments' explanatory power. In the second stage, estimates from more centrally located firms dominate those from periphery firms in both size and significance. Specifically, no significance in column (1) and (2) and marginal significance in column (3) and (4) have been recorded, an evidence of weak interdependencies amongst "remotely" located firms. In contrast, the estimated coefficients of $PeerR\&D \times GroupH$ are 2-5 times larger, except for column (4). Even in the column (4), the point estimates suggest 1% smaller reaction of focal firms from *GroupL* than those from *GroupH*, conditional on 10 percent change in peers' R&D investment. This difference is non-trivial. Regardless of which centrality proxies are employed, our heterogeneity findings are consistent with the information flow hypothesis, that is if peer effects represent information exchange, more centrally located firms collect more information and are influenced by peers to larger extent.

Heterogeneity effects from other learning factors

Another test on heterogeneity effects relates to motivations behind the learning behavior amongst firms and the efficiency of learning. Argued by Dodgson (1993), the more uncertain the external environment is, the more motivated firms are engaged into learning. Following this reasoning, we put forth a hypothesis, that is operating under more competition pressure, stronger peer effects are present. In contrast, when firms themselves possess dominance in the product market and are hence less subject to uncertainties, peer effects tend to be weaker. Competition level is depicted by a Lerner Index measure proposed by Aghion et al. (2005).

The empirical specification remains the same. As before, categorical variables are constructed based on pre-shock value of corresponding proxies. Table C10 in the appendix suggests that instruments are valid in terms of negative correlation to matching endogenous variables and strong statistical significance at 1% level. Second stage instrumental variable estimates are reported in table 3.9. According to column (1), comparison between point estimates (0.24 versus 0.63) reveals that firms, who operate in highly competitive industries, are more sensitive to peers' decisions. Furthermore, the statistical significance of peer decisions in *Group_H* also outweighs that of *Group_L*. It resonates our argument that fierce competition environment drives greater incentive to learn from peers and thus enhances peer effects, vice versa. Moreover, this result can be interpreted as the evidence against collusion argument. As is acknowledged, the more competitive the product market is, the more attempted individual firms are to deviate from the agreed R&D engagement. Put differently, collusion is difficult either to be formed or to be sustained conditional on higher level competition. Were collusion the cause of peer effects, we would expect stronger peer effects within more concentrated industries and weaker effects within more competitive sectors, which is opposed to the results above.

The outcome of learning depends on various factors, among them is the amount of information available to independent directors. It can be justified in two folds. Firstly, information is the basis of learning process. Under the single and double-loop learning framework (Argyris, 1976), organizational learning begins with information collection from all relevant parties. Only when some threshold is hit, can firm-level collective knowledge base be developed to guide decision makings. Moreover, the information demanded by monitoring and counseling is usually in essence soft. Interlock is one of the few inflow sources. In a word, having more interlocks facilitates the loop process and intensifies the peer effects. Secondly, more interlocks nurture synergy effects. For instance, information of different sources can be compared and integrated to reduce informational asymmetry, to formulate more accurate expectation and to reduce the chance of being misled by cheap talks, etc. The information amount is proxyed by number of contemporaneous interlocked peers.

The positive moderating effects of information amount is confirmed provided the coefficients in the second column. Firms receive material peer influence when they are interlocked with more firms. In comparison, focal firms whose interlock counts are categorized by *GroupL* exhibit less responsiveness. Noticeably, the point estimate of *GroupH* (0.54) is almost two times larger than that of *GroupH* (0.28). The marked contrast agrees with the "learning hypothesis" in the sense that more access to private information via independent directors strengthens learning process, leading to more intense interdependencies.

Third heterogeneous effect digs deeper into quality of the information retracted from interlocked peers, namely industrial diversity. Not only quantity but also knowledge breath matters in the innovation activities in that with more diverse sources of knowledge input comes greater chance of having complementary knowledge effects (Leiponen, 2005), which is of fundamental importance to product innovation (Luca and Atuahene-Gima, 2007). In addition, exposing to more "foreign knowledge" renders new ideas, "out of the box" thinking and prevents decision makers from relying too heavily on familiar information. Leiponen and Helfat (2009) have shown empirical evidence that the possibility of innovation success increases in knowledge broadness. Striving for such synergy effects, focal firms are eager to stretch out to more industries through interlocks, which, in turn, augments sensitivity to peers' decisions. The proxy of knowledge breath is the number of peers' non-duplicating industries.

Column (3) shows that point estimate of endogenous peer investment categorized into "with higher informational diversity" is significantly larger than the coefficient of the other endogenous variable $PeerR\&D \times GroupL$. The qualitative difference is also partially reflected in the significance level, with p value of 0.03 versus 0.05 for *GroupH* and *GroupL* respectively. Conditional on the learning efficiency gain from synergy of multiple industry knowledge, this result confirms the positive moderating effects of information diversity on peer effects.

Taking all heterogeneity evidence on motivation, informational amount and diversity together yields the inference that peer effects are more likely to be the consequence of informational exchange through the delegation of independent directors. Admittedly, our results only provide suggestive evidence.

3.6.2 Other possible mechanisms

As discussed in the theory section, strategic predatory theory and CEO reputation building theory are also potential reasons behind the peer effects in R&D decisions. In this section, we offer some preliminary evidence to refute these two possibilities.

To induce more R&D spending from financially vulnerable firms such that their liquidity is to be drained, deep pocket firms intentionally invest more aggressively than they would if predatory never took place. Trapped into winning the R&D competition, financially weak firms end up with increasing R&D spending and peer effects arise. The asymmetry of financial resources between focal and peers matters lies at the center of predatory argument. Peer effects should only appear when weak focal firms are plotted against, but not in situations where focal firms are financially slack. Put differently, if predatory works, financially disadvantaged firms are allured into R&D competition and react more violently, compared with deep pocket players. We follow Grennan (2019) and use measurement of cash volatility over cash (defined as cash and equivalent normalized by total book asset) in the base period to proxy for financial vulnerability. The higher this proxy is, the more vulnerable is the firm. As before, we sort vulnerability measure in ascending order and categorize first half distribution as less vulnerable firms and the last half as vulnerable firms. All other settings remain unchanged.

According to Table 3.10, instruments are working properly. At odds with the previous argument, compared with financially struggling focal firms, financially slack focal firms respond more violently to peers, provided the point estimates of 0.44 and 0.33, respectively. The implication that deep pocket firms are more engaged into R&D competition and being preyed disagrees with predatory argument.

Regarding the CEO reputation building theory, younger CEOs are more ambitious and are more willing to mimic the R&D strategy of other sophisticated CEOs to earn themselves a positive image in the job market (Grennan, 2019). Following her work, we capture this reputation building incentive with age. In the similar way, a categorical variable is constructed, indexing focal firms led by young CEOs (younger than the median) and those led by senior CEOs (older than the median).

Results in Table 3.10 speak against the CEO reputation building theory. The point estimate of $PeerR\&D \times GroupH$ is 0.62, almost 3 times as large as that of $PeerR\&D \times GroupL$, 0.23. The difference between two groups is also reflected in the statistical significance, suggesting that older CEOs are more prone to copying their peers actions than younger counterparts. In fact, the finding that elderly CEOs (who also tend to be more experienced) value peers actions is more in line with the learning theory.

To sum up, previous empirical investigations do not provide supportive evidence to either predatory or reputation building argument. Combining with the findings from last section, learning theory agrees better with data from Chinese listed firms. However, we should also be cautious provided that these theoretical mechanisms are not mutually exclusive. It is highly likely that other mechanisms might have played a role, in additional to learning theory.

3.7 Extensions

3.7.1 Extensions to intra- VS inter-industrial peers network

So far, we do not distinguish interlocked peers. They operate either in the same industry as focal firms or in different industries. Dividing the whole network into two sub-networks, namely networks constructed via only intra-industry or inter-industry interlocks, allows us to i) cleanse industry-level common effects and to ii) get some hints on the role played by collusion/strategic alliances, as suggest by hypotheses iv) and v).

After constructing inter and intra-industry interlocked peers subgroup respectively, similar instrumental regression specification is applied. Note that instrument is separately reconstructed, namely intra and inter-industrial lost peers respectively. The industry classification system employed here was designed and implemented by China Securities Regulatory Commission (CSRC) in 2012. This two-digit coding system covers 90 subdivisions. According to the summary statistics, about 14% of interlock linkages occur within industries. However, if interlocks were chosen randomly, that is all intra and inter-industry firms have equal chance of being selected as interlock, the likelihood of obtaining intra-interlock is around 4%. According to the t-test, averagely speaking firms put more weights on intra-industry peers. Nevertheless, it is worth mentioning that there is difference across industries. The suggestive preference of intra-industry interlocks over inter-industry ones is another piece of evidence that firms' selection of interlocks is based on strategic grounds.

For brevity, only the instrumental variable regression results based on first difference variables are reported in Table 3.11. Subjected to the small number of observations, the weak IV statistics for intra-industry peers sub-sample is relatively small. As before, estimated coefficients in the first stage are negative and significant. In general, the instrument is still valid. θ in column (1) is insignificant and positive, suggesting mild responsiveness between intra-industry interlocked firms. Admittedly, validity of the instrumental variable and the accuracy of the IV estimates are restricted by short of observations. However, we contend that intra-industrial peer effects tend to be weak. Firstly, point estimate is both insignificant and smaller than the coefficient derived from inter-industrial network. Secondly, as a robustness test, we split the full sample of dyadic dataset into inter and intra industry pairs sub-samples and estimating Difference-in-Difference effects in OLS setting respectively. Matching evidence has been reported in Table C8. Specifically, among interlocked firms in the same industry, the coefficient of interaction term ($Dummy\_Post \times Dummy\_Treat$) is 0.038, both smaller in size and weaker in significance than that of inter-industry peer sub-sample (0.064).

On the contrary, estimated coefficient based on inter-industry interlocks in column (3) delivers a clear message, namely peer effects exist. The estimate is not only significant at 1.3% level, but also of greater economic meaning (0.38). It seems interlocks cross sectors drive our main results in Table 3.4.

Two important messages are conveyed in the significant peer effects among inter-industry interlocks. Firstly, peer effects remain strong even if industry-level common factors are absent. In turn, it lends creditability to our main results. Secondly, little can be deduced concerning the underlying theories. Though interlocks within boundaries of industries are seemingly more likely to be observed, empirical evidence in this section provides no decisive evidence to support or reject collusion theory. The strong influence from cross-industry peers can be possibly attributed to learning or strategic alliances. However, no further implications can be made without detailed information on strategic alliances or collusion.

3.7.2 Extensions to second degree peers network

In the previous analysis, peers are defined as firms that are directly linked to focal firms. In this section, we extend the first-degree peers to second-degree peers, i.e., peers to whom the focal firm has no direct interlock but indirect links can be established through a third firm. An easy but straightforward example is that firm A and C are not directly interlocked. However, both A and C have independent directors sitting on the board of firm B. In this way, firm A is defined as second degree peer of firm C, verse visa. The instrument is adjusted such that the lost peers are instead the lost second degree peers due to the break of first-degree connection. For instance, in the previous example, connecting independent directors who sit on the board of firm A and B are laid off and no interlock remain between Firm A and B. Then for firm A, the lost second-degree peer is now firm C. The new instrument is still valid following the same reasoning.

From Table 3.12, it is noted that the statistically significant negative correlation between new instrumental variable and the endogenous *PeerR&D* remains in the first stage, although the explanatory power becomes weaker because of more noise introduced in the process of adding another layer to the interlock network. According to the second stage, the significant peer effects are identified, both in level and in change. The point estimates are respectively 0.73 and 0.56, seemingly larger than the corresponding estimates when peers are of first-degree. However, after scaling the coefficients by standard deviation, the coefficient size is comparable. Our findings suggest that peer effects are not restricted to the local network but rather widely spread to higher degree peers. In this manner, a tiny variation on individual level eventually ends up in variation of multiple magnitude on aggregated level, a phenomena named multiplier effects(Glaeser et al., 2003).

3.7.3 Extensions to innovation outcomes

Our previous heterogeneous effects point to learning theory as the most plausible explanation for peer effects. A further question is how such learning behavior influences on firm performance. Depending on which assumption, learning can either benefit or harm firms innovation outcome. The target of this section is to provide some suggestive empirical evidence.

The patent information comes from CSMAR dataset, including application, grant, expiration, rejection counts for all three types of patents (namely invention, utility model and design) at different levels (initiated by head-quarter, subsidiaries and joint-venture firms). Our focus is fixed on the invention, which should represents the highest level of innovation ability. The outcome variables are counts of granted and rejected inventions, summed at all levels. We assume that information is sent and received instantly, therefore peers' actions are captured by contemporaneous peer patent counts. Unlike decisions that are real-time adjustable, output such as patent counts takes time to be effective. To allow for this time lag effects, i) the timespan of interlock network structure is enriched up till 2017, as in the robustness test in Table C4; ii) time lag between endogenous peers' patent and the instruments is set to be two years. The latter can be justified as follows, though interlock has been disrupted by the shock, the influence of previous interlocks remains to be sensed in patent output in the next two following years. To be consistent, all controls are lagged by three years. Lagged dependent variables up to three years are included to account for the dynamics [21].

According to column (2) and (4) of the Table 3.13, the validity of our previous instrument can be generalized, judging from the negative and significant first stage estimates. Point estimation of the coefficient θ is 0.49 and -0.21 for invention grants and rejections, respectively. It implies that 10 percent increase in peers' successful invention applications results in 4.9 percent increase by focal firms. Conversely, facing 10% increase in peers' failures, focal firms diminish their rejections by 2.1%. It seems that firms learn from peers' success and meanwhile draw lessons from their failures. This asymmetry conforms to the efficient learning.

Interestingly, patent application, grant or rejection counts of utility model and design do not seem to be influenced by peer effects. The distinct contrast reflects that only the most valuable "intelligence" has been transferred across firms, which points to the efficiency of such informational exchange channel. In a word, our results provide suggestive evidence of efficiency improvement by learning from peers through exchange of core knowledges.

3.7.4 Extensions to product market peers and geographical peers

This section extends to two other commonly seen reference groups in the literature, using instruments originated from previous findings. One of the difficulties in identifying peer effects within industry/location is controlling endogenous factors, which stem from observable and unobservable innovation-relevant industry/geographical specific fundamentals (correlated problem) or factors driving both

[21] The sharp contrast of statistical significance of lagged dependent variables between column (1)/(3) and column (2)/(4) implies that dynamics contribute only to focal firms' outcomes, but not to peers.

reference group selection and decisions of interest (self-selection problem). While the former can be partially solved by adding reference group level observables or fixed effects, the latter demands carefully designed instruments. Provided that peer effects through interlocks have been established in previous analysis and that majority of interlocks are across industries/locations, we propose instruments which allow us to overcome potential common factors, on top of controlling for reference group $\times$ time fixed effects.

The instruments are in the spirit of Bramoulle et al. (2009). The idea is to exploit exogenous characteristics of peers' peers to control for endogeneity problem. Exclusive conditions come from "uniqueness" of peers' peers, which is presumably orthogonal to focal firms' decision of interest. To be concrete, the instrument is the average R&D spending of industry-peers' interlocked firms who do not operate in the same two-digit industries as both focal and peer firms. Similarly, in case of geographical oriented peer effects, the instrumental variable is average R&D of peers' peer whose head-quarters are located in different provinces than focal and peer firms. This instrument is valid. On the one hand, the existence of peer effects through social network implies correlation to endogenous peers' R&D. On the other hand, operation across sectors and locations introduces exogenous elements, independent of industry or location specific common effects. In order to further avoid the pseudo causality stemming from some common institutional factors (e.g., industry motivates firms to select interlocked firms in a particular pattern or any other industry oriented self-selection problems), $Year \times IND$ (two-digit) and $Year \times LOCA$ (Province) fixed effects are included.

The results of industry oriented peer effects are reported in the Table 3.14. In specification of column (1) and (2), samples are restrained to only those industry-peers who are interlocked to at least one firm. According to the first-stage estimates, the instrument is positively correlated to endogenous *PeerR&D_IND*, as suggested by the previous positive interlock peer effects. According to Kleibergen-Paap statistics, inclusion of hundreds fixed effects clearly attenuates the instrument's explanatory power, which might incur some concerns over weak instrument problem. In column (2), except for *PeerDebt*, the estimated coefficients of peer measures in the second stage are all insignificant. The insignificance indicates that industry-level common factors are mostly controlled, which frees our estimates from correlated effects. Negative industry peer effects are reported in column (1), suggesting that upon observing increase in R&D investment from industry peers, focal firms respond by lowering their own R&D spendings, a gesture of accommodating competition (Sundaram et al., 1996). In other words, the innovation strategies among Chinese firms are in essence strategic substitutes. This result matches empirical findings that Chinese listed companies are mainly characterized by average negative competitive strategy measures (CSM)[22], i.e., firms competing in strategic substitutes with industry peers (Liu and Lian, 2012). It is worth mentioning that the negative sign automatically excludes correlated effects as an alternative explanation since exposure to common environments only renders co-movement.

Results of comparable empirical setting with geographical peers are displayed in column (3) and (4). Despite the weak power of our instrument, the first stage coefficient has positive sign, echoing well with our previous findings of peer effects among interlocks. Province common factors seem to be captured by fixed effects, as is implied by the insignificance of all four peer measures. In the second stage, positive sign of IV estimates is observed, confirming the positive "co-agglomerate effects" in innovation activities suggested by Jaffe et al. (1993); Audretsch and Feldman (1996). Meanwhile firms' R&D investments do not seem to significantly boost neighbors' R&D strategies[23]. The knowledge or information interactions due to local commonality does not contribute to innovation strategy in Chinese context, as opposed to Glaeser et al. (1992). Sample selection of only large and listed firms who have sufficient information and thus have lower desire for local externalities can be a plausible reason.

In summary, based on inter-industry/province interlocked peers as instruments to overcome identification problems, we find negative peer effects in R&D investment at industry level and weakly positive spillover effects within provinces. However, we need to be cautious about the interpretation of this finding provided the low explanatory power of the instruments.

3.8 Conclusion

This paper investigates whether interlocked peers' decisions exert influence on firm R&D decisions and why such peer effects arise. In order to overcome the self-selective interlocks, we exploit a quasi-experiment event based on a Chinese policy intervention to fight against corruption. More specifically, the Chinese government imposed a regulation on senior officers in the party, public institutions (universities, research institutes) and state-owned enterprises, demanding them cease their service as independent directors on boards in listed companies. This generates exogenous disconnections of interlocks among firms if the resigned independent directors were

[22]Applying proposed methodology by Sundaram et al. (1996) on data of Chinese listed companies over 1999-2009 yields average/median CSM of -0.029/-0.022, respectively. Almost 60% of observations are characterized by negative CSM, especially in major industries like manufacturing.

[23]One thing worth noting is that the significance level of estimates *PeerR&D* does not agree with OLS estimation, where point estimates are 0.167 and significant at 0.001 level. This discordance highlights the importance of tackling correlated effects problem to the investigation of causal peer effects.

bridging multiple firms. Based on an instrument capturing the variation in peers' R&D induced by the lost peers, we are able to identify peer effects in R&D expenditure decisions among interlocked firms. Our results provide evidence that peer effects do exist. 1% increase in peers' R&D spending leads focal firms to raise R&D by, on average, 0.39% and vice versa. Difference-in-Difference analysis using pairwise model corroborates by showing that policy induced interlock breaks render more idiosyncratic innovation investments.

In addition, such peer effects are not evenly distributed among firms. Firms who are located more centrally in the network, who operate under pressure of fierce competition, who are interlocked to more peers and who have access to peers with more diverse industrial backgrounds, tend to be characterized by stronger interdependency in innovation strategies. These findings are more consistent with the learning arguments. The information spillover effects, in turn, reinforce the function of advisory channel in Chinese context. Moreover, as opposed to both strategic predatory and CEO reputation building theory, financially vulnerable firms and firms with more ambitious CEOs are no more sensitive to peer decisions than their counterparts.

Finally, further extensions to different network structures, innovation performance and reference groups are conducted. Peer effects are strong when peers consist of only inter-industry firms, but not so when peers are from the same industry. Replacing direct peers with second-degree peers, we find non-trivial influence of indirectly interlocked firms' decisions on focal firms, suggesting corporate decisions' interconnectedness can be further spread to the global network. Furthermore, the observation of positive peer effects in invention grants and negative peer effects in invention rejections is consistent with efficiency effects of peer effects in innovation input on patent output. Building on presence of peer effects through interlocks, our results point to a negative and prominent effects of industry peers on R&D policy. The sign implies that focal firms accommodate peers' aggressive R&D investment by lowering own R&D spendings, a sign of strategic substitutes. In addition, positive albeit weak neighborhood effects have been identified. Contrary to the theory of Glaeser et al. (1992), synergy effects due to technological and informational geographic externalities do not appear among Chinese listed firms.

Our results have some important policy implications. Firstly, for policy makers, the peer effects matter and should be taken into consideration when designing policies. Some exogenous shocks do not only affect firm at individual level, but also cause more violent fluctuations at aggregate level due to the spillover effects, an inherited attribute of peer effects. Secondly, the information flow within networks can be controlled to achieve particular goals. For instance, given the network structure, by selecting the location of information disclosure source, direction, path or even speed of information transmission can be partially manipulated. Thirdly, though with good intention, some unexpected costs of policies should also be taken into account. In our case, aiming at fighting against corruption and benefiting Chinese economy and listed firms in the long run, the policy, nevertheless, artificially blocks the valuable information exchange channel and ultimately renders more idiosyncratic decisions. Regarding firms, the most important message is that the decisions are not bounded only within individual firms but rather embedded in a broader network. The knowledge of this fact helps decision makers to process the innovation decision in a more systematic manner. Another important message is that peer effects spur firms innovation performance. Together with learning explanation, the soft albeit valuable information through independent directors matters in supporting innovation activities. The key question follows for companies is how to sustain such mutual-beneficial information exchange mechanism. Moreover, firms have already strategically selected interlocks and should continue doing so to meet customized needs for special strategic plans.

Bibliography

Adams, Rene B and Daniel Ferreira, "A Theory of Friendly Boards," *The Journal of Finance*, 2007, *62* (1), 217–250.

_ , Benjamin E Hermalin, and Michael S Weisbach, "The Role of Boards of Directors in Corporate Governance: A Conceptual Framework and Survey," *Journal of Economic Literature*, 2010, *48* (1), 58–107.

Adhikari, Binay K. and Anup Agrawal, "Peer Influence on Payout Policies," *Journal of Corporate Finance*, 2018, *48*, 615 – 637.

Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt, "Competition and Innovation: an Inverted-U Relationship*," *The Quarterly Journal of Economics*, 2005, *120* (2), 701–728.

Angrist, Joshua D and Joern-Steffen Pischke, *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton, NJ: Princeton university press, 2008.

Argyris, Chris, "Single-Loop and Double-Loop Models in Research on Decision Making," *Administrative Science Quarterly*, 1976, *21* (3), 363–375.

Audretsch, David B. and Maryann P. Feldman, "R&D Spillovers and the Geography of Innovation and Production," *The American Economic Review*, 1996, *86* (3), 630–640.

Balsmeier, Benjamin, Achim Buchwald, and Joel Stiebale, "Outside Directors on the Board and Innovative Firm Performance," *Research Policy*, 2014, *43* (10), 1800–1815.

_, Lee Fleming, and Gustavo Manso, "Independent Boards and Innovation," *Journal of Financial Economics*, 2017, *123* (3), 536 – 557.

Banerjee, Ritesh, Cohen-Cole Ethan, and Zanella Giulio, "Demonstration Effects in Preventive Care," *FRB and Boston Quantitative Analysis Unit Working Paper*, 2007, *QAU7* (6), 1–43.

Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch, "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades," *Journal of Political Economy*, 1992, *100* (5), 992–1026.

Billett, Mattew T, Jon A Garfinkel, and Yi Jiang, "The Channels of Capital Supply, Financial Intermediates, and Competition in Peer Effects," *SSRN working papers*, 2017, pp. 1–59.

Bird, Andrew, Alexander Edwards, and Thomas G. Ruchti, "Taxes and Peer Effects," *The Accounting Review, Forthcoming*, 2018, pp. 1–41.

Bolton, Patrick and David S. Scharfstein, "A Theory of Predation Based on Agency Problems in Financial Contracting," *The American Economic Review*, 1990, *80* (1), 93–106.

Bramoulle, Yann, Habiba Djebbari, and Bernard Fortin, "Identification of Peer Effects Through Social Networks," *Journal of Econometrics*, 2009, *150* (1), 41 – 55.

Brian, Boyd, "Corporate Linkages and Organizational Environment: A Test of the Resource Dependence Model," *Strategic Management Journal*, 1990, *11* (6), 419–430.

Brown, James R. and Bruce C. Petersen, "Cash Holdings and R&D Smoothing," *Journal of Corporate Finance*, 2011, *17* (3), 694 – 709.

Brown, Jennifer L and Katharine D Drake, "Network Ties Among Low-Tax Firms," *The Accounting Review*, 2014, *89* (2), 483–510.

Bursztyn, Leonardo, Florian Ederer, Bruno Ferman, and Noam Yuchtman, "Understanding Mechanisms Underlying Peer Effects: Evidence From a Field Experiment on Financial Decisions," *Econometrica*, 2014, *82* (4), 1273–1301.

Bustamante, Maria Cecilia and Laurent Fresard, "Does Firm Investment Respond to Peers' Investment?," *SSRN working papers*, 2018, pp. 1–60.

Chan, Kenneth S., Vinh Q.T. Dang, and Isabel K.M. Yan, "Chinese Firms' Political Connection, Ownership, and Financing Constraints," *Economics Letters*, 2012, *115* (2), 164 – 167.

Chan, Tat Y., Jia Li, and Lamar Pierce, "Compensation and Peer Effects in Competing Sales Teams," *Management Science*, 2014, *60* (8), 1965–1984.

Chen, Hsiang-Lan and Wen-Tsung Hsu, "Family Ownership, Board Independence, and R&D Investment," *Family Business Review*, 2009, *22* (4), 347–362.

Chen, Shenglan and Hui Ma, "Peer Effects in Decision-making: Evidence from Corporate Investment," *China Journal of Accounting Research*, 2017, *10* (2), 167 – 188.

Chuluun, Tuugi, Andrew Prevost, and Arun Upadhyay, "Firm Network Structure and Innovation," *Journal of Corporate Finance*, 2017, *44*, 193 – 214.

Clarke, Donald C, "The Independent Director in Chinese Corporate Governance," *Delaware Journal of Corporate Law*, 2006, *31* (1), 125–228.

Core, John, Inna Abramova, and Rodrigo Verdi, "Geographic Spillovers and Corporate Decisions," *SSRN Working paper*, 2016, pp. 1–33.

D, Baysinger Barry, Kosnik Rita D, and Turk Thomas A, "Effects of Board and Ownership Structure on Corporate R&D Strategy," *Academy of Management Journal*, 1991, *34* (1), 205–214.

Deutsch, Yuval, "The Impact of Board Composition on Firms' Critical Decisions: A Meta-Analytic Review," *Journal of Management*, 2005, *31* (3), 424–444.

Dodgson, Mark, "Organizational Learning: A Review of Some Literatures," *Organization Studies*, 1993, *14* (3), 375–394.

Dougal, Casey, Christopher A Parsons, and Sheridan Ttitman, "Urban Vibrancy and Corporate Growth," *The Journal of Finance*, 2014, *70* (1), 163–210.

Duflo, Esther, Pascaline Dupas, and Michael Kremer, "Peer Effects, Teacher Incentives, and the Impact of Tracking: Evidence from a Randomized Evaluation in Kenya," *American Economic Review*, August 2011, *101* (5), 1739–74.

Evans, William N., Wallace E. Oates, and Robert M. Schwab, "Measuring Peer Group Effects: A Study of Teenage Behavior," *Journal of Political Economy*, 1992, *100* (5), 966–991.

Falato, Antonio, Dalida Kadyrzhanova, and Ugur Lel, "Distracted Directors: Does Board Busyness Hurt Shareholder Value?," *Journal of Financial Economics*, 2014, *113* (3), 404 – 426.

Faleye, Olubunmi, Rani Hoitash, and Udi Hoitash, "The Costs of Intense Board Monitoring," *Journal of Financial Economics*, 2011, *101* (1), 160 – 181.

Fama, Eugene F. and Michael C. Jensen, "Separation of Ownership and Control," *The Journal of Law and Economics*, 1983, *26* (2), 301–325.

Fan, Joseph P.H., T.J. Wong, and Tianyu Zhang, "Politically Connected CEOs, Corporate Governance, and Post-IPO Performance of China's Newly Partially Privatized Firms," *Journal of Financial Economics*, 2007, *84* (2), 330 – 357.

Fan, Yang and Mu-Jeung Yang, "Ties that Differentiate: How Board Networks Shape Innovation and Competitive Positioning," *Washington university working paper*, 2017, pp. 1–42.

Fracassi, Cesare, "Corporate Finance Policies and Social Networks," *Management Science*, 2017, *63* (8), 2420–2438.

Friedkin, Noah E., "Theoretical Foundations for Centrality Measures," *American Journal of Sociology*, 1991, *96* (6), 1478–1504.

Galbiati, Roberto and Giulio Zanella, "The Tax Evasion Social Multiplier: Evidence from Italy," *Journal of Public Economics*, 2012, *96* (5), 485 – 494.

Geoffrey, Martin, Goezuebueyuek Remzi, and Becerra Manuel, "Interlocks and Firm performance: The Role of Ucertainty in the Directorate Interlock-performance Relationship," *Strategic Management Journal*, 2013, *36* (2), 235–253.

Glaeser, Edward L., Bruce I. Sacerdote, and Jose A. Scheinkman, "The Social Multiplier," *Journal of the European Economic Association*, 2003, *1* (2), 345–353.

_ **, Hedi D. Kallal, Jose A. Scheinkman, and Andrei Shleifer**, "Growth in Cities," *Journal of Political Economy*, 1992, *100* (6), 1126–1152.

Graham, Bryan S., "Identifying Social Interactions Through Conditional Variance Restrictions," *Econometrica*, 2008, *76* (3), 643–660.

Grennan, Jillian, "Dividend Payments as a Response to Peer Influence," *Journal of Financial Economics*, 2019, *131* (3), 549 – 570.

Gul, Ferdinand A, Donghui Wu, and Zhifeng Yang, "Do Individual Auditors Affect Audit Quality? Evidence from Archival Data," *The Accounting Review*, 2013, *88* (6), 1993–2023.

Haunschild, Pamela R. and Christine M. Beckman, "When Do Interlocks Matter?: Alternate Sources of Information and Interlock Influence," *Administrative Science Quarterly*, 1998, *43* (4), 815–844.

Helmers, Christian, Manasa Patnam, and P. Raghavendra Rau, "Do Board Interlocks Increase Innovation? Evidence from a Corporate Governance Reform in India," *Journal of Banking and Finance*, 2017, *80*, 51 – 70.

Hoskisson, Robert E, Michael A Hitt, Richard A Johnson, and Wayne Grossman, "Conflicting Voices: The Effects of Institutional Ownership Heterogeneity and Internal Governance on Corporate Innovation Strategies," *Academy of Management journal*, 2002, *45* (4), 697–716.

Jaffe, Adam B., Manuel Trajtenberg, and Rebecca Henderson, "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations*," *The Quarterly Journal of Economics*, 1993, *108* (3), 577–598.

John, Kose and Dalida Kadyrzhanova, "Peer Effects in Corporate Governance," *SSRN Working paper*, 2008, pp. 1–47.

Kamien, Morton I., Eitan Muller, and Israel Zang, "Research Joint Ventures and R&D Cartels," *The American Economic Review*, 1992, *82* (5), 1293–1306.

Kang, Jun-Koo, Wei-Lin Liu, Angie Low, and Le Zhang, "Friendly Boards and Innovation," *Journal of Empirical Finance*, 2018, *45*, 1 – 25.

Kaustia, Markku and Ville Rantala, "Social Learning and Corporate Peer Effects," *Journal of Financial Economics*, 2015, *117* (3), 653 – 669.

Kor, Yasemin Y, "Direct and Interaction Effects of Top Management Team and Board Compositions on R&D Investment Strategy," *Strategic Management Journal*, 2006, *27* (11), 1081–1099.

Kremer, Michael and Dan Levy, "Peer Effects and Alcohol Use among College Students," *Journal of Economic Perspectives*, 2008, *22* (3), 189–206.

Leary, Mark T and Michael R Roberts, "Do Peer Firms Affect Corporate Financial Policy?," *The Journal of Finance*, 2013, *69* (1), 139–178.

Leiponen, Aija, "Skills and Innovation," *International Journal of Industrial Organization*, 2005, *23* (5), 303 – 323.

_ **and Constance E. Helfat**, "Innovation Objectives, Knowledge Sources, and the Benefits of Breadth," *Strategic Management Journal*, 2009, *31* (2), 224–236.

Lin, Hui, Youyang Xu, and Feng Liu, "An Empirical Study on Framing Effects in China's Capital Market," *Economic Research Journal*, 2016, (12), 161–175.

Liu, Fengliang and Hongquan Lian, "The Relationship Between the Competitive Strategy in Product Market and Financing Decision," *Journal of Business Economic (in Chinese)*, 2012, *244* (2), 44–52.

Luca, Luigi M. De and Kwaku Atuahene-Gima, "Market Knowledge Dimensions and Cross-Functional Collaboration: Examining the Different Routes to Product Innovation Performance," *Journal of Marketing*, 2007, *71* (1), 95–112.

Luis, Diestre and Rajagopalan Nandini, "Are All Sharks Dangerous? New Botechnology Ventures and Partner Selection in R&D Alliances," *Strategic Management Journal*, 2012, *33* (10), 1115–1134.

Manski, Charles F., "Identification of Endogenous Social Effects: The Reflection Problem," *The Review of Economic Studies*, 1993, *60* (3), 531–542.

Martin, Stephen, "R & D Joint Ventures and Tacit Product Market Collusion," *European Journal of Political Economy*, 1996, *11* (4), 733 – 741.

Mas, Alexandre and Enrico Moretti, "Peers at Work," *American Economic Review*, 2009, *99* (1), 112–45.

Mazzola, Erica, Giovanni Perrone, and Dzidziso Samuel Kamuriwo, "The Interaction Between Inter-firm and Interlocking Directorate Networks on Firm's New Product Development Outcomes," *Journal of Business Research*, 2016, *69* (2), 672 – 682.

Patnam, Manasa, "Corporate Network and Peer Effects in Firm Policies," *Working paper*, 2013, pp. 1–61.

Petersen, Mitchell A., "Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches," *The Review of Financial Studies*, 2009, *22* (1), 435–480.

Qing, Ye, Liangyu Zhao, and Sichen Liu, "A Study of Politician-to-firm Revolving Door of Independent Directors: Evidence from a Natural Experiment," *Economic Research (in Chinese)*, 2016, (6), 98–113.

Renneboog, Luc and Yang Zhao, "Us Knows Us in the UK: On Director Networks and CEO Compensation," *Journal of Corporate Finance*, 2011, *17* (4), 1132 – 1157.

Riitta, Katila, Rosenberger Jeff, and Eisenhardt Kathleen, "Swimming with Sharks: Technology Ventures, Defense Mechanisms and Corporate Relationships," *Administrative Science Quarterly*, 2008, *53* (2), 295–332.

Sacerdote, Bruce, "Peer Effects with Random Assignment: Results for Dartmouth Roommates*," *The Quarterly Journal of Economics*, 2001, *116* (2), 681–704.

Scharfstein, David S. and Jeremy C. Stein, "Herd Behavior and Investment," *The American Economic Review*, 1990, *80* (3), 465–479.

Sinkula, James M., "Market Information Processing and Organizational Learning," *Journal of Marketing*, 1994, *58* (1), 35–45.

Sundaram, Anant K., Teresa A. John, and Kose John, "An Empirical Analysis of Strategic Competition and Firm Values the Case of R&D Competition," *Journal of Financial Economics*, 1996, *40* (3), 459 – 486.

Thomas, Dalziel, Gentry Richard J, and Bowerman Michael, "An Integrated Agency-Resource Dependence View of the Influence of Directors' Human and Relational Capital on Firms' R&D Spending," *Journal of Management Studies*, 2011, *48* (6), 1217–1242.

Trogdon, Justin G., James Nonnemaker, and Joanne Pais, "Peer Effects in Adolescent Overweight," *Journal of Health Economics*, 2008, *27* (5), 1388 – 1399.

Waldinger, Fabian, "Peer Effects in Science: Evidence from the Dismissal of Scientists in Nazi Germany," *The Review of Economic Studies*, 2012, *79* (2), 838–861.

Wong, Ling Heng Henry, Andre F. Gygax, and Peng Wang, "Board Interlocking Network and the Design of Executive Compensation Packages," *Social Networks*, 2015, *41*, 85 – 100.

Zimmerman, David J., "Peer Effects in Academic Outcomes: Evidence from a Natural Experiment," *The Review of Economics and Statistics*, 2003, *85* (1), 9–23.

Tables

Table 3.1: Descriptive statistics

Variable	Description	Mean	Std. Dev	25 th	Median	75 th	Obs
R&D	R&D in Chinese Yuan (level)	1.19e+08	2.97e+08	1.73e+07	3.93e+08	9.11e+07	7,609
	Natural logarithm of R&D (in level)	17.50	1.43	16.67	17.49	18.32	7,609
	Natural logarithm of R&D (in First Difference)	0.14	0.50	-0.04	0.11	0.30	5,160
PeerR&D	R&D in Chinese Yuan (level)	1.41e+08	2.62e+08	3.20e+07	6.28e+07	1.21e+08	7,677
	Natural logarithm of the mean of interlocked peers' R&D (in level)	18.00	1.15	17.28	17.96	18.61	7,677
	Natural logarithm of the mean of interlocked peers' R&D (in First Difference)	0.174	0.90	-0.17	0.13	0.48	5,232
IV R&D	Natural logarithm of the mean of lost interlocked peers' R&D (in level)	1.57	5.10	0	0	0	7,706
Size	Total asset in absolute terms (RMB)	1.03e+10	4.22e+10	1.27e+9	2.54e+09	5.74e+09	7,706
	Natural logarithm of *Size*	21.85	1.24	20.96	21.66	22.47	7,706
Tang	Fixed asset/total asset	0.22	0.15	0.11	0.19	0.31	7,706
Debt	Total book liability/Total book asset	0.40	0.20	0.23	0.38	0.55	7,706
Cash	Cash and cash equivalents / Total book asset	0.191	0.15	0.08	0.14	0.26	7,705
PeerSize	Mean of peers' *Size*	21.92	0.94	21.3	21.84	22.39	7,706
PeerTang	Mean of peers' *Tang*	0.22	0.10	0.15	0.21	0.28	7,706
PeerDebt	Mean of peers' *Debt*	0.41	0.14	0.31	0.41	0.49	7,706
PeerCash	Mean of peers' *Cash*	0.19	0.11	0.11	0.16	0.23	7,705

Table 3.2: Balancing test between control and treatment firms

Panel A (Year=2013)	Treatment group		Control group		Difference	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	t-value
$\Delta R\&D$	0.15	0.53	0.14	0.51	-0.015	-0.42
$\Delta PeerR\&D$	0.17	0.77	0.17	0.87	-0.001	-0.02
$\Delta Size$	0.12	0.16	0.12	0.20	0.002	0.16
$\Delta Tang$	0.011	0.066	0.014	0.069	0.003	0.71
$\Delta Debt$	0.02	0.06	0.015	0.07	-0.005	-0.93
$\Delta Cash$	-0.033	0.09	-0.04	0.09	-0.01	1.60
Panel B (Year=2014)	Treatment group		Control group		Difference	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	t-value
$\Delta R\&D$	0.12	0.43	0.126	0.57	0.009	0.25
$\Delta PeerR\&D$	0.13	0.84	0.17	0.94	0.044	0.75
$\Delta Size$	0.13	0.26	0.16	0.26	0.02	1.24
$\Delta Tang$	0.0004	0.07	0.004	0.06	0.003	0.74
$\Delta Debt$	0.01	0.08	0.006	0.003	-0.004	-0.75
$\Delta Cash$	-0.024	0.08	-0.023	0.08	0.001	0.19

$^{***}, ^{**}, ^{*}$ indicates significance level of 1%, 5%, 10%.

T values listed above are based on two sided t-tests.

All variables above are measured in first differences.

Table 3.3: Peer effects in R&D investment based on reduced-form estimates

							Placebo-test
	R&D	*R&D*	*R&D*	Δ*R&D*	Δ*R&D*	Δ*R&D*	Δ*R&D*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IV R&D	-0.006***	-0.0055***	-0.0055***	-0.006***	-0.006***	-0.006***	0.0008
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.0018)
Size		0.51***	0.52***		0.37***	0.37***	0.37***
		(0.06)	(0.06)		(0.05)	(0.05)	(0.05)
Tang		0.17	0.18		0.25*	0.23*	0.24*
		(0.19)	(0.19)		(0.13)	(0.13)	(0.13)
Debt		-0.04	-0.04		-0.14	-0.15	-0.16
		(0.15)	(0.15)		(0.14)	(0.14)	(0.14)
Cash		-0.23**	-0.23**		-0.23**	-0.25***	-0.25***
		(0.11)	(0.11)		(0.09)	(0.09)	(0.09)
PeerSize			0.044**			0.05***	0.05***
			(0.018)			(0.02)	(0.017)
PeerTang			0.05			0.06	0.06
			(0.13)			(0.14)	(0.14)
PeerDebt			-0.004			-0.06	-0.05
			(0.10)			(0.09)	(0.09)
PeerCash			0.09			0.08	0.08
			(0.11)			(0.10)	(0.10)
Firm fixed effect	Yes	Yes	Yes	No	No	No	No
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-value	61.12	53.21	39.16	6.35	9.73	7.99	6.89
Obs	5,202	5,059	5,032	5,160	3,190	3,165	3,165

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

Except for contemporaneous *PeerR&D*, all other controls are one year lagged.

In column (1) through (3), R&D are measured in levels and fixed effects IV model is applied.

In column (4) through (7), R&D are measured in first differences and pooled IV model is applied.

In column (7), drop-outs are randomly assigned.

Table 3.4: Peer effects in R&D investment based on instrumental variable estimates

	R&D (1)	First-stage (2)	*R&D* (3)	First-stage (4)	*R&D* (5)	First-stage (6)	Δ*R&D* (7)	First-stage (8)	Δ*R&D* (9)	First-stage (10)	Δ*R&D* (11)	First-stage (12)
PeerR&D	0.40**		0.38**		0.36**		0.35***		0.37***		0.39***	
	(0.17)		(0.16)		(0.15)		(0.11)		(0.11)		(0.13)	
IV R&D		-0.014***		-0.014***		-0.015***		-0.017***		-0.017***		-0.016***
		(0.004)		(0.004)		(0.004)		(0.003)		(0.004)		(0.004)
Size			0.50***	0.023	0.52***	-0.016			0.37***	-0.001	0.37***	0.004
			(0.066)	(0.077)	(0.07)	(0.075)			(0.05)	(0.07)	(0.05)	(0.07)
Tang			0.23	-0.16	0.23	-0.134			0.23	0.04	0.22	0.045
			(0.20)	(0.23)	(0.11)	(0.20)			(0.15)	(0.22)	(0.15)	(0.22)
Debt			-0.02	-0.033	-0.03	-0.019			-0.09	-0.13	-0.11	-0.11
			(0.17)	(0.26)	(0.17)	(0.26)			(0.16)	(0.23)	(0.16)	(0.23)
Cash			-0.09	-0.36*	-0.10	-0.35*			-0.20*	-0.07	-0.22*	-0.06
			(0.14)	(0.21)	(0.14)	(0.21)			(0.11)	(0.19)	(0.11)	(0.19)
PeerSize					-0.02	0.17***					0.06***	-0.032
					(0.03)	(0.033)					(0.02)	(0.03)
PeerTang					0.29	-0.67***					0.19	-0.32
					(0.18)	(0.22)					(0.17)	(0.21)
PeerDebt					0.20	-0.56***					0.11	-0.44***
					(0.14)	(0.18)					(0.12)	(0.17)
PeerCash					0.32*	-0.61***					-0.26*	-0.47**
					(0.16)	(0.20)					(0.14)	(0.19)
Firm fixed effect	Yes		Yes		Yes		No		No		No	
Year fixed effect	Yes		Yes		Yes		Yes		Yes		Yes	
Kleibergen-Paap rk Wald F	15.09		14.31		16.26		29.70		23.20		22.05	
Obs	4,859		4,707		4,674		5,140		3,187		3,162	

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

Except for contemporaneous *PeerR&D*, all other controls are one year lagged.

Table 3.5: Balancing test at pair level

Variables	Treatment group	Control group	difference	t-test
Panel A: Without matching				
Diff_R&D	0.59	0.57	0.02	0.77
Diff_Size	0.70	0.72	-0.02	-1.00
Diff_Tang	0.12	0.11	0.017***	3.07
Diff_Debt	0.20	0.20	0.006	0.78
Diff_Cash	0.78	0.64	0.14***	3.45
Panel B: With matching				
Diff_R&D	0.57	0.6	-0.03	1.13
Diff_Size	0.72	0.7	0.023	0.96
Diff_Tang	0.11	0.11	-0.003	0.47
Diff_Debt	0.19	0.19	0.01	0.05
Diff_Cash	0.63	0.63	-0.01	0.06

***,**,* indicate a significance at level of 1%, 5% and 10%.

Table 3.6: Difference-in-Difference estimation based on pair information

	Treatment group	Control group	difference	P-val
Panel A	Non-matching & without Covariates			
Baseline	0.57	0.59	-0.02	0.45
Follow-up	0.61	0.58	0.03	0.18
Diff-in-Diff			0.051**	0.022
Panel B	Non-matching & with Covariates			
Baseline	0.5	0.52	-0.025	0.3
Follow-up	0.52	0.49	0.03	0.17
Diff-in-Diff			0.057*	0.09
Panel C	Matching based on kernel Propensity Score			
Baseline	0.57	0.6	-0.03	0.26
Follow-up	0.61	0.57	0.04	0.07*
Diff-in-Diff			0.066**	0.04

**,* indicate a significance at level of 1%, 5%.

Table 3.7: Difference-in-Difference estimation using OLS

	(1)	(2)	(3)	(4)
Dummy_Post	-0.012 (0.017)	-0.017 (0.015)	-0.022 (0.019)	-0.022 (0.021)
$Dummy\_Post \times Dummy\_Treat$	0.055* (0.041)	0.046* (0.025)	0.061** (0.031)	0.061* (0.036)
$Diff\_Size$		0.06** (0.03)	0.18** (0.09)	0.18** (0.09)
$Diff\_Tang$		0.13 (0.11)	-0.01 (0.19)	-0.01 (0.19)
$Diff\_Debt$		-0.052 (0.10)	-0.17 (0.17)	-0.17 (0.18)
$Diff\_Cash$		-0.03 (0.02)	-0.029 (0.030)	-0.025 (0.032)
Cluster Choice	Pair	Pair	Pair	Two-way cluster
Pair fixed effect	Yes	No	Yes	Yes
Firm fixed effect	No	Yes	No	No
R-Squared	0.835	0.57	0.84	0.84
Obs	2,579	2,579	2,579	2,579

***,**,* indicates significance level of 1%, 5%, 10%.

All covariates are lagged one year.

Table 3.8: Heterogeneity effects: Network centrality

	Degree (1)	*Betweenness* (2)	*Closeness* (3)	*EigenVector* (4)
$PeerR\&D \times GroupL$	0.2	0.11	0.25*	0.33*
	(0.13)	(0.18)	(0.13)	(0.17)
$PeerR\&D \times GroupH$	0.57**	0.55***	0.50**	0.43**
	(0.24)	(0.19)	(0.22)	(0.18)
GroupL	0.03	0.03	0.02	-0.002
	(0.03)	(0.04)	(0.03)	(0.03)
Size	0.37***	0.36***	0.37***	0.36***
	(0.06)	(0.06)	(0.06)	(0.06)
Tang	0.23	0.25	0.24	0.21
	(0.16)	(0.16)	(0.16)	(0.16)
Debt	-0.17	-0.15	-0.18	-0.15
	(0.18)	(0.17)	(0.18)	(0.18)
Cash	-0.29**	-0.28**	-0.29**	-0.29**
	(0.13)	(0.12)	(0.13)	(0.13)
PeerSize	0.06**	0.05**	0.06**	0.06**
	(0.02)	(0.02)	(0.02)	(0.02)
PeerTang	0.12	0.11	0.14	0.14
	(0.18)	(0.18)	(0.18)	(0.18)
PeerDebt	0.04	0.07	0.04	0.03
	(0.13)	(0.13)	(0.13)	(0.13)
PeerCash	0.33**	0.31**	0.32**	0.30
	(0.15)	(0.15)	(0.15)	(0.15)
Kleibergen-Paap rk Wald F Statistic	9.43	3.47	5.04	10.52
Firm fixed effect	Yes	Yes	Yes	Yes
Obs	2,864	2,864	2,864	2,864

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

Except for endogenous variables, all other controls are one year lagged.

Table 3.9: Heterogeneity effects: Product competition, interlock counts and informational diversity

	Competition_LernerIndex	Interlock number	Informational diversity
	$\Delta R\&D$	$\Delta R\&D$	$\Delta R\&D$
	(1)	(2)	(3)
$PeerR\&D \times GroupL$	0.24*	0.28**	0.38**
	(0.13)	(0.14)	(0.19)
$PeerR\&D \times GroupH$	0.63**	0.54**	0.45**
	(0.27)	(0.25)	(0.20)
$GroupL$	0.07*	-0.01	-0.01
	(0.03)	(0.03)	(0.04)
$Size$	0.34***	0.36***	0.36***
	(0.07)	(0.06)	(0.06)
$Tang$	0.23	0.25	0.19
	(0.17)	(0.16)	(0.17)
$Debt$	-0.12	-0.14	-0.12
	(0.20)	(0.18)	(0.19)
$Cash$	-0.23*	-0.28**	-0.33**
	(0.13)	(0.13)	(0.13)
$PeerSize$	0.05**	0.05**	0.06**
	(0.02)	(0.02)	(0.02)
$PeerTang$	0.13	0.16	0.15
	(0.19)	(0.19)	(0.19)
$PeerDebt$	0.07	0.06	0.11
	(0.14)	(0.13)	(0.14)
$PeerCash$	0.30*	0.35**	0.37**
	(0.16)	(0.16)	(0.16)
Cragg-Donald Wald F Statistic	5.64	8.21	8.76
Year fixed effect	Yes	Yes	Yes
Obs	2,864	2,864	2,864

***,**,* indicates significance level of 1%, 5%, 10%.
Standard errors are clustered by firms and are reported in parentheses.
Except for endogenous variables, all other controls are one year lagged.
First stage results are reported in Table C10.

Table 3.10: Other possible mechanisms: Strategic predatory theory and CEO-level reputation building

	Strategic predatory theory			Reputation building		
	$\Delta R\&D$	$PeerR\&D \times GroupL$	$PeerR\&D \times GroupH$	$\Delta R\&D$	$PeerR\&D \times GroupL$	$PeerR\&D \times GroupH$
	(1)	(2)	(3)	(4)	(5)	(6)
$PeerR\&D \times GroupL$	0.44**			0.23*		
	(0.19)			(0.14)		
$PeerR\&D \times GroupH$	0.33**			0.62**		
	(0.16)			(0.31)		
$IV R\&D \times GroupL$		-0.016***	-0.0005		-0.019***	0.001
		(0.005)	(0.001)		(0.005)	(0.001)
$IV R\&D \times GroupH$		0.002*	-0.018***		0.00003	-0.015***
		(0.001)	(0.005)		(0.001)	(0.006)
$GroupL$	-0.008	0.13***	-0.16***	0.03	0.17***	-0.11***
	(0.03)	(0.02)	(0.02)	(0.04)	(0.02)	(0.03)
$Size$	0.36***	0.06	0.0003	0.37***	-0.003	0.03
	(0.06)	(0.05)	(0.06)	(0.07)	(0.06)	(0.06)
$Tang$	0.21	-0.04	0.04	0.18	0.05	0.03
	(0.16)	(0.15)	(0.17)	(0.19)	(0.18)	(0.18)
$Debt$	-0.14	-0.10	-0.01	-0.04	0.02	-0.16
	(0.18)	(0.15)	(0.22)	(0.22)	(0.20)	(0.18)
$Cash$	-0.30**	0.05	0.09	-0.33**	-0.02	0.11
	(0.13)	(0.13)	(0.15)	(0.15)	(0.16)	(0.16)
$PeerSize$	0.06**	-0.01	-0.02	0.04	-0.02	0.01
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
$PeerTang$	0.11	0.03	-0.25	0.15	-0.06	-0.16
	(0.19)	(0.15)	(0.16)	(0.22)	(0.17)	(0.17)
$PeerDebt$	0.04	-0.16	-0.18	0.12	-0.12	-0.27*
	(0.13)	(0.13)	(0.12)	(0.16)	(0.13)	(0.14)
$PeerCash$	0.28*	-0.04	-0.41***	0.38**	-0.40**	-0.02
	(0.16)	(0.14)	(0.15)	(0.17)	(0.16)	(0.14)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F		9.71			3.80	
Obs		2,864			2,447	

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

Except for endogenous variables, all other controls are one year lagged.

All variables are in first differences. Settings with level variables render similar results.

Table 3.11: Extensions to intra-industry peers VS inter-industry peers

	Intra-industry peers		Inter-industry peers	
	$\Delta R\&D$	First-stage	$\Delta R\&D$	First-stage
	(1)	(2)	(3)	(4)
PeerR&D	0.28		0.38**	
	(0.25)		(0.15)	
IVR&D		-0.022**		-0.016***
		(0.009)		(0.004)
Size	0.29***	0.18	0.38***	-0.02
	(0.10)	(0.17)	(0.06)	(0.08)
Tang	0.17	0.007	0.32**	-0.17
	(0.32)	(0.37)	(0.16)	(0.25)
Debt	-0.21	-0.19	-0.08	-0.07
	(0.29)	(0.56)	(0.18)	(0.25)
Cash	-0.18	0.24	-0.25**	0.01
	(0.24)	(0.31)	(0.12)	(0.20)
PeerSize	-0.02	0.17**	0.04**	-0.03
	(0.06)	(0.07)	(0.02)	(0.03)
PeerTang	0.20	-0.10	0.21	-0.27
	(0.25)	(0.34)	(0.17)	(0.21)
PeerDebt	-0.11	0.002	0.12	-0.46**
	(0.19)	(0.35)	(0.13)	(0.19)
PeerCash	0.02	-0.35	0.24*	-0.48**
	(0.25)	(0.39)	(0.14)	(0.20)
Year fixed effect	Yes		Yes	
Kleibergen-Paap rk Wald F	6.32		15.00	
Obs	654		2,910	

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

Except for contemporaneous *PeerR&D*, all other controls are one year lagged.

All variables are in first differences. Settings with level variables render similar results.

Table 3.12: Extensions to peer effects in R&D for second degree peers

	R&D (1)	First-stage (2)	$\Delta R\&D$ (3)	First-stage (4)
PeerR&D	0.73**		0.56***	
	(0.33)		(0.20)	
IVR&D		-0.009***		-0.012***
		(0.003)		(0.003)
Size	0.51***	-0.02	0.36***	-0.041
	(0.07)	(0.06)	(0.07)	(0.07)
Tang	-0.044	0.29	0.024	0.27
	(0.24)	(0.21)	(0.19)	(0.22)
Debt	-0.19	0.079	-0.37*	-0.28
	(0.22)	(0.20)	(0.22)	(0.21)
Cash	-0.018	-0.01	-0.016	-0.001
	(0.012)	(0.011)	(0.01)	(0.012)
PeerSize	-0.08	0.09***	0.08**	-0.121***
	(0.05)	(0.03)	(0.04)	(0.034)
PeerTang	0.13	-0.40*	0.10	-0.09
	(0.26)	(0.24)	(0.19)	(0.26)
PeerDebt	-0.017	-0.033	-0.14	0.032
	(0.18)	(0.20)	(0.14)	(0.20)
PeerCash	0.005	-0.011	0.008	-0.024
	(0.015)	(0.016)	(0.014)	(0.018)
FirmFE Fixed effect	Yes	Yes	No	No
YearFE Fixed effect	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F	8.31		14.38	
Obs	4,898		3,352	

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

Except for contemporaneous *PeerR&D*, all other controls are one year lagged.

Table 3.13: Extensions to innovation outcomes

	Invention grants		Invention rejections	
	Inv_Grt	First-stage	*Inv_Rej*	First-stage
	(1)	(2)	(3)	(4)
PeerInno	0.49**		-0.21*	
	(0.25)		(0.13)	
IVInno		-0.12***		-0.01***
		(0.02)		(0.001)
L.DepVar	0.17***	0.02	0.22***	0.003
	(0.02)	(0.02)	(0.02)	(0.01)
L2.DepVar	-0.01	-0.01	-0.08***	-0.01
	(0.02)	(0.02)	(0.02)	(0.01)
L3.DepVar	-0.12***	-0.02	-0.10***	-0.002
	(0.02)	(0.02)	(0.02)	(0.02)
Size	-0.06	-0.06	-0.06	0.003
	(0.06)	(0.07)	(0.05)	(0.06)
Tang	-0.06	0.33	0.01	0.20
	(0.25)	(0.23)	(0.21)	(0.20)
Debt	0.06	0.04	-0.11	-0.16
	(0.20)	(0.23)	(0.17)	(0.19)
Cash	-0.21	-0.04	-0.62***	-0.35**
	(0.19)	(0.20)	(0.16)	(0.16)
PeerSize	0.03	-0.05*	0.001	-0.04
	(0.03)	(0.03)	(0.02)	(0.02)
PeerTang	-0.13	0.06	0.16	0.16
	(0.19)	(0.20)	(0.15)	(0.18)
PeerDebt	-0.03	-0.28*	-0.20	-0.29*
	(0.17)	(0.17)	(0.14)	(0.15)
PeerCash	-0.05	-0.38*	-0.33*	-0.34*
	(0.22)	(0.21)	(0.18)	(0.18)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F	36.85		21.01	
Obs	6,358		6,358	

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

All variables are in first differences. Settings with level variables render similar results.

Table 3.14: Extensions to industry/geographical peers

	Industry peers		Geographical peers	
	$\Delta R\&D$	First-stage	$\Delta R\&D$	First-stage
	(1)	(2)	(3)	(4)
PeerR&D_IND	-0.88*		0.34	
	(0.51)		(0.30)	
IVR&D		0.14*		0.045***
		(0.07)		(0.014)
Size	0.26***	-0.017***	0.29***	0.039**
	(0.04)	(0.01)	(0.04)	(0.02)
Tang	0.20*	-0.036*	0.19	-0.16
	(0.11)	(0.02)	(0.13)	(0.10)
Debt	-0.15	-0.01	-0.07	0.09
	(0.14)	(0.013)	(0.14)	(0.07)
Cash	-0.01**	-0.0003	-0.01	0.001
	(0.004)	(0.001)	(0.004)	(0.003)
PeerSize	-0.023	-0.42*	0.042	-0.18***
	(0.27)	(0.23)	(0.06)	(0.04)
PeerTang	-0.74	-0.71*	-0.05	0.63**
	(0.81)	(0.41)	(0.27)	(0.30)
PeerDebt	-2.01**	-0.16	0.06	-0.07
	(0.064)	(0.40)	(0.18)	(0.22)
PeerCash	-0.037	-0.022	-0.001	-0.011
	(0.032)	(0.02)	(0.01)	(0.014)
$Year \times IND$ Fixed Effects	Yes	Yes	No	No
$Year \times LOCA$ Fixed Effects	No	No	Yes	Yes
Kleibergen-Paap rk Wald F	3.49		9.83	
Obs	4,910		4,316	

***,** ,* indicates significance level of 1%, 5%, 10%.
Standard errors are clustered by firms and are reported in parentheses.
All variables are in first differences. Settings with level variables render similar results.

3.9 Appendix

Test on the exogeneity of instrument

The exogeneity of instrument is tested in this table. Our instrument is regressed on measure of both focal and peer firms fundamentals. Although the dependent variable remains to be *IVR&D*, covariates in columns (1) and (3) are in levels, while covariates in the rest columns are in first differences. Independent variables in first two columns are taking contemporaneous values and lagged one year in last two columns.

Table C1: Exogeneity test of instrumental variable

	IVR&D	Δ*IVR&D*	*IVR&D*	Δ*IVR&D*
	Contemporaneous Vars.		One-year-lead Vars.	
	(1)	(2)	(3)	(4)
Size	-0.33	-0.16	0.001	0.13
	(0.27)	(0.37)	(0.39)	(0.30)
Tang	-0.95	-0.67	-0.47	0.69
	(1.22)	(1.20)	(1.39)	(1.01)
Debt	1.63*	0.88	0.41	0.21
	(0.89)	(0.97)	(1.08)	(0.76)
Cash	0.98	0.98	0.41	1.13*
	(0.88)	(0.83)	(1.10)	(0.65)
Firm fixed effect	Yes	No	Yes	No
Year fixed effect	Yes	Yes	Yes	Yes
Obs	7,499	5,058	5,130	5,058

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

Robustness checks

In Tables C2 and C3 we perform various robustness checks based on the specification in column (11) from Table 3.4, that is variables in first differences with both focal and peers' control variables. First stage results are listed next to the main IV results. In column (1), we add more controls from both sides, namely *Sale*, *ROA* and $Tobin'Q$. In column (3), one year lagged dependent variable is added to account for the dynamics. In column (5), we control for exogenous events from industry and year by supplementing $Ind * Year$ fixed effects. To further increase exogeneity, specification (7) differs in using R&D spending of lost peers in 2013, instead of value in 2014 as in the main analysis. Column (9) constructs the instrument based on only those events that explicitly attribute resignation to the policy enforcement. In last specification, we include the number of lost peers as another potential instrument choice. In Table C3, we replace R&D expenditure with controls, *Size*, *Tang*, *Debt* and *Cash*, to testify whether controls are sufficiently exogenous.

Table C2: Robustness checks of basic specification

	Δ*R&D* (1)	First-Stage (2)	Δ*R&D* (3)	First-Stage (4)	Δ*R&D* (5)	First-Stage (6)	Δ*R&D* (7)	First-Stage (8)	Δ*R&D* (9)	First-Stage (10)	Δ*R&D* (11)	First-Stage (12)
PeerR&D	0.38***		0.37***		0.30**		0.38***		0.38**		0.38***	
	(0.147)		(0.14)		(0.14)		(0.16)		(0.17)		(0.13)	
IVR&D		-0.016***		-0.016***		-0.015***		-0.01***		-0.015***		-0.018***
		(0.004)		(0.004)		(0.004)		(0.002)		(0.005)		(0.007)
IVLostPeer												0.01
												(0.06)
L.DepVar			-0.21***	-0.034								
			(0.07)	(0.035)								
Size	0.32***	-0.05	0.44***	0.018	0.34***	-0.04	0.37***	0.007	0.37***	0.01	0.37***	0.004
	(0.081)	(0.11)	(0.06)	(0.076)	(0.05)	(0.08)	(0.05)	(0.07)	(0.054)	(0.07)	(0.05)	(0.07)
Tang	0.30*	-0.058	0.24	0.017	0.19	0.07	0.22	0.08	0.22	0.05	0.22	0.04
	(0.16)	(0.24)	(0.15)	(0.22)	(0.14)	(0.23)	(0.15)	(0.22)	(0.15)	(0.22)	(0.15)	(0.22)
Debt	0.008	-0.12	-0.14	-0.10	-0.18	-0.09	-0.11	-0.11	-0.11	-0.15	-0.11	-0.11
	(0.20)	(0.34)	(0.16)	(0.24)	(0.15)	(0.25)	(0.16)	(0.23)	(0.16)	(0.23)	(0.16)	(0.23)
Cash	-0.167	0.04	-0.32***	-0.07	-0.20*	-0.07	-0.22*	-0.04	-0.22*	-0.06	-0.22*	-0.06
	(0.15)	(0.26)	(0.12)	(0.19)	(0.11)	(0.19)	(0.11)	(0.19)	(0.11)	(0.19)	(0.11)	(0.19)
PeerSize	0.007	0.009	0.063***	-0.034	0.056***	-0.04	0.06***	-0.03	0.06***	-0.03	0.06***	-0.03
	(0.04)	(0.07)	(0.02)	(0.03)	(0.02)	(0.03)	(0.021)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
PeerTang	0.011	-0.17	0.15	-0.32	0.18	-0.36*	0.19	-0.34	0.19	-0.35*	0.19	-0.32
	(0.187)	(0.24)	(0.16)	(0.21)	(0.16)	(0.21)	(0.17)	(0.21)	(0.18)	(0.21)	(0.17)	(0.21)
PeerDebt	0.047	-0.24	0.10	-0.46***	0.01	-0.31*	0.11	-0.43**	0.11	-0.44***	0.11	-0.44***
	(0.13)	(0.21)	(0.12)	(0.17)	(0.11)	(0.17)	(0.13)	(0.17)	(0.13)	(0.17)	(0.12)	(0.17)
PeerCash	0.19	-0.31	0.21	-0.49***	0.21	-0.50**	0.25*	-0.46**	0.25*	-0.47**	0.26*	-0.48**
	(0.17)	(0.23)	(0.13)	(0.19)	(0.13)	(0.20)	(0.15)	(0.19)	(0.15)	(0.19)	(0.14)	(0.19)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	No	No	No	No	No	No	No	No	No	No
$IND*Year$ FE	No	No	No	No	Yes	Yes	No	No	No	No	No	No
Cragg-Donald Wald F	19.82		21.46		17.05		21.37		10.09		11.03	
Hansen J Statistic											0.14, p-val=0.71	
Obs	2,498		3,145		3,162		3,162		3,162		3,162	

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

PeerR&D is contemporaneous and all other controls are one year lagged.

Except for instrument, all variables are in first differences. Accordingly, 2SLS model is applied.

Table C3: Robustness checks on other covariates

	Size (1)	First-Stage (2)	*Tang* (3)	First-Stage (4)	*Debt* (5)	First-Stage (6)	*Cash* (7)	First-Stage (8)
PeerDep	-0.16		0.02		0.004		-0.23	
	(0.23)		(0.18)		(0.16)		(0.38)	
IVDep		-0.005***		-0.088***		-0.078***		-0.079***
		(0.002)		(0.02)		(0.015)		(0.03)
Size			0.03***	-0.007	0.032***	-0.006	-0.04***	-0.002
			(0.007)	(0.007)	(0.01)	(0.01)	(0.008)	(0.007)
Tang	-0.27***	-0.16			-0.01	-0.051	0.02	0.027
	(0.09)	(0.17)			(0.03)	(0.22)	(0.026)	(0.03)
Debt	0.26***	0.03	-0.008	-0.09			0.05**	-0.007
	(0.09)	(0.18)	(0.02)	(0.24)			(0.02)	(0.021)
Cash	-0.22***	-0.18	-0.05***	-0.01	-0.12***	-0.015		
	(0.07)	(0.12)	(0.02)	(0.02)	(0.018)	(0.02)		
PeerSize			-0.008***	-0.001	-0.002	-0.006	-0.002	-0.005*
			(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
PeerTang	-0.06	-0.30**			-0.01	-0.025	0.014	0.05***
	(0.09)	(0.15)			(0.02)	(0.026)	(0.026)	(0.018)
PeerDebt	-0.11	-0.50***	0.03**	-0.31*			0.05	0.10***
	(0.13)	(0.11)	(0.01)	(0.17)			(0.04)	(0.018)
PeerCash	-0.19	-0.54***	0.033**	0.006	-0.006	-0.02		
	(0.14)	(0.14)	(0.015)	(0.02)	(0.016)	(0.03)		
Firm fixed effect	No	No	No	No	No	No	No	No
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F	5.73		18.26		26.94		7.47	
Obs	3,212		3,212		3,242		3,211	

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

PeerR&D is contemporaneous and all other controls are one year lagged.

Except for instrument, all variables are in first differences. Accordingly, 2SLS model is applied.

Table C4: Robustness checks on sample expansion and enriched instrument

	R&D	First-Stage	*R&D*	First-Stage	*ΔR&D*	First-Stage	*ΔR&D*	First-Stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$IV_{previous}$	$IV_{previous}$	$IV_{enriched}$	$IV_{enriched}$	$IV_{previous}$	$IV_{previous}$	$IV_{enriched}$	$IV_{enriched}$
PeerR&D	0.28*		0.29***		0.29*		0.26**	
	(0.16)		(0.11)		(0.16)		(0.12s)	
IV R&D		-0.014***		-0.017***		-0.007***		-0.008***
		(0.004)		(0.003)		(0.002)		(0.001)
Size	0.60***	-0.05	0.61***	-0.05	0.31***	-0.007	0.31***	-0.01
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
Tang	0.31*	-0.20	0.35**	-0.16	0.02	0.12	0.06	0.13
	(0.16)	(0.18)	(0.16)	(0.17)	(0.13)	(0.16)	(0.13)	(0.15)
Debt	-0.27**	-0.06	-0.29**	-0.10	-0.14	-0.14	-0.16*	-0.13
	(0.11)	(0.14)	(0.12)	(0.15)	(0.10)	(0.13)	(0.10)	(0.14)
Cash	-0.20*	-0.39***	-0.02*	-0.03***	-0.29***	-0.06	-0.02***	-0.005
	(0.12)	(0.14)	(0.01)	(0.01)	(0.08)	(0.12)	(0.006)	(0.01)
PeerSize	-0.07	0.32***	-0.08**	0.32***	0.02	-0.002	0.02	-0.003
	(0.05)	(0.02)	(0.04)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
PeerTang	0.12	-0.60***	0.15	-0.61***	0.09	-0.41***	0.08	-0.34**
	(0.14)	(0.17)	(0.13)	(0.16)	(0.12)	(0.14)	(0.11)	(0.14)
PeerDebt	0.08	-0.30***	0.12	-0.39***	0.08	-0.23***	0.08	-0.18
	(0.10)	(0.13)	(0.10)	(0.14)	(0.09)	(0.11)	(0.08)	(0.12)
PeerCash	0.02	-0.16	0.01	-0.03***	0.07	-0.35***	0.004	-0.01
	(0.12)	(0.16)	(0.01)	(0.01)	(0.12)	(0.14)	(0.007)	(0.01)
Firm fixed effect	Yes	Yes	Yes	Yes	No	No	No	No
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F	15.91		34.52		16.66		29.54	
Obs	8,511		8,500		6,360		6,354	

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

PeerR&D is contemporaneous and all other controls are one year lagged.

Except for instrument, all variables are matched with dependent variable at the table header.

Table C5: Placebo test with counter-factual data structure

	Reduced	Instrumental		Reduced	Instrumental	
	R&D	*R&D*	First-Stage	Δ*R&D*	Δ*R&D*	First-Stage
	(1)	(2)	(3)	(4)	(5)	(6)
PeerR&D		-0.001			-0.04	
		(0.13)			(0.13)	
IV R&D	0.0001		-0.013***	0.0005		-0.013***
	(0.002)		(0.004)	(0.002)		(0.004)
Size	0.39***	0.39***	0.02	0.29***	0.29***	0.01
	(0.06)	(0.06)	(0.10)	(0.06)	(0.06)	(0.10)
Tang	0.28	0.28	-0.45	0.25*	0.24	-0.37
	(0.17)	(0.18)	(0.31)	(0.15)	(0.16)	(0.31)
Debt	0.13	0.13	0.26	-0.008	0.01	0.46
	(0.17)	(0.17)	(0.36)	(0.15)	(0.16)	(0.31)
Cash	-0.07	-0.07	-0.56**	-0.09	-0.11	-0.50
	(0.12)	(0.15)	(0.27)	(0.10)	(0.12)	(0.23)
PeerSize	0.02	0.02	0.07	0.04**	0.04	-0.10**
	(0.03)	(0.03)	(0.04)	(0.02)	(0.02)	(0.04)
PeerTang	0.08	0.08	-0.32	0.007	0.01	0.14
	(0.16)	(0.17)	(0.30)	(0.13)	(0.13)	(0.30)
PeerDebt	0.12	0.13	-0.18	-0.07	-0.07	0.05
	(0.14)	(0.15)	(0.25)	(0.10)	(0.10)	(0.22)
PeerCash	0.16	0.17	-0.29	0.03	0.03	0.04
	(0.15)	(0.15)	(0.27)	(0.09)	(0.09)	(0.25)
Firm fixed effect	Yes	Yes	Yes	No	No	No
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F		10.37			10.00	
Obs	3,531	3,201		1,899	1,897	

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

PeerR&D is contemporaneous and all other controls are one year lagged.

Except for instrument, all variables are matched with dependent variable at the table header.

Table C6: First step of pair model methodology following equation (3)

	R&D
Size	0.86*** (0.023)
Tang	-0.54*** (0.19)
Debt	-0.98*** (0.014)
Cash	-0.04*** (0.007)
$Year \times IND$ (2-digit)	Yes
Obs	6,987

***,**,* indicates significance level of 1%, 5%, 10%.
The standard errors reported in parentheses are clustered at each firm level.
All controls are lagged one year.
Industry × Year fixed effects are included.

Table C7: Descriptive statistics of pair model

Variable	Description	Mean	Std. Dev	Median	Obs
$Diff\_R\&D$	$\ln(1+\text{abs}(\varepsilon_{i,t}\text{-}\varepsilon_{j,t}))$	0.589	0.39	0.534	2,578
$Diff\_Size$	$\ln(1+\text{abs}(Size_{i,t-1}\text{-}Size_{j,t-1}))$	0.696	0.42	0.662	2,806
$Diff\_Tang$	$\ln(1+\text{abs}(Tang_{i,t-1}\text{-}Tang_{j,t-1}))$	0.12	0.10	0.10	2,806
$Diff\_Debt$	$\ln(1+\text{abs}(Debt_{i,t-1}\text{-}Debt_{j,t-1}))$	0.196	0.13	0.174	2,790
$Diff\_Cash$	$\ln(1+\text{abs}(Cash_{i,t-1}\text{-}Cash_{j,t-1}))$	0.61	0.62	0.39	2,806

Table C8: Robustness of heterogeneity investigation on intra VS inter industry interlocks based on Difference-in-Difference setting

	Intra-industry interlocks only (1)	Inter-industry interlocks only (2)
Dummy_Post	0.019 (0.053)	-0.027 (0.02)
$Dummy\_Post \times Interlock$	0.038 (0.065)	0.064* (0.036)
$Diff\_Size$	0.049 (0.23)	0.20** (0.10)
$Diff\_Tang$	0.28 (0.37)	-0.07 (0.21)
$Diff\_Debt$	-0.15 (0.49)	-0.17 (0.18)
$Diff\_Cash$	0.001 (0.056)	-0.034 (0.033)
Pair fixed effect	Yes	Yes
R-Squared	0.88	0.83
Obs	393	2,186

***,**,* indicates significance level of 1%, 5%, 10%.
Standard errors are reported in parentheses, cluster at either pair level or by two-way algorithm
All covariates are lagged one year.

Table C9: First stage regression of Table 3.8

	Degree		*Betweenness*		*Closeness*		*EigenVector*	
	$End \times GroupL$	$End \times GroupH$	$End \times GroupL$	$End \times GroupH$	$End \times GroupL$	$End \times GroupH$	$End \times GroupL$	$End \times GroupH$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$IV R\&D \times GroupL$	-0.02***	-0.001	-0.017***	0.0002	-0.023***	-0.001	-0.02***	-0.0008
	(0.006)	(0.001)	(0.007)	(0.001)	(0.006)	(0.001)	(0.006)	(0.001)
$IV R\&D \times GroupH$	0.002*	-0.014***	0.001	-0.016***	0.002**	-0.013***	0.002**	-0.015***
	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)
$GroupL$	0.17***	-0.1***	0.18***	-0.10***	0.28***	-0.11***	0.18***	-0.12***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$Size$	0.06	0.004	0.03	0.03	0.06	0.001	0.06	-0.01
	(0.07)	(0.04)	(0.06)	(0.04)	(0.06)	(0.05)	(0.06)	(0.05)
$Tang$	0.05	-0.04	0.08	-0.07	0.11	-0.11	0.02	0.001
	(0.19)	(0.13)	(0.17)	(0.16)	(0.17)	(0.15)	(0.17)	(0.16)
$Debt$	-0.13	0.01	-0.06	-0.05	-0.22	0.10	-0.16	0.05
	(0.23)	(0.13)	(0.22)	(0.14)	(0.21)	(0.16)	(0.21)	(0.16)
$Cash$	0.10	0.05	0.10	0.06	0.11	0.04	0.12	0.03
	(0.17)	(0.12)	(0.16)	(0.13)	(0.16)	(0.13)	(0.16)	(0.13)
$PeerSize$	-0.02	-0.01	-0.02	-0.01	-0.008	-0.02	0.001	-0.03
	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
$PeerTang$	-0.12	-0.07	-0.09	-0.10	-0.04	-0.16	-0.02	-0.19
	(0.18)	(0.12)	(0.17)	(0.14)	(0.17)	(0.14)	(0.16)	(0.15)
$PeerDebt$	-0.19	-0.16	-0.10	-0.26**	-0.22*	-0.14	-0.31**	-0.05
	(0.14)	(0.11)	(0.13)	(0.12)	(0.13)	(0.12)	(0.13)	(0.13)
$PeerCash$	-0.16	-0.29**	-0.16	-0.29**	-0.16	-0.28**	-0.25*	-0.20
	(0.17)	(0.12)	(0.16)	(0.13)	(0.15)	(0.13)	(0.15)	(0.14)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	2,864	2,864	2,864	2,864	2,864	2,864	2,864	2,864

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

InddirShare is lagged by one year.

Table C10: First-stage results of heterogeneity effects in Table 3.9

	Competition_LernerIndex		Informational diversity		Interlock counts	
	$PeerR\&D \times GroupL$	$PeerR\&D \times GroupH$	$PeerR\&D \times GroupL$	$PeerR\&D \times GroupH$	$PeerR\&D \times GroupL$	$PeerR\&D \times GroupH$
	(1)	(2)	(3)	(4)	(5)	(6)
$IVR\&D \times GroupL$	-0.02***	0.002**	-0.021**	-0.0003	-0.020***	0.001
	(0.005)	(0.001)	(0.006)	(0.001)	(0.007)	(0.001)
$IVR\&D \times GroupH$	-0.001	-0.014***	0.001	-0.013***	-0.0001	-0.014***
	(0.001)	(0.005)	(0.001)	(0.004)	(0.0009)	(0.004)
GroupL	0.16***	-0.11***	0.19***	-0.09***	0.18***	-0.11***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Size	0.02	0.04	0.03	0.03	-0.03	0.06
	(0.06)	(0.06)	(0.07)	(0.04)	(0.06)	(0.05)
Tang	0.05	-0.02	0.16	-0.15	0.14	-0.10
	(0.15)	(0.18)	(0.18)	(0.14)	(0.18)	(0.16)
Debt	0.01	-0.12	-0.07	-0.05	0.05	-0.11
	(0.18)	(0.20)	(0.23)	(0.13)	(0.21)	(0.15)
Cash	0.22	-0.07	0.14	0.001	0.07	0.12
	(0.17)	(0.11)	(0.17)	(0.12)	(0.17)	(0.12)
PeerSize	-0.03	-0.001	-0.02	-0.004	-0.01	-0.02
	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)
PeerTang	-0.11	-0.10	0.03	-0.22*	0.02	-0.20
	(0.16)	(0.14)	(0.18)	(0.12)	(0.17)	(0.14)
PeerDebt	-0.16	-0.18	-0.29	-0.17	-0.21	-0.24**
	(0.14)	(0.11)	(0.14)	(0.11)	(0.14)	(0.12)
PeerCash	-0.28*	-0.17	-0.09	-0.36***	-0.16	-0.33***
	(0.16)	(0.12)	(0.17)	(0.11)	(0.16)	(0.12)
Year fixed effect	Yes		Yes		Yes	
Obs	2,864		2,864		2,864	

***,**,* indicates significance level of 1%, 5%, 10%.

Standard errors are clustered by firms and are reported in parentheses.

Network dynamics in year 2014 and 2015

In this section, we investigate the possibility of creating new interlocks in 2014 and 2015 to examine firms' reaction to the policy in 2014 and 2015. Dependent variable is a dummy variable taking value of one when focal firm has new connection established to at least one firm and zero otherwise. We regress this binary variable on treatment dummy, indicative of whether the firm lost peer due to the policy or not, and other control variables including *Size*, *ROA*, *Debt*, *Cash*, *Boardsize* and *IndRatio* [24]. Standard logit model is being applied. Table C11 reports results of specifications with (Columns (2) and (4)) and without (Columns (1) and (3)) industry fixed effects (2-digit industry classification code by CRSC), based on cross-sectional new link created in 2014 (Column (1) and (2)) and in 2015 (Column (3)and (4)).

Table C11: Result of new interlocks in 2014 and 2015

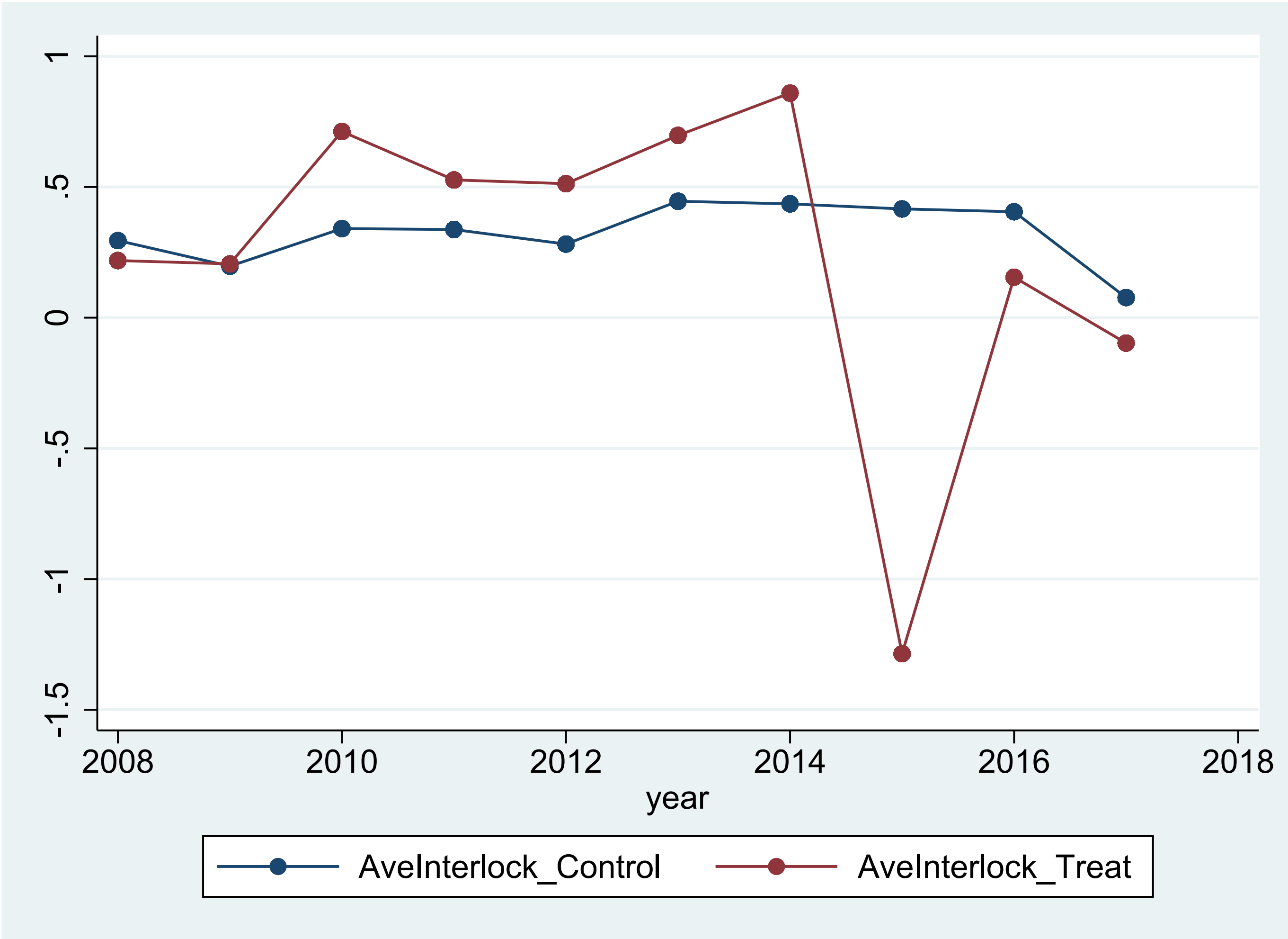
	*DumNew*_2014 (1)	*DumNew*_2014 (2)	*DumNew*_2015 (3)	*DumNew*_2015 (4)
DumTreat	0.12 (0.12)	0.16 (0.12)	0.036 (0.12)	0.031 (0.12)
Size	0.009 (0.048)	-0.007 (0.052)	0.048 (0.045)	0.11** (0.05)
ROA	0.21 (1.07)	0.19 (1.15)	-0.017 (1.08)	-0.96 (1.14)
Debt	0.06 (0.30)	-0.20 (0.34)	0.032 (0.30)	-0.15 (0.33)
Cash	0.15 (0.42)	-0.26 (0.46)	1.03** (0.45)	0.68 (0.49)
BoardSize	0.052 (0.034)	0.065* (0.036)	0.043 (0.034)	0.067* (0.036)
IndRatio	0.55 (0.97)	0.65 (1.01)	-0.93 (1.00)	-0.71 (1.06)
Industry fixed effect	No	Yes	No	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Obs	1,972	1,961	2,059	2,053

***,**,* indicates significance level of 1%, 5%, 10%.
Standard errors are clustered by firms and are reported in parentheses.

Results show that neither in 2014 nor in 2015 were affected firms, firms lost peers because of policy shock, more likely to recruit new independent directors to compensate for the lost interlock channels, in comparison with control firms, firms without losing any interlocked peers.

[24] *Boardsize* denotes the total numbers of board members, while *IndRatio* measures the ratio of independent directors over the total board members.

Figure 3.1: Plot of average interlock trend over years between control group and treatment group



Chapter 4.

Conclusion

Schumpeter's theory of economic development and the following theories contend that the economic cycle creates fluctuations of opportunity costs, which in turn lead to counter-cyclical innovation expenditure. On the contrary, empirical evidence of both pro-cyclical and a-cyclical R&D has been recorded. We try to compromise the gap by absorbing important factors specifically credit constraint and innovation subsidy. Similar to Aghion, the counter-cyclicality of R&D investment does exist in Germany. More importantly, the credit constraint significantly turns R&D expenditure into less counter-cyclical, pointing to pro-cyclical moderating effects. However, the effects of credit constraints seem to be offset by R&D subsidy, given that pro-cyclicality effects fade away among subsidized firms. Finally, treatment effects estimation based on the EU enlargement and economic recession provides supporting evidence for our main findings.

Our empirical results might be interesting for policy makers. It is suggested that subsidy does help firms solve credit constraint problem. However, subsidized SMEs act like deep pocket firms in the sense that they do not counter-cyclically adjust their R&D investments, ignoring the efficiency gain from cyclical opportunity cost. Meanwhile, monitoring over the allocation and spending of subsidy is necessary to ensure the efficiency. Secondly, the pro-cyclical effects of credit constraint are so large in Germany that net pro-cyclical pattern might appear. This indicates the severity of credit constraint, which again points to the necessity of sufficient financing channels or innovation subsidy. Beside R&D grants, the reduction of tax can be another plausible option.

Not bounded by economic interests, independent directors can presumably better monitor managers and counsel decision makers with their previous related information. However, factors such as insufficient access to private information, limited time and dedication, etc, prevent them actively engaging into serving the firm. Based on an exogenous policy enforcement to increase in board independence in Chinese listed firms, we create a quasi-natural setting. The results suggest that the increase of independent directors' presence on boards leads to higher growth of total factor productivity and more innovation output. More importantly, advisory can better justify the positive contribution in innovation, whereas monitoring function exerts more material influences on productivity. Lastly, the positive effects are more pronounced for firms being controlled by non-state ownership and operating under less competitive product markets.

Our results have some important policy implications. Firstly, the introduction of independent directors benefits Chinese firms as a whole. The asymmetric efficiency effects in productivity and innovation underlie uneven monitoring and advisory functions in exercising different responsibilities, highlighting the necessary to design optimal balancing between two functions. From firms' perspective, independent directors should be valued as precious human capital. To best exploit them, firms should manipulate the internal organizational environment to create an “independent director friendly environment".

Interlock network arises from sharing same independent directors on several boards, through which a special social linkage is established. Various theories posit that the interdependency can be transferred to decision making, with different directions and intensities depending on specific assumptions and mechanisms. Exploiting an instrumental variable capturing the drop-outs’ R&D investment as a result of the policy requirement, we firstly empirically identify the positive peer effects in R&D investment among interlocked firms. Point estimates suggest that ten percent increase in peers’ R&D expenditure leads to on average four percent increase in focal firms’ R&D input. Heterogeneity effects speak in favour of learning theory as the underlying mechanism, i.e., peer effects tend to be stronger among firms who are located more centrally in the network, who face fiercer product competition, whose independent directors are more educated and when interlocked peers cover more industries. Lastly, similar findings can be generalized when peers are limited to only interlocks across industries and when indirect (second-degree) interlocks are involved. Firms’ innovation performance seems to benefit from such peer effects, given the positive and negative spillover effects in invention grants and in invention rejections, respectively. Significantly negative and weakly positive peer effects characterize the interdependency of innovation decisions among firms within industries and locations.

The results are concerned with both policy makers and individual firms. Taking the positive externalities of decision making among interlocked firms into account, policy makers can intentionally guide the spillover process of managerial practices, new technologies, products, etc. If learning is the mechanism, the information transmission direction and speed can be manipulated. Secondly, when designing the policy, some potential side-effects should be foreseen. Regarding firms, innovation decisions are not made within the boundary of individual firms, but embedded in various types of broader networks. Furthermore, firms can strategically choose potential interlocking targets to achieve their demand for information. Provided the efficiency improvement from peer effects, firms should make best use of such informational exchange mechanism, especially for soft information based activities such as innovation.