The Growth of Chinese R&D and Innovation

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Abstract

China's GDP has grown at a tremendous rate over the last 40 years, but its total R&D expenditure has grown even more. We construct a model of firm dynamics which produces endogenous increases in R&D and productivity. We then take the model to the data and find that R&D expenditure as a percentage of GDP should have plateaued in the absence of government incentives. Also, Chinese firm productivity would have lagged more than 10 years behind without foreign technology spillovers. Finally, we assess the efficacy of various R&D policies. Giving greater R&D subsidies to less productive firms is more efficient, while giving greater subsidies to firms with lower R&D expenditures is not as efficient.

JEL Classification: E22; G32; O3; L11

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1 Introduction

Since the economic reforms of 1978, China has experienced rapid modernization and remarkable economic development. In addition to sustained economic growth and fast factor accumulation, R&D investment outpacing GDP and capital expenditure is another noteworthy feature of China's economic miracle. R&D expenditure as a share of GDP has steadily risen by 2.77 times over the past two decades, growing much faster than in most developed and developing economies. To advance our understanding of China's economic development and shed light on the mechanics of economic growth, a natural question to ask is, why has R&D grown so much? This very linear increase in R&D has also occurred without obvious structural changes after the 1978 reform. In this paper, we construct a model of endogenous R&D growth and firm heterogeneity to study this phenomenon along the transition.

We begin by documenting the dynamics of aggregate R&D expenses in China for 1996-2015 which is viewed as a period of fast economic development. We find substantial R&D growth during that period: both the R&D-to-GDP ratio and R&D-to-gross capital ratio more than doubled. We then augment our analysis using firm-level data, which confirms our empirical finding of strong R&D growth. Moreover, we exploit the disaggregated firm-level data and document firm heterogeneity in R&D and innovation. We find that Chinese firms behave differently from their US counterparts. In particular, we find that Chinese firms' R&D intensity decreases with firm size; their innovation efficiency increases with firm size; their share of radical innovation is independent of firm size. These unique and distinguishable patterns regarding Chinese R&D and innovation also are worth a close look and careful examination.

To explain the stylized facts of Chinese R&D behavior and shed light on the design of effective R&D and economic policies, we build a dynamic model of R&D and capital investment featuring adjustment costs and foreign knowledge spillover. In the model, firms use capital to produce a homogeneous good. They make decisions on R&D investment, capital investment, and dividend distribution. To improve their competitive positions,

firms invest in R&D, but face knowledge spillover and innovation risks. In addition, adjusting R&D expenditure and physical capital stock incurs costs. We estimate our model by starting the model at near zero capital and zero R&D in 1978 and then match moments in 2007. Again, we do this because a steady-state or balanced growth path equilibrium cannot generate the observed dynamics. Our model successfully replicates the firm-level dynamics of R&D-to-capital, R&D-to-sales, and capital-to-sales ratios, as well as the heterogeneity in R&D and innovation across firm size.

We further perform counterfactual experiments. We find that R&D expenditure as a percentage of GDP should have plateaued in the absence of government incentives. Also, Chinese firm productivity would have lagged more than 10 years behind without foreign technology spillovers. The policy experiments ultimately suggest that firms with lower productivity and higher R&D expenditures should be subsidized the most.

This paper contributes to the literature along several dimensions. Empirically, it establishes an important fact regarding China's economic growth, which, in turn, has important implications for the mechanics of economic growth. One of the seminal papers on China's GDP growth is Song, Storesletten, and Zilibotti (2011). They document a puzzling phenomenon in China—simultaneous increases in the return to domestic capital and capital account deficits—and build a model that features financial frictions and resource reallocation to explain it. Our paper focuses on another critical source of economic growth—R&D investment—and examines its role in endogenously improving China's productivity growth.

Moreover, we find that Chinese firms behave in a different manner from US firms. Using US data, Klette and Kortum (2004) find no close relationship between firm size and R&D intensity, while Akcigit and Kerr (2018) find that both innovation efficiency and innovation quality decrease with firm size. The differences between US and Chinese firms' R&D and innovation behavior, together with the tremendous rise in Chinese R&D-to-GDP ratio, deserve close attention and warrant an explanation.

Theoretically, we contribute to the endogenous growth literature. There is a large body of research on this topic that provides theoretical foundations for how innovation

translates to productivity and economic growth. Acemoglu, Aghion, and Zilibotti (2006): emphasize the importance of entrepreneurial skills for innovation and economic growth as an economy approaches the world technology frontier. Acemoglu and Cao (2015) and Akcigit and Kerr (2018): link economic growth with firm entry and exit, in particular, the entry of new firms that engage in radical innovation and the exits of incumbents that undertake incremental innovation. Acemoglu, Akcigit, Alp, Bloom, and Kerr (2018) also focus on the selection between low- and high-productivity firms. Their results suggest that taxing firms, instead of subsidizing R&D, helps free up skilled labor tied up with low-productivity firms and promote economic growth. Our paper differs from previous studies in two aspects. First, we place emphasis on the role of firms' R&D investment in realizing innovation and improving productivity. Second, we focus on the transitional dynamics rather than a balanced growth path, and analyze the impacts of R&D policies during economic transition. This exercise offers insight on possible areas of improvements that have been missed by previous studies.

The paper is organized as follows. Section 2 presents stylized facts of Chinese firms' R&D and innovation behavior. Section 3 lays out the model to provide an explanation for the empirical observations. Sections 4 and 5 estimate the model and demonstrate its ability to reproduce key features of data. Section 6 performs counterfactual experiments and discusses policy implications. Section 7 concludes.

2 Empirical Facts

To motivate our study and discipline our quantitative analysis, we in this section document empirical regularities for Chinese firms' R&D and innovation behavior at both aggregate level and disaggregated firm level. We first show the dynamics of aggregate R&D investment, then document the heterogeneity in R&D and innovation across firms.

2.1 Aggregate-level Growth

With the introduction of its first economic reform in 1978, China experienced a secular and sharp increase in R&D. Figure 1 plots the growth of R&D expenses in China over a period of 20 years. We construct two measures—R&D-to-GDP ratio and R&D-to-gross capital stock ratio—from OECD and FRED databases.

[Figure 1 about here.]

As shown in Figure 1, the R&D-to-GDP ratio in China increased from 0.56% in 1996 to 2.06% in 2015, and the R&D-to-capital ratio rose from 0.2% to 0.5%, both of which more than doubled over the period. As a comparison, we also show the patterns for the other three largest economies in the world. Evidently, Germany, Japan and USA also increased their spending on R&D during the same period, yet at a slower pace.

We complement our aggregate patterns with firm-level analysis. The sample is formed from the China Stock Market & Accounting Research (CSMAR) Database and China Wind Financial Database, both of which contain detailed information for Chinese listed firms. We follow a common convention of dropping financial and utility firms and calculate the average R&D-to-sales and R&D-to-net capital ratios from 2007 when R&D data became available in the database. Results are plotted in Figure 2. The sharp increase in R&D intensity documented at the aggregate level is also found at the firm level. The average R&D-to-sales and R&D-to-net capital ratios rise from 1.8% and 9% to 4.5% and 32%, respectively.

[Figure 2 about here.]

We then use the same sample of firms to examine whether and how the fraction of R&D performers in China evolves over time. As shown in the bottom panel of Figure 2, there has been a gradual increase in the share of R&D performers among listed firms in the past decade, with the ratio climbing from 40% to more than 80% in recent years. The increase in R&D performers may partially contribute to the steady increase in Chinese R&D expenditure documented in Figure 1.

2.2 Firm-level Heterogeneity

We further explore CSMAR, Wind, and State Intellectual Property Office (SIPO) databases and exploit their property of firm-level data. In particular, we analyze cross-sectional heterogeneity across different-sized firms. We show results with a sample of nonfinancial and nonutility listed firms, and collect their financial information from CSMAR, R&D information from Wind, and patent information from SIPO.

2.2.1 Sample Description

Table 1 presents the summary statistics for our sample over the period 2007 to 2015. On average, these firms have RMB 2.82-billion total assets, RMB 0.42-billion net capital, RMB 1.44-billion sales, and 1,725 employees. They invest heavily in R&D. R&D expenses, on average, account for 3.8% of sales, 1.9% of total assets, and 24% of net capital.

[Table 1 about here.]

We next take a detailed look at firm heterogeneity in R&D intensity and innovation behavior. We form 10 portfolios on the basis of firms' beginning-of-period total assets, and derive the distribution of each variable of interest over time. Specifically, for each period, we form 10 equal-sized groups of firms based on firm size which is measured by the beginning-of-period total assets, then compute the average value for each group. We repeat this process for each period. All variables of interest are winsorized at the top and bottom 1%.

2.2.2 R&D Intensity by Firm Size

We measure R&D intensity by R&D-to-sales ratio and depict results in Figure 3. It suggests that there is a monotonic relationship between R&D-to-sales ratio and firm size. More specifically, small firms tend to investment more in R&D compared to large firms. This pattern is found in all years since 2008.[1]

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[1]In 2007, the largest firm had a particularly high R&D investment rate.

[Figure 3 about here.]

We test this result formally using regression model (1) specified below:

$$\text{R\&D intensity}_{i,t} = \beta_0 + \beta_1 \text{firm size}_{i,t} + D_{\text{state owned}} + \alpha_i + \delta_{I,t} + \epsilon_{i,t}, \qquad (1)$$

where both the dependent variable and firm size are in logarithm form. In addition to firm size, we include a dummy variable for state-owned firms, firm fixed effects, and industry-specific year fixed effects. The state-owned dummy is included to capture the possibility that state-owned firms behave differently due to the Chinese Government's targeted policies and their specific characteristics. Firm fixed effects are added to control for unobserved time-invariant cross-sectional heterogeneity, and industry-specific year dummies are included to absorb macroeconomic shocks in each of the major sectors. Estimation results are reported in column (1) of Table 2.

[Table 2 about here.]

The coefficient estimate of firm size suggests that a 10-percent increase in firm size is associated with a 1.26 percent drop in R&D-to-sales ratio, approximately one-third of our sample mean. This negative relationship is robust to alternative measures of R&D intensity. Figure 4 uses R&D-to-net capital ratio as the proxy, and the same empirical feature is found.

[Figure 4 about here.]

2.2.3 Innovation Efficiency by Firm Size

We further explore firms' heterogeneity in innovation efficiency which is defined as the number of granted patents per R&D dollar invested. We treat missing granted patents as zeros if firms have positive R&D expenditure.

[Figure 5 about here.]

Figure 5 shows a consistent cross-sectional pattern: larger firms tend to be more innovation efficient. For every dollar spent on R&D investment, large firms are more likely to convert R&D expenses into patents. This relationship is statistically significant. Column (3) of Table 2 suggests that a 10% increase in firm size is associated with a 0.18% rise in innovation efficiency.

2.2.4 Share of Invention Patents by Firm Size

Finally, we examine whether firms of different sizes devote R&D resources to different types of innovation—radical innovation vs. incremental innovation. There are three types of patents in China: invention patents, utility model patents, and design patents. We classify the former as radical innovation and the latter two as incremental innovation.

[Figure 6 about here.]

Figure 6 plots the share of radical innovation in each size group over time. The pattern indicates that the fraction of major innovation is independent of firm size, which is confirmed by the near-zero coefficient of firm size reported in column (4) of Table 2.

2.2.5 Robustness

One concern with our findings of heterogeneity in R&D and innovation behavior across firm size is that our sample may not be representative of the population. That is, listed firms may behave differently compared with private firms. To alleviate this concern, we use data from the Chinese Annual Survey of Manufacturing (ASM) conducted by China's National Bureau of Statistics (NBS). The sample includes all manufacturing firms with annual sales more than 5 million RMB.

As R&D data are unavailable after 2007, we use one-year observations to examine the relationship between firm size and R&D choices and exploit cross-firm variation. We deviate from our baseline regression model (1) by replacing industry-year fixed effects with year and industry fixed affects, and replacing firm fixed effects with province fixed effects. We focus on firms with positive R&D expenses and report estimation results in

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column (4) of Table 2. As shown, larger firms tend to have a lower R&D-to-sales ratio, which is consistent with our finding derived from a sample of listed firms. This validates our use of public firms to document the empirical regularities of average Chinese firms' R&D decisions

2.2.6 Summary and Discussion

In summary, our sample suggests the following stylized facts regarding the R&D and innovation behavior of nonfinancial and nonutility Chinese firms:

1. R&D investment outgrows GDP and capital expenditure;

2. Share of innovative firms increases steadily over time;

3. R&D intensity decreases with firm size;

4. Innovation efficiency increases with firm size; and

5. Share of radical innovation is independent of firm size.

Our findings (3)-(5) suggest that Chinese firms behave in a different manner from their U.S. counterparts. In particular, Klette and Kortum (2004) find no close relationship between firm size and R&D intensity, while Akcigit and Kerr (2018) find that both innovation efficiency and innovation quality decrease with firm size. These differences, in addition to the tremendous rise in Chinese R&D-to-GDP ratio, deserve close attention and warrant an explanation which comes next.

3 Model

In this section, we develop a model to rationalize the empirical facts documented in Section 2. Our model is both an extension and simplification of Gao and Zhao (2018) which in turn is built upon Hopenhayn (1992) and Hennessy and Whited (2005). The model also draws inspiration from endogenous growth theory, but with equal attention paid to cross-sectional patterns.

In the model, time is discrete, the horizon is infinite, and firms are risk-neutral. Firms make optimal decisions on R&D investment, capital investment, and dividend distribution. They are heterogeneous in their R&D expenses, capital stock, and productivity levels, but face the same optimization problem. As such, we refer to a single firm from this point on without loss of generality.

In what follows, we specify the firm's production technology, transitional dynamics of idiosyncratic productivity, and R&D and capital accumulation processes. We then state the firm's problem.

3.1 Production and Endogenous Productivity

A firm uses predetermined capital stock k to produce a homogeneous numeraire good y, subject to idiosyncratic productivity z. The firm's production function is specified as

$$y = zk^{\alpha},$$

where the parameter $\alpha > 0$ controls the returns-to-scale technology property.

The firm's productivity level is endogenously determined. The direction of productivity movement is given by

$$\Pr(z' > z) = \frac{(1-\phi)D}{1+D}; \quad \Pr(z' = z) = \frac{1-\phi+\phi D}{1+D}; \quad \Pr(z' < z) = \frac{\phi}{1+D},$$

where a prime denotes a variable in the subsequent period, ϕ represents the degree of innovation efficiency, and D is the firm's total knowledge input which will be detailed later. This specification follows Xu (2008). It implies that higher R&D expenses improves the firm's productivity by raising the likelihood of realizing higher productivity.

Moreover, we assume that the firm's future productivity level z' depends on its current knowledge stock captured by its current productivity z. The transition function follows

Gao and Zhao (2018) and is specified as

$$\Pr(z'|z' > z) = \frac{\frac{1}{(z'-z)^\rho}}{\sum\limits_{z'>z}\frac{1}{(z'-z)^\rho}}; \quad \Pr(z'|z' < z) = \frac{\frac{1}{(z-z')^\rho}}{\sum\limits_{z'<z}\frac{1}{(z-z')^\rho}},$$

where the parameter ρ controls the degree innovation volatility. As ρ approaches $-\infty$, the transition induces movement to the furthest value with probability 1. As ρ approaches 0, the transition induces equal chance movement to any of the possible states. Finally, as ρ approaches ∞, the transition induces movement to the closest value with probability 1.

The complete transition function for productivity is given by

$$\Gamma(z'|z) = \begin{cases} \bar{z} \geq z' > z & \text{with probability } \Pr(z' > z) \times \Pr(z'|z' > z), \\ z' = z & \text{with probability } \Pr(z' = z), \\ \underline{z} \leq z' < z & \text{with probability } \Pr(z' < z) \times \Pr(z'|z' < z), \end{cases}$$

which is a product of the movement direction probability $\Pr(z' > z)$ with the value conditional on direction probability $\Pr(z'|z' > z)$.

3.2 R&D and Capital Investment

To analyze how the firm makes investment decisions to optimize its problem, we next describe the laws of motion for R&D and capital, as well as the associated real frictions that would impede a firm's resource reallocation.

The firm's total knowledge input is the sum of its own R&D expenditure (d) and the foreign technology spillover (ω), which is given by

$$D = d + \omega.$$

This specification assumes that when innovating a product, the firm can learn more advanced technologies via foreign spillover, in addition to relying on their own R&D investment. Furthermore, we assume that adjusting knowledge investment level incurs

costs (Bloom, 2007), and the R&D adjustment cost function takes the following form,

$$A_d(d_{-1}, d) = \eta_0 \mathbf{1}_{d \neq d_{-1}} + \eta_2 \frac{(d - d_{-1})^2}{d + d_{-1}},$$

where subscript -1 indicates a variable in the preceding period, and η_0 and η_2 govern the degree of fixed and convex R&D adjustment costs, respectively. R&D flow adjustment costs capture the idea that a large share of R&D expenses goes to scientists and engineers' salaries, and the turnover in these skilled workers can induce large losses (Brown, Fazzari, and Petersen, 2009; Hall, 1993).

Aside from investing in R&D, the firm can allocate resources toward capital stock by capital investment, i, which is given by,

$$i = k' - (1 - \delta)k,$$

where the parameter $\delta \in (0, 1)$ is the capital depreciation rate. Similarly, the firm incurs adjustment costs from the purchase or sale of capital, which is defined as:

$$A_k(k, k') = \gamma_0 \mathbf{1}_{k' \neq k} + \gamma_2 \frac{(k' - k)^2}{k' + k},$$

where γ_0 and γ_2 control the degree of fixed and convex capital adjustment costs (Abel and Eberly, 2002; Cooper and Haltiwanger, 2006).

3.3   The Firm's Problem

We now proceed to formally state a firm's optimization problem. The firm aims to maximize its equity value by managing its R&D and capital investment policies.

At the beginning of each period, the firm observes current-period productivity z. It then pays operating costs and produces output with existing capital stock. It also decides how to allocate internal resources by choosing the optimal levels of capital and R&D investment. The remaining funds are distributed to shareholders.

These assumptions imply that the dividend payment can be written as

$$e(z, d_{-1}, d, k, k') = zk^\alpha - \tau_c \mathbf{1}_{\{\pi(z,d,k)>0\}}\pi(z, d, k) - c_v zk - d - [k' - (1-\delta)k] - A_d(d_{-1}, d)$$
$$- A_k(k, k') + \tau_{rd}d,$$

where τ_c is the corporate tax rate, τ_{rd} is the R&D tax credit rate, and $\pi(z, d, k)$ is the firm's taxable income which is given by

$$\pi(z, d, k) = zk^\alpha - c_v zk - d - \delta k.$$

In the specification of dividend payment, $c_v zk$ is the operating cost, which is variable and strictly convex in output; and $\tau_{rd}d$ is R&D subsidies. Note that the equity flow $e(z, d_{-1}, d, k, k')$ cannot go negative. That is, firms are not allowed to borrow externally by issuing equity, and can only finance investments using internal resources (Song, Storesletten, and Zilibotti, 2011). We will relax this assumption later to check the robustness of our main results.

The firm maximizes the expected discounted dividends, then it's problem can be summarized by the following Bellman equation:

$$V(d_{-1}, k, z) = \max_{d, k'}\{(1 - \tau_d)e(z, d_{-1}, d, k, k') + \frac{1}{1 + r + \theta}\mathbb{E}V(d, k', z')\},$$

where τ_d is the dividend distribution tax, r is the real interest rate, and θ proxies for future uncertainty. The parameter θ is introduced to ensure bounded firm value due to technology outgrowing the fixed interest rate, and can be thought of as a reduced-form approach to capture political uncertainty and/or the possibility of exogenous exit.

The evolution of the firm distribution is given by,

$$\mu'(d, k', z') = \int I(d_{-1}, k, z)d\Gamma(z'|z)d\mu(d_{-1}, k, z),$$

where the indicator function $I(d_{-1}, k, z) = \mathbf{1}_{\mathcal{D}(d_{-1},k,z)=d}\mathbf{1}_{\mathcal{K}(d_{-1},k,z)=k'}$. Although we specify

the law of motion for the distribution, we focus on the transitional dynamics instead of a stationary equilibrium in simulation. In particular, we start with a panel of firms with all state variables at the lower bound as the initial state to coincide with China's reform and opening-up in 1978. Then, we simulate the economy for thirty periods to match data in 2007. The details are laid out in the next section.

4   Model Estimation

In this section, we estimate our model described above using aggregate and firm-level data in 2007. We first calibrate some parameters outside of the model. These parameters are listed in Panel A of Table 3. We then use simulated method of moments (SMM) to estimate the remaining parameters by matching data, and report estimates in Panel B. We solve our model at annual frequency and construct empirical moments from the NBS database.

4.1   Parameterization

The real interest rate r is set to 2%, which is the average value for the period 1980 to 2007 and is close to the value used in Song, Storesletten, and Zilibotti (2011). The real interest rate has fluctuated quite a bit in the last 40 years. While this value may appear low compared with that often used in the macroeconomics literature, we have an additional parameter θ—which represents exogenous exit and/or political uncertainty—to discount future cash flows.

In 2007, investors that hold shares longer than one year were taxed at 10 percent. We therefore set τ_d to be 10%. The corporate income tax rate τ_c comes directly from our sample, which is calibrated to the average rate paid in 2007 and set at 23%. The Chinese tax code is so complicated that firms actually pay a rate significantly lower than the statutory rate. Since 2006, 150% of R&D expenses are tax deductible. We therefore set the R&D tax subsidy rate τ_{rd} at 11.5%, half of the income tax rate. The value of τ_{rd} will be changed later on when we perform experiments to gauge the effect of tax incentives

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on R&D expenditures. Finally, the capital depreciation rate δ is set to 13%, which is the mean value reported by firms in our sample.

[Table 3 about here.]

The remaining parameters are estimated using SMM and are identified as follows. Returns to scale α is inferred from the cross-sectional dispersion of sales, and productivity scale ζ is estimated to match the absolute level of median sales. R&D fixed adjustment cost η_0 and convex adjustment cost η_2 are identified from the share of non-R&D performers and the autocorrelation of R&D investment, respectively. Similarly, capital adjustment costs γ_0 and γ_2 are estimated using the median level and autocorrelation of capital stock. Parameter estimates are reported in Panel B of Table 3.

Our estimated parameters reveal the following patterns. First, Chinese manufacturing firms operate their production via a near constant returns-to-scale technology and face sizeable production costs. Their R&D adjustment costs and capital adjustment costs are significant, with the former greater than the latter. Second, the foreign technology spillover is sizeable and helps to spur the initial economic growth in China. Chinese firms' innovation efficiency is estimated to 0.293, which implies substantial uncertainties involved in the innovation process. The innovation volatility parameter is 4.755 and suggests a low probability of realizing high productivity conditional on innovation success. Moreover, future uncertainty θ is large and leads to an additional 9.7% discount on future cash flow.

4.2 Targeted Moments

The targeted moments are presented in Table 4. As stated in the previous section, these moments are from 2007 and are computed from the manufacturing survey of the National Bureau of Statistics (NBS) of China. We match both cross-sectional and firm-specific moments, and all first moments are in millions of 2005 RMB. Note that we do not normalize in a fashion similar to many other papers in the growth literature, because we do not focus on a steady-state or a balanced growth path. Put differently, if we normalize

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each moment by a firm's total assets, there is no true notion of growth. A change in the capital-to-assets ratio can be caused by many reasons other than economic growth.

[Table 4 about here.]

Overall, most empirical targets are well matched. Precisely, our model matches the empirical cross-sectional distributions and autocorrelations of capital stock and sales well. The mean and autocorrelation of R&D investment are also close to their corresponding data moments. However, our model undershoots the share of non-R&D performers and produces a less dispersed distribution of R&D investment compared with data, 0.524 vs. 0.885 and 0.140 vs. 0.684, respectively.

5   Quantitative Results

In this section, we study the implications of economic growth and cross-sectional heterogeneity generated from our estimated model and compare the results with the observed empirical patterns documented in Section 2.

5.1   Aggregate Time Series Patterns

We begin by analyzing the time-series dynamics of R&D to capital, R&D to sales, and capital to sales ratios. Model results are plotted in the left panels of Figure 7, accompanied by their empirical counterparts on the right. Note that due to the unavailability of time-series R&D data in the NBS database, the empirical dynamics are derived from CSMAR which gives R&D ratios significantly different from NBS. As such, we focus on the overall dynamics rather than the level of ratios.

[Figure 7 about here.]

As shown in the upper two panels of Figure 7, our model successfully reproduces the upward trend in the R&D-to-capital ratio. Specifically, the model-implied R&D to

capital ratio is close to zero before 1990 and starts to rise since then. This steady secular increase in R&D to capital ratio is consistent with the pattern exhibited in the data.

The dynamics of the R&D-to-sales ratio is plotted in the upper-middle panels. The movement generated from our model again tracks the data closely. The data display a steady rise in the R&D-to-sales ratio over time, with the growth rate slowing down in recent years. Similarly, our model-implied R&D to sales ratio starts to increase in 1990s and begins to plateau over the last few years.

The time-series patterns of the capital-to-sales ratio over the past thirty years are illustrated in the lower-middle panels of Figure 7. Overall, our model is consistent with the observed decline in this ratio. Intuitively, as firms move up in technology, more sales can be generated by a given level of capital. However, the data exhibit a temporary increase in the capital-to-sales ratio from 2012 to 2015, which cannot be reproduced by our model. We conjecture that this sharp and transitory increase arises from the lagged impacts of China's four-trillion-yuan stimulus package fueled by bank loans in 2009.

Moreover, our model generates a steady and approximately linear increase in the share of R&D performers from 47% in 2007 to 77% in 2017, plotted in the bottom left panel of Figure 7. Compared with our model, the data exhibit a noticeable jump for the period 2009-2012. From our experiments in the next section, we show that R&D policies implemented during that period can partially explain the steeper increase in the data.

5.2   Cross-sectional Heterogeneity

We next exploit the feature of firm heterogeneity in our model and examine the relationship between innovation behavior and firm size. To this end, we simulate an economy consisting of 5,000 firms for 40 periods and use the generated panel of firms to perform regression analyses.

We deviate slightly from the regression models specified in Subsection 2.2 by excluding state-owned dummy and year fixed effects, because of the absence of these features in our model. We measure firm size by firms' current-period capital stock, treat positive

productivity growth as successful innovation, and classify innovation as invention if productivity moves up by more than 50%. Regression results are reported in Table 5.

[Table 5 about here.]

Our model can account for two salient features of the data. First, larger firms tend to have a lower R&D intensity. Second, the share of radical innovations in total innovations is independent of firm size. The former suggests the potential substitutability between capital investment and R&D investment. The latter is generated by our model assumption about the productivity transition, that is, the realization of radical innovation is solely controlled by innovation volatility ρ which is constant across firms.

Our model fails to explain the positive relation between innovation efficiency and firm size observed in the data. We conjecture that this data-model discrepancy arises from our assumption that firms' ability to absorb foreign technology spillover is homogeneous across firms. Allowing the spillover absorption rate to depend on firms' technology level can possibly solve the issue.

Overall, we demonstrate that our model is able to reproduce key empirical regularities at both firm and aggregate levels. This strengthens the model's reliability as a laboratory to perform counterfactual experiments, which we examine next.

6 Experiments and Policy Implications

6.1 Counterfactual Experiments

In our first experiment, we double the R&D tax subsidy in 2008 and see what occurs. Figure 8 illustrates the results. The R&D-to-capital ratio as well as the R&D-to-sales ratio rise right after the tax subsidy increase. From 2008 to the present day, China has implemented a series of industrial policies to promote R&D. These subsidies likely allowed Chinese firms to avoid the plateau of R&D relative to other macro variables.

[Figure 8 about here.]

For the following experiments, we investigate the importance of the foreign technology spillover to Chinese firms (see Figure 9). We find that the foreign technology spillover is especially important at the outset. If we halve the foreign technology spillover, China R&D and capital stock would have lagged behind by around 10 years. This difference also builds up over time.

However, if the foreign technology spillover is instead halved in 2008 as shown in Figure 10), the impacts are substantially lower. R&D and capital actually increase in the short-run while sales decrease relative to the case where spillovers remain at the original level throughout the time period. R&D increases to mitigate the loss in foreign technology spillovers while capital acts as a buffer against innovation shocks. Firms cannot issue external finance nor hold cash so capital is the only buffer source. Overall, the biggest impact of this shock is on firm value since reduced spillovers imply much lower expected discounted future profits.

[Figure 9 about here.]

[Figure 10 about here.]

Finally, we assess the effectiveness of various R&D policies in Table 6. The policies are constructed so that they incur the same cost as the experiment where the R&D tax subsidy is doubled in 2008. The first policy gives more tax subsidies to firms with lower R&D expenditures. Firms above median R&D expenditures are given zero tax subsidies while those above the median are given a subsidy such that the program cost is the same as a flat 23% tax subsidy. This policy is inefficient since all the moments drop. The second policy targets smaller firms with less capital. This policy is again inefficient even though R&D expenditures actually rise a bit. The overall firm value impact is -0.5%. The last policy, on the other hand, gives more tax subsidies to firms with lower productivity shocks. We find that the policy is more efficient since R&D expenditure, capital, sales, and firm value all increase quite substantially even though the program cost is the same.

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6.2 Policy Implications

The combined results of the policy experiments suggest that low productivity firms with high R&D expenditures should be subsidized the most. The intuition is that, sometimes, firms performing a large amount of research can still be unlucky and not come up with innovating products or ideas. There is no exit in our economy but drawing down R&D is a costly endeavor due to high R&D adjustment costs. A firm facing a bad productivity shock will be forced to dramatically reduce R&D expenditures as well as capital in the absence of subsidies. If the low productivity firm can maintain its R&D expenditures, it doesn't face the deadweight losses due to adjustment and will likely improve its productivity in the future.

[Table 6 about here.]

7 Conclusion

China's rise in R&D relative to other macro variables suggest that it has promising future prospects. However, we must first understand the reasons behind the increase in R&D before we look to the future. In this paper, we construct a model of firm dynamics which aims to explain this phenomenon. We find that government incentives likely contributed to the remarkably linear secular increase in the R&D-to-GDP ratio, especially after 2007.

In addition, our model suggests that foreign technology spillovers are quite important for the innovation in Chinese firms. Finally, we show that R&D policies which target certain types of firms can be more effective than flat subsidies. In particular, granting tax subsidies to low productivity but R&D intensive firms produce the best outcomes.

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8 Appendix

8.1 Variable Definitions

We define the variables used in the regressions as follows:

Firm size is defined as logged total assets.

Share of R&D performers is the ratio of positive-R&D firms over total firms. We treat missing R&D observations as zeros.

R&D intensity is R&D-to-sales ratio. We focus on observations with positive R&D.

Innovation efficiency is the ratio of logged granted patents over logged R&D expenses. We treat missing granted patents as zeros if firms have positive R&D expenses.

Share of invention patents is the ratio of granted invention patents to total granted patents. We measure total granted patents as the sum of invention patents, utility model patents and design patents.
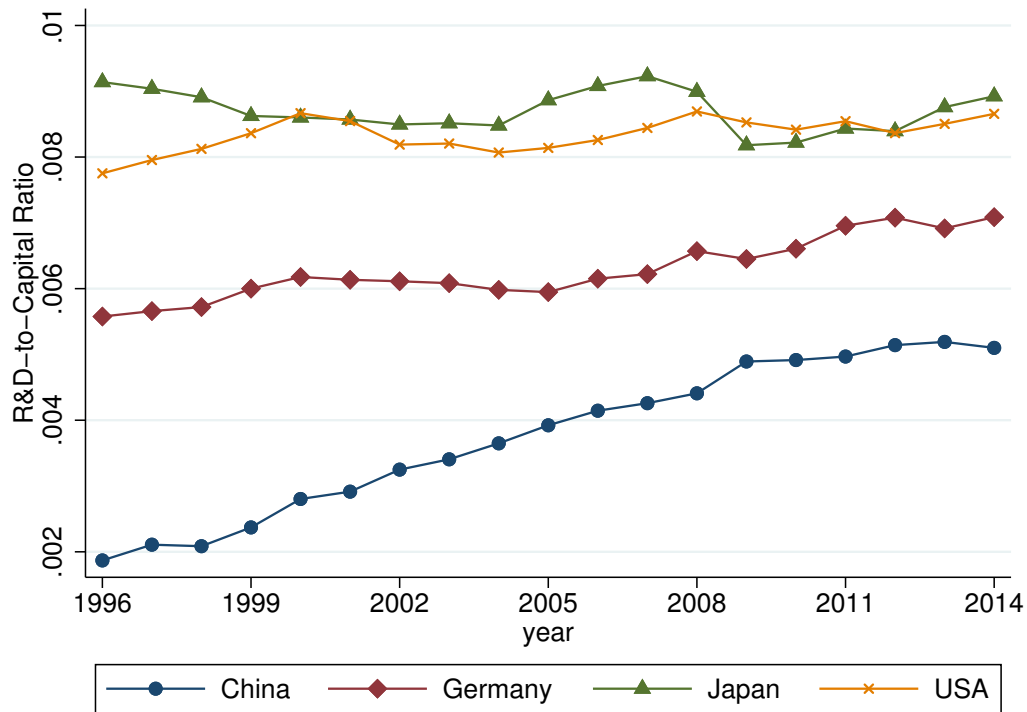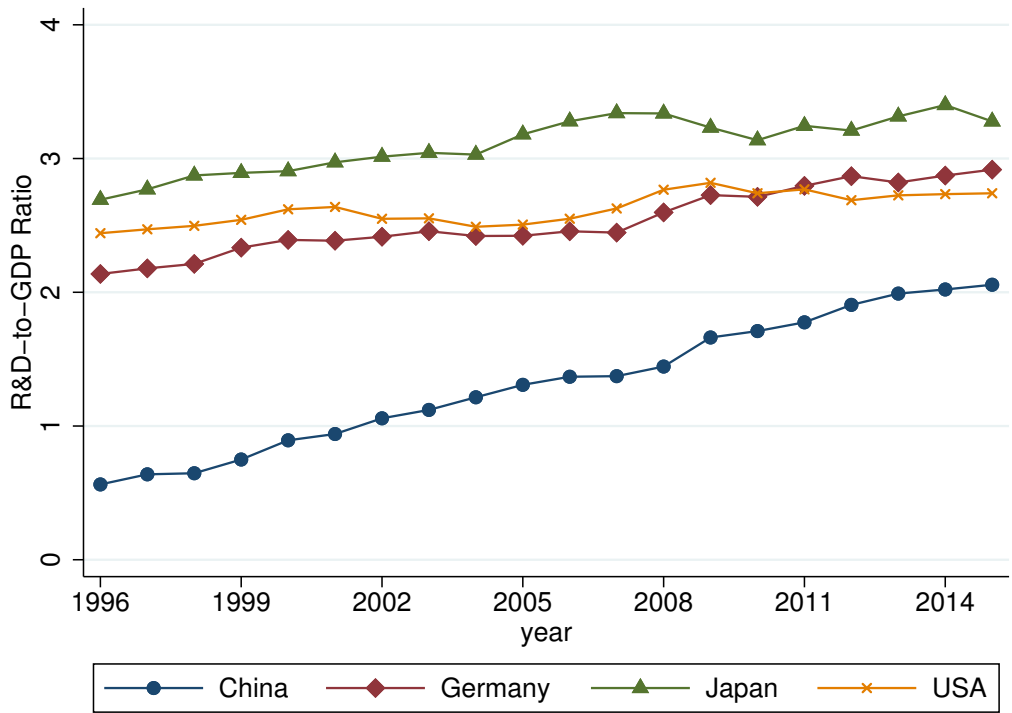
Figure 1: **R&D Intensity by Country.** This figure plots R&D intensity for China, Germany, Japan, and US over the period 1996-2015. We construct the sample from OECD and FRED databases. We plot (i) the ratio of gross domestic R&D spending to gross domestic product (top panel) and (ii) the ratio of gross domestic R&D spending to physical capital stock (bottom panel).
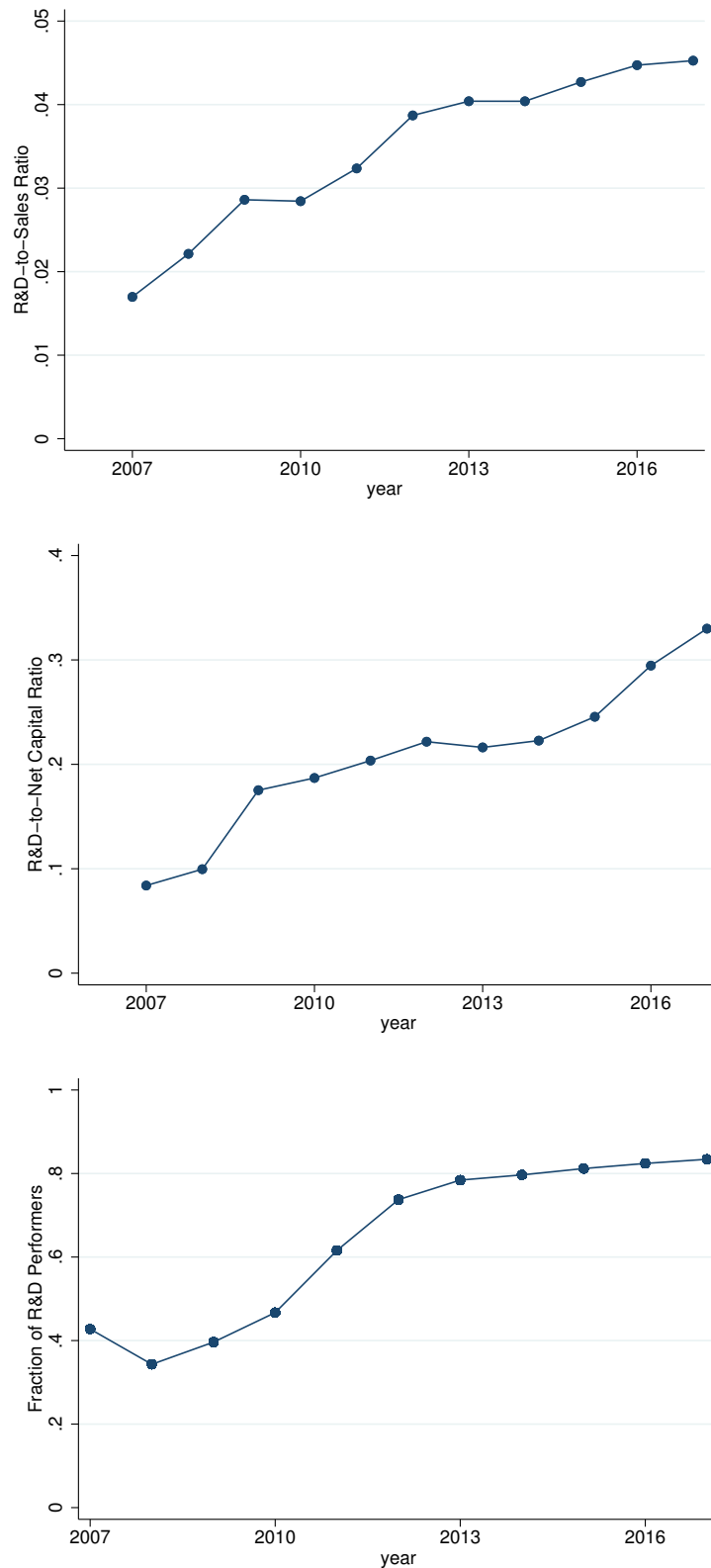
Figure 2: **R&D Dynamics: Firm-level Evidence.** This figure plots R&D dynamics for Chinese nonfinancial and nonutility listed firms over the period 2007-2017. We construct the sample from CSMAR and Wind databases. We plot (i) the ratio of R&D spending to sales (top panel), (ii) the ratio of R&D spending to net physical capital stock (middle panel), and (iii) the share of R&D performers (bottom panel).
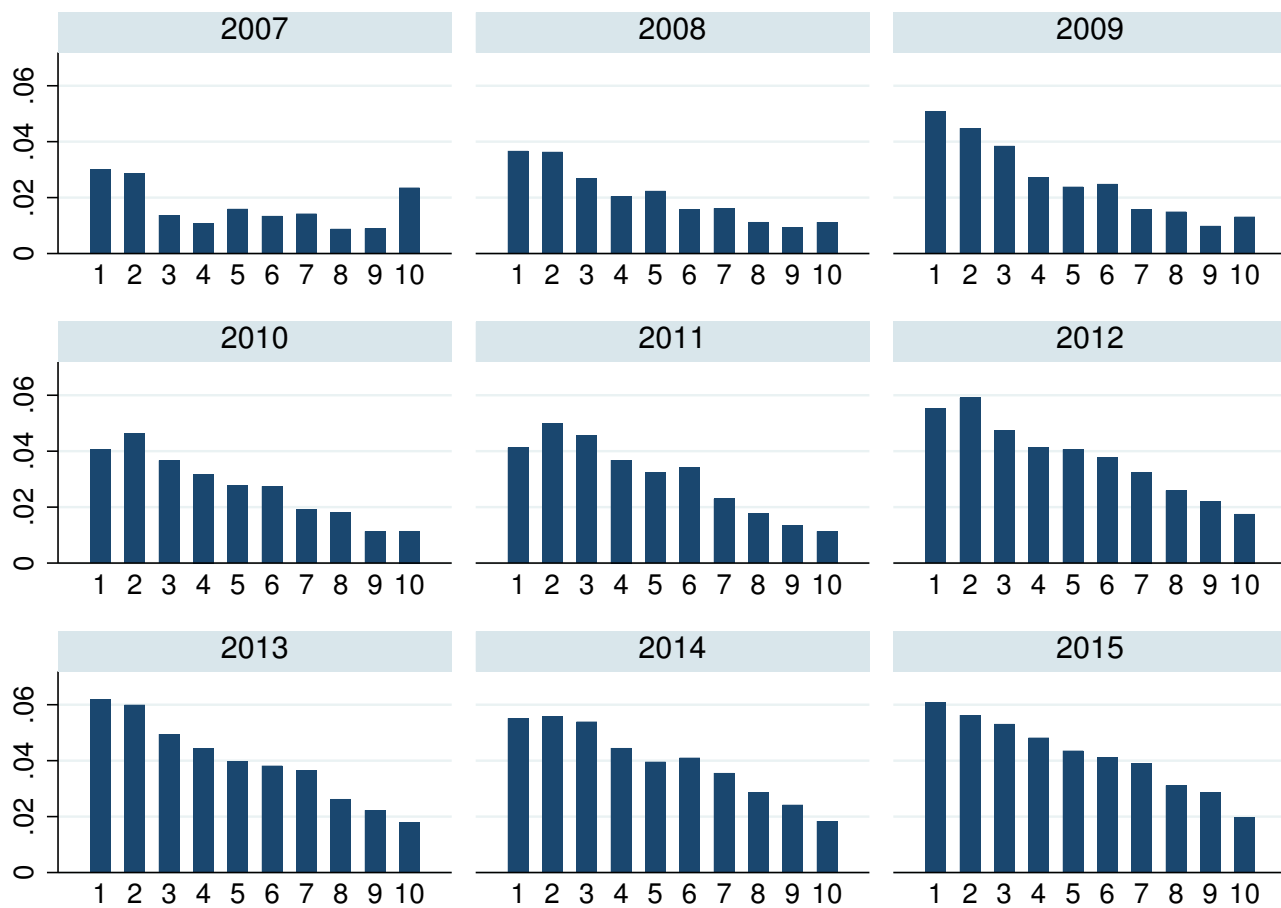
Figure 3: **R&D Intensity by Firm Size I.** This figure plots R&D intensity by firm size over the period 2007-2015. We measure R&D intensity with R&D-to-sales ratio and firm size as lagged total assets. We focus on observations with positive R&D. We construct the sample from CSMAR and Wind databases and drop financial and utility firms.
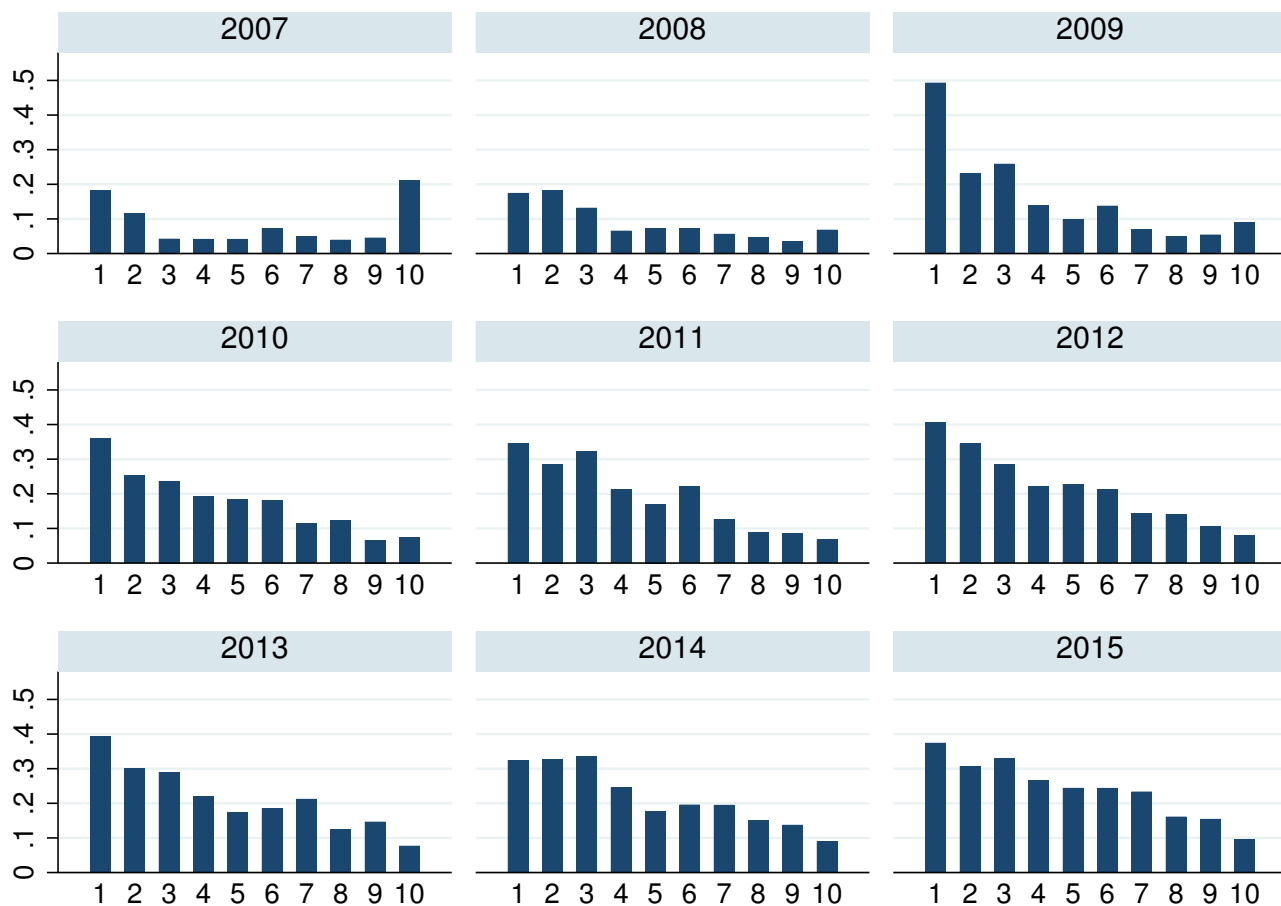
Figure 4: **R&D Intensity by Firm Size II.** This figure plots R&D intensity by firm size over the period 2007-2015. We measure R&D intensity with R&D-to-net capital ratio and firm size as lagged total assets. We focus on observations with positive R&D. We construct the sample from CSMAR and Wind databases and drop financial and utility firms.
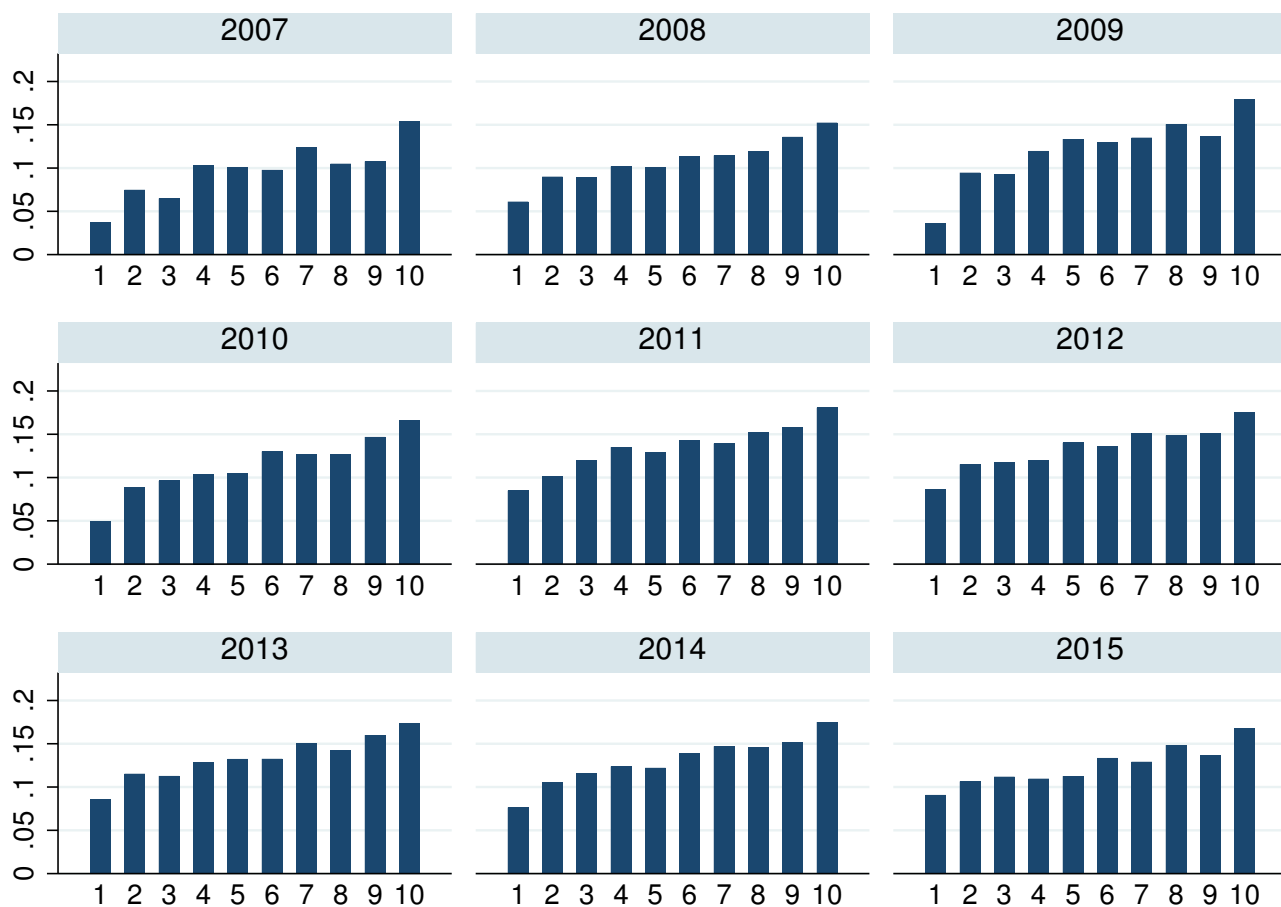
Figure 5: **Innovation Efficiency by Firm Size.** This figure plots innovation efficiency by firm size over the period 2007-2015. We define innovation efficiency as the number of granted patents per R&D dollar invested, and measure firm size as lagged total assets. We treat missing granted patents as zeros if firms have positive R&D expenses. We construct the sample from CSMAR and Wind databases and drop financial and utility firms.
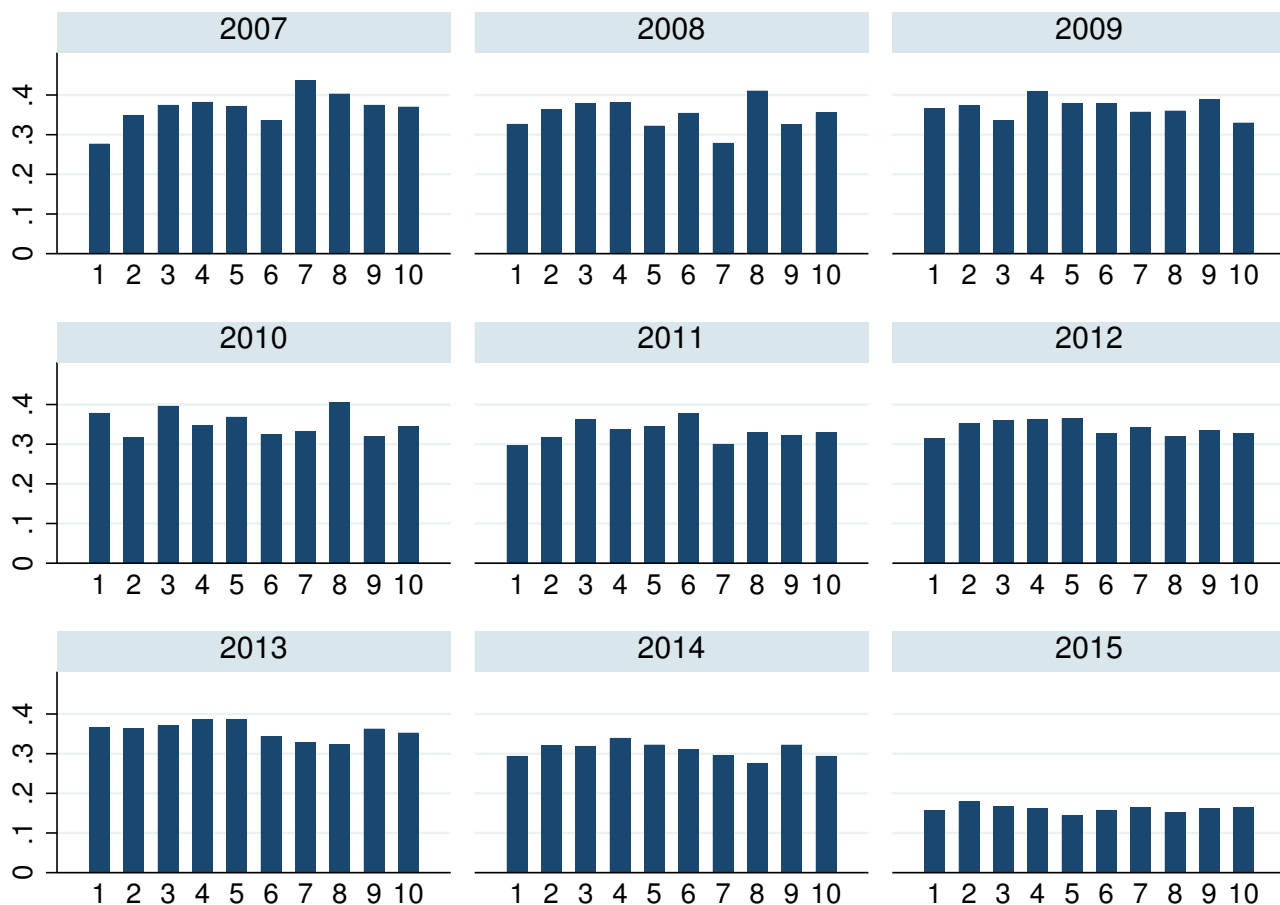
Figure 6: **Share of Invention Patents by Firm Size.** This figure plots the share of granted invention patents over total granted patents by firm size over the period 2007-2015. We treat missing patent observations as zeros, define total granted patents as the sum of invention patents, utility model patents and design patents, and measure firm size as lagged total assets. We construct the sample from CSMAR and Wind databases and drop financial and utility firms.
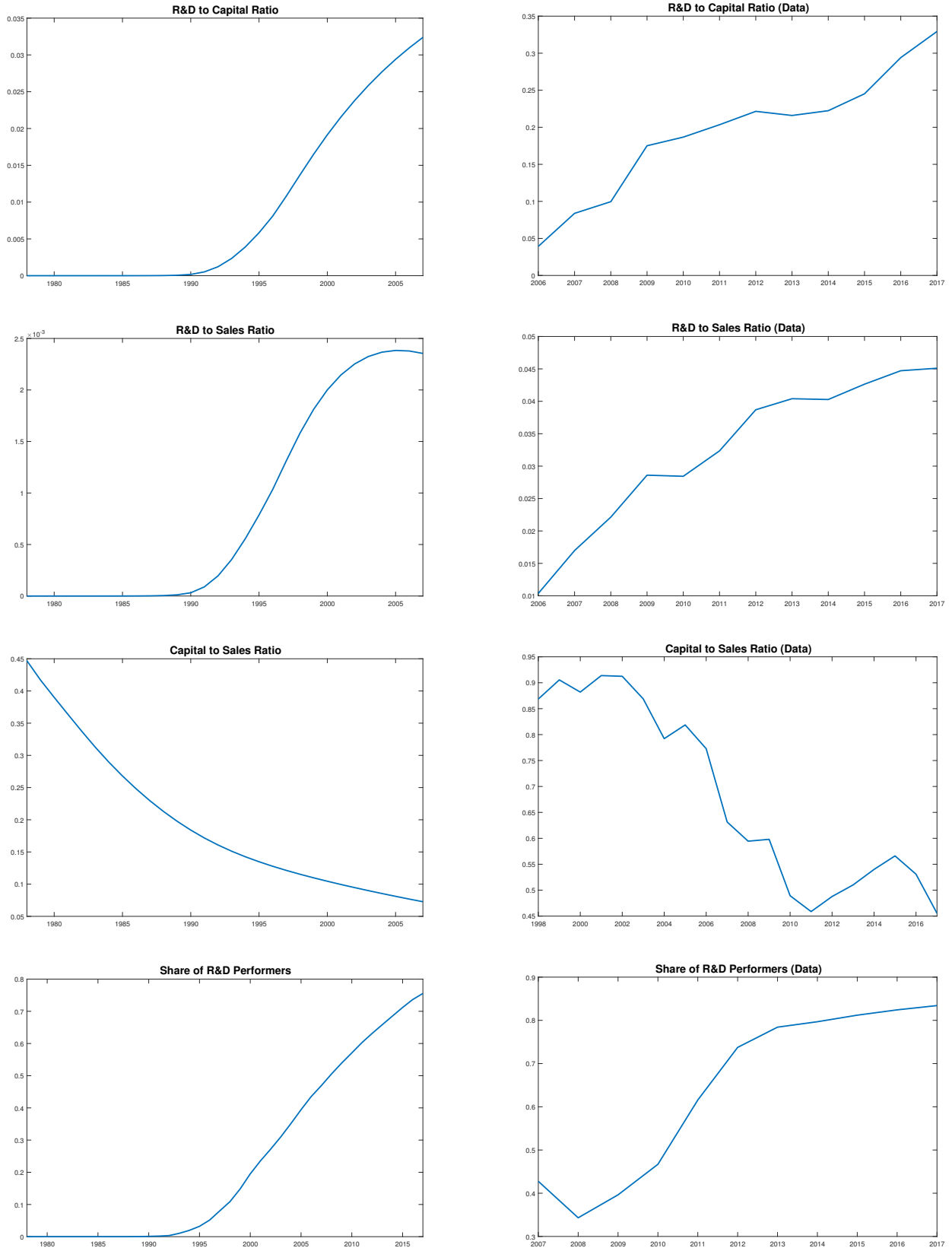
Figure 7: **Aggregate Over-time Patterns.** This figure plots the over-time dynamics of (i) R&D-to-capital ratio (upper panels), (ii) R&D-to-sales ratio (upper-middle panels), (iii) capital-to-sales ratio (lower-middle panels), and (iv) share of R&D performers (bottom panels). The model-implied transitional dynamics is on the left and the empirical transition is on the right.
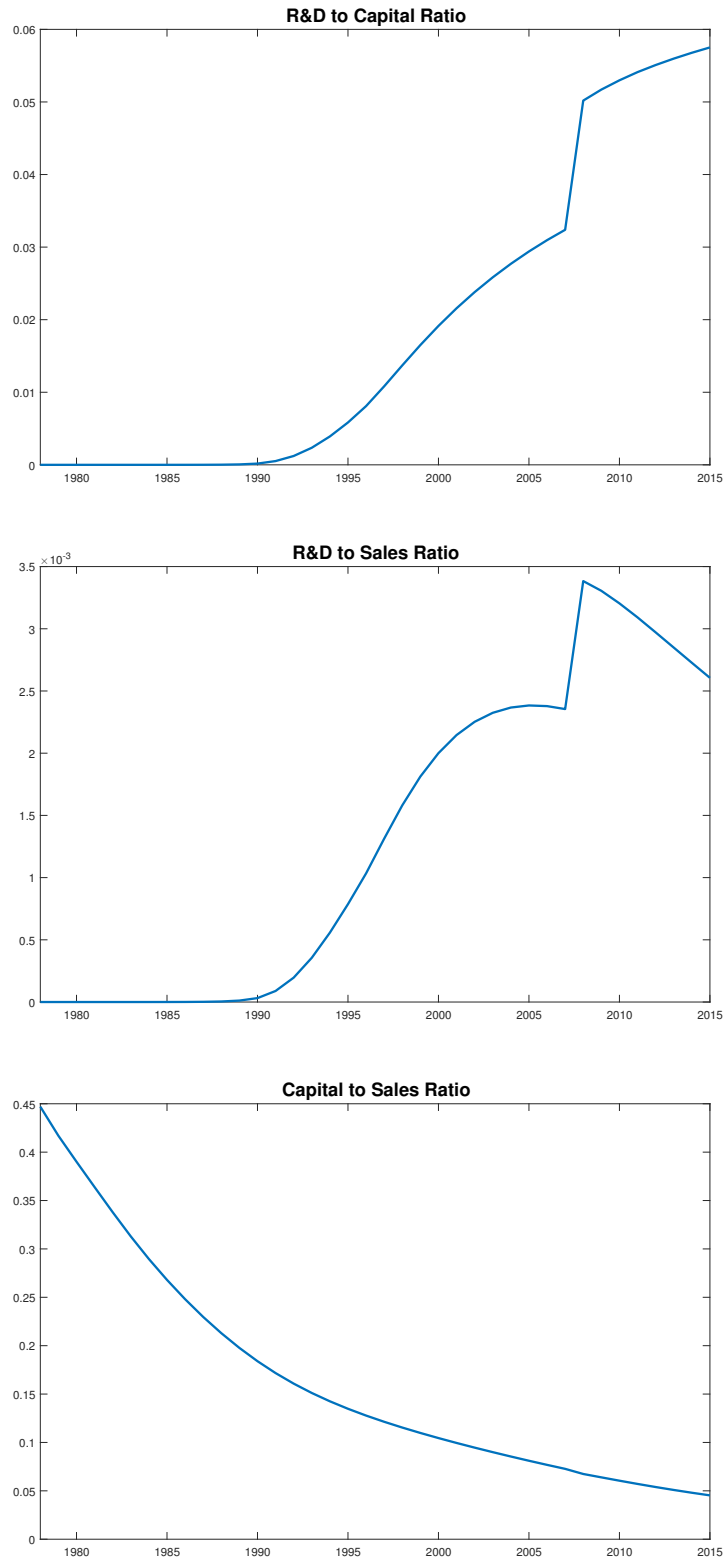
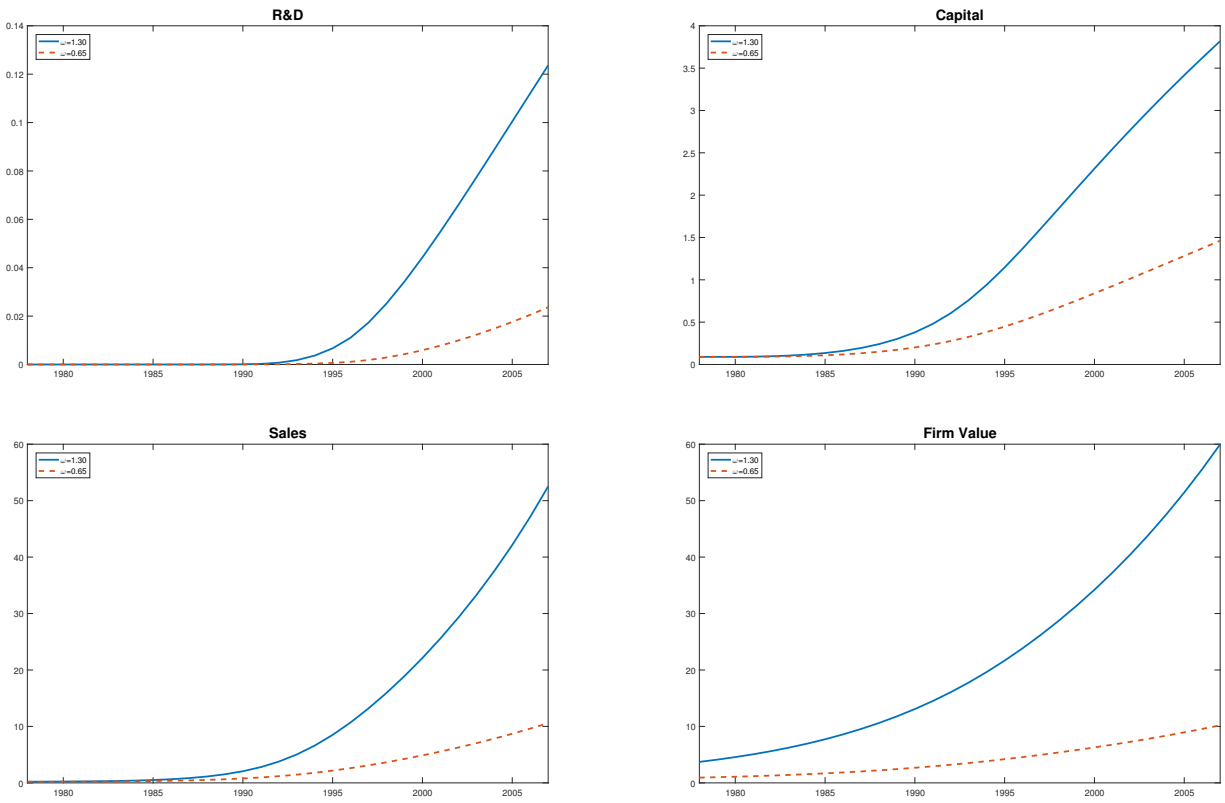Figure 8: The tax subsidy is doubled from 11.5% to 23% at 2008 in this experiment.

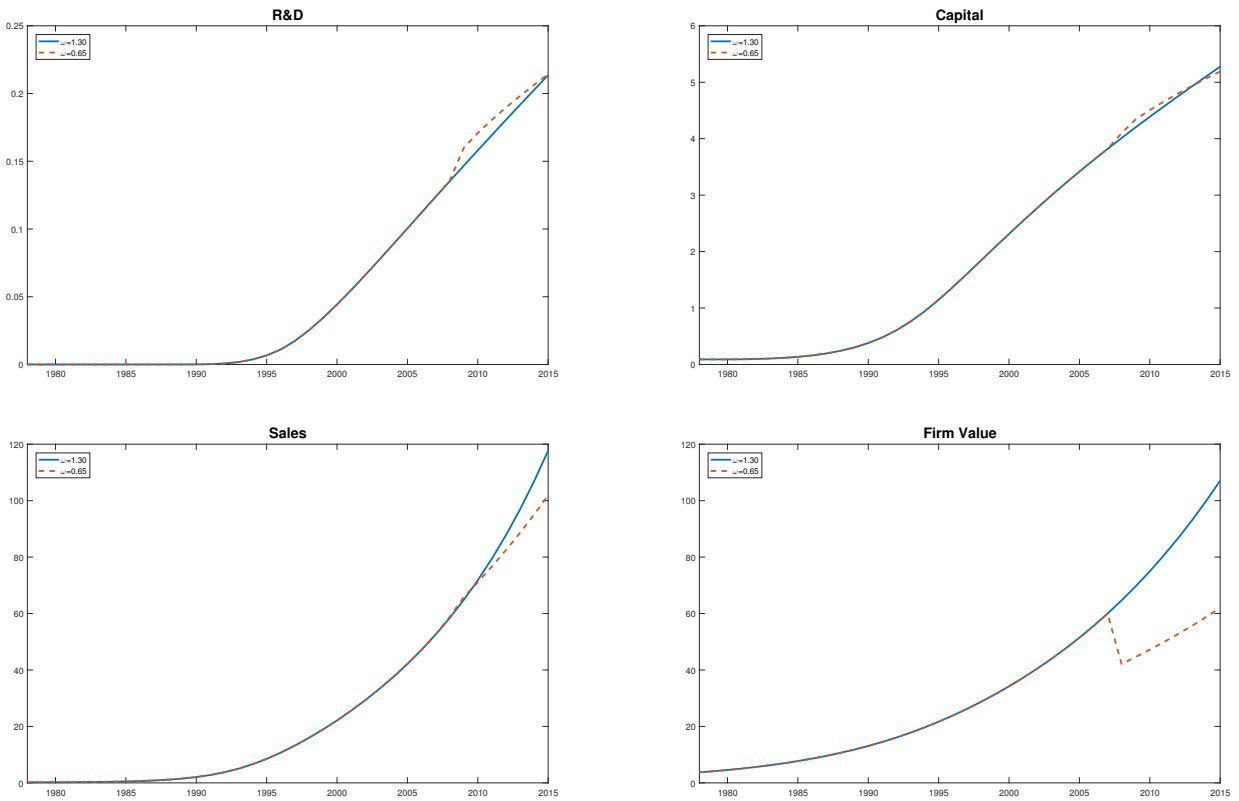Figure 9: The foreign techonology spillover is halved from 1.30 to 0.65 at 1978 in this experiment.

Figure 10: The foreign techonology spillover is halved from 1.30 to 0.65 at 2008 in this experiment.

Table 1: **Summary Statistics**

Variables	Mean	Std. Dev.	1%	99%	Obs.
Total assets (log)	21.76	1.368	18.74	25.63	20,014
Net capital (log)	19.86	1.797	14.81	24.28	19,977
Sales	21.09	1.612	16.60	25.22	19,869
Labor (log)	7.453	1.417	3.296	11.02	19,198
R&D (log) (R&D> 0)	16.91	1.531	12.73	20.95	18,656
R&D-to-sales	0.038	0.052	0.000	0.240	12,186
R&D-to-total assets	0.019	0.020	0.000	0.091	12,195
R&D-to-capital	0.240	1.445	0.000	3.242	12,193
Number of granted patents	46.59	200.6	0	642	12,331
Number of granted invention	13.45	98.01	0	174	12,331

Table 1 presents descriptive statistics for key variables in our sample. The sample is constructed from CSMAR, Wind and SIPO databases for the period 2007-2015. We focus on non-financial and non-utility firms, and keep firms with positive total assets, positive operating income, and non-negative R&D expenses.

Table 2: **Firms' R&D and Innovation Behavior by Firm Size**

	(1)	(2)	(3)	(4)
Database	CSMAR	CSMAR	CSMAR	NBS
	R&D	Innovation	Share of	R&D
Variable	intensity	efficiency	invention	intensity
Firm size (log)	-0.126***	0.018***	-0.005	-0.036***
	(0.032)	(0.002)	(0.009)	(0.011)
State-owned dummy	-0.332***	-0.004	-0.034	-0.043
	(0.125)	(0.007)	(0.022)	(0.056)
Industry-Year FE	Yes	Yes	Yes	No
Firm FE	Yes	Yes	Yes	No
Industry FE	No	No	No	Yes
Province FE	No	No	No	Yes
R-squared	0.251	0.503	0.274	0.183
No. of Obs.	16,793	16,796	13,827	30,097
No. of Firms.	2,496	2,497	2,494	30,097

Table 2 reports how firms' R&D and innovation behavior varies by firm size. We consider firms' R&D intensity (column 1), innovation efficiency (column 2), and share of granted invention patents over total granted patents (column 3). The sample covers non-financial and non-utility Chinese listed firms for the period 2007-2015. Heteroskedasticity-consistent standard errors reported in parentheses are clustered by firms. In column (4), we use a sample of manufacturing firms from the National Bureau of Statistics (NBS) of China in 2007 to perform a robustness test. We use observations in 2007 due to the unavailability of R&D data from 2008 on, and exploit cross-sectional variation by running an OLS regression. Heteroskedasticity-consistent standard errors reported in column (4) are clustered by sectors. Significance levels are indicated by *, **, and *** for 10%, 5%, and 1%, respectively.

Table 3: **Model Parameterizations**

Table 3 summarizes the parameters used to solve the model. Panel A reports the parameters calibrated separately from data or borrowed from other studies. Panel B presents estimation results by taking parameters in Panel A as given and jointly matching selected data moments.

Panel A: Parameters Calibrated Separately

Real interest rate (r)	0.02
Dividend distribution tax (τ_d)	0.10
Corporate income tax (τ_c)	0.23
R&D tax subsidy (τ_{rd})	0.115
Depreciation rate (δ)	0.13

Panel B: Parameters Estimated by SMM

Returns to scale (α)	0.940
Productivity scale (ζ)	1.790
R&D fixed adjustment cost (η_0)	0.499
R&D convex adjustment cost (η_2)	4.076
Capital fixed adjustment cost (γ_0)	0.021
Capital convex adjustment cost (γ_2)	2.207
Foreign technology spillover (ω)	1.295
Innovation efficiency (ϕ)	0.293
Innovation volatility (ρ)	4.755
Future uncertainty (θ)	0.097
Variable cost (c_v)	0.828

Table 4: **Simulated Model Moments: Targeted Moments**

Table 4 reports both data and corresponding model moments. Data moments are calculated based on a sample of firms from the National Bureau of Statistics of China in 2007.

Moments	Data	Model
(i) R&D:		
Mean	0.130	0.124
Standard deviation	0.684	0.140
Autocorrelation	0.717	0.956
Fraction of firms with zero R&D	0.885	0.524
(ii) Capital:		
25th percentile	1.630	2.023
Median	4.340	4.149
75th percentile	12.28	6.698
Autocorrelation	0.953	0.984
(iii) Sales:		
25th percentile	13.03	10.20
Median	26.50	28.69
75th percentile	61.69	77.14
Autocorrelation	0.953	0.983

Table 5: **Firms' R&D and Innovation Behavior by Firm Size: Simulated Data**

Variable	(1) R&D intensity	(2) Innovation efficiency	(3) Share of invention
Firm size (log)	-0.675***	-3.445***	-0.004
	(0.014)	(0.087)	(0.003)
Firm FE	Yes	Yes	Yes
R-squared	0.155	0.055	0.004
No. of Obs.	34,331	30,554	25,465
No. of Firms	3,777	3,683	3,625

Table 5 reports how firms' R&D and innovation behavior varies by firm size. We consider firms' R&D intensity (column 1), innovation efficiency (column 2), and share of granted invention patents over total granted patents (column 3). Heteroskedasticity-consistent standard errors reported in parentheses are clustered by firms. Significance levels are indicated by *, **, and *** for 10%, 5%, and 1%, respectively.

Table 6: **R&D Policies**

Table 6 shows the effects of R&D policies which target a particular subset of firms. In the second column, firms with lower R&D expenditures are given more subsidies. In the third and fourth columns, firms with lower capital stock and productivity are given more subsidies.

Target	Lower d	Lower k	Lower z
R&D expenditure	-5.7%	4.0%	47.9%
Capital	-2.5%	-6.4%	4.9%
Sales	-1.4%	-4.3%	12.8%
Firm value	-1.0%	-0.5%	7.9%