Discussion Paper No. 15-006

China's R&D Explosion – Analyzing Productivity Effects Across Ownership Types and Over Time

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January 2015

Abstract: In the past years Chinese firms increased their spending on R&D substantially and worked on achieving a higher quality level of R&D. We analyze whether different R&D activities show a positive influence on total factor productivity (TFP) for firms of different ownership types and across two time periods. Our panel dataset with annual information allows us to study listed firms over the two time periods 2001-2006 and 2007-2011. Privately owned enterprises (POEs) not only obtain higher returns from own R&D than majority and minority state-owned enterprises (SOEs), they are also able to increase their leading position. Overall strong increases in the size of patent stocks are related to a decreasingly positive or even vanishing influence on TFP. POEs not only produce R&D of the highest quality but are also the only ownership type profiting from higher quality. Up to now research collaborations allow almost no benefit with the only exception stemming from domestic collaborations with individuals. Our comprehensive analysis depicts strengths but also weaknesses of the corporate sector in China. We derive implications for the further development of economic policies.

JEL Classification: O32, O33

Keywords: productivity, R&D, China, ownership type, patents

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1 Introduction

By now it has become consensus that a sustainable development of the Chinese economy is increasingly dependent on productivity gains instead of input factor accumulation. Unleashed by China's transition from a planned towards a mixed market economy, competition and privatization have contributed to total factor productivity (TFP) gains ever since (Brandt et al. 2012, Hsieh & Klenow 2009). Throughout the past years, China's corporate sector has witnessed an unprecedented rise in R&D activities – observable by increases in R&D expenditures and patent applications of private and state-owned firms. Although the positive effect of R&D on productivity is well documented in the literature (e.g., Griliches & Mairesse 1991 for developed economies, Hu 2001 for China up to the 1990s), China's recent stunning surge in different R&D activities has not been investigated from that perspective.

In this study we analyze whether the rise in R&D activities shows a positive and sustained influence on productivity of Chinese firms. Our analysis focuses on differences between majority and minority state ownership as well as private ownership and on differences in the impact of R&D activities throughout the time periods 2001-2006 and 2007-2011. We investigate different aspects of R&D activities to allow not only for increasing quantity but also for differences in the quality and technological sophistication of R&D as well as considering the effectiveness of collaborative research activities.

Before 2001, China's R&D expenditures were below 1% of its GDP but doubled since then to exceed 2% in 2013. While this ratio is slightly above the EU-28 level, China now takes the second rank behind the US in terms of total R&D investments. Similarly, patent applications have experienced a remarkable surge and reached more than 700,000 in 2013 – making China's patent office (SIPO) the global leader in terms of receiving national applications since 2011. Also in other legislations, such as Europe or the US, the Chinese share of patent applications increases strongly. However, so far it remains unclear whether China's rise in R&D activities corresponds to higher TFP. Critics claim that the enormously rising number of patent applications will only impact TFP growth if the economic value and technological sophistication of the underlying inventions is substantially improved (World Bank 2012).

We address this issue by analyzing how R&D activities of the recent decade contribute to Chinese firms' productivity. Previous studies have examined the influence of R&D on productivity only until the late 1990s. In these years, however, research was predominantly carried out by a few state-owned firms. From the beginning of the 2000s, R&D investments not only increased strongly but also improved in quality. Furthermore, against the background of China's economic transition, a large number of minority state-owned and private-owned firms have joined China's innovation efforts and contributed vigorously to R&D activities of China's corporate sector. In this study we are therefore able to derive novel evidence for the productivity effects of R&D activities for state and non-state firms throughout the time period 2001 to 2011. Since China's "Medium- to Long-term Plan for Science and Technology Development (2006-2020)" (MLP) has brought considerable changes to its innovation policy, we separately investigate the time periods before and after its implementation. Against this background, we examine how heterogeneity in the volume, economic value, technological sophistication, and collaboration mechanisms of R&D activities influence the productivity of Chinese firms.

For our empirical analysis we compile a unique panel dataset which covers the population of Chinese firms listed at the stock exchanges of mainland China. For the operationalization of our main variables, we combine accounting data including information on R&D expenditures with national patent applications. Our R&D variables provide rich information about forward citations, the share of high-tech patents, and domestic as well as international R&D collaborations. To account for potential endogeneity issues in productivity estimations, we follow the methodology proposed by Levinsohn & Petrin (2003). In addition, we verify the robustness of our main results by applying, first, the approach of Olley and Pakes (1996) and, second, system GMM estimation.

We briefly foreshadow our findings. Privately owned enterprises (POEs) not only achieve higher returns from own R&D than majority and minority state-owned enterprises (SOEs), they are also able to increase their leading position. Thus, exposure to competition seems to be beneficial for the efficiency of these firms. Overall strong increases in the size of patent stocks are related to a decreasingly positive or even vanishing influence on TFP. This outcome could be a result of an economic policy that puts much more emphasis on quantity instead of quality. POEs not only achieve research of the highest quality but are also the only ownership type profiting from higher quality. Up to now research collaborations bestow almost no benefit with the only exception stemming from domestic collaborations with individuals. In the future, it may be possible to achieve better outcomes, if increasing competition is leading firms to engage in collaborations that truly lead to knowledge gains and cost savings.

The remainder of this paper is structured as follows. Section 2 provides information on the institutional background, Section 3 discusses prior literature and Section 4 explains our empirical method. We describe our data sources and our sample in Section 5 and present our results in Section 6. Section 7 derives implications and Section 8 concludes.

2 Institutional Background

State-owned firms versus non-state sector

Beginning with China's "reform and opening" in 1978, the transition from a centrally-planned to a mixed-market economy has been paralleled by a shift of economic activities from the state to the non-state sector. Non-state-owned firms were allowed to enter a number of previously prohibited industries and operated in increasingly deregulated and competitive markets (Xu 2011). While smaller non-state collectives in light industries mainly produced and sold consumer products at market prices, China's larger state-owned firms in heavy industries remained shielded from competitors and sold capital goods according to a dual-price system (Zhu 2012).[1] Despite the introduction of modern management techniques which linked income to firm performance, the state sector's lack of competition, binding input and output quotas, and soft budget constraints facilitated a divergence in TFP growth between firms in the state and the non-state sector (Jefferson et al. 1996).

Throughout the second reform decade from 1988 to 1998, the government let the non-state sector grow but kept employment in the state sector constant in order to avoid social instability (Heilmann 2008). State-owned firms were still obliged to sell a share of their products below market prizes but were protected from looming bankruptcy by preferential access to credit (Holz 2003, p. 75). In contrast, firms in the non-state sector were facing hard budget constraints for investment and had to excel against a growing number of entrants started by entrepreneurs or emanating from restructured state entities and foreign-invested firms (Naughton 2007, p. 309). As a result, TFP growth in the domestic non-state sector remained above the growth rate of the state sector (Jefferson et al. 2000).

Since 1998, deep structural transformation accelerated the privatization of former state-owned firms and, subsequently, the establishment of private firms has become formally legalized (Zhu 2012). Throughout the late 1990s and early 2000s, many state-owned firms and collectives were closed or privatized (Yusuf et al. 2006, p. 86). When measured by either the number of firms or share in industrial gross output, the state sector has lost considerably in economic importance. For instance, the contribution of state-owned firms to gross industrial output has decreased from above 70% in the early 1990s to around 20% in 2001 and has reached 8% in 2012 (NBS 2014).

However, even after 30 years of reforms, the socialist legacy is still apparent at state-owned firms, for example through higher levels of capital accumulation, preferential access to

[1] The dual price system is characterized by the coexistence of prices fixed by the government for a selection of high-priority goods with prices allowed to adjust according to supply and demand for an increasing share of remaining products.

financial resources, profits from monopoly rights in a number of industries,[2] and protection from foreign competition (Zhu 2012, Branstetter & Feenstra 2002, Amiti & Jovorcik 2008). Excessive labor from the shrinking state sector has been partially absorbed by the non-state sector. In addition, non-state firms have benefited from rural-urban migration and demographic trends which, until recently, have contributed to a surplus of Chinese labor which kept wages competitively low. Reflected in differences in factor endowment, production in the state sector remains more capital intensive whereas the non-state sector is more labor intensive.

Following the latest wave of structural reforms and China's accession to the World Trade Organization (WTO) in 2001, the possibility of bankruptcy for unprofitable firms in the state sector and the reduction of excessive labor ultimately contributed to enormous TFP gains. For 1998 and 2007, Zhu (2012) reports an annual average TFP growth rate of 5.50% for the state sector which, for the first time since the reforms, has outpaced the growth rate of 3.67% in the non-state sector. These trends are confirmed by Jefferson et al. (2008) who examine multi-factor productivity by ownership type throughout the time period 1998 to 2005 and report a growth rate of 15.63% for the state sector – roughly twice as high as in the non-state sector.

While there is conflicting evidence for China's overall TFP growth rate and the contribution of TFP to output (see Tian & Yu 2012 for a meta-analysis), recent studies have investigated drivers of TFP at the firm level and have pointed out that a significant portion of TFP gains can indeed be attributed to the reallocation of resources from the state to the non-state sector. For China's manufacturing firms, Hsieh & Klenow (2009) evaluate the contribution of capital and labor reallocation among incumbents on aggregate TFP growth between 1998 and 2005. They find that a more efficient allocation within manufacturing

[2] These industries include energy, transportation, telecommunication, banking, entertainment, education, and health care.

industries contributes 2 percentage points to annual TFP growth and that competition increases aggregated TFP by raising within-firm productivity as well as by a more efficient allocation of inputs to more productive firms. Based on the same data set, Brandt et al. (2012) study the effects of entrants for the time period 1998 to 2007 and find that net entries of firms account for over two thirds of total TFP growth.

R&D activities in the economy

Despite substantial gains from improving resource allocation, this source of TFP growth will abate with increasing levels of efficiency in the economy. In addition, political and institutional barriers have prevented further efforts to privatize the remaining state sector so far. As an alternative source through which China's TFP growth may be sustained, Jefferson et al. (1999) propose investments in industrial R&D. Throughout China's planned and early transition period, R&D was mainly performed by research institutes and, to a lesser extent, by universities while firms functioned as pure manufacturing units (Hong 2008, Liu 2009). China's command economy aimed at plan fulfillment and provided firms with little incentives to engage in intramural R&D activities or R&D collaborations with universities or research institutes. The resulting lack of industry-science collaboration negatively impacted the industrial applicability of domestic R&D and thus considerably reduced the development of new products and production processes by firms (Liu & White 2001).

In 1999, China's State Council decided to accelerate economic development through innovation, high technology, and industrialization (Liu et al. 2011). In the following years, R&D operations have increasingly been relocated from research institutes to firms in state and non-state sectors. In addition, China's accession to the WTO strengthened the protection of intellectual property rights through the enforcement of the Agreement on Trade-Related Aspects of Intellectual Property Rights (Kim et al. 2012). After 2006, China's "Medium- to Long-term Plan for Science and Technology Development (2006-2020)" (MLP) has again provided a considerable stimulus for China's innovation policy, with a main emphasis on increasing the economy's technological sovereignty.

Indeed, China's R&D activities have intensified substantially in the time period after 2001, as observed by considerable increases in R&D investments and in invention patent applications by domestic actors (see Figure 1). From 1990 until 2001, the ratio of R&D expenditures to GDP stagnated below 1% and patents had only increased from around 6,000 to 30,000 applications annually. After 2001, China's R&D to GDP ratio surpassed the 1% benchmark of developing countries and even doubled afterwards to reach 2% in 2013 – which is slightly above the EU-28 level. In terms of the volume of R&D investments, China now takes the second rank behind the US. Similarly, patent applications have experienced a remarkable surge and reached 700,000 in 2013 – making China the leading country in annual patent applications since 2011.

Against this background, the industrial contribution to inputs and intermediate outputs of invention has become clearly observable. In 2012, firms have contributed 76% to domestic gross R&D expenditures and 59% to domestic invention patent applications. As R&D activities obtained a larger prominence in economic policy, measures to support R&D also professionalized. For the mid-1990s, Guan and Yam (2015) show that financial incentives of the government, i.e. tax credits, special loans, and R&D grants, have a neutral or negative effect on patents. Boeing (2014) finds that R&D subsidies, on average, cause a crowding-out of firms' own R&D investments throughout the time period 2001 to 2006. However, for the time period after the enforcement of the MLP, 2007 to 2011, Deng & Hu (2014) investigate R&D activities of occasional R&D performers and find an increase in the amount and the continuity of R&D investments as well as in the number of patent applications – indicating an improving effectiveness of policy measures after 2006. The increase in the effectiveness of China's R&D programs is confirmed by Guo et al. (2014). Throughout the time period 1999 to 2011, the authors show a positive effect for Innofund subsidies (i.e., subsidies by the

Innovation Fund for Small and Medium Technology-based Firms) on patent applications which becomes significantly stronger after 2005.

With respect to China's surge in patent applications, for the time period 2001 to 2007 Li (2012) shows that the enforcement of provincial patent subsidies has contributed to the increase in patent applications and that a larger fraction of applications got granted. In line with the implementation of the MLP in 2006, Lei et al. (2013) study the effect of local patent subsidies for filing fees and grant rewards on applications and grants of Chinese invention patents. Their findings suggest that the number of applications per patentee increases while the number of claims per patent and the corresponding grant rate remains constant. The authors infer that financial incentives for grants motivate patentees to split up inventions to yield a maximum number of patents – possibly leading to a decrease of the average economic value of patent applications after 2006. Thus, while policy measures have become more effective in stimulating R&D investment and patent applications after 2006, they may also have contributed to a decline in the average value of patents filed by Chinese applicants.

R&D collaborations

Firms can conduct their R&D collaborations with other firms or with research institutes. Guan et al. (2006) investigate how several forms of technology exchange influence the innovative performance of Chinese firms. For collaboration with domestic partners and international partners they expect but cannot confirm a positive influence on innovative performance.

In line with China's increasing emphasis on industrial R&D, hundreds of research institutes have been transformed into more commercially-oriented entities or directly restructured into firms (Jakobson 2007) while universities started to conduct more applied R&D and founded numerous firms as spin-offs (Eun et al. 2006, Hu & Mathews 2008). Following the enforcement of China's "Bayh-Dole Act" in 1999, which allowed universities to patent research outcomes derived from government-funded R&D, and the decentralization of national R&D activities, formal science-industry collaborations, as observable by joint patent applications, have increased in recent years (Hong 2008). In line with the argument that knowledge externalities are geographically constrained, Hong & Su (2013) find in general that geographical proximity is supportive to university-industry collaborations in China. In addition, greater distance increases the probability of collaboration for highly prestigious universities as they are sought out by industry partners to solve specialist problems. However, despite the increase in university-industry collaborations, Fu & Li (2012) find that collaboration with Chinese universities does not contribute significantly to firms' sales of products which are new to the market.

3 Prior Evidence on the R&D-productivity Relationship

A series of prior studies has examined productivity returns to R&D activities based on Chinese firm level data. In his seminal study, Hu (2001) uses cross-sectional data on 813 firms for 1995 to investigate the effect of R&D expenditures on TFP. The data of this study is restricted to high-tech firms of the Haidian District of Beijing, thus covering the most sophisticated firms at the time. After excluding domestic privately-owned firms due to their limited number, he investigates the effects of firms' own investment in R&D and the effect of R&D expenses subsidized by the government. Using OLS estimation, his results show a significant R&D elasticity of 0.08%, i.e. a 1% increase in own R&D leads to a statistically significant increase of 0.08% in TFP. In the instrumental variable (IV) specification, the elasticity increases to 0.32%. For R&D subsidies, both specifications indicate an insignificant effect on TFP. By reestimating the IV specification according to ownership types, Hu (2001) finds significant returns to own R&D investments for almost all groups with firms owned by the government having the lowest output elasticity. Since R&D intensities vary little across ownership types, this finding suggests that firms in the non-state sector yield higher returns to R&D.

Jefferson et al. (2006) investigate the influence of R&D on several performance measures for approximately 20,000 large- and medium-size manufacturing firms from the state- and non-state-sector, grouped according to seven different ownership types. They conduct a cross-sectional analysis including lagged regressors covering the years 1997-1999. Using an IV approach, the authors estimate returns to R&D based on a Cobb-Douglas production function with the restriction that R&D elasticities are assumed to be constant across all ownership types. Differences in the effectiveness of R&D are then calculated by transforming the elasticity into returns resulting in unusually high returns between 55% to 178%. The relatively high returns of 138% for SOEs are in contrast to Hu (2001) and may be due to the high ratio of output to R&D of this specific ownership type.

Hu and Jefferson (2004) estimate returns to R&D for 88 R&D-performing large- and medium-sized, mainly state-owned, industrial firms located in Beijing throughout the time period 1991-1997. Besides an R&D expenditure equation, they also estimate a production function and a profit function. For the Cobb-Douglas production function, they find a significant elasticity for R&D which, after being transformed into returns, shows a declining influence on productivity over time.

Focusing on the complementarity between in-house R&D and technology transfer via the acquisition of disembodied technology, Hu et al. (2005) analyze data on approximately 10,000 of China’s large- and medium-sized firms over the time period 1995 to 1999. The authors estimate a production function with interaction terms confirming a complementary relationship between in-house R&D and technology transfer from both domestic and international sources. When restricting the sample to foreign invested firms (FIEs), the complementarity between in-house R&D and technology transfer from international sources vanishes, as these firms might not be dependent on this form of knowledge.

Zhang et al. (2003) apply the method of stochastic frontier analysis to examine the impact of R&D investments of 8,341 Chinese industrial firms for the year 1995. The authors confirm Hu's (2001) finding that state-owned firms have the lowest returns to R&D. In addition, Zhang et al. (2003) find that the R&D intensity of firms is not endogenous to their own R&D efficiency since state-owned firms report relatively high levels of R&D intensities. Due to their negligible importance at the time, POEs had to be excluded from the analysis.

What these studies have in common is their focus on the time period before China's accession to the WTO in 2001, as they use cross-sectional or panel data from the period 1991 to 1999. Consequently, the evidence derived reflects a situation in which China's R&D activities were at relatively low levels. This is in stark contrast to the increase in R&D investments and patent applications observable after 2001. Furthermore, these studies could not take into account the performance of purely privately-owned firms as all firms were more or less state-owned. The recent surge in the number of POEs demands a specific analysis of their performance. As prior studies rely on cross-sectional data or rather short panels, they are not able to investigate changes in the effectiveness of R&D over time. We are not aware of more recent studies covering the influence of firm-level R&D on productivity, which is probably due to the difficulty of obtaining comprehensive information on R&D expenditures.

4 Method

4.1 Dealing with Endogeneity

When estimating production functions, we have to deal with the problem that firms adjust their input factors to current productivity shocks. As the productivity shocks are unobserved, this leads to a correlation between the error term and the input factors and thus to biased coefficient estimates. In a setting with two input factors, one would typically expect the coefficient on the variable factor (labor) to be overestimated and the coefficient on the fixed factor (capital) to be underestimated. Several approaches have been developed to break the correlation between the unobserved productivity shock and the choice of input factors, each with their own advantages and disadvantages.

Guided by theoretical expectations about expected biases in results, we select the appropriate estimation method for our data by comparing OLS results to the approaches developed by Levinsohn and Petrin (2003) and Olley and Pakes (1996). Applying all three approaches, we estimate a standard Cobb-Douglas production function in two variants: first, with gross output as dependent variable and labor, capital and material costs as main input variables and, second, with value added as dependent variable and labor and capital as main input variables.

The main method used for our analysis is the control function approach developed by Levinsohn & Petrin (2003), (LP in the following), which treats labor and intermediates as variable input factors and capital as a quasi-fix input factor. The authors present an estimator that uses intermediate inputs as proxy for the unobserved productivity shock. Their approach can be explained as follows: first the demand function of intermediates is computed which is assumed to be directly related to productivity. Then, in the second step, they build on this intermediate demand function to reveal the unobservable productivity as a function of the intermediate input and capital. In the estimation the unobservable error term is not expected to correlate with the independent variables. Since the approach of LP seems adequate for our setting, we primarily rely on this estimator for our analysis.

We also investigate the appropriateness of the control function approach developed by Olley and Pakes (1996), (OP in the following). The approach of OP relies on investments as a proxy for the productivity shock. In the standard form, OP uses a three-stage estimation with one stage used to model the exit of firms. We find exit of firms – measured as exit from the stock market – to be very rare in our data. We therefore adjust the OP algorithm to only include the control for simultaneity but not the control for selection. One potential disadvantage of OP compared to LP is the need to restrict the sample to observations with positive values for investment. The resulting loss of efficiency is of limited importance in our dataset as only 0.4% of observations show zero investments. From a theoretical point of view a more important argument in favor of LP is that intermediates may respond more smoothly to productivity shocks than investment. If firms face non-convex adjustment costs, they may not fully adjust the investment level to the realization of the productivity shock. According to Levinsohn & Petrin (2003) this may be especially the case for firms outside of fully developed Western economies.

The LP approach chosen for our main analysis only controls for the potential endogeneity of the input factors labor, material, and capital but the R&D activities of the Chinese firms are also potentially endogenous inputs. For example, large investments in R&D are a costly endeavor that only firms with sufficient financial resources can afford. Since a high productivity is positively related to profitability, there may be a danger of reverse causality. As we are not able to control for the potential endogeneity of the R&D activities with the LP approach, our results should accordingly be interpreted as correlations.

We take up this limitation in our robustness checks. In addition to reporting results with the alternative control function approach of OP, we report results with lagged R&D variables for both the LP and OP procedure. By using lagged variables, we drive a wedge in the time dimension between the realization of the productivity shock and the decision on the input factors thus alleviating the potential endogeneity of R&D. In addition, we report system GMM results that are able to instrument the R&D variables as well. This estimation method is rather demanding concerning the data used since identification relies only on the variation within a given firm and since several tests on the auto-correlation of the error term and the validity of the instruments need to be passed. It turns out that our data does not completely comply with the requirements of these tests.

4.2 Specification of the Regression Models

The variables reflecting R&D activities (e.g., R&D stock, patent stock) are of main interest for our study; especially in their interactions with ownership dummy variables and time period dummies. This way, we seek to carve out differences with regard to R&D activities which are driven by ownership type and/or are changing over time. As general control variables we include presence in a policy zone, engagement in an industry where FDI is encouraged, regional income levels, industry dummies, year dummies, and province dummies. Thus, we control for a broad set of factors which might influence firms' productivity.

We estimate basic production functions (table 4) and include, first, R&D stock (table 5) and, second, patent stock (table 6). Thereafter, we account for quality-adjusted R&D efforts (table 7) and research collaborations (table 8). While the baseline model of each table uses R&D stock or patent stock to consider R&D efforts, we use – in the other models of these tables – the following approach to investigate the effect of ownership types and time periods for various R&D activities: we split the regressor $R\&D_{it}$ indicating one specific R&D activity (such as R&D stock or patent stock) in J categories with d_j indicating the category as a dummy variable:

$$\ln(\text{Gross output}_{it}) = \beta_0 + \beta_1 \ln(\text{Labor}_{it}) + \beta_2 \ln(\text{Capital}_{it}) + \beta_3 \ln(\text{Material}_{it}) + \sum_{j=1}^{J}\left(\gamma_j R\&D_{\text{it}}\mathrm{d}_{\mathrm{j}}\right) + \sum_{k=1}^{K}\left(\delta_k \mathrm{x}_{\mathrm{k\,it}}\right) + \varepsilon_{it}$$

Ownership type has three categories (i.e., J = 3) and the period of time has two categories (i.e., J = 2). If we combine the three ownership types with the two time periods, six categories result (i.e., J = 6). We use this approach for multiple variables reflecting different facets of R&D activity. $x_{k\,it}$ indicates additional control variables.

Concerning ownership type, we split the R&D stock into three new variables (that is, one variable each for majority SOEs, minority SOEs, and POEs). This allows us to scrutinize the effect of R&D according to the ownership structure of the firm. Correspondingly, we divide the sample into an early period, 2001-2006, and a late period, 2007-2011. Accordingly, we split R&D stock in two variables – either for the earlier period or the later period. The later period coincides with the period after the MLP was launched in 2006. The MLP laid out the innovation policies for the coming decade. It can be almost seen as an exogenous policy shock as much more emphasis was given to incentives for R&D activity and the incentives came from the highest level of the government (Liu et al. 2011). Furthermore, from 2007 on, firms had an incentive to patent and to collaborate in order to be classified as high-tech firm and to receive support in the form of subsidies from the government.

5 Data

5.1 Data Sources and Sample

Our dataset includes comprehensive information about Chinese firms listed in the A-share segment of the two stock exchanges in mainland China, Shanghai and Shenzhen. We obtained accounting data from the global database Compustat for the time period from 2001 to 2011 and complemented the data with employment information from Datastream. R&D expenditures for the years 2001 to 2005 were manually collected from annual reports (CNINFO), whereas for the years 2006 to 2011 they were obtained from the Chinese database WIND. As the role of ownership is one focus of the analysis, we included time variant information on the share of state ownership from the Chinese database RESSET. Patent data is obtained from the April 2013 version of the EPO Worldwide Patent Statistical Database (PATSTAT). The procedure of matching patent data to firm data is described in detail in appendix A. Our sample of listed firms includes many of China's largest firms and firms with political or economic importance (Du & Xu 2009). Only domestic firms, which are defined by the China Securities Regulatory Commission (2002, 2006) as firms in which the ownership share of foreign parties does not exceed 20%, can be listed on the stock exchanges of

Shanghai and Shenzhen. We start our analysis in the year 2001 because R&D and patenting activities by Chinese firms were not widespread before.[3]

Initially, our data includes 2,363 firms for which we have 16,734 observations with non-missing accounting information.[4] We exclude 2,436 observations from the financial and the retail sector because R&D activities are of limited importance in these sectors. In order to eliminate outliers, we delete firm-year observations that exhibit values above the 99th or below the 1st percentile of the following ratios: revenue-to-employees, revenue-to-capital, revenue-to-material, employees-to-capital, employees-to-material, and material-to-capital. Our full estimation sample is based on information for 1,927 firms for which we have 12,443 observations.

Due to the dynamic development of the Chinese stock market, our panel data is unbalanced. We start of in the year 2001 with 790 firms, increasing to 1,776 firms in 2011. On average a firm is observed 6.5 times. The stock markets in Shanghai and Shenzhen were both founded in 1990 and then dynamically increased the number of listings. Until the mid-2000s, the central government determined stock issuance quotas to maintain a balance between the regions at China's stock markets (Pistor & Xu 2005). Provinces with sound economic performance obtained higher quotas and provincial governments selected firms for initial public offerings (Du & Xu 2009). The resulting composition of listed firms adequately reflects China's economic development, with an emphasis on better performing firms. For example, manufacturing firms from coastal provinces represent the majority while the remaining industries and provinces are included to a lesser extent. Figures 2 and 3 show the development of firm locations between 2001 and 2011. As we have only a few delistings in our sample, the unbalancedness of our panel data is driven by the expansion of the stock

[3] The financial information of listed Chinese firms is now sufficiently precise so that it can be used for high-quality research (see, e.g., Fisman & Wang 2010, Kato & Long 2006).

[4] This initial data covers the near-population of listed firms. The stock market of mainland China consists of only two stock exchanges. In the year 2011 we cover 98.3% of the 1,411 firms listed in Shenzhen and 95.5% of the 931firms listed in Shanghai.

market and not by the exit of unsuccessful firms. We therefore do not expect biases in our results from the unbalancedness *per se*. However, one has to keep in mind that our analysis is representative for the most successful firms in China.

5.2 Definition of Main Variables

This section defines our main variables. Detailed definitions for all variables, used deflators, and references to data sources can be found in appendix B (see table B1). As output variable of our production function we use two measures: gross output and value added of the firm. Concerning the former, we use total revenues whereas, concerning the latter, value added is calculated as revenue minus material costs.

The basic components of the production function are labor, capital and – dependent on the specification of the model – material costs. With respect to labor, we use the number of employees of the firms and regarding capital, we use deflated net fixed assets denoted in RMB. Material costs are calculated as the difference between deflated costs of goods sold and labor costs, also denoted in RMB.

To compute R&D assets, we use the time series of each firm's R&D expenditures and compute the R&D stock applying the declining balance formula following Hall et al. (2005) with a depreciation rate of 15%. To be precise, the R&D stock in year *t* is the R&D expenditures of that year plus the R&D stock in year *t-1* depreciated by 15%. To account for those firms publishing no R&D expenditures – either because they actually conduct no R&D or because they refrain from reporting R&D spending – we created a dummy variable that turns 1 if no R&D stock can be established, and 0 otherwise.

Concerning the patent variables, three important methodological aspects need to be noted. First, the Chinese patent system consists of innovation, utility, and design patents. As innovation patents are the most valuable and have the highest novelty standard, we concentrate on those. Second, we base our measures on patent families instead of patent applications since the number of families more closely corresponds to the number of inventions. When compiling patent families, we rely on the INPADOC family definition available in PATSTAT which combines all applications that share at least one priority into one family. Third, when calculating stocks we apply the usual 15% annual depreciation rate (Hall et al. 2005) to account for the fact that technology becomes obsolete over time.

We transform our measure of state ownership, which is ranging from 0% to 100%, into a set of three dummy variables representing the ownership category: first, privately-owned firms without any state holding of the shares (POEs); second, state-owned with the state holding more than 50% of the shares (majority SOEs); and third, state-owned with a the state holding a less than 50% but more than 0% of the shares (minority SOEs). Dummy variables are time variant, i.e. firms can be allocated to different ownership types over time.

5.3 Descriptive Statistics

Table 1 presents the descriptive statistics of our sample for all Chinese firms in total and, in addition, for the three subsamples according to firms' ownership type. Our main sample consists of 12,443 observations for 1,927 firms. 18.4% of all observations in the total sample can be attributed to majority SOEs, 34% to minority SOEs, and 47.6% to POEs. On average, the firms in our sample have 4,687 employees. The standard deviation of 18,490 reflects a broad range of firm size also indicated by a minimum of nine employees and a maximum of more than 550,000 employees. On average, the firms yield revenues of 4,404 million RMB and a capital stock of 1,820 million RMB, again exhibiting a broad range. Majority SOEs are generally two to three times larger than minority SOEs and POEs.

As basic R&D activities, we measure both R&D stock and patent stock. On average, Chinese firms have annual R&D expenditures of 32.8 million RMB which accumulate to an average stock of 76.6 million RMB. There is no R&D activity reported for 52.4% of all observations. In contrast to the clear size advantage of majority SOEs as measured by standard accounting figures, POEs and majority SOEs exhibit an R&D stock of similar size, which is higher than that of minority SOEs. The average annual number of applications for patents amounts to 7.5 patents leading to a stock of 20.2 patents. The difference in patenting activity is again indicated by a rather large standard deviation and a maximum for the patent stock of 18,812 patents.[5] With regard to patent stock, the original size pattern reverses: POEs have the highest numbers of patent filings whereas majority SOEs have the lowest. Here it can be seen that a lower state ownership share is accompanied by more intensive R&D efforts.

Concerning the quality level of firms' R&D efforts, we find that firms' patents were able to induce on average 0.053 forward citations during a 3-year time window after publication. The share of patents relating to at least one high-tech technology classification yields 18.2% on average. Regarding these quality characteristics of firms' patent portfolios, we again find higher values for those firms where ownership share of the state is smaller: POEs yield 0.059 forward citations compared to 0.033 for majority SOEs. Also, the share of high-tech patents is higher for POEs (18.8%) than for majority SOEs (14.5%).

On average, firms hold a stock of 4.2 patents which are jointly filed with national co-applicants and 0.26 patents with international co-applicants.[6] With regard to this R&D activity, POEs also exhibit a higher number of patents (6.75) than minority SOEs (1.66) and majority SOEs (0.62). Yet this pattern does not hold true for patents jointly filed with international co-applicants. Here, minority SOEs have clearly the highest activity with a mean of 0.43 whereas majority SOEs have a mean of 0.23 and POEs a mean of only 0.16.

15.2% of all observations concern firms located in policy zones and 58% of the observations are subject to a firm operating in an industry where FDI is encouraged by the Chinese government. POEs have a higher probability of being located in policy zones and

[5] The distribution of the patent stock variable is very skew. The firms with the largest (depreciated) patent stocks are ZTE (18,811 patents), China Petroleum & Chemical Corporation (4,254 patents), and TCL (1,561). These are among the firms that also show up in other publications as largest applicants (e.g., WIPO 2014).

[6] Since our measure of co-applications is meant to identify collaborations across firm borders, we have to be careful to eliminate collaboration partners which belong to the same group as the focal firm. As 32% of all national collaborations with a firm as a partner happened actually within a group, this is a quite important phenomenon in our data.

operating in an industry where FDI is encouraged whereas majority SOEs are more likely to be shielded from international competition. The mean of regional GDP per capita is 47,210 RMB with POEs being located in regions with higher income.

As the Chinese economy develops at a high pace, it is of interest to investigate the firm characteristics across time. Table 2 sets out – in a similar manner as table 1 – two subsamples for different time periods: the years 2001 through 2006 and 2007 through 2011. Concerning all financial metrics, we find that Chinese firms are growing at a rapid pace: the firms on average have 3,827 employees in the earlier period and 5,388 in the later period. The increasing importance of R&D activities can clearly be seen when analyzing the R&D stock. In the period of 2001 to 2006 this variable shows an average value of 15.9 million RMB in contrast to a mean of 126.1 million RMB in the later period. Correspondingly, the share of observations where no R&D stock could be observed decreases significantly (74.1% vs. 34.6%). Similarly, the patent stock yields 6.2 patents in the earlier period and 31.6 patents in the later period. The dummy indicating that no patent activity could be observed shrinks from 62.5% to 32.6%.

Concerning the quality of firms' R&D, the firms collected 0.037 forward citations on average in the earlier period and 0.060 in the later. Recall that for any patent – either filed in the earlier or in the later period – the same time window of three years is applied to collect citations. However, the high-tech share of patents in the portfolio does not increase correspondingly: we find that in the earlier period 17.7% of firms' patents were filed in high-tech IPC classes and 18.3% in the later period. Whereas the stock of patents filed jointly with national co-applicants rises significantly from 0.94 patents to 5.68 patents, the patents filed jointly with international co-applicants exhibits a smaller increase: from 0.23 in the earlier period to only 0.27 in the later period.

As one would expect from the rapid transformation of the Chinese economy, the distribution of ownership types changes substantially from the earlier to the later period. In the earlier period, a largely even distribution can be observed: 30.0% of all observations are majority SOEs, 37.7% are minority SOEs and 32.3% are POEs. In the later period, this distribution strongly shifts to more private ownership stakes. Majority SOEs only amount to 7.8%, minority SOEs to 30.0%, and 62.2% of all observations concern POEs.

Being located in a policy zone is not a characteristic that changes in a major way between the two time periods but, in the later period, more observations are in industries where FDI is encouraged (62.5% vs. 48.0%).

Table 3 shows the industry distribution of our sample. The high share of firms from the manufacturing sector (75.9%) is representative for the overall Chinese economy. However, the sample also contains firms from the other sectors of the economy, such as agriculture, mining, construction, and information technology.

6 Empirical Analysis

6.1 Basic Production Functions

Table 4 presents the estimations of the basic production functions. Here, we compare different estimation methods and different regression specifications. With regard to different estimation methods, we estimate the basic production function with OLS, LP and OP. Concerning different specifications, we employ gross output and valued added as dependent variables. These variations lead to six different models. Note that the input variables enter the regression models in the form of logarithms. All models include a full set of industry, province, and year dummies.

For comparison we report first the biased OLS results with gross output as dependent variable (model 1). Due to unobserved productivity shocks, we expect an upward bias for the coefficients of the variable input factors labor and material and a downward bias for capital.

Following, we describe the results using the LP approach in detail (model 2) and thereafter briefly compare these results to the other estimation techniques. As generally anticipated, we observe a significant coefficient for labor (0.100 with $p < 0.001$), for capital (0.279 with $p < 0.001$), and also for material (0.591 with $p < 0.001$).[7] Concerning R&D activities, we also find a significant coefficient for the R&D stock (0.004 with $p < 0.001$). The fact of not having any R&D expenditures is not significantly related to productivity (-0.008 with $p > 0.1$). With respect to ownership types, we find that minority SOEs exhibit a 4.3% lower productivity ($p < 0.01$) than majority SOEs. The spread is lower for POEs with a difference of -2.8% ($p < 0.05$).[8] If the firm is located in a policy zone, it has a 2.6% higher productivity ($p < 0.1$). Chinese FDI guidelines define in which industries FDI is encouraged. Consequently, the level of foreign competition varies. If a firm is doing business in an industry in which FDI is encouraged, we find productivity to be 4.1% ($p < 0.001$) lower compared to firms in other industries. This is consistent with Kamal (2014) who finds partially negative effects of foreign invested firms on domestic firms. In order to control for the level of development of the local economy, we include GDP per capita at the regional level. This variable accounts for agglomeration effects, the quality of the infrastructure, and the educational level of the labor force and thus for the quality of the labor input. In model 2, this variable is insignificant but in other specifications it has a positive significant effect.

When comparing the coefficients for the input factors between LP (model 2) and OLS (model 1), we find a very similar coefficient for labor. For the fixed input factor capital we find, as theoretically expected, a higher coefficient in LP than in OLS, whereas for material

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[7] Estimating a production function for a large sample of large and medium sized manufacturing firms, Jefferson et al. (2006, p. 358) find similar input coefficients (labor 0.121, capital 0.120, material 0.749). Our coefficient for material corresponds roughly to material's average value share of 0.621 in the sample. Chinese firms employ a relatively high share of intermediate products in their production processes.

[8] Earlier studies covering time periods in the 1990s throughout the mid-2000s have mostly found lower productivity levels for SOEs than for POEs (see Tian & Yu 2012 for a survey of that literature). However, more recent studies by Zhu (2012) and Jefferson et al. (2008) observe higher TFP growth rates for SOEs after 1998 – a trend which is reflected by our data in TFP levels. Furthermore, note that only listed firms are included in our sample. Until the early 2000s, stock market listings were restricted to well-performing SOEs while the number of POEs has only later been increasing due to the privatization of listed firms and new listings of POEs. In contrast to most SOEs, not all of China's well-performing POEs have gone public in Mainland China, e.g. Huawei and Lenovo are not listed in Shanghai or Shenzhen. Thus, a bias towards well-performing SOEs and a higher TFP growth rate of the state sector may explain why we find higher TFP levels for majority SOEs than for POEs. But also note that when we only differentiate between SOEs as a whole and POEs, the difference between the two groups is not significant.

we observe, also as theoretically expected, the reverse pattern. We therefore conclude that the approach of LP is generally appropriate for dealing with endogeneity in our setting.

We also compare the results of the control function approach by OP (model 3) to OLS (model 1).[9] Coefficients on the variable inputs labor and material have a similar size. However, the coefficient on capital is smaller in OP even though theoretically it should be larger than the downward-biased coefficient of OLS. We infer from the results that accounting for productivity shocks by using investment in the control function is less suitable for our specific dataset. As a side argument for LP as main method, we note that this approach results in almost constant returns to scale (0.97 with $p < 0.1$), whereas OP shows decreasing returns to scale with a value of 0.85 ($p < 0.001$). However, as OP is a method commonly used in the literature, we will nevertheless report robustness checks with this method.

Finally, we compare the results of the gross output specifications (models 1-3) to the results of the value added specifications (models 4-6). As the labor coefficient should be overestimated in OLS (model 4) it is reasonable to find a smaller coefficient in LP (model 5) and a weakly smaller coefficient in OP (model 6). However, the capital coefficient is also decreasing in LP and OP, which is not what we would have expected theoretically. The value added specification is less flexible compared to the gross output specification because it constrains material inputs to a one-to-one relationship with gross output. As the value added specifications do not comply with theoretical expectations and also due to their lower flexibility, we choose the LP approach with gross output as dependent variable as the main specification for the remainder of the study.[10]

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[9] The number of observations is lower in OP compared to LP as observations with zero investment have to be disregarded.

[10] The specification with value added has more observations than the one with gross output because in the data cleaning procedure we eliminate the highest and lowest percentile in the ratios of the main input and output variables. As the value added specification has one fewer input, more observations remain.

6.2 Effectiveness of R&D Activities Across Ownership Types and Over Time

6.2.1 Effectiveness of R&D

In Table 5, we investigate the effectiveness of R&D by ownership type and over time. Across the models set out in table 5, we introduce various specifications highlighting different context dependent effects of the R&D stock. As described above, we split the R&D stock in new variables based on the context of the observation. For each of the three ownership types, we create the R&D stock variable based on whether the observation belongs to a majority SOE, a minority SOE, or a POE (model 2 in table 5). This allows us to compare the effectiveness of R&D based on the organizational setting of the firm. Then, in model 3 of table 5, we proceed similarly for the two periods of time we analyze. Again, we split the R&D stock according to whether the observation belongs to the earlier period of 2001 to 2006 or to the later period of 2007 to 2011. Model 3 in table 5 then presents all combinations of the three ownership types and the two periods of time which leaves us with an R&D stock split in six new variables.

Model 3 of table 4 is the baseline model which we, for convenience, also display in table 5 (model 1). In model 2 the variable R&D stock is removed but replaced by a threefold split according to the ownership types. In other words, interaction effects of R&D stock and the three ownership types are included in the specification. The results show that the R&D stock of majority SOEs, minority SOEs, and POEs have significantly positive coefficients, which can be interpreted as elasticities. Yet, the elasticity of POEs' R&D stock has the largest size (0.005 with $p < 0.001$) in comparison to the elasticity of majority SOEs (0.002 with $p < 0.05$) and minority SOEs (0.004 with $p < 0.001$). This indicates that throughout the entire period of 2001 through 2011 those Chinese firms owned privately are most effective with their R&D spending. To make the results more tangible, we also calculate returns to R&D.[11] For majority SOEs, minority SOEs and POEs they are 12.1%, 13.8%, and 15.8%, respectively. Given that the R&D intensity at POEs is higher than at SOEs (0.95% for POEs versus 0.72% for minority and 0.57% for majority SOEs) we conclude that POEs are actually more efficient in working with their R&D resources. The higher returns to R&D are not a reflection of starting from a lower level of R&D intensity.

In model 3, we again split the R&D stock according to the time of observation. The R&D stock for those observations in the years 2001 through 2006 is positively significant and yields a coefficient of 0.003 ($p < 0.001$). The R&D stock in the period from 2007 to 2011 is also positive and significant but its coefficient is larger (0.006 with $p < 0.001$). This indicates that the effectiveness of R&D expenditures increases over time. Translating the elasticities into returns clearly reveals the progress that Chinese firms have made in benefitting from their investment into R&D. Returns to R&D increase from 9.3% in the early time period to 20.2% in the later one. In model 4, we not only split the R&D stock by ownership type or time but, rather, by both variables leading to six regressors. Here, we find that the POEs in the period from 2007 to 2011 show the highest effectiveness of their R&D (0.007 with $p < 0.001$) whereas the majority SOEs in the earlier period only show a marginally significant effect of their R&D (0.002 with $p < 0.1$). The difference in the coefficients of R&D over time is significant for minority SOEs and for POEs but not for majority SOEs. Furthermore, to investigate a diverging development of effectiveness over time, we test whether the difference in the coefficients is larger for POEs than for majority SOEs. As our test indicates a difference which is significant at the 10% level, we find that not only the effectiveness of R&D is increasing over time but, moreover, that the differences between ownership types are

[11] To obtain returns we multiply the elasticities with the ratio "gross output/R&D stock" calculated at the mean of the corresponding variables.

increasing.[12] Put differently, we find a diverging increase in the effectiveness of R&D for POEs compared with majority SOEs.

6.2.2 Effectiveness of Patented Research Output

Concerning patented research, we proceed in the similar way as denoted in table 5. Table 6 presents various regression specifications where we split the patent stock according to ownership type, period of time, or both. The baseline model (model 1) of table 6 builds on the baseline model of table 5 with one addition: the variable patent stock is included in the model in addition to R&D stock and, with it, a dummy variable reflecting the fact that no patents could be found for this firm. The results of model 1 in table 6 show no major difference in comparison to model 1 of table 5. The coefficient of patent stock is positively significant (0.018 with $p < 0.01$) indicating that patents have an effect on productivity. Model 2 of table 5 shows the elasticities for the patent stock segmented by ownership type, which are not significantly different from each other. The patent stock for majority SOE shows the largest coefficient among the ownership types (0.021 $p < 0.01$). The coefficient of minority SOEs is 0.016 ($p < 0.05$) and the coefficient of POEs is 0.019 ($p < 0.001$). Concerning the development across time, we find in model 3 of table 5 that the coefficient of patent stock is 0.032 ($p < 0.001$) for the earlier period and, statistically significantly lower, 0.015 ($p < 0.01$) for the later period. This indicates that the contribution of patent applications is decreasing over time. To the best of our knowledge, this research is the first presenting the implications from the Chinese patent explosion explicitly for the real economy. Whereas Li (2012) finds an increase in the number of patent filings for Chinese firms after the introduction of patent subsidies and Lei et al. (2013) complement this result by documenting that the increased number is achieved by filing narrower patents, our results directly relate patent filings to

[12] This result cannot be explained by SOEs only remaining in sectors where R&D is of lesser importance such as mining and utilities. Even though the share of SOE in manufacturing is decreasing from 64% at the beginning of our sample period, it still stands at 38% at the end. Furthermore, we are controlling for the industry-specific importance of R&D via dummy variables.

productivity. When the patent stock is split into six categories allowing us to investigate the effect of patented research across ownership type and over time (model 4), we document a significantly positive effect on productivity for firms of all ownership types for the earlier period. Interestingly, for the later period, we find no significant effect for majority SOEs, whereas minority SOEs exhibit a positively significant coefficient of 0.013 ($p < 0.05$) and POEs show a higher coefficient of 0.018 which is also highly significant ($p < 0.001$). POEs are also the only ownership type that does not exhibit a statistically significant decline in the coefficient over time. Apparently, firms with a lower state ownership follow a commercially oriented but not policy-induced patenting strategy.

6.2.3 Effectiveness of High-Quality Research

In table 7, we investigate the effectiveness of high-quality research. Model 1 of table 7 builds on model 1 of table 6 but also includes two more variables: the average PCT citations collected by each patent family during a 3-year window and the high-tech share of patents. We find that average PCT citations have a positively significant effect on productivity (0.044 with $p < 0.001$). Further, the high-tech share within the patent portfolio is also significant and positive (0.049 with $p < 0.05$). Model 2 of table 7 splits both variables according to their ownership type. Concerning average PCT citations, we only find the coefficient for POEs to be significant and positive (0.048 with $p < 0.05$). The same can be observed for the high-tech share: here, again, only the coefficient for POEs is significantly positive (0.063 with $p < 0.05$). This indicates that only POEs are able to translate high-quality patents into higher productivity. Model 3 includes a split of both variables according to the period of time. Here, average PCT citations show a significantly positive coefficient – but only for the later period of 2007 to 2011 (0.045 with $p < 0.05$). We make the same observation for the high-tech share as this variable is also only significant for the later period (0.072 with $p < 0.01$). When accommodating both ownership type and period of time in the regression model (model 4), we find that only POEs in the later period show a significantly positive effect for both variables, average PCT citations (0.051 with $p < 0.01$) and high-tech share (0.074 with $p < 0.01$).[13] Our results show POEs excel other firms in translating high-quality research into tangible outcomes. Whereas the descriptive statistics show R&D of lower quality for majority SOEs, minority SOEs achieve higher or comparable quality as POEs but apparently fail to translate their quality into productivity increases.

6.2.4 Effectiveness of Research Collaborations

For investigating the effectiveness of research collaborations, we include the patent stock of patents jointly filed with national and international co-applicants in the regression models. Table 8 presents these results in the same known way with splitting these two variables according to ownership type and time period of the observations. In the baseline model (model 1 of table 8), we find a weakly significant effect for patents jointly filed with national co-applicants (0.024 with $p < 0.1$) but no effect for patents filed with international co-applicants. When splitting these two variables according to ownership type (model 2), jointly filed patents with national co-applicants only show a significant effect for POEs (0.023 with $p < 0.1$). Apparently, collaborations do drive productivity but only for POEs. When splitting these variables according to the time period (model 3), a significant effect can be found for patents filed with national co-applicants – but only in the later period from 2007 to 2011 (0.23 with $p < 0.1$). Model 4 again includes the six variables for each type of collaboration. Here, we find a significant effect for POEs in the later period. The coefficient is positive and significant for collaborations with national co-applicants (0.026 with $p < 0.05$). Collaborations with international co-applicants do not show a significant effect.[14]

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[13] Minority SOEs show a marginally significant effect for high-tech share in the later time period ($p < 0.1$).

[14] An alternative way of broadening the knowledge base of the firm is to work with researchers of foreign nationality or with Chinese researchers based abroad. We checked whether these activities would increase firm productivity but found a significant negative effect for POEs, for the later time period, and for POEs in the later time period. It seems that POEs started to invest in this mechanism but that up to now costs are higher than benefits.

The positive effect for national collaborations for POEs suggests that private firms are able to absorb knowledge from the outside. To improve our understanding of R&D collaborations, we scrutinize the collaboration partners and divide those according to their type. We were surprised to find that collaborations with firms, universities, and research institutes were all insignificant. This is consistent with prior survey evidence for ICT firms which has shown that collaborations with universities are not only still quite infrequent but are further rarely the source of core technology for firms (Wu & Zhou, 2012). Only collaborations with individuals exhibit a positively significant effect. Based on discussions with practitioners familiar with Chinese patent filing strategies, we were able to identify two categories of collaborations with individuals. First, it is possible that the individual is a manager or an employee of the firm. The invention might be additionally assigned to an individual to give specific honors to the employee or in order to retain the property right even if the firm would go into bankruptcy. In both cases, it could be an indication that the invention is especially valuable but it would not be a true collaboration because firm boundaries are not crossed. Second, the person can be a self-employed inventor or a consultant working for firms on a contractual basis. Only these cases should be classified as true collaborations. Unfortunately, we cannot differentiate between these two cases as we do not have access to the names of employees.

It is possible that we do not find an influence of collaboration for large firms because the variety of their activities blurs an unambiguous effect. We therefore investigated the result for individual national collaboration partners separately for firms below and above the median number of employees. However, these results confirmed our findings of the overall sample. Importantly, when splitting the sample according to different measures of absorptive capacity, we never find a significant positive effect for collaborations with other firms, universities, or research institutes.[15]

From the overall view on our results we have to conclude that in the Chinese innovation system most collaborations do not enable the firms to increase their productivity. In the past, firms pretended to have collaborations with organizations such as universities or research institutes. A survey of Chinese manufacturers found that more than half of the firms enter into collaborations for the primary reason of accessing government funds. Product development and technology transfer are only of secondary importance. Rather, firms and organizations divide government funds without true R&D collaborations (EAC, 2014).

6.3 Robustness Checks

Endogeneity of the variables is a major concern in any study estimating the productivity effects of R&D activities. We choose the control function approach developed by Levinsohn & Petrin (2003) as the method fitting best for the setting for our main analysis. However, we were concerned whether our results are robust concerning the use of other methods. In table 9, we therefore report summary results for the use of alternative approaches. As a first robustness check, we use the approach by LP but lag all R&D-related variables by one year to drive a wedge between the decision on R&D and the realization of output (panel A). Next, we employed the approach by Olley & Pakes (1996) with concurrent (panel B) and lagged R&D-related variables (panel C). Furthermore, we tried our best to find a system GMM

[15] We broadened our investigations of collaborations by considering the dimensions of quality, geographical proximity, and organizational integration. In order to analyze whether we would get an effect by looking at institutions of especially high quality, we separated out universities participating in the 985 program and research institutes belonging to CAS but collaborations with neither group showed a positive significant effect on TFP. We tested whether geographical proximity would facilitate knowledge transfer by looking separately at collaborations with universities located in the same city as the headquarter of the firm. Again, we found no significant effect. Finally, we tried to investigate the influence of having a co-applicant that is a joint venture partner at the same time. Because joint ventures offer a closer form of collaboration due to the organizational integration of researchers, we expected a positive effect for this collaboration form. However, we found only six firms with this specific type of co-applications and furthermore, only for two firms the joint venture partner was from outside the group structure of the focal firm. Due to these rare occasions we were not able to run a regression analysis but we learned that this type of activity is not common.

specification that does not violate the requirement concerning the autocorrelation of the error term and which passes the test for over-identifying restrictions for the instruments. In our preferred specification, we use input factors concurrently without additionally controlling for further lags in the input factors or including a lagged dependent variable. We treat the input factors as endogenous and the R&D variables as predetermined. Whereas this specification always passes the test of over-identifying restrictions at the 5% level, we were not able to find a specification which passes the test for no autocorrelation of second order (panel D). Given this limitation, the results from system GMM should be interpreted cautiously.

Our results do not show major differences are thus mainly confirmed by the different methods. Panels A-D reveal that no other ownership type has a higher coefficient for R&D stock than POEs. Also, all four methods indicate higher returns to R&D for the later period of time. The reverse pattern for the patent stock is also confirmed by panel A-D, as elasticities of patenting have decreased over time. The control function approaches of panel A-C tend to confirm our findings with respect to the productivity effect of high-quality research. Higher average citations and a higher share of high-tech patents increase productivity for POEs and have a positive effect in the later time period. System GMM always exhibits positive coefficients but at differing degrees of significance. One reason for this deviation could be that our data does not fully comply with the requirements of this method. Finally, results concerning collaborations are confirmed by OP in panel B. The other methods tend to corroborate the positive coefficients for national collaborations and the negative ones for international collaborations but with partially differing significance levels.

7 Implications

Our study yields three main implications for our understanding of innovation activities in Chinese firms. From these implications, we are in turn able to derive important policy implications.

First, we observe a strong divergence in the influence R&D activities have on productivity according to ownership type. POEs generally yield higher benefits from R&D efforts and thus outperform SOEs. This is not only true in the earlier period (2001-2006) but POEs can even increase their advantage in exploiting their R&D activities over time. The group of POEs consists of privatized SOEs and newly founded private firms. POEs were much more exposed to competition than the remaining (earlier established) SOEs as the latter had preferential access to resources such as capital and enjoyed protected markets. This unequally competitive environment gave POEs strong incentives to implement business strategies guided by market needs. They learned how to better allocate resources – increasing their performance over time. An alternative explanation for our finding could be the selection of especially productive firms for privatization. Unfortunately, the literature does so far not provide evidence on the prior efficiency of firms selected for privatization. Our results show that the transformation from a firm population with many SOEs to a population with more POEs has been a successful transition policy for China. An important policy implication of our research is therefore that market forces can be relied upon to increase the effectiveness of R&D.

Second, the strongly increasing amount of patent applications does not directly translate into increasing productivity. Patented R&D efforts do drive productivity but as patent filings increase, the productivity impact of new patent applications decreases strongly or even vanishes. The returns to patenting may decrease due to policy measures that reward quantity over quality. Widespread patent subsidies have now led to a drastic inflation in patent filings (Li 2012). With majority SOEs, the development has gone so far that patent applications have become disconnected from the productivity development. As patent applications require resources for examination and a plethora of applications makes the system less transparent, the government might want to shift the focus of its innovation policy from quantity to quality of applications. Now that organizations in China have learnt how to deal with and use intellectual property rights, firms and universities need a more nuanced approach to decide which inventions are "worth to file". The subsidies and policy targets of the past biased these decisions in the direction of quantity.

Third, Chinese firms still face limitations with regard to technology transfer and absorbing knowledge. China's policies strongly emphasized the learning of and the knowledge transfer to domestic organizations. However, Chinese firms still have difficulties in absorbing knowledge. Our results show very limited benefits from R&D collaborations. One solution could be that government programs encourage and require "real" R&D collaborations between partners beyond the sharing of subsidies. Providing the right incentives to universities and research institutes to engage in technology transfer and to enter in R&D collaborations could complement this policy. Additionally, increasing market pressure could force firms into mutually beneficial R&D collaborations with the aims of reducing development costs and gaining competitive advantage.

8 Summary and Future Avenues for Research

This study investigates the effect of different R&D activities on TFP of publicly listed Chinese firms for the time period 2001-2011. We focus on the influence of ownership structure and investigate dynamics by taking two time periods into account. When analyzing the benefits of investments in R&D, important differences become apparent. Specifically, we find that POEs benefit most from R&D investments. Furthermore, only POEs benefit from sophisticated R&D efforts (i.e., highly cited patented research, research in high-tech). This is good news given the steadily increasing importance of POEs. Concerning the development over time, Chinese firms of all ownership types achieve higher returns on R&D investments in later periods, which may be a reflection of an increasingly efficient allocation of R&D resources in the Chinese corporate sector. But our results also show that the strongly rising number of patent filings does not materialize *per se* in higher productivity. Precisely, as more patents are filed, their effectiveness diminishes or even vanishes. Further, up to now there are limited benefits arising from R&D collaborations: only domestic collaborations with individuals show a positive influence on productivity.

There are various avenues for future research. An important research question to be answered is investigating the underlying mechanisms of the superior R&D performance of POEs. Do POEs excel other firms due to higher levels of competition, due to differences in the quality of the firm management, or due to less governmental influence on firm strategies? In addition, it would be worthwhile to investigate whether privatization is leading to higher efficiency or whether it is the other way round. Taking into account the economic implications of state ownership, future inquiry should thus investigate the transformation and performance of different organizational forms of Chinese firms.

Acknowledgements: We would like to thank Georg Licht, Carsten Herrmann-Pillath, Rolf Fare, Masahisa Fujita, Yundan Gong, Dietmar Harhoff, , Can Huang, Keun Lee, Xibao Li, Xiaoxuan Lu, Hong Ma, Franco Malerba, Tsutomu Miyagawa, Masami Miyashita, Pierre Mohnen, Barry Naughton, Pete Suttmeier, Tetsuo Wada, and Yinchu Wang for helpful discussions. We thank seminar participants at RIETI, Tokyo, Japan; Tsinghua University's SEM and School of Public Policy; the State Information Center, Beijing, China; UNU-MERIT, Maastricht, The Netherlands; as well as conference participants of Academy of Management (AoM) Meeting in Philadelphia, USA (2014); Annual Conference of the European Policy for Intellectual Property Association (EPIP), Paris, France (2013); European Association for Research in Industrial Economics (EARIE), Evora, Portugal (2013); Annual Conference of the Academy of Innovation and Entrepreneurship (AIE), Oxford, UK (2013); the "CISS – Competition and Innovation Summer School" in Turunc, Turkey (2012); the "DRUID – Innovation and Competitiveness Conference" in Copenhagen, Denmark (2012); the Third Asia-Pacific Innovation Conference in Seoul, Korea (2012); and the GLOBELICS Conference in Hangzhou, China (2012) for valuable comments. Furthermore we would like to thank Violeta Shtereva, Yu Lijing, and Wang Yihan for excellent research assistance.

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Tables and Figures

Table 1: Descriptive statistics - firm characteristics according to ownership category

	Total				Majority SOE		Minority SOE		POE	
	100.0%				18.4%		34.0%		47.6%	
	12,443				2,283		4,236		5,924	
Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Labor (number of employees)	4,687	18,490	9	552,810	8,298	32,155	4,078	14,346	3,730	12,903
Gross output (million RMB)	4,404	37,118	3	1,633,479	9,181	55,105	3,321	27,316	3,336	34,350
Value added (million RMB)	1,216	10,945	0.5	602,143	2,719	20,850	935	8,291	854	6,115
Capital (million RMB)	1,820	13,530	0.5	465,724	3,979	21,154	1,468	9,523	1,239	12,045
Material (million RMB)	3,177	30,049	0.5	1,706,566	6,465	40,210	2,371	19,264	2,487	31,677
R&D expenditures (million RMB)	32.785	269.031	0	11,166	52.467	489.449	23.900	155.218	31.552	205.687
R&D stock (million RMB)	76.628	568.300	0	21,253	82.421	665.667	63.701	452.756	83.639	600.797
No R&D (dummy)	0.524		0	1	0.662		0.591		0.422	
Patent applications	7.456	103.431	0	5,937	5.476	29.703	6.942	86.320	8.586	129.622
Patent stock	20.188	317.200	0	18,812	11.731	65.958	16.432	161.466	26.134	436.997
No patents (dummy)	0.460		0	1	0.567		0.486		0.400	
Average PCT citations (3 years) #	0.053	0.206	0	7	0.033	0.110	0.051	0.236	0.059	0.206
High-tech share of patents (%) #	0.182	0.296	0	1	0.145	0.279	0.188	0.302	0.188	0.297
National coapplications #	4.198	137.346	0	7,869	0.617	3.528	1.656	23.796	6.752	187.917
International coapplications #	0.258	3.155	0	89	0.231	1.913	0.429	4.344	0.161	2.492
Policy zone (dummy)	0.152		0	1	0.134		0.151		0.157	
FDI encouraged (dummy)	0.580		0	1	0.489		0.547		0.625	
Regional GDP/capita (RMB)	47,210	19,966	1,351	276,553	40,671	18,136	45,012	18,868	50,375	20,482

Notes: The statistics are calculated for the overall sample of 1,927 firms (12,443 observations. #Calculation for 1,385 firms with at least one patent application (6,717 observations). SOE = state-owned enterprise. POE = privately owned enterprise.

Table 2: Descriptive statistics - firm characteristics according to time period

	2001-2006		2007-2011	
	44.9%		55.1%	
	5,586		6,857	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Labor (number of employees)	3,827	13,848	5,388	21,521
Gross output (million RMB)	2,807	23,903	5,705	45,067
Value added (million RMB)	884	8,644	1,487	12,506
Capital (million RMB)	1,367	10,123	2,188	15,762
Material (million RMB)	1,903	17,283	4,216	37,322
R&D expenditure (million RMB)	14.216	269.453	47.911	267.755
R&D stock (million RMB)	15.942	104.733	126.066	756.124
No R&D (dummy)	0.741		0.346	
Patent applications	2.899	39.127	11.168	134.671
Patent stock	6.168	72.589	31.610	421.914
No patents (dummy)	0.625		0.326	
Average PCT citations (3 years) #	0.037	0.198	0.060	0.209
High-tech share of patents (%) #	0.177	0.312	0.183	0.289
National coapplications #	0.935	13.757	5.675	165.262
International coapplications #	0.233	2.151	0.269	3.516
Majority SOE (dummy)	0.300		0.078	
Minority SOE (dummy)	0.377		0.300	
POE (dummy)	0.323		0.622	
Policy zone (dummy)	0.142		0.156	
FDI encouraged (dummy)	0.480		0.625	
Regional GDP/capita (RMB)	38,277	16,664	51,253	20,025

Notes: The statistics are calculated for the overall sample of 1,927 firms (12,443 observations. #Calculation for 1,385 firms with at least one patent application (6,717 observations). SOE = state-owned enterprise. POE = privately owned enterprise.

Table 3: Industry composition

Industry	**Code**	**No. firms**	**%**
Agriculture	A	47	2.44
Mining	B	40	2.08
Manufacturing: food & beverages	C0	88	4.57
Manufacturing: textiles & apparel	C1	93	4.83
Manufacturing: wood & furniture	C2	11	0.57
Manufacturing: paper & printing	C3	49	2.54
Manufacturing: petro-chemistry & plastics	C4	268	13.91
Manufacturing: electronics	C5	114	5.92
Manufacturing: metal & non-metals	C6	216	11.21
Manufacturing: machinery & instruments	C7	477	24.75
Manufacturing: pharma & biological products	C8	127	6.59
Manufacturing: other	C9	20	1.04
Utilities	D	57	2.96
Construction	E	43	2.23
Information Technology	G	142	7.37
Social Services	K	56	2.91
Communication and Culture	L	15	0.78
Conglomerates	M	64	3.32
Total		**1,927**	**100**

Note: The industries are specified according to the classification of the China Securities Regulatory Commission.

Table 4: Basic production functions

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Method	OLS	LP	OP	OLS	LP	OP
Dependent variable	Ln (gross output)	Ln (gross output)	Ln (gross output)	Ln (value added)	Ln (value added)	Ln (value added)
Ln (labor)	0.094***	0.100***	0.087***	0.392***	0.269***	0.347***
	(0.007)	(0.005)	(0.006)	(0.016)	(0.015)	(0.014)
Ln (capital)	0.123***	0.279***	0.055***	0.462***	0.379***	0.250***
	(0.007)	(0.046)	(0.010)	(0.014)	(0.024)	(0.024)
Ln (material)	0.717***	0.591***	0.703***			
	(0.007)	(0.043)	(0.007)			
Ln (R&D stock)	0.004***	0.004***	0.003**	0.014***	0.010***	0.011***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
No R&D	0.000	-0.008	0.001	0.010	-0.024	0.013
	(0.013)	(0.013)	(0.015)	(0.032)	(0.032)	(0.027)
Minority SOE	-0.048***	-0.043***	-0.041***	-0.118***	-0.076**	-0.099***
	(0.012)	(0.012)	(0.010)	(0.031)	(0.025)	(0.027)
POE	-0.036**	-0.028*	-0.035**	-0.123***	-0.048+	-0.118***
	(0.013)	(0.012)	(0.013)	(0.034)	(0.026)	(0.029)
Policy zone	0.021	0.026+	0.013	0.082*	0.073*	0.055
	(0.015)	(0.014)	(0.014)	(0.039)	(0.032)	(0.040)
FDI encouraged	-0.061***	-0.041***	-0.065***	-0.167***	-0.094***	-0.171***
	(0.010)	(0.011)	(0.009)	(0.023)	(0.021)	(0.022)
Regional GDP/capita	0.024*	0.017	0.024*	0.101***	0.046*	0.097**
	(0.011)	(0.013)	(0.011)	(0.027)	(0.022)	(0.028)
Constant	2.872***			6.433***		
	(0.147)			(0.338)		
Returns to scale (RTS)	0.934	0.970	0.845	0.854	0.648	0.597
Test constant RTS, $\chi^2(3)$ / $\chi^2(2)$	175.20***	3.15+	180.47***	156.84***	223.09***	269.33***
(p-value)	(0.000)	(0.076)	(0.000)	(0.000)	(0.000)	(0.000)
N	12,443	12,443	12,428	12,782	12,782	12,751
Firms	1,927	1,927	1,927	1,969	1,969	1,969
R^2	0.966			0.763		

Notes: All regressions contain industry, province, and year dummies. Reference category: majority SOE. Concerning OLS estimation: standard errors are clustered by firm. The standard errors of Olley & Pakes (1996) estimations are calculated by bootstrapping with 50 replications. +, *, **, *** indicate significance levels of 10, 5, 1, and 0.1 percent, respectively. SOE = state-owned enterprise. POE = privately owned enterprise.

Table 5: Effectiveness of R&D

	(1)	(2)	(3)	(4)
Ln (labor)	0.100***	0.099***	0.099***	0.099***
	(0.005)	(0.007)	(0.006)	(0.006)
Ln (capital)	0.279***	0.286***	0.229***	0.260***
	(0.046)	(0.044)	(0.041)	(0.040)
Ln (material)	0.591***	0.583***	0.626***	0.602***
	(0.043)	(0.049)	(0.038)	(0.041)
Ln (R&D stock)	0.004***			
	(0.001)			
x Majority SOE		0.002*		
		(0.001)		
x Minority SOE		0.004***		
		(0.001)		
x POE		0.005***		
		(0.001)		
x 2001-2006			0.003***	
			(0.001)	
x 2007-2011			0.006***	
			(0.001)	
x Majority SOE x 2001-2006				0.002+
				(0.001)
x Majority SOE x 2007-2011				0.004**
				(0.001)
x Minority SOE x 2001-2006				0.003**
				(0.001)
x Minority SOE x 2007-2011				0.005***
				(0.001)
x POE x 2001-2006				0.003*
				(0.001)
x POE x 2007-2011				0.007***
				(0.001)
No R&D	-0.008	-0.007	-0.010	-0.009
	(0.013)	(0.013)	(0.013)	(0.012)
Minority SOE	-0.043***	-0.056***	-0.043***	-0.053***
	(0.012)	(0.014)	(0.011)	(0.015)
POE	-0.028*	-0.056**	-0.030*	-0.050**
	(0.012)	(0.018)	(0.012)	(0.018)
Policy zone	0.026	0.026	0.025	0.025
	(0.014)	(0.018)	(0.019)	(0.015)
FDI encouraged	-0.041***	-0.042***	-0.042***	-0.042***
	(0.011)	(0.011)	(0.008)	(0.008)
Regional GDP/capita	0.017	0.018	0.017	0.018+
	(0.013)	(0.012)	(0.011)	(0.010)

Notes: Levinsohn & Petrin (2003) estimation with ln(gross output) as dependent variable. All regressions contain industry, province, and year dummies. Reference category: majority SOE. +, *, **, *** indicate significance levels of 10, 5, 1, and 0.1 percent, respectively. SOE = state-owned enterprise. POE = privately owned enterprise. The statistics are calculated for the 12,443 observations of the 1,927 firms.

Table 6: Effectiveness of patented research

	(1)	(2)	(3)	(4)
Ln (labor)	0.097***	0.097***	0.097***	0.097***
	(0.007)	(0.006)	(0.007)	(0.006)
Ln (capital)	0.298***	0.298***	0.294***	0.299***
	(0.052)	(0.047)	(0.047)	(0.047)
Ln (material)	0.557***	0.557***	0.562***	0.558***
	(0.054)	(0.046)	(0.048)	(0.048)
ln (R&D stock)	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
No R&D	-0.006	-0.006	-0.007	-0.007
	(0.010)	(0.014)	(0.012)	(0.014)
Ln (patent stock)	0.018**			
	(0.006)			
x Majority SOE		0.021**		
		(0.007)		
x Minority SOE		0.016*		
		(0.006)		
x POE		0.019***		
		(0.005)		
x 2001-2006			0.032***	
			(0.007)	
x 2007-2011			0.015**	
			(0.005)	
x Majority SOE x 2001-2006				0.036***
				(0.008)
x Majority SOE x 2007-2011				0.007
				(0.008)
x Minority SOE x 2001-2006				0.027**
				(0.008)
x Minority SOE x 2007-2011				0.013*
				(0.006)
x POE x 2001-2006				0.032**
				(0.010)
x POE x 2007-2011				0.018***
				(0.005)
No patents	-0.019+	-0.019	-0.012	-0.013
	(0.011)	(0.012)	(0.014)	(0.013)
Minority SOE	-0.046***	-0.041**	-0.045***	-0.043**
	(0.010)	(0.012)	(0.011)	(0.013)
POE	-0.031*	-0.029*	-0.030**	-0.034*
	(0.012)	(0.014)	(0.011)	(0.014)
Policy zone	0.019	0.019	0.019	0.019
	(0.012)	(0.014)	(0.017)	(0.013)
FDI encouraged	-0.041***	-0.041***	-0.041***	-0.041***
	(0.008)	(0.010)	(0.008)	(0.009)
Regional GDP/capita	0.015	0.015	0.014	0.014
	(0.009)	(0.012)	(0.012)	(0.010)

Notes: Levinsohn & Petrin (2003) estimation with ln(gross output) as dependent variable. All regressions contain industry, province, and year dummies. Reference category: majority SOE. +, *, **, *** indicate significance levels of 10, 5, 1, and 0.1 percent, respectively. SOE = state-owned enterprise. POE = privately owned enterprise. The statistics are calculated for the 12,443 observations of the 1,927 firms.

Table 7: Effectiveness of high-quality research

	(1)	(2)	(3)	(4)
Ln (labor)	0.097***	0.097***	0.097***	0.097***
	(0.006)	(0.006)	(0.006)	(0.006)
Ln (capital)	0.294***	0.294***	0.293***	0.292***
	(0.041)	(0.045)	(0.041)	(0.045)
Ln (material)	0.563***	0.562***	0.563***	0.565***
	(0.096)	(0.046)	(0.040)	(0.076)
ln (R&D stock)	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
No R&D	-0.007	-0.007	-0.007	-0.007
	(0.015)	(0.013)	(0.012)	(0.012)
Ln (patent stock)	0.017**	0.017***	0.016**	0.016**
	(0.005)	(0.004)	(0.005)	(0.005)
No patents	-0.010	-0.010	-0.012	-0.012
	(0.013)	(0.010)	(0.013)	(0.013)
Average PCT citations	0.044***			
	(0.012)			
x Majority SOE		0.135		
		(0.100)		
x Minority SOE		0.032		
		(0.027)		
x POE		0.048*		
		(0.020)		
x 2001-2006			0.039	
			(0.029)	
x 2007-2011			0.045*	
			(0.019)	
x Majority SOE x 2001-2006				0.058
				(0.058)
x Majority SOE x 2007-2011				0.315
				(0.241)
x Minority SOE x 2001-2006				0.044
				(0.066)
x Minority SOE x 2007-2011				0.019
				(0.035)
x POE x 2001-2006				0.005
				(0.048)
x POE x 2007-2011				0.051**
				(0.019)

Table 7: Effectiveness of high-quality research (continued)

	(1)	(2)	(3)	(4)
High-tech share of patents	0.049*			
	(0.021)			
x Majority SOE		-0.024		
		(0.042)		
x Minority SOE		0.054		
		(0.034)		
x POE		0.063*		
		(0.027)		
x 2001-2006			0.009	
			(0.025)	
x 2007-2011			0.072**	
			(0.026)	
x Majority SOE x 2001-2006				-0.051
				(0.055)
x Majority SOE x 2007-2011				0.029
				(0.073)
x Minority SOE x 2001-2006				0.031
				(0.037)
x Minority SOE x 2007-2011				0.071+
				(0.040)
x POE x 2001-2006				0.028
				(0.043)
x POE x 2007-2011				0.074**
				(0.024)
Minority SOE	-0.046***	-0.050***	-0.046**	-0.048***
	(0.009)	(0.011)	(0.014)	(0.011)
POE	-0.031**	-0.036**	-0.030*	-0.033**
	(0.010)	(0.010)	(0.012)	(0.012)
Policy zone	0.018	0.019	0.018	0.018
	(0.015)	(0.014)	(0.013)	(0.016)
FDI encouraged	-0.041***	-0.041***	-0.040***	-0.041***
	(0.008)	(0.009)	(0.009)	(0.009)
Regional GDP/capita	0.014	0.014	0.014+	0.014
	(0.011)	(0.012)	(0.008)	(0.012)

Notes: Levinsohn & Petrin (2003) estimation with ln(gross output) as dependent variable. All regressions contain industry, province, and year dummies. Reference category: majority SOE. +, *, **, *** indicate significance levels of 10, 5, 1, and 0.1 percent, respectively. SOE = state-owned enterprise. POE = privately owned enterprise. The statistics are calculated for the 12,443 observations of the 1,927 firms.

Table 8: Effectiveness of research collaborations

	(1)	(2)	(3)	(4)
Ln (labor)	0.097***	0.097***	0.098***	0.097***
	(0.007)	(0.007)	(0.006)	(0.006)
Ln (capital)	0.300***	0.301***	0.300***	0.300***
	(0.044)	(0.044)	(0.044)	(0.053)
Ln (material)	0.553***	0.553***	0.553***	0.554***
	(0.044)	(0.049)	(0.045)	(0.060)
ln (R&D stock)	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
No R&D	-0.006	-0.006	-0.006	-0.006
	(0.012)	(0.012)	(0.010)	(0.012)
Ln (patent stock)	0.013*	0.013*	0.013*	0.013*
	(0.006)	(0.006)	(0.006)	(0.005)
No patents	-0.024+	-0.024*	-0.023+	-0.023+
	(0.013)	(0.012)	(0.014)	(0.013)
Ln (national coapplications)	0.024+			0.034
	(0.013)			(0.041)
x Majority SOE		0.026		
		(0.030)		
x Minority SOE		0.026		
		(0.026)		
x POE		0.023+		
		(0.013)		
x 2001-2006			0.033	
			(0.023)	
x 2007-2011			0.023+	
			(0.012)	
x Majority SOE x 2001-2006				0.034
				(0.041)
x Majority SOE x 2007-2011				0.018
				(0.028)
x Minority SOE x 2001-2006				0.055
				(0.034)
x Minority SOE x 2007-2011				0.015
				(0.018)
x POE x 2001-2006				0.014
				(0.028)
x POE x 2007-2011				0.026*
				(0.012)

Table 8: Effectiveness of research collaborations (continued)

	(1)	(2)	(3)	(4)
Ln (international coapplications)	-0.020			
	(0.029)			
x Majority SOE		-0.016		
		(0.041)		
x Minority SOE		-0.025		
		(0.033)		
x POE		-0.016		
		(0.031)		
x 2001-2006			-0.003	
			(0.036)	
x 2007-2011			-0.031	
			(0.026)	
x Majority SOE x 2001-2006				-0.035
				(0.089)
x Majority SOE x 2007-2011				0.007
				(0.122)
x Minority SOE x 2001-2006				-0.022
				(0.032)
x Minority SOE x 2007-2011				-0.028
				(0.044)
x POE x 2001-2006				0.057
				(0.088)
x POE x 2007-2011				-0.040
				(0.030)
Minority SOE	-0.046***	-0.046***	-0.046***	-0.046***
	(0.008)	(0.010)	(0.011)	(0.012)
POE	-0.031**	-0.031*	-0.031**	-0.032*
	(0.010)	(0.013)	(0.012)	(0.013)
Policy zone	0.020	0.020	0.020	0.021
	(0.015)	(0.016)	(0.014)	(0.014)
FDI encouraged	-0.041***	-0.041***	-0.041***	-0.042***
	(0.009)	(0.010)	(0.009)	(0.010)
Regional GDP/capita	0.014	0.014	0.014	0.014
	(0.010)	(0.012)	(0.010)	(0.010)

Notes: Levinsohn & Petrin (2003) estimation with ln(gross output) as dependent variable. All regressions contain industry, province, and year dummies. Reference category: majority SOE. +, *, **, *** indicate significance levels of 10, 5, 1, and 0.1 percent, respectively. SOE = state-owned enterprise. POE = privately owned enterprise. The statistics are calculated for the 12,443 observations of the 1,927 firms.

Table 9: Overview of results for alternative estimation approaches

Panel A: Levinsohn & Petrin (lags)

		Ownership breakdown			Time breakdown	
		Majority SOE	**Minority SOE**	**POE**	**2001-2006**	**2007-2011**
(1)	Ln (R&D stock)	0.001	0.003*	0.005***	0.002*	0.005***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
(2)	Ln (patent stock)	0.017*	0.016**	0.026***	0.027***	0.017***
		(0.008)	(0.006)	(0.006)	(0.007)	(0.005)
(3)	Average PCT citations	0.045	0.030	0.071+	0.029	0.052*
		(0.087)	(0.020)	(0.038)	(0.029)	(0.026)
	High-tech share of patents	0.006	0.039	0.060*	0.011	0.074*
		(0.042)	(0.033)	(0.030)	(0.029)	(0.029)
(4)	Ln (national coapplications)	0.003	0.026	0.010	0.023	0.012
		(0.027)	(0.029)	(0.018)	(0.022)	(0.015)
	Ln (international coapplications)	0.001	-0.036	0.005	-0.006	-0.026
		(0.051)	(0.045)	(0.049)	(0.031)	(0.033)
	10,667 observations – 1,674 firms					

Panel B: Olley and Pakes

		Ownership breakdown			Time breakdown	
		Majority SOE	**Minority SOE**	**POE**	**2001-2006**	**2007-2011**
(1)	Ln (R&D stock)	0.002	0.003*	0.003***	0.002**	0.003**
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
(2)	Ln (patent stock)	0.025**	0.021**	0.027***	0.037***	0.023***
		(0.008)	(0.007)	(0.005)	(0.008)	(0.005)
(3)	Average PCT citations	0.092	0.024	0.049*	0.033	0.042*
		(0.077)	(0.024)	(0.023)	(0.028)	(0.019)
	High-tech share of patents	-0.007	0.061*	0.065**	0.027	0.070**
		(0.044)	(0.030)	(0.024)	(0.027)	(0.024)
(4)	Ln (national coapplications)	0.014	0.025	0.021+	0.029	0.021+
		(0.026)	(0.199)	(0.013)	(0.023)	(0.012)
	Ln (international coapplications)	-0.019	-0.010	-0.003	0.003	-0.017
		(0.051)	(0.050)	(0.037)	(0.037)	(0.034)
	12,428 observations – 1,927 firms					

Table 9: Overview of results for alternative estimation approaches (continued)

Panel C: Olley and Pakes (lags)

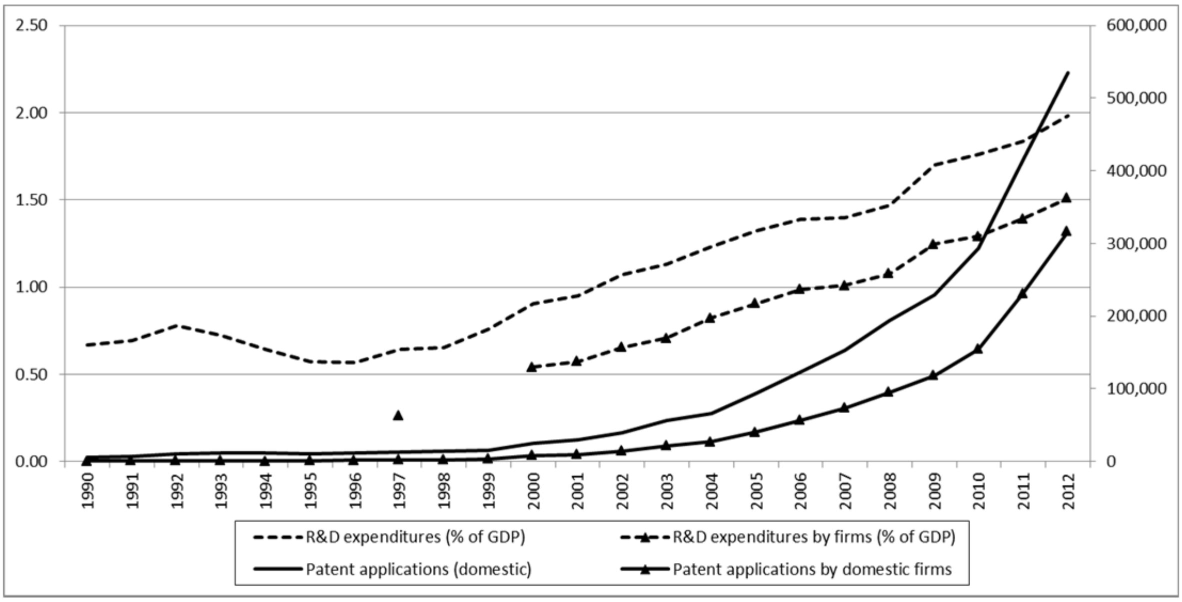
		Ownership breakdown			Time breakdown	
		Majority SOE	**Minority SOE**	**POE**	**2001-2006**	**2007-2011**
(1)	Ln (R&D stock)	0.0005	0.002+	0.003**	0.002*	0.003*
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
(2)	Ln (patent stock)	0.020*	0.022**	0.035***	0.035***	0.023***
		(0.009)	(0.008)	(0.007)	(0.007)	(0.007)
(3)	Average PCT citations	-0.014	0.028	0.071	0.028	0.040
		(0.080)	(0.022)	(0.044)	(0.037)	(0.027)
	High-tech share of patents	0.031	0.052	0.063**	0.030	0.075**
		(0.052)	(0.033)	(0.024)	(0.028)	(0.027)
(4)	Ln (national coapplications)	-0.009	0.025	0.012	0.024	0.011
		(0.031)	(0.026)	(0.016)	(0.025)	(0.016)
	Ln (international coapplications)	-0.004	-0.024	0.016	-0.004	-0.015
		(0.047)	(0.048)	(0.040)	(0.034)	(0.039)
		10,653 observations – 1,674 firms				

Panel D: System-GMM

		Ownership breakdown			Time breakdown	
		Majority SOE	**Minority SOE**	**POE**	**2001-2006**	**2007-2011**
(1)	Ln (R&D stock)	0.0005	0.003*	0.003*	0.002*	0.007***
		(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
(2)	Ln (patent stock)	0.050***	0.027***	0.021***	0.037***	0.025***
		(0.011)	(0.008)	(0.007)	(0.009)	(0.007)
(3)	Average PCT citations	0.130	0.026	0.035	0.035+	0.046+
		(0.112)	(0.020)	(0.047)	(0.021)	(0.025)
	High-tech share of patents	0.010	0.018	0.011	0.001	0.036
		(0.059)	(0.038)	(0.041)	(0.035)	(0.032)
(4)	Ln (national coapplications)	0.074**	0.032	0.030*	0.055*	0.041**
		(0.028)	(0.024)	(0.015)	(0.024)	(0.014)
	Ln (international coapplications)	-0.057	0.014	-0.011	-0.043	-0.016
		(0.037)	(0.025)	(0.030)	(0.035)	(0.028)
		12,443 observations – 1,927 firms				

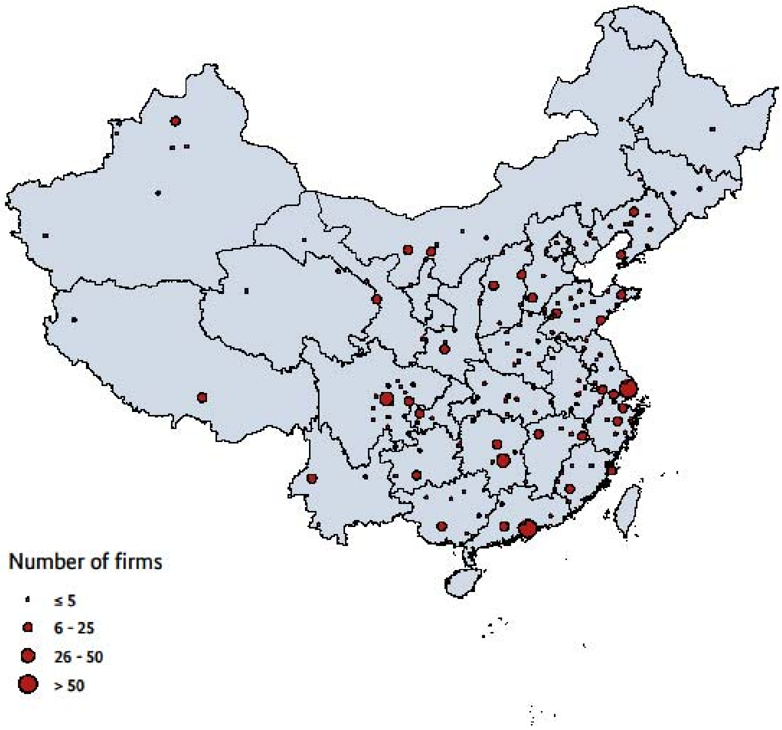
Notes: Panels A to D are each showing abbreviated results from eight regression results with ln(gross output) as dependent variable. For the mentioned specifications (1) to (4) separate regressions were run for the ownership and the time breakdown. Only the coefficients of the broken down R&D activities are shown in this table. All regressions contain the full set of variables mentioned in Table 4. +, *, **, *** indicate significance levels of 10, 5, 1 and 0.1 percent, respectively. SOE = state-owned enterprise. POE = privately owned enterprise.

Figure 1: Development of R&D expenditures and patenting



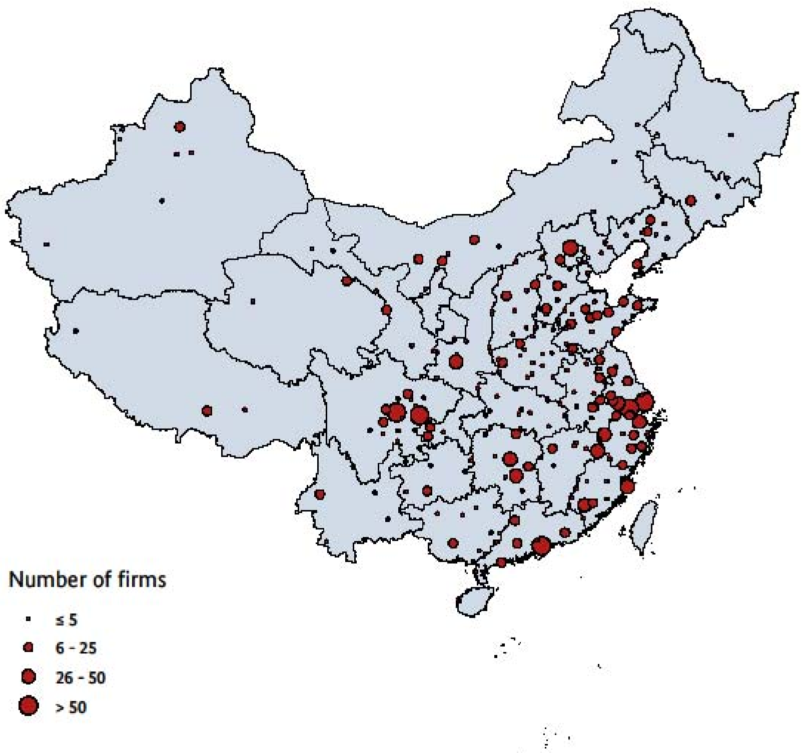
Sources: Data for R&D expenditures taken from China's Statistical Yearbooks on Science and Technology; data for patent applications taken from China's State Intellectual Property Office.

Figure 2: Firm locations in 2001



Source: Data of the authors.

Figure 3: Firm locations in 2011



Source: Data of the authors.

Appendix A: Matching Procedure

When matching the patent information to the firm data, one has to take care of several complications to arrive at appropriate corporate patent portfolios. We derive various variants of the firm name to obtain potential matches which are then manually checked.

Our name patterns take the following issues into account: first, spelling errors or systematic abbreviations might occur in the names of the patent owners. Second, the patent law allows Chinese patent applicants to use their Chinese name in Chinese characters, their Chinese name in Pinyin format, their English firm name, or any combination thereof. PATSTAT converts the name into Pinyin format if the firm has originally used Chinese characters in its applicant name. We therefore constructed several name patterns for the matching process in order to reconcile complete patent portfolios. For example, the firm "China International Marine Containers" files patents under its full English name but also under the abbreviations "CIMC" or "China Int Marine Containers" and under the Pinyin formats "Zhongguo Guoji Haiyun Jizhuangxiang" and "Zhong Ji Jituan". Third, we included a list of historic firm names to take care of name changes. With the approach described above, we compiled all possible variations of firm names and compiled all their patent applications on the aggregate firm level (i.e., the ultimate owner).

This approach allowed us to aggregate consistent firm level patent portfolios even if firms are large conglomerates consisting of multiple legal entities with varying names.

Appendix B: Variable Definitions

Table B1: Variable Definitions and Data Sources

Variable	Definition
Production function	
Gross output	Total revenue in million RMB deflated to 2005 prices with an industry-specific (2-digit level) deflator for value added. Data sources: Compustat for accounting information, National Bureau of Statistics for deflators.
Value added	Value added in million RMB deflated to 2005 prices. Calculated as deflated revenue minus the difference of deflated costs of goods sold and labor costs. Costs of goods sold and labor costs are deflated using the producer price index. Data sources: Compustat for accounting information, National Bureau of Statistics for deflators.
Labor	Number of employees is used as measurement for the input factor labor. Data source: Datastream.
Capital	Property, plant and equipment in million RMB deflated to 2005 prices is used as measurement for the input factor capital (net fixed assets). Adjusted for inflation by a fixed assets deflator. Data sources: Compustat for accounting information, National Bureau of Statistics for deflators.
Material	Material costs in million RMB deflated to 2005 prices. Calculated as difference of deflated costs of goods sold and labor costs. Data source: Compustat.
R&D stock	Stock of R&D expenditures in million RMB deflated to 2005 prices. Accumulated over the period 2001-2011 computed with the recurring balance formula applying a depreciation rate of 15% and a growth rate of 8% before the first observation. Data sources: Accounting information from annual reports for 2001-2006, WIND for 2007-2011; National Bureau of Statistics for deflators.

Patent stock	Stock of invention patent families in a firm's portfolio. All patent families are counted by the year of their earliest application (priority). They are accumulated from the founding of the firm until 2011. We apply an annual depreciation rate of 15%. Data source: PATSTAT April 2013.
Average PCT citations	Number of citations received from PCT applications in a 3-year time window divided by patent stock. Both citations and patent stock are depreciated with an annual rate of 15%. Data source: PATSTAT April 2013.
High-tech share of patents	Share of patents in the patent stock that have at least one technology class listed in the classification by EUROSTAT as belonging to the high-tech sector.
National coapplications	Number of patent families that list a second applicant from within China. Co-applicants belonging to the same group as the focal firm are excluded. Data source: PATSTAT April 2013.
International coapplications	Number of patent families that list a second applicant from without China. Co-applicants belonging to the same group as the focal firm are excluded. Data source: PATSTAT April 2013.
Ownership type	Time variant dummy variables controlling for ownership status: – Privately-owned without state holding (POE). – State-owned with the state holding more than 50% of the shares (majority SOE). – State-owned with the state holding a less than 50% but more than 0% of the shares (minority SOE). Data source: RESSET.
Operational environment	
Policy zone	Time variant dummy variable which equals 1 if the firm's headquarter is located either in a Science & technology industrial park (STIP) or in an Economic & technology development zone (ETDZ). The allocation is based on a comparison of the 6-digit postcode of the firm's headquarter with the 6-digit postcode of the zone. Data source: Local Governments. In the time period 1998-2010 the Central Government recognized 82 STIPs with the aim to generate technology spillovers between indigenous firms and 113 ETDZs with the aim to foster

	internationalization strategies of firms. See Liu & Wu (2011) for entry conditions and preferential treatment of firms located in these zones.
Foreign direct investment (FDI) encouraged	A time variant dummy variables indicating if FDI is encouraged in the industry of the firm according to the *Catalogue of Industries for Guiding Foreign Investment*. The catalogue was amended in the years 1997, 2002, 2005 and 2007. Sources: National Development and Reform Commission, Ministry of Commerce.
Regional GDP per capita	Regional GDP per capita in RMB as a proxy to control for city and county-level agglomeration effects. Real values at 2005 prices are calculated by using a GDP deflation index. We observe GDP per capita annually for 284 cities and counties. Based on the 4-digit city-level postcode of the firm's headquarter each firm is matched with the closest city or county for which GDP per capita data is available. Data source: China Economic Information Network.
Control variables	
Industry	Dummy variables according to the Chinese Securities Regulatory Commission (CSRC). 2-digit level for manufacturing, 1-digit level for the rest. Data source: Compustat.
Province	Dummy variables controlling for each of the 31 provinces in which our firms are located. These variables are based on the 6-digit postcode of the firm's headquarter. Data source: Compustat.
Year	Dummy variables controlling for the year of observation.