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What Can Explain the Chinese Patent Explosion?

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Abstract

We analyse the ``explosion'' of patent filings by Chinese residents both domestically and in the United States during the early 2000s, employing a unique dataset of 374,000 firms matching patent applications to manufacturing census data. Our analysis reveals that patenting is highly concentrated among a small number of firms, operating in the information and communication technology sector. Although increases in patent filings by these companies are partly driven by increased R\&D intensity, our analysis suggests that the explosion of patent filings at the Chinese patent office is driven by factors other than underlying innovative behavior, including government subsidies that encourage patent filings directly.

Key words: China, firms, patents

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1 Introduction

China's economic success over the past decades has been widely regarded as the result of its ability to produce manufactured goods at low cost, building on the availability of cheap labour and scale economies, while relying on existing technologies of production. China's ability to upgrade its technology base and move up the value-chain is frequently argued to be hampered by weak (intellectual) property rights enforcement (Zhao, 2006). More recently, however, the notion that China is catching up fast in terms of scientific and technological innovation has gained considerable ground. The number of domestic invention patent filings with the Chinese patent office (SIPO) has increased at an average rate of 32% per annum from around 15,600 to over 700,000 during the period 1999-2013.[1] Utility patent filings by Chinese residents[2] with the U.S. patent office (USPTO) grew at an annual rate of 35% to nearly 15,500 over the same period, albeit from a low base of 271 in 1999.[3] This patent "explosion" at home and abroad is paired with strengthened statutory intellectual property (IP) rights protection (Park, 2008) and an increased interest by policymakers in the role of IP in fueling domestic innovation, with a particular focus on foreign technology transfer and incentives to invest in R&D. Accordingly, the recent National Patent Development Strategy (2011-2020) envisions an increase in the number of annual patent applications (including invention, utility patents and designs) from 1.2 million in 2010 to 2 million in 2015. The plan also foresees a doubling of the number of patent applications filed by Chinese applicants abroad over the same time horizon. These ambitious targets reflect a positive outlook in parts of the literature on Chinese innovation, the Chinese IP rights system, and Chinese development in general (Fischer and von Zedtwitz, 2004; Subramanian, 2011).

At the same time, there is some evidence to suggest that most of the innovation in China is of merely incremental nature and hence the corresponding patents protect "small inventive steps" (Puga and Trefler, 2010). While such incremental innovation may still be valuable and in fact account in large part for China's success (Breznitz and Murphree, 2011), the concern is that the recent increase in patent applications is produced overwhelmingly by inventions embodying little technological progress. Recent empirical evidence suggests that patent subsidies, introduced by local governments in virtually all Chinese provinces from 1999 onwards, have also played an important role in explaining the "explosive" growth of Chinese patenting (Li, 2012; Dang and Motohashi, 2015). Boeing and Mueller (2015) suggest that patent quality of PCT filings[4]

[1] Data from the World Intellectual Property Organization (WIPO).

[2] Throughout the paper we use 'Chinese firms' and 'Chinese residents' interchangeably. Our firm-level data covers indigenous firms as well as subsidiaries of foreign multinationals. U.S. utility patents correspond to invention patents in China.

[3] Data taken from various USPTO Performance and Accountability Reports.

[4] Filings under the 'Patent Cooperation Treaty' allow an inventor to simultaneously seek protection in a large number of countries using a single application.

by Chinese applicants is low by international comparison and that quality has been decreasing over time as the number of filings has increased. They also find some evidence for a negative correlation between patent quality and filing subsidies.

The view that China's patent explosion over the past two decades was driven largely by an increase in the patenting of low quality inventions — fueled by public incentive schemes — stands in stark contrast to earlier findings in the literature, which explained the recent increase in Chinese firms' patenting activity by an influx of FDI, the opening of the economy in particular through China's WTO accession, and a major overhaul of the legal framework in form of amendments of the patent law (Hu and Jefferson, 2009). Despite widespread doubts about the link between innovative prowess and the Chinese patent explosion in the media and in policy circles,[5] there is no quantitative analysis based on representative firm-level data that investigates the determinants of the Chinese patent explosion during its critical years in the early 2000s.

We analyze the recent "explosion" in the number of patent applications by manufacturing firms registered in China with SIPO as well as the USPTO, which is by far the most important destination for Chinese patent filings abroad (Wunsch-Vincent et al., 2015). In contrast to the study by Hu and Jefferson (2009) our analysis is focused on "invention" patents which are subject to substantive examination for novelty and inventiveness in both constituencies; this prevents our analysis from being distorted by the vast number of utility models and design patents with low innovative content that do not require substantive examination by the Chinese or U.S. patent offices. Apart from separately analysing the determinants of patenting with SIPO and the USPTO, we infer information on underlying inventions by assessing *where* companies seek patent protection: only domestically with SIPO or (also) with the USPTO. Not only are the direct and indirect costs associated higher in the U.S., but inventions are required to overcome a higher novelty hurdle in patent examination during our sample period. These differences suggest that a comparison of patents filed with the USPTO and SIPO reveals additional information on the underlying invention and the corresponding patentees.

We construct a representative firm-level dataset that combines invention patent data and company financials. We match SIPO and USPTO patents filed between 1985 and 2006 to around 316,000 manufacturing firms contained in China's Annual Survey of Industrial Enterprises (ASIE) compiled by the National Bureau of Statistics of China (NBS) for the period 1999-2006.[6] The period covered represents perhaps the most inter-

[5] In particular *The Economist* magazine has voiced repeated concerns that "merely churning out patents does little to advance innovation" (Dec 13th 2014; see also Oct 14th 2010).

[6] Our regressions also include firms which are not part of our Qin/Oriana bridge dataset (see Section 2): we empirically account

esting period in state innovation and IP policy as well as firm innovation activity in China: it encompasses aggressive opening up to FDI, policy commitments related to WTO-entry in 2001, a substantial increase in exporting, an amendment to the patent law, increased government incentives to patent and an accelerated pace of privatisation (Fischer and von Zedtwitz, 2004; Naughton, 2007; Hu and Mathews, 2008; Li, 2012; Dang and Motohashi, 2015).

Our descriptive analysis shows that a small number of Chinese companies concentrated in the information and communication technology (ICT) equipment industry accounts for a large share of the dramatic increase in USPTO patents held by Chinese residents, with underlying technologies mostly related to electronics and semiconductors. This select group of firms also accounts for a substantial share of SIPO patents though there is a larger number of companies across a wider range of industries obtaining domestic patent protection. The concentration of patenting in an industry that has moved from "Patent Portfolio Races" during the 1990s (Hall and Ziedonis, 2001) to outright "Patent Wars" (*Financial Times*, 17th October 2011) casts some doubt on the underlying technological value of the steep increase in patent counts produced by Chinese firms in this sector. Previous empirical work on Chinese patenting missed this concentration since analysis was based on aggregate data (Sun, 2000; Hu and Mathews, 2008; Hu, 2010) or self-reported patenting without distinction between low-sophistication design or utility and more substantive invention patents (Hu and Jefferson, 2009). Comparing the descriptive statistics for patenting with non-patenting firms, and for those firms patenting in the U.S. with those exclusively patenting in China, reveals a large number of significant differences to motivate our empirical analysis.

We rely on the patent production function approach (Pakes and Griliches, 1980; Hall and Ziedonis, 2001) to explain the patenting decision and number of patent filings by Chinese companies with SIPO and the USPTO, respectively. Apart from the standard predictors of patenting, such as R&D expenditure, firm size, and age, we are particularly interested in the importance of a firm's exporting behavior, financial constraints, as well as province-level patent subsidies in predicting patenting behaviour. There is a large literature showing a positive effect of innovation on exporting (Salomon and Shaver, 2005; Lachenmaier and Woessmann, 2006; Girma et al., 2008; Harris and Li, 2009; Ganotakis and Love, 2011; Melitz and Trefler, 2012), which suggests that exporting in turn should predict patenting provided the patents reflect underlying innovations. Similarly, financial variables are key determinants of corporate innovation activities (Brown et al., 2009, 2012; Guariglia and Liu, 2014) and may help identify structural differences between types of firms based on where they chose to safeguard their IP rights. Finally, with specific reference to China

for selection from the larger ASIE (374,000 firms) into the integrated ASIE-Qin/Oriana (316,000 firms) dataset.

there is recent evidence which suggests that state subsidies are an important element in explaining patent filings of Chinese firms (Li, 2012; Dang and Motohashi, 2015; Lei et al., 2015) and we add information on provincial patent filing subsidy schemes to our patent production functions.

Our findings confirm that patent filings with SIPO are in part driven by state incentive schemes, and we further document a negative correlation between export intensity and domestic patenting. In contrast, for USPTO patentees resident in China the incentive variable is insignificant and export intensity is positively correlated with foreign patenting. Those companies in China filing with the USPTO are substantially larger in terms of number of workers than those only filing domestically. Financial constraints play an important role in innovation behaviour but do not appear to be a source of differential firm behaviour eliciting qualitative differences. Our findings thus suggest that domestic patenting in China, on average, is driven by state incentives and distinct 'types' of firms (in terms of size and export intensity) compared with those firms patenting overseas with the USPTO.

Our analysis contributes to the literature on innovation and economic development (Nordhaus, 1969; Penrose, 1973) by exploring the drivers behind a dramatic shift in the number of patent filings in China. Our results illustrate that large increases in domestic patenting activity *per se* cannot be seen as indicative of associated changes in innovative behavior in a developing country context. The strong concentration of patenting in ICT that we find in China on the one hand, and the impact of public incentive programs as well as the inverse export-patenting relationship on the other, further caution that a broader technological take-off is not (yet) occurring. That said, other successful Asian economies have seen similar concentrations in patenting activity, in particular during the early take-off phases.[7]

The remainder of this paper is organized as follows. Section 2 discusses the construction of our dataset. Section 3 explains our empirical strategy. Sections 4 and 5 discuss some descriptive evidence and our analytical results. Section 6 offers some brief concluding thoughts.

2 Data

2.1 Firm-level Data

Our firm-level data come from China's Annual Survey of Industrial Enterprises (ASIE) compiled by the National Bureau of Statistics of China (NBS). ASIE includes the whole population of state-owned firms

[7] Mahmood and Singh (2003) point to a strong concentration of USPTO patents (1970-1999) among assignees in South Korea and Singapore as the top 50 assignees hold 85% and 70% of each country's USPTO patents, respectively.

as well as all non-state-owned companies with annual sales above CNY5 million (around US$600,000). On average, over 200,000 firms from all regions of China are included each year, accounting for 95% of total Chinese industrial output and 98% of industrial exports, covering 39 two-digit industries, of which 30 belong to manufacturing industries. Our data cover four distinct years in the period 2001-6, with a sample of over 800,000 observations from 374,000 firms. Key variables include a unique firm identifier, R&D expenditure (representing the binding constraint for analysis: in the version of ASIE available to us this variable is only reported in 2001, 2002, 2005, and 2006), exports, ownership, output, sales, employment, and industry of operation.[8]

2.2 Patent Data

The patent data come from the European Patent Office's PATSTAT database (version 10/2010). We extract patents filed by Chinese residents (this includes indigenous and foreign(-invested) firms). Our analysis focuses on the application date of a patent. We obtain information on the grant status of patent filings from a 2014 version of PATSTAT to account for a grant lag of several years.

2.3 Matching/Bridge

Due to the absence of a unique identifier shared by the firm-level and patent data, the main data problem consists in matching patents to firms. This is generally challenging for a number of reasons (Helmers et al, 2011); in the case of China, matching is even more difficult due to the different ways in which firm names can be recorded: using (a) Chinese characters, (b) pinyin transcription, (c) a translation of the Chinese names into English, and (d) any mix of (a)-(c).

The Chinese census data contain only firm names using Chinese characters (a), whereas PATSTAT contains (b), (c) and (d). In principle, to match patents to firms we would have to either transcribe firms' names contained in ASIE or the assignee names in PATSTAT. Instead we identified an alternative solution: the Qin and Oriana databases provided by Bureau Van Dijk offer firm-level balance sheet data for individual firms in the Asia-Pacific region. The combination of Qin/Oriana contain data for about 451,000 Chinese firms for 2001-2009. The advantage of using Qin/Oriana is that these report firm names using the Latin alphabet as well as the ASIE unique firm identifier. This allows us to link Qin/Oriana to ASIE through the unique

[8] In line with the existing literature (e.g. Guariglia and Liu, 2014), we exclude observations with negative values of output, sales, exports, capital or intermediate inputs; and further observations with total assets less than total fixed assets or total liquid assets or with total sales less than exports.

identifier and to use Qin/Oriana firm names to match with assignee names contained in PATSTAT. While this approach allows us to match patent data to Chinese firms, it also has some limitations, which together with suggested remedies are discussed in a supplementary appendix.

Our integrated dataset matching ASIE to Qin/Oriana covers 316,000 firms, while the full ASIE sample for 2001-6 contains 374,000 firms (average $T_i = 2.3$). Tables A-1 and A-2 in the supplementary appendix contain information and descriptive statistics on the sample of firms used in our regression analysis.

3 Empirical Strategy

Our objective is to analyze the drivers behind the explosion in patent filings in China. The existing evidence is ambivalent about the factors that have contributed to the rapid rise in patent filings. On the one hand, Hu and Jefferson (2009) suggest that patenting in China is explained by increases in FDI, China's WTO accession, and improvements in the legal framework and enforceability of IP, with the latter two empirically captured by time dummies. On the other, there is a widely-held view that SIPO rubber-stamps patent filings which protect at best low-value, incremental inventions (Puga and Trefler, 2010), and that filings are largely driven by government incentives which target patenting directly (Li, 2012; Dang and Motohashi, 2015; Lei et al., 2015).

To explore the determinants of patenting in China we use the patent production function approach (Pakes and Griliches, 1980; Hall and Ziedonis, 2001) that relates a firm's patent filings to a standard set of variables, such as R&D expenditure, firm size and age. In light of the export-innovation literature, we extend the standard patent production equation to include a firm's export intensity: there is strong theoretical and empirical evidence pointing to a positive association between innovation and exporting, and if patent filings are driven by innovation we would expect exporting to predict patenting (Salomon and Shaver, 2005; Girma et al., 2008; Melitz and Trefler, 2012). Our extended specification also includes financial variables that are key determinants of corporate innovation activities (Brown et al., 2009, 2012; Guariglia and Liu, 2014). To test directly for the role of subsidies in the patent explosion, we include a province-level indicator for the availability of government patent subsidies in the model.

Our main interest is in our ability to predict patent filings with SIPO by companies resident in China using the patent production function approach, which allows us to analyze the determinants of the Chinese patent explosion. To provide a benchmark against which to compare our results on the predictors of patent filings with SIPO, we use the same production function to predict patent filings by Chinese residents with the

USPTO: since patent filings in the U.S. are subject to a different standard than filings with SIPO (for a detailed discussion see Supplementary Appendix D), comparing the determinants of USPTO and SIPO patent filings by the same set of companies in China offers additional insights on the determinants of the patent explosion in China. More specifically, controlling for all standard determinants of firm-level innovation and patenting including a set of variables capturing financial constraints, if patenting with SIPO is driven by factors other than innovation, we expect in particular export intensity to predict filings only at the USPTO but not SIPO. In contrast, due to the policy drive to promote domestic patenting directly, we expect patent subsidies to predict filings only with SIPO but not the USPTO.

We test these hypotheses through a number of alternative empirical models which are all variations of the Pakes and Griliches (1980) patent production approach. We begin with the patenting decision, where we disregard the patent count and focus merely on the prevalence of patenting. We employ binary choice models to analyse two dichotomous outcomes, namely patenting with SIPO and patenting with the USPTO, in a standard random utility formulation (Greene and Hensher, 2010).

We address selection into our integrated dataset, a subsample of ASIE, as part of our analysis of the patenting decision by modelling selection and patenting jointly: in bivariate probit models for USPTO and SIPO patenting, respectively (results available on request), and then in trivariate probit models jointly estimating selection, patenting with the USPTO, and patenting with SIPO.[9] The formal representation of the trivariate probit model is

$$\begin{pmatrix} \mathbf{1}_{\{\text{sipo}\}_{ipt}} \\ \mathbf{1}_{\{\text{uspto}\}_{ipt}} \\ \mathbf{1}_{\{\text{ss}\}_{ipt}} \end{pmatrix} = \Phi\left(\begin{matrix} \alpha^1 + \mathbf{INNOV}'_{ipt}\boldsymbol{\beta}^1 + \mathbf{EX}'_{ipt}\boldsymbol{\gamma}^1 + \mathbf{FIN}'_{ipt}\boldsymbol{\delta}^1 + \mathbf{INCENT}'_{ipt}\boldsymbol{\eta}^1 + \boldsymbol{X}'_{ipt}\boldsymbol{\theta}^1 + d_p^1 + d_t^1 \\ \alpha^2 + \mathbf{INNOV}'_{ipt}\boldsymbol{\beta}^2 + \mathbf{EX}'_{ipt}\boldsymbol{\gamma}^2 + \mathbf{FIN}'_{ipt}\boldsymbol{\delta}^2 + \mathbf{INCENT}'_{ipt}\boldsymbol{\eta}^2 + \boldsymbol{X}'_{ipt}\boldsymbol{\theta}^2 + d_p^2 + d_t^2 \\ \alpha^3 + \mathbf{INNOV}'_{ipt}\boldsymbol{\beta}^3 + \mathbf{EX}'_{ipt}\boldsymbol{\gamma}^3 + \mathbf{FIN}'_{ipt}\boldsymbol{\delta}^3 + \mathbf{INCENT}'_{ipt}\boldsymbol{\eta}^3 + \boldsymbol{X}'_{ipt}\boldsymbol{\theta}^3 + d_p^3 + d_t^3 \end{matrix} , \Sigma \right),$$

where $\Phi(\cdot, \Sigma)$ is a multivariate normal distribution, $\mathbf{1}_{\{.\}}$ represents binary variables ('sipo' and 'uspto' for at least one patent application with SIPO and USPTO, respectively; 'ss' is the sample selection equation), and d_p^j and d_t^j are province (see below) and time fixed effects. We enter five groups of covariates to analyse the association of patenting with firm-level innovation effort (INNOV), export behaviour (EX) and financial constraints (FIN), as well as government patenting incentives (INCENT), on top of additional control variables (X) related to firm size, age, and ownership type.[10] In an additional specification we account for unobserved heterogeneity potentially distorting our results by including provincial dummies in the trivari-

[9] Addressing selection in these nonlinear models does not require an exclusion restriction from the selection equation: identification is in principle given through functional form (Greene and Hensher, 2010).

[10] Full details of all variables and controls included in the models are contained in the supplementary appendix.

ate probit models. The results from this exercise (available on request) are qualitatively in line with those presented here.[11]

In order to gauge the reliability of our results in the face of potential endogeneity of our regressors, we estimate instrumental variable (IV) probit models adopting first or first and second lags of all variables (except firm age, ownership, and time dummies) as instruments.[12]

A second set of regressions then analyses the number of patent applications and grants by estimating non-linear functions which relate the patent count to firm characteristics, using the same sets of covariates as above. We treat our panel as repeated cross-sections (see Bound et al., 1984), in the spirit of previous work on China by Hu and Jefferson (2009), but like these authors consider fixed effects Poisson models for robustness (see below). In empirical practice the choice between different approaches is primarily driven by the 'overdispersion' problem of the Poisson estimator (Cameron and Trivedi, 2005; Hilbe, 2011). The Negative Binomial estimator enables us to introduce a separate dispersion parameter κ to overcome this issue:[13] the formal model representation of these estimators is

$$
\begin{aligned}
Pr(Y_{it} = y_{it}) &= [exp(-\lambda_{it})\lambda_{it}^{n}]/(y_{it}!) \\
Pr(Y_{it} = y_{it}) &= \frac{\Gamma(y_{it} + \lambda_{it}^{1-c}/\kappa)}{y_{it}!\Gamma(\lambda_{it}^{1-c}/\kappa)} (1 + \kappa\lambda_{it}^{c})^{-\lambda_{it}^{1-c}/\kappa} (1 + \lambda_{it}^{-c}/\kappa)^{y_{it}}
\end{aligned}
$$

with y_{it} the patent count and $\lambda_{it} = exp(\boldsymbol{Z}_{it}'\boldsymbol{\varphi})$, where for convenience of notation we have expressed the five sets of covariates and dummies detailed above with matrix $\boldsymbol{Z}$ and their respective coefficient vectors with $\boldsymbol{\varphi}$.

We also present results from a fixed effects (FE) Poisson model, where the inclusion of firm fixed effects limits the sample to 'innovating firms.' This reduces the number of observations from 804,766 to 507 (170 firms) in the USPTO and 7,113 (2,327 firms) in the SIPO analysis, but allows us to account for time-invariant unobserved heterogeneity thus giving an interpretation closer to causality than in our pooled regressions.

In our analysis innovation effort is proxied by R&D expenditure. We employ contemporaneous R&D

[11] It is well-known that the inclusion of a large number of fixed effects in nonlinear models creates serious bias due to the incidental parameter problem. This problem should not create any difficulties for a mere 30 province dummies, however China's vast economic heterogeneity creates a separate problem here in that nine (two) provinces have no firms with any patent applications with USPTO (SIPO) over the 4-year sample period, which means that firms from these provinces are dropped.

[12] Additional analysis (results available on request) replaces the dependent variable of at least one patent application with that of at least one granted patent, which can act as a basic proxy for the quality of innovations — results are qualitatively identical.

[13] Tests for the statistical significance of κ reject the Poisson estimator in favour of the NegBin alternative in all cases.

expenditure (Pakes and Griliches, 1980) deflated by employment[14] to avoid confounding the R&D effect with that of firm size (Hall and Ziedonis, 2001). Log R&D expenditure per worker is entered as linear and squared terms to allow firms in different tails of the distribution to impact patenting decisions and patent counts differentially.

Inspired by the export-innovation literature we include the export intensity of a firm (export deflated by sales) as an additional determinant of patenting. Our regressions separately control for firms with zero exports and for "pure exporters" (Defever and Riano, 2013) with export intensity in excess of 90% — this cut-off is based on investigating a kernel density estimate for this variable.

Recent work by Brown et al. (2009) and Brown et al. (2012) on advanced economies and Guariglia and Liu (2014) on China highlighted the importance of financial constraints as key determinants of corporate innovation strategies. We therefore include measures for firm liquidity, leverage and cash flow as additional covariates.[15]

The municipal government of Shanghai started handing out patent filing subsidies in 1999 and by 2007, 80% of Chinese provinces had adopted such subsidy schemes (Dang and Motohashi, 2015). There are substantial differences in subsidy programmes across provinces (Li, 2012) and many cities also offer their own patent subsidies (Lei et al., 2015); some programmes offer filing or examination subsidies, others pay out a cash reward only after successful grant. Some provincial and city governments fully reimburse filing and examination fees, others only reimburse a fraction of the fees. Others even determine subsidy amounts on a case-by-case basis. We use data collected by Dang and Motohashi (2015) on the presence and strength of provincial-level incentives targeting patenting directly, where our focus is on filing subsidies. This data substantially extends the information on subsidy schemes used in an earlier study by Li (2012) as it differentiates subsidy schemes between those that provide full or partial reimbursement of fees. It represents the most comprehensive available dataset on patent subsidies in China. Other studies on the effect of patent subsidies have used more limited data, Lei et al. (2015) for example use data for six cities in the Jiangsu Province and Boeing and Mueller (2015) only rely on a year dummy variable to capture the introduction of a subsidy programme. Further details about the data used in our analysis and the evolution of patent subsidies across provinces over time are provided in the supplementary appendix.

Our choice of additional firm-level controls is guided by standard suggestions in the literature, namely

[14] We add dummies for firms with zero R&D expenditure (87% of observations).

[15] We define liquidity as the difference between a firm's current liquid assets and liabilities, normalised by total assets; and leverage as the ratio of total liabilities to total assets. Because R&D is treated as a current expense for accounting purposes we add R&D expenses to the standard measure of net cash flow (after-tax earnings plus depreciation) to obtain gross cash flow (see Himmelberg and Petersen, 1994); this cash flow variable is then normalised by total assets.

measures for size and age (both in logs), as well as characteristics with particular relevance for China, namely ownership type and province dummies (the latter as a robustness exercise, results available on request). Firm size is measured by employment and meant to capture possible economies of scale in patent production. In an OECD country context firm age is intended to capture the experience of older firms in the management of the patent application process (Hall and Ziedonis, 2001), however in a China emerging from a planned economy, this is an additional indicator for socialist period legacy. Ownership (our designation is based on paid-in capital share in excess of 50%, following Guariglia et al., 2011) includes two types of foreign-invested enterprises (FIEs) distinguishing those from Hong Kong, Macao and Taiwan (HMT) and elsewhere (other). We further distinguish Private, State-Owned (SOEs), Collective and Other Chinese firm types. We prefer to investigate the 'direct' effect of foreign direct investment (FDI) on patenting behaviour rather than relying on proxies suggested in the literature to capture 'knowledge spillovers' from FDI (Hu and Jefferson, 2009). We add year dummies to all models which allows us to chart the changes in patenting over time. All standard errors reported are clustered at the firm-level.

4 Descriptive Evidence

Our integrated dataset enables us to produce a number of powerful insights into Chinese patenting through simple descriptive statistics. Tables 1 and 2 list the top-10 companies patenting with the USPTO and SIPO, respectively. These tables are constructed using the patent data for the entire time horizon 1985 to 2006 for the firms in our integrated dataset.

Table 1 illustrates the concentration of USPTO patents among a small number of companies: the top-10 assignees account for slightly less than 75% of USPTO patents. Interestingly, three companies, Hongfujin (1), Fuzhun (3) and Futaihong (6), are subsidiaries of the Taiwanese-owned multinational Foxconn Technology Group, the world's largest contract manufacturer of 3C (Computer, Communication, Consumer electronics) products. These three subsidiaries account for 35% of total USPTO patent filings in our matched dataset, adding in communications giant Huawei brings the tally to over 50%. As shown in the last column of Table 1, with the exception of Sinopec, Nuctech, and BYD, all top-10 USPTO patentees are in 3C industries. Table 2 shows SIPO patent filings, with the top-10 companies accounting for over half of all patents. Here the dominant player is Huawei, filing nearly a quarter of SIPO patents, whereas only one Foxconn subsidiary, Hongfujin, is among the top-10. Again, with the exception of Sinopec, BYD and Baoshan, all companies listed in Table 2 are in 3C industries. Note that there is a significant overlap of companies in Tables 1 and

2: six companies appear in both lists, with four of these in 3C industries.

Table 1: Top 10 Chinese companies filing with USPTO (1985-2006)

Rank	Company	Patents	Share	Main Industry affiliation♮
1	Hongfujin Precision Industry (Foxconn)	513	21.75	Electronic computer (404)
2	Huawei Technology	399	16.92	Communications equipment (401)
3	Fuzhun Precision Industry (Foxconn)	214	9.07	Electronic computer (404)
4	China Petroleum Chemical (Sinopec)	156	6.61	Petroleum, Natural Gas Exploration (079)
5	Semiconductor Manufacturing Int.	127	5.38	Electronic apparatus (405)
6	Futaihong Precision Industry (Foxconn)	100	4.24	Communications equipment (401)
7	ZTE	61	2.58	Communications equipment (401)
8	Innocom Technology (Shenzhen)	39	1.65	Communications equipment (401)
9	Lenovo	38	1.61	Electronic computer (404)
9	Nuctech	38	1.61	Special equipment (369)
10	BYD	33	1.39	Automobiles (372)
	Other	640	27.14	
	Total	2,358	100.0	

Notes: ♮ Chinese GB/T 3-digit industry code in brackets.

Table 2: Top 10 Chinese companies filing with SIPO (1985-2006)

Rank	Company	Patents	Share	Main Industry affiliation♮
1	Huawei Technology	15,588	23.35	Communications equipment (401)
2	ZTE	4,578	6.86	Communications equipment (401)
3	LG Electronics Appliances Tianjin	4,244	6.36	Household electrical apparatus (395)
4	Hongfujin Precision Industry (Foxconn)	3,708	5.56	Electronic computer (404)
5	China Petroleum Chemical (Sinopec)	1,977	2.95	Petroleum, Natural Gas Exploration (079)
6	AU Optronics	1,362	2.04	Electronic computer (404)
7	Lenovo	1,137	1.70	Electronic computer (404)
8	BYD	835	1.12	Automobiles (372)
9	LG Electronics Shanghai	775	1.16	CCO (409)
10	Baoshan Iron & Steel	756	1.13	Ferrous metal smeltering and rolling (320)
	Other	31,781	47.77	
	Total	66,741	100.00	

Notes: ♮ Chinese GB/T 3-digit industry code in brackets. CCO – Communications, computers & other electronic equipment

Apart from asking who patents, the question of what is patented is equally important. We classify USPTO and SIPO patents according to the type of innovation they protect: product or process innovation or a combination of the two. There is a common perception in the literature that patents protecting product inventions reflect genuine innovations whereas process patents are of less innovative content as they only indicate new ways of producing some output by existing means. We read random subsamples of 1,900 USPTO and 980 SIPO patents.[16] Table A-3 in the supplementary appendix shows a breakdown of patents filed by Chinese residents according to the innovation type they protect. For USPTO patents nearly half cover product inno-

[16]In the case of SIPO patents claims must be retrieved from the original patent documents which are only available in Chinese.

vations and only 20% process innovations. The pattern looks different in the case of SIPO patents: merely 30% protect product innovations and 37% process innovations. This analysis suggests that inventions that are patented in China but not in the U.S. are more likely to protect process innovations. In contrast, results for USPTO patents indicate that the share of patents protecting product innovations is substantially higher.

Table 3: Descriptive Analysis of Patenting Behaviour

	[1] Patents					[2] Patents				
	None	Any	Diff	t-stat	p	SIPO	USPTO	Diff	t-stat	p
Innovation effort										
ln(R&D pw)	-0.037	0.218	-0.256	**-44.64**	0.000	0.212	0.306	-0.094	**-2.13**	0.017
	[0.001]	[0.011]	[0.006]	**-22.56**	0.000	[0.012]	[0.044]	[0.044]	**-2.06**	0.020
Export behaviour										
Exports/Sales	0.178	0.171	0.007	**1.68**	0.046	0.157	0.349	-0.192	**-14.02**	0.000
	[0.000]	[0.004]	[0.004]	**1.92**	0.027	[0.003]	[0.018]	[0.014]	**-10.40**	0.000
>90% Export/Sales	0.117	0.070	0.047	**12.59**	0.000	0.059	0.214	-0.154	**-13.39**	0.000
	[0.000]	[0.003]	[0.003]	**15.81**	0.000	[0.003]	[0.018]	[0.011]	**-8.43**	0.000
Zero Exports	0.724	0.536	0.188	**35.86**	0.000	0.546	0.406	0.140	**6.16**	0.000
	[0.001]	[0.006]	[0.005]	**32.22**	0.000	[0.006]	[0.022]	[0.023]	**6.23**	0.000
Size and age										
ln(Workers)	4.726	5.748	-1.022	**-79.99**	0.000	5.701	6.374	-0.673	**-11.33**	0.000
	[0.001]	[0.015]	[0.013]	**-66.68**	0.000	[0.016]	[0.058]	[0.059]	**-11.19**	0.000
ln(Firm age)	2.093	2.401	-0.307	**-29.98**	0.000	2.401	2.396	0.005	0.13	0.449
	[0.001]	[0.010]	[0.010]	**-29.90**	0.000	[0.011]	[0.043]	[0.040]	0.11	0.454
Financial constraints										
Liquidity	0.059	0.092	-0.033	**-8.88**	0.000	0.091	0.095	-0.003	-0.28	0.391
	[0.000]	[0.003]	[0.004]	**-10.29**	0.000	[0.003]	[0.012]	[0.012]	-0.27	0.395
Leverage	0.583	0.557	0.027	**7.79**	0.000	0.557	0.553	0.004	0.40	0.343
	[0.000]	[0.003]	[0.003]	**9.51**	0.000	[0.003]	[0.010]	[0.010]	0.41	0.340
Cash flow	0.105	0.099	0.006	**2.90**	0.002	0.098	0.108	-0.010	**-1.77**	0.038
	[0.000]	[0.001]	[0.002]	**3.99**	0.000	[0.001]	[0.007]	[0.006]	-1.47	0.071
Patent subsidies										
Filing	0.511	0.586	-0.075	**-15.45**	0.000	0.586	0.589	-0.002	-0.13	0.449
	[0.000]	[0.005]	[0.005]	**-15.40**	0.000	[0.005]	[0.018]	[0.019]	-0.13	0.448
Obs	797,400	7,366				6,851	515			
Firms	371,745	2,512				2,334	178			

Notes: We carry out separate two-sample t-tests in order to compare various firm-level and regional characteristics for [1] non-patenting vs patenting firms, and [2] firms patenting with SIPO vs those patenting with USPTO. The p-value indicates the probability value for a one-sided test. We test each relationship assuming equal or unequal variances across samples (though the means reported are for the former only), hence we obtain two sets of t-statistics and corresponding p values: the test statistics in the first (second) row for each variable assume equal (unequal) variances. For illustration t-statistics in bold indicate statistical significance at the 5% level.

Although there is clear evidence for substantial concentration of patenting among a small number of firms with either jurisdiction, we can also distinguish the observable characteristics between firms which (a) do and do not patent, and in turn between those which (b) patent with SIPO and the USPTO. Table 3 provides the respective unconditional mean comparison with associated one-sided t-tests. The columns on the left compare characteristics for patentees with non-patenting firms, highlighting the correlation between patenting and innovation effort (R&D expenditure). While export intensity is qualitatively similar, non-patenting firms have a higher propensity to be non-exporters or pure exporters — both of the latter findings ring true with reference to work on productivity and exporting (Melitz and Trefler, 2012; Defever and Riano, 2013). Patenting firms are larger, older and have higher liquidity than non-patenting firms, while state incentives to patent are higher in provinces where patenting firms are located. These results echo the findings of Guariglia and Liu (2014) who use new product sales as an indicator of innovation. Our simple analysis of means also finds significant differences between firms patenting (a) with the USPTO or (b) (only) with SIPO (in the columns on the right of the table): among the characteristics which distinguish USPTO patentees from those firms which patent only domestically, the higher R&D expenditure, export-to-sales ratio, and firm size are particularly noteworthy. A number of characteristics are also surprisingly unimportant in this comparison, notably the financial variables (except for cash flow) and the provincial-level subsidies for patent applications.

5 Results

5.1 Patenting decision

We begin our discussion with the empirical results for the (binary) patenting decision. Table 4 reports results for the 4-year sample for which R&D expenditure is observed.[17] In all cases the data for the ASIE sample (ASIE-Qin/Oriana match and ASIE-only firms) is used and near the top of each table panel we indicate whether we account for selection into the integrated ASIE-Qin/Oriana sample.

Columns [1] and [2] represent simple probit models for the patenting decision with SIPO or USPTO, while in column [3] we add a sample selection equation for ASIE-Qin/Oriana firms which is estimated jointly with the two patenting decision equations (results for bivariate probit estimating selection and SIPO or USPTO patenting jointly yield qualitatively very similar results and are available on request). The trivariate probit results suggest that our matched-sample regression does not suffer significant selection bias and that estimating patenting equations for SIPO and USPTO separately only affects estimation and inference at the margin. The remaining columns then attempt to counter concerns over endogeneity by instrumenting with the first lag and first and second lags in columns [4]-[6] (in column [6] we additionally instrument R&D expenditure using first lags). In the absence of obvious external instruments, these specifications provide some indication of the robustness of our main findings in column [3] to endogeneity concerns.

[17] Appendix Table F-1 shows the linear probability results.

Table 4: Binary Choice Models

	[1]	[2]	[3]		[4]		[5]		[6]	
	Probit		Trivariate Probit		IV Probit		IV Probit		IV Probit	
Dep. Variable	SIPO	USPTO	SIPO	USPTO	SIPO	USPTO	SIPO	USPTO	SIPO	USPTO
Selection			×	×						
Instruments					1st lag		1st & 2nd lags		1st lag – incl. R&D	
Innovation effort										
ln(R&D pw)	**0.190** **[0.010]*****	**0.208** **[0.030]*****	**0.190** **[0.009]*****	**0.206** **[0.028]*****	**0.177** **[0.020]*****	**0.201** **[0.033]*****	**0.047** **[0.014]*****	**0.198** **[0.035]*****	**0.308** **[0.059]*****	**0.350** **[0.063]*****
ln(R&D pw)^2	**0.034** **[0.009]*****	**0.055** **[0.027]****	**0.034** **[0.008]*****	0.039 [0.025]	**0.033** **[0.009]*****	0.041 [0.030]	0.005 [0.005]	0.040 [0.029]	-0.001 [0.061]	0.150 [0.097]
Export behaviour										
Export/Sales	**-0.264** **[0.051]*****	**0.266** **[0.149]***	**-0.268** **[0.051]*****	**0.264** **[0.138]***	**-0.472** **[0.121]*****	0.169 [0.200]	-0.040 [0.060]	0.375 [0.276]	**-0.418** **[0.135]*****	0.242 [0.262]
>90% Export/Sales	-0.066 [0.045]	0.011 [0.104]	-0.072 [0.045]	-0.034 [0.098]	-0.011 [0.104]	-0.028 [0.176]	0.042 [0.051]	**-0.360** **[0.200]***	-0.018 [0.111]	-0.099 [0.216]
Zero Exports	**-0.181** **[0.024]*****	0.066 [0.092]	**-0.187** **[0.024]*****	0.012 [0.086]	**-0.309** **[0.045]*****	-0.570 [0.160]	**-0.169** **[0.027]*****	0.082 [0.146]	**-0.282** **[0.046]*****	-0.008 [0.127]
Size and age										
ln(Workers)	**0.188** **[0.008]*****	**0.277** **[0.030]*****	**0.188** **[0.008]*****	**0.249** **[0.026]*****	**0.193** **[0.012]*****	**0.299** **[0.035]*****	**0.095** **[0.013]*****	**0.284** **[0.056]*****	**0.195** **[0.018]*****	**0.302** **[0.026]*****
ln(Firm age)	-0.004 [0.010]	-0.045 [0.030]	-0.005 [0.010]	-0.041 [0.028]	**-0.026** **[0.012]****	**-0.091** **[0.038]****	**-0.030** **[0.007]*****	**-0.098** **[0.044]****	**-0.026** **[0.013]****	**-0.088** **[0.033]****
Financial constraints										
Liquidity	**0.123** **[0.037]*****	**0.234** **[0.128]***	**0.122** **[0.036]*****	**0.215** **[0.122]***	0.120 [0.095]	**0.498** **[0.201]****	**-0.202** **[0.037]*****	**0.567** **[0.214]*****	0.083 [0.134]	**0.605** **[0.158]*****
Leverage	-0.043 [0.040]	0.106 [0.138]	-0.052 [0.040]	0.029 [0.131]	-0.135 [0.082]	0.305 [0.197]	**-0.226** **[0.032]*****	**0.371** **[0.210]***	-0.156 [0.105]	**0.379** **[0.170]****
Cash flow	**-0.247** **[0.051]*****	-0.140 [0.196]	**-0.263** **[0.051]*****	-0.272 [0.209]	**-0.271** **[0.102]*****	0.371 [0.270]	**0.095** **[0.052]***	0.247 [0.267]	**-0.309** **[0.127]****	0.332 [0.268]

Continued overleaf

Table 4: Binary Choice Models (continued)

	[1] Probit	[2]	[3] Trivariate Probit		[4] IV Probit		[5] IV Probit		[6] IV Probit	
Dep. Variable	SIPO	USPTO	SIPO	USPTO	SIPO	USPTO	SIPO	USPTO	SIPO	USPTO
Selection			×	×						
Instruments					1st lag		1st & 2nd lags		1st lag – incl. R&D	
Patent subsidies										
Filing subsidy	**0.187**	0.089	**0.176**	0.081	0.572	0.083	**2.339**	-1.024	0.666	-0.194
	[0.023]***	[0.078]	**[0.021]*****	[0.064]	[0.536]	[0.198]	**[0.063]*****	[0.674]	[0.884]	[0.175]
Ownership type										
FIE (other)	**0.111**	0.114	**0.106**	0.119	0.015	-0.053	**-0.439**	0.212	-0.015	-0.006
	[0.040]***	[0.100]	**[0.040]*****	[0.097]	[0.122]	[0.110]	**[0.031]*****	[0.179]	[0.192]	[0.105]
FIE (HMT)	**0.108**	0.082	**0.100**	0.117	0.050	0.002	**-0.294**	0.189	0.033	0.040
	[0.042]***	[0.101]	**[0.042]****	[0.095]	[0.093]	[0.105]	**[0.029]****	[0.139]	[0.142]	[0.103]
Private	**0.059**	-0.118	**0.060**	-0.081	**0.061**	**-0.209**	**0.039**	**-0.147**	**0.056**	**-0.212**
	[0.031]*	[0.079]	**[0.031]***	[0.074]	**[0.033]***	**[0.079]*****	**[0.017]****	**[0.082]***	**[0.033]***	**[0.080]*****
Collective	-0.062	-0.236	-0.065	-0.213	-0.084	**-0.527**	**-0.143**	-0.333	-0.090	**-0.526**
	[0.044]	[0.158]	[0.045]	[0.149]	[0.051]	**[0.207]****	**[0.025]*****	[0.210]	[0.057]	**[0.218]****
Other	**0.132**	0.08	**0.151**	0.155	0.101	0.012	0.015	0.087	0.0921	0.002
	[0.062]**	[0.153]	**[0.061]****	[0.146]	[0.067]	[0.155]	[0.036]	[0.156]	[0.067]	[0.131]
Further Controls	×	×	×	×	×	×	×	×	×	×
Year dummies	×	×	×	×	×	×	×	×	×	×
Smith-Blundell test of exogeneity					13.14	12.96	53.57	17.51	104.8	8.75
					p=.00	p=.11	p=.00	p=.03	p=.00	p=.12
Instruments Partial R^2							0.00 – 0.75	0.00 – 0.75	0.00 – 0.75	0.00 – 0.75
Hansen J Statistic							44.45	6.45		
							p=.00	p=.60		
Observations	804,766	804,766	804,766	804,766	637,557	637,557	459,613	459,613	637,557	637,557
Firms	374,257	374,257	374,257	374,257	300,379	300,379	240,967	240,967	300,379	300,379

Notes: The dependent variable in all models is a dummy equal to one for a firm patenting with SIPO (USPTO) in year t and zero otherwise. All models employ the 4-year dataset with observed R&D expenditure, with the top and bottom 1% of observations winsorized for R&D expenditure, firm size, export/sales ratio, firm age, as well as the three financial variables. Model [3] accounts for sample selection by ways of modelling inclusion in the integrated ASIE-Qin/Oriana sample jointly with the patenting decision (using multivariate probit). All models [4] to [6] use lagged values (either 1st lag or 1st and 2nd lag as indicated in the column header) of the three export variables, firm size, the three financial constraints variables and the patent subsidy variable as instruments. Model [6] in addition uses the first lag of the R&D expenditure variable as instrument (similarly for the squared term). All variables and 'Further Controls' are detailed in Table A-4 in the supplementary appendix. Statistically significant coefficients and their standard errors appear in bold. We further highlight the covariates for which there is a statistically significant difference between the coefficients in the SIPO and USPTO equations. Standard errors are clustered at the firm level.

Note however that diagnostic tests yield diverging results in the SIPO and USPTO models which suggest that for the SIPO equation our instrumentation strategy violates the exclusion restriction and should therefore not be interpreted as causal.

Conditioning on pure and non-exporters, our various SIPO models suggest a significant negative relationship between export intensity and patenting behaviour, which is in stark contrast to the findings in the existing literature. There is further a significant positive relationship with government incentives to file patents and the decision to apply for a SIPO patent. These models further provide evidence for a significant positive effect of innovation effort on the patenting decision, while firm size, foreign or private ownership, and financial constraints are also significant and have the expected signs.[18] On the whole the SIPO results indicate that the patenting decision is (partly) driven by government incentives, supporting the findings of Li (2012), Dang and Motohashi (2015) and Lei et al. (2015), and further that more export-intensive firms, contrary to a Melitz-type prediction of the exporting-productivity relationship, have a lower propensity to patent than their peers exporting lower shares of their output.

Turning to the USPTO models many of our results are statistically insignificant, likely due to the limited number of patentees. Nevertheless we find a significant and strong relationship between the patenting decision and innovation effort, firms size, some measures of financial constraints as well as export intensity, respectively. The coefficients on government incentives are uniformly low and statistically insignificant. Coefficients on export intensity are positive and large but not uniformly statistically significant across all models.

We further highlight those covariates for which there is a statistically significant difference for coefficients between the SIPO and USPTO equations: most strikingly, the export-innovation nexus is positive (though not necessarily statistically significant) and thus in line with the literature for USPTO equations, while filing subsidies are now even negative (in our IV models), albeit statistically insignificant. Results for indicators of financial constraints show similar deviation between SIPO and USPTO patentees, though only in the IV specification with the smallest sample size (column [5]), which is also the specification where results for patent subsidies deviate statistically significantly. We obtain qualitatively similar results when including a set of 2-digit SIC industry dummies to confirm that despite the dominance of the ITC sector our results are not driven by sector of operation.[19]

[18] The coefficient on the cash-flow variable deviates from the existing literature on China (e.g. Guariglia and Liu, 2014) in that firms do not appear credit-constrained. Our analysis investigates patents (for SIPO: 0.39% of observations are non-zero) as opposed to (self-reported) new product sales (10.26% of observations are non-zero) in these authors' work. Hence, differences in results may be due to that fact that patented inventions commonly represent only a subset of firms' product innovations where

Table 5: Binary Choice Models – Marginal Effects

	[1]		[2]		[3]						[4]				[5]				[6]			
	Probit				Bi-variate Probit						IV-Probit (1st lag)				IV-Probit (1st & 2nd lag)				IV-Probit (1st lag incl. R&D)			
	SIPO		USPTO		SIPO only		USPTO only		Both		SIPO		USPTO		SIPO		USPTO		SIPO		USPTO	
	Effect	Ratio	Effect	Ratio	Effect	Ratio	Effect	Ratio	Effect	Ratio	Effect	Ratio	Effect	Ratio	Effect	Ratio	Effect	Ratio	Effect	Ratio	Effect	Ratio
Patenting incidence																						
Unconditional	.393%		.034%		.367%		.008%		.026%		.393%		.034%		.393%		.034%		.393%		.034%	
Continous variables																						
Export/Sales	-.093%		.011%		-.093%		.013%		.002%		-.333%		.014%		-.256%		.066%		-.286%		.014%	
ln(Workers)	.045%	-2.1	.009%	1.2	.040%	-2.3	.002%	5.2	.005%	0.5	.058%	-5.8	0.024%	.6	.108%	-2.4	.025%	2.6	.060%	-4.3	.017%	3.8
ln(Firm age)	.000%	4633	.000%	73.8	.000%	-3095	.000%	212	.000%	59.2	-.001%	490	-.001%	-9.8	-.004%	61.8	-.002%	-36.7	-.001%	449	-.001%	-72.9
Liquidity	.004%	-23.2	.002%	6.7	.003%	-29.8	.001%	22.7	.001%	3.0	.005%	-62.1	0.011%	1.3	.000%	-3658	.021%	3.2	.005%	-50.4	.020%	3.3
Leverage	.000%	-250	.000%	46.1	.000%	226	.000%	1817	.000%	-527	.004%	-88.8	.002%	6.0	.013%	-19.5	.006%	10.4	.003%	-76.9	.006%	11.8
Cash flow	-.009%	10.0	.000%	-38.2	-.009%	10.5	.000%	35.3	.001%	2.8	-.014%	23.2	-.006%	-2.3	-.011%	24.4	-.003%	-20.5	-.021%	12.3	-.003%	-23.4
Dummy variables																						
Zero Exports	-.184%	0.5	.006%	1.9	-.185%	.5	.003%	4.3	-.001%	-2.7	-.376%	.9	.008%	1.8	-.327%	.8	.003%	19.5	-.354%	.7	-.001%	-59.1
>90																						
Filing subsidy	.168%	-0.6	.008%	1.4	.161%	-0.6	.001%	15.6	.006%	0.4	.570%	-0.6	-.013%	-1.0	6.906%	0.0	.008%	8.6	.436%	-0.6	-.026%	-2.5
FIE (other)	.113%	-0.8	.011%	1.0	.103%	-0.9	.004%	3.1	.010%	0.2	.047%	-7.1	.000%	-202	-.817%	0.3	.002%	36.9	.071%	-3.6	-.001%	-77.9
FIE (HMT)	.107%	-0.9	.008%	1.3	.096%	-1.0	.004%	3.5	.009%	0.3	.085%	-3.9	.006%	2.3	-.471%	0.5	.007%	9.4	.111%	-2.3	.006%	11.8
Private	.053%	-1.8	-.010%	-1.1	.057%	-1.6	-.003%	-4.2	-.003%	-0.8	.058%	-5.8	-0.017%	-0.8	.033%	-7.8	-.014%	-4.8	.053%	-4.8	-.017%	-3.9
Collective	-.056%	1.7	-.015%	-0.7	-.048%	1.9	-.004%	-2.9	-.009%	-0.3	-.090%	3.7	-.033%	-0.4	-.559%	0.5	-.026%	-2.5	-.092%	2.8	-.042%	-1.6
Other	.143%	-0.6	.008%	1.5	.142%	-0.7	.005%	2.5	.012%	0.2	.135%	-2.5	.001%	12.4	.078%	-3.3	.012%	5.6	.122%	-2.1	.000%	270

Notes: We present the partial effects and related statistics for the bivariate models in Table 4. Note that in the case of the continuous variables these are *not* average partial effects for the mean or partial effects at the average, but all provide the average partial effect on the propensity to patent of moving from the 75th percentile to the 85th percentile of the distribution of the variable in question. We adopt this strategy due to the nature of the export-sales ratio variable, which is zero for the median firm. In the lower panel of the table we present the effect of a discrete change for the binary variables indicated from the base level (0). Next to the partial effects we report the ratio of the partial effect of export intensity (export-sales ratio) relative to that of each other variable; for instance, a value of -23.2 for 'Liquidity' in column [1] indicates that the partial effects of 'Liquidity' and 'Export/Sales' have opposite signs and that in terms of magnitudes the latter is 23.2 times as large as the former. We provide these ratios for the dummy variable discrete marginal changes as well, even though these are strictly not comparable.

What are the quantitative implications of the differences detected between SIPO and USPTO patentees? Table 5 shows the marginal effects for the coefficients shown in Table 4. For the continuous variables we focus on a hypothetical shift of a firm from the 75th to the 85th percentile of the distribution, which in the case of export intensities equates to values of 12% and 76%, respectively. The marginal effects for export intensity in the SIPO equations range between -0.1% in the probit and -0.3% in the IV probit specifications, while they are between 0.01% and 0.07% in the USPTO equations: these figures are modest in absolute terms, although we highlight the generally low propensities to patent at the top of the table. In addition, as we indicate in the columns marked 'Ratio', the export-intensity 'effect' is a multiple of the marginal effects of other firm characteristics such as firm age and size or financial constraints (note that only results for the continuous variables are directly comparable).

5.2 Patent count analysis

We now turn to the empirical analysis of patent production, which we investigate using count regression models. We present results from three different models with distinct setup and interpretation: first, we analyse a Negative Binomial for counts of patent applications with SIPO and the USPTO in columns [1] and [2] of Table 6, respectively. These were found to be favoured over standard Poisson regressions based on a direct statistical comparison (LR test). These estimates provide insights into whether firm characteristics are associated with differential numbers of patent applications between the two jurisdictions. Second, we analyse fixed effects Poisson models in columns [3] and [4], which limit the sample to 'innovating' firms with at least one SIPO or USPTO patent application over the 4-year time horizon. The interpretation of these models is whether any changes in R&D, export behaviour, financial variables, etc. *within patenting firms over time* are associated with higher or lower patent counts; since many unobserved determinants of patenting are plausibly captured by the firm fixed effects this gets us closer to a causal interpretation of the results than the previous count data models — note however that the average number of observations per firm in these FE Poisson models is merely 3.1, thus offering precious little time series variation to identify precisely any within-firm effects. Third, we move from counts of patent applications to those of *granted patents* in the analysis in columns [5] and [6]. The patent filings-to-grant-ratio for a firm can be interpreted as a first indication of the quality of its patent filings. We find that only around 63% of SIPO filings are

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financial constraints are potentially less relevant.

[19] We prefer the results *without* industry fixed effects since inclusion of sectoral dummies reduces the sample size in the USPTO regression by around 25%: there are no USPTO patent filings in six sectors (Leather and fur; Furniture; Paper; Printing; Rubber and Transport Equipment) which implies that there is no variation in the dependent variable for observations in these sectors and they are thus automatically dropped from the sample. There is further non-convergence in the trivariate probit model if we introduce industry dummies. Full results are available on request.

eventually granted whereas 83% of USPTO filings are, which motivates the analysis in columns [5] and [6].

The patent count models in columns [1] and [2] show similar patterns in terms of sign and statistical significance between SIPO and USPTO patent counts as were detected in the binary choice models of the patenting decision. Innovation effort is positively associated with higher patent counts in line with earlier findings by Hu and Jefferson (2009). Export intensity (not investigated by these authors), in contrast, indicates a clear divergence between SIPO and USPTO counts, where the export-patenting nexus is negative (positive) for the former (latter). U.S. patent count is driven by larger and younger firms in comparison with SIPO patent counts. Firm financial variables have the expected signs but differences between jurisdictions are not statistically significant. Patenting incentives have a uniformly positive impact on patent counts (not always statistically significant) — this may be counter-intuitive, but further investigation reveals that the positive USPTO coefficient is driven by firms patenting in *both* jurisdictions.[20] Firm ownership dummies indicate that all non-state-owned firm types are more prolific USPTO patentees, whereas for SIPO this is only the case among Western FIEs, consistent with earlier findings by Choi et al. (2011) — again the difference across jurisdictions is not statistically significant. All of these results are virtually identical if we use granted patent counts in columns [5] and [6] instead of application counts.

The fixed effects results provide some qualitative indications that increases in export intensity have opposite effects on SIPO and USPTO patent counts, although these results are very imprecisely estimated. Similarly the results for filing subsidies, albeit statistically insignificant in either equation, are once again in line with the previous patterns in favour of SIPO patenting.[21]

The reported coefficients, *ceteris paribus*, are differences in the logs of predicted counts for unit increases in the regressors. We also obtained incident rate ratios (IRR), which compute the relative increase or decrease (coefficients in excess of/below 1, respectively) in patent counts in response to a unit change in the regressor (reported in Table 7) — for size and age this unit change implies a doubling of the variable due to logarithmic transformation. In the models in columns [1] and [2] the *relative* IRR for export intensity yields a twelve-fold difference between SIPO (patent count reduced to 40%) and USPTO (patent count more than quadruples),[22] that for firm size an almost three-fold difference (SIPO count doubles, USPTO

[20] When we limit the SIPO patent analysis to firms which do not have USPTO patents and vice versa the results for the subsidy variable are as follows: 0.903 [t=4.00] (SIPO equation), -0.307 [t=-0.88] (USPTO equation).

[21] Note that the interpretation of the firm ownership dummies is very different in these panel FE models: these estimates now indicate the impact of a *change* in ownership, and with the results driven by a small number of observations we do not report these estimates to avoid confusion.

[22] A 'unit increase' for a variable defined as a ratio between 0 and 1 is clearly difficult to interpret. For convenient interpretation we re-estimated this model using the *logarithm* of export intensity instead of the level, where a unit increase implies a doubling

Table 6: Count Data Models

	[1]	[2]	[3]	[4]	[5]	[6]
	NegBin		FE Poisson		NegBin	
Dep. Variable	SIPO	USPTO	SIPO	USPTO	SIPO	USPTO
Patent Applications	×	×	×	×		
Granted Patents					×	×
Innovation effort						
ln(R&D pw)	**1.122**	**1.049**	**0.127**	0.079	**1.214**	**1.079**
	[0.176]***	**[0.139]*****	**[0.056]****	[0.104]	**[0.189]*****	**[0.146]*****
ln(R&D pw)^2	**0.336**	**0.295**	**0.057**	-0.083	**0.393**	**0.376**
	[0.094]***	**[0.118]****	**[0.029]****	[0.112]	**[0.101]*****	**[0.128]*****
Export behaviour						
Exports/Sales	**-0.978**	**1.514**	-0.564	0.782	-0.498	**1.623**
	[0.429]**	**[0.566]*****	[0.653]	[1.134]	[0.378]	**[0.614]*****
>90% Export/Sales	0.119	-0.420	0.220	-0.294	0.040	-0.451
	[0.296]	[0.385]	[0.395]	[0.725]	[0.337]	[0.402]
Zero Exports	-0.103	0.582	**-0.300**	**-0.854**	0.277	0.624
	[0.334]	[0.435]	**[0.134]****	**[0.357]****	[0.238]	[0.480]
Firm size and age						
ln(Workers)	**0.643**	**1.699**	**0.214**	0.180	**0.667**	**1.715**
	[0.086]***	**[0.145]*****	**[0.109]****	[0.508]	**[0.095]*****	**[0.156]*****
ln(Firm age)	**-0.162**	**-0.566**	-0.035	**0.771**	-0.143	**-0.553**
	[0.094]*	**[0.119]*****	[0.096]	**[0.341]****	[0.100]	**[0.121]*****
Financial constraints						
Liquidity	0.536	**2.447**	0.101	-0.258	**0.884**	**2.739**
	[0.432]	**[0.690]*****	[0.202]	[0.756]	**[0.459]****	**[0.722]*****
Leverage	**0.742**	**2.364**	-0.146	0.111	**0.999**	**2.720**
	[0.443]*	**[0.622]*****	[0.358]	[0.745]	**[0.497]****	**[0.683]*****
Cash flow	**-1.181**	-0.619	0.223	0.139	**-1.407**	-0.845
	[0.541]**	[0.842]	[0.299]	[0.745]	**[0.539]*****	[0.961]
Patenting incentives						
Filing subsidy	**1.003**	**0.884**	0.863	0.239	**0.887**	**0.820**
	[0.249]***	**[0.321]*****	[0.658]	[1.023]	**[0.272]*****	**[0.337]****
Ownership type						
FIE (other)	**1.201**	**1.807**			1.066	**2.037**
	[0.722]*	**[0.476]*****			[0.779]	**[0.500]*****
FIE (HMT)	0.762	**1.378**			0.590	**1.513**
	[0.669]	**[0.434]*****			[0.701]	**[0.418]*****
Private	-0.276	**0.808**			-0.483	**1.103**
	[0.678]	**[0.341]****			[0.726]	**[0.335]*****
Collective	-0.626	**0.930**			-0.822	**1.008**
	[0.746]	**[0.462]****			[0.813]	**[0.477]****
Other	0.086	**2.319**			0.018	**2.687**
	[0.700]	**[0.618]*****			[0.760]	**[0.623]*****
Further Controls	×	×	×	×	×	×
Year dummies	×	×	×	×	×	×
LR (p-value)	0.00	0.00			n/a	n/a
$\sum \lvert\hat{y}_i - y_i\rvert$	0.13	0.02			0.25	0.03
AIC	51,177	4,738			37,908	4,009
LL full model	-25,559	-2,339	-7,336	-512	-18,924	-1,974
Observations	804,766	804,766	7,113	507	804,766	804,766
Non-zero obs.	0.39%	0.03%			0.28%	0.03%
Firms	374,257	374,257	2,327	170	374,257	374,257

Notes: The dependent variable in all models is the patent count with SIPO or USPTO as indicated. All variables and 'Further Controls' are detailed in Table A-4 in the supplementary appendix. IRR reports the incidence rate ratios — see text for details. Statistically significant coefficients (10% level) and standard errors are printed in bold. In Models [3] and [4] we omit reporting coefficients for the ownership dummies since these now indicate the patent productivity of firms switching ownership, which is misleading in the general setup of our analysis. Standard errors are clustered at the firm level.

Table 7: Count Data Models: Incidence Rate Ratios (IRR)

	[1]	[2]		[3]	[4]		[5]	[6]	
	NegBin			FE Poisson			NegBin		
	SIPO	USPTO	Ratio	SIPO	USPTO	Ratio	SIPO	USPTO	Ratio
IRR									
ln(R&D pw)	3.07	2.85	0.9	1.14	1.08	1.0	3.37	2.88	0.9
ln(R&D pw)^2	1.40	1.34	1.0	1.06	0.92	0.9	1.48	1.35	0.9
Export/Sales	0.38	4.55	12.1	0.57	2.19	3.8	0.61	4.55	7.5
>90% Export/Sales	1.13	0.66	0.6	1.25	0.75	0.6	1.04	0.66	0.6
Zero Exports	0.90	1.79	2.0	0.74	0.43	0.6	1.32	1.78	1.4
ln(Workers)	1.90	5.47	2.9	1.24	1.20	1.0	1.95	5.46	2.8
ln(Firm age)	0.85	0.57	0.7	0.97	2.17	2.2	0.87	0.57	0.7
Liquidity	1.71	11.55	6.8	1.11	0.77	0.7	2.42	11.54	4.8
Leverage	2.10	10.63	5.1	0.86	1.11	1.3	2.72	10.62	3.9
Cash flow	0.31	0.54	1.8	1.25	1.16	0.9	0.24	0.54	2.2
Filing subsidy	2.73	2.42	0.9	2.37	1.26	0.5	2.43	2.42	1.0
FIE (other)	3.33	6.09	1.8				2.90	6.09	2.1
FIE (HMT)	2.15	3.97	1.8				1.80	3.97	2.2
Private	0.76	2.24	3.0				0.62	2.25	3.6
Collective	0.53	2.53	4.7				0.44	2.54	5.8
Other	1.09	10.17	9.3				1.02	10.16	10.0
Obs	804,766	804,766		7,113	507		804,766	804,766	
Firms	374,257	374,257		2,327	170		374,257	374,257	

Notes: In this table we report the obtained incident rate ratios (IRRs) for the count data models in Table 6. These represent the relative increase or decrease (coefficients in excess of/below 1, respectively) in patent counts in response to a unit change in the regressor — for size and age this unit change implies a doubling of the variable due to logarithmic transformation. The columns marked ratio report the relative IRR between USPTO and SIPO equations: for instance, export intensity yields a twelve fold difference in the IRR between USPTO (patent count quadruples) and SIPO (patent count reduced to 30%). Statistical tests indicate that the IRRs between SIPO and USPTO differ for the export intensity and firm size variables in both negative binomial models of patent applications and patent grants.

count quintuples). For firm age a log unit increase sees SIPO patent count drop to 85% of the previous level, and USPTO counts to 55%, a one-and-a-half-fold difference. Similar figures are obtained if we carry out this exercise for the models using granted patents in columns [5] and [6].[23]

6 Conclusion

What is behind the recent Chinese patent explosion? Is China transitioning rapidly from imitating technology to producing genuine innovation? What impact does the patent explosion have on the Chinese economy and on the rest of the world? While answers to these questions are of immediate concern to policy makers in China and beyond, their empirical investigation has to date been severely hampered by data limitations:

of the ratio. The IRR for SIPO applications is then 0.95, that for USPTO 1.64, with a (statistically significant) 1.7-fold difference between the two. The IRRs for size and age are virtually unchanged.

[23] All magnitudes quoted are identical, with the exception of export intensity, where the difference is now seven-fold: the SIPO count reduces to 60%, the USPTO count increases by a factor of 4.5.

there were no data available for Chinese firms that included companies' actual patent filings or that could distinguish between invention patents and the less innovative utility and design patents. We overcome these constraints and construct a dataset that contains domestic invention and U.S. utility patent filings by 316,000 manufacturing firms registered in China. We employ the data to chart the developments from 1985-2006 and to investigate the factors associated with the Chinese patent explosion over 2001-6, accounting for concerns over selection into our regression sample from survey data representative of large and medium-sized enterprises in China.

Our answer to what lies behind the Chinese patent explosion is unambiguous: a handful of companies account for the overwhelming share of patents. Does this imply there is evidence for wider technological take-off among Chinese companies? Our analysis suggests most likely not: patenting is concentrated in very few industries and even within these is undertaken by very few albeit highly active companies. What is more, the most patent-active companies both with the USPTO and SIPO operate in the ICT sector, an industry that has become notorious for its patent battles, technological standards (including standard-essential patents), and patent pools requiring firms to arm themselves with sufficiently large patent portfolios.

Our results also point to clear differences in the determinants for the patenting decision as well as patent counts between SIPO and USPTO patentees. While the latter are positively associated with export intensity as suggested by the existing literature on export behavior and innovation, we find SIPO filings to be negatively associated. This suggests that patenting with the Chinese patent office may be to a large extent driven by factors other than underlying innovative behavior: firms patenting with SIPO are found to be responding to state incentives in the form of patent subsidies. This underscores the importance of incentives put in place by local governments to promote patenting directly.

From a policy point of view this implies that innovation policy objectives formulated in terms of numbers of patents (such as in the recent '12th Five-Year-Plan') may not have the desired outcome: merely promoting the filing of patents that do not protect innovative technologies may create a number of unintentional adverse consequences. For instance, patent thickets — shown to exist in ICT (von Graevenitz et al., 2013) — are likely to emerge, increasing transaction costs for companies and potentially raising barriers to entry (Hall et al., 2015). Such patenting behaviour may furthermore lead to an escalation of patent litigation similar to the explosion of patent actions witnessed in the U.S. over the past decade (PWC, 2014).

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SUPPLEMENTARY APPENDIX

A Data Construction and Descriptive Statistics

Following the merging of ASIE and Qin-Oriana data we match the integrated dataset with PATSTAT data for SIPO innovation and USPTO utility patents. We drop firms that are only contained in Qin-Oriana. This results in 2,358 USPTO and 66,741 SIPO patents matched to firms for the 1985-2006 period. For the regression analysis ('R&D sample', constrained to the years 2001, 2002, 2005, 2006) we furthermore exclude those operating outside the manufacturing sector, which yields 732,036 firm-year observations from 315,968 firms. In order to address concerns about selection into the Qin-Oriana sample we use the full ASIE sample available to us and account for selection in a number of empirical models — this comprises 804,766 firm-year observations from 374,257 firms, so that our integrated sample makes up around 91% of this larger sample.

Table A-1: R&D Sample — Chinese and US Patents

SIPO										
	4-year R&D sample					Full 1999-2006 sample				
year	**firms†**	**patents**	**mean**	**sd**	**max**	**firms†**	**patents**	**mean**	**sd**	**max**
1999						75,912	720	0.009	0.779	88
2000						89,324	1,312	0.015	1.036	153
2001	122,202	1,760	0.014	1.316	391	122,202	1,760	0.014	1.316	391
2002	146,828	4,691	0.032	3.461	1,009	146,828	4,691	0.032	3.461	1,009
2003						167,024	8,051	0.048	4.828	1,496
2004						242,822	13,817	0.057	5.878	2,082
2005	232,048	18,918	0.082	8.968	3,779	232,048	18,918	0.082	8.968	3,779
2006	230,958	27,044	0.117	14.697	6,570	230,958	27,044	0.117	14.697	6,570
Total	732,036	52,413	0.072	9.815	6,570	1,307,118	76,313	0.058	7.966	6,570
USPTO										
	4-year R&D sample					Full 1999-2006 sample				
year	**firms†**	**patents**	**mean**	**sd**	**max**	**firms†**	**patents**	**mean**	**sd**	**max**
1999						75912	28	0.000	0.034	4
2000						89324	104	0.001	0.097	10
2001	122,202	211	0.002	0.154	16	122202	211	0.002	0.154	16
2002	146,828	257	0.002	0.168	19	146828	257	0.002	0.168	19
2003						167024	344	0.002	0.211	55
2004						242822	682	0.003	0.305	94
2005	232,048	802	0.003	0.425	146	232048	802	0.003	0.425	146
2006	230,958	1,290	0.006	0.763	263	230958	1290	0.006	0.763	263
Total	732,036	2,560	0.003	0.501	263	1307118	3718	0.003	0.405	263

Notes: The left panel indicates firm and patent counts in our regression sample (constrained to four years by the availability of R&D expenditure), the right panel for reference reports the same for the full integrated panel for 1999-2006. † Note that in each individual year this column reports the number of firms, whereas in the 'Total' row this reports the number of observations. We do not report the medians and minimum patent counts, since these are zero in all years of either dataset for USPTO and SIPO, respectively.

Table A-2: Descriptive Statistics

PANEL A: Sample of 315,968 firms (ASIE-Qin/Oriana integrated 4-year sample)

variable	type	obs	mean	median	sd	min	max
Patents							
SIPO patents	count	732,036	0.072	0	9.815	0	6,570
USPTO patents	count	732,036	0.003	0	0.501	0	263
Innovation effort							
R&D per worker	continuous	724,343	1.083	1.000	0.695	0	5.292
Missing R&D	dummy	732,036	0.011	0		0	1
Zero R&D	dummy	732,036	0.874	1		0	1
Firm characteristics							
Export/Sales	continuous	732,036	0.183	0	0.351	0	1
Zero Exports	dummy	732,036	0.121	0		0	1
Export/Sales>90%	dummy	732,036	0.714	1		0	1
Conglomerate	dummy	732,036	0.001	0		0	1
Labour	continuous	732,036	228	108	374	10	2,584
Age	continuous	732,036	12	8	11	1	53
Leverage	continuous	732,036	0.585	0.595	0.289	0.011	1.556
Liquidity	continuous	732,036	0.060	0.064	0.312	-0.919	0.786
Cash flow	continuous	732,036	0.105	0.061	0.167	-0.213	0.902
State incentives							
Filing subsidy	categorical	731,440	0.514	1		0	1
Missing subsidy	dummy	732,036	0.001	0		0	1
Ownership type (Paid-in Capital)							
FIE (Other)	dummy	732,036	0.079	0		0	1
FIE (HMT)	dummy	732,036	0.083	0		0	1
Private	dummy	732,036	0.654	1		0	1
SOE	dummy	732,036	0.078	0		0	1
Collective	dummy	732,036	0.095	0		0	1
Other	dummy	732,036	0.015	0		0	1

PANEL B: Full ASIE 4-year Sample of 374,257 firms

variable	type	obs	mean	median	sd	min	max
Patents							
SIPO patents	count	804,766	0.065	0	9.361	0	6,570
USPTO patents	count	804,766	0.003	0	0.477	0	263
Innovation effort							
R&D per worker	continuous	795,575	1.082	1.000	0.689	0	5.292
Missing R&D	dummy	804,766	0.011	0		0	1
Zero R&D	dummy	804,766	0.875	1		0	1
Firm characteristics							
Export/Sales	continuous	804,766	0.178	0	0.347	0	1
Zero Exports	dummy	804,766	0.722	1		0	1
Export/Sales>90%	dummy	804,766	0.117	0		0	1
Conglomerate	dummy	804,766	0.001	0		0	1
Labour	continuous	804,766	224	105	371	10	2,584
Age	continuous	804,766	12	8	11	1	53
Leverage	continuous	804,766	0.583	0.593	0.291	0.011	1.556
Liquidity	continuous	804,766	0.059	0.064	0.313	-0.919	0.786
Cash flow		804,766	0.105	0.060	0.168	-0.213	0.902
State incentives							
Filing subsidy	categorical	804,059	0.512	1		0	1
Missing subsidy	dummy	804,766	0.001	0		0	1
Ownership type (Paid-in Capital)							
FIE (Other)	dummy	804,766	0.078	0		0	1
FIE (HMT)	dummy	804,766	0.081	0		0	1
Private	dummy	804,766	0.656	1		0	1
SOE	dummy	804,766	0.079	0		0	1
Collective	dummy	804,766	0.096	0		0	1
Other	dummy	804,766	0.015	0		0	1

Notes: pw — per worker. R&D pw is reported in thousands of real RMB 2000 values. Ownership type uses majority paid-in capital, not official registration, following Guariglia, Liu and Song (2011). The integrated dataset covers 90.7% of all firms contained in ASIE. Where observations are missing we add a zero value and account for their inclusion with a separate dummy (e.g. Missing subsidy, Missing R&D).

Table A-3: Product vs. Process Innovation (1985-2006)

Innovation Type	USPTO		SIPO			
			excl. US Equivalents		incl. US Equivalents♮	
	Share	Patents	Share	Patents	Share	Patents
Product	46.81	895	29.90	293	29.89	634
Process	20.35	389	36.94	362	36.71	697
Product & Process	32.85	628	33.16	325	33.40	799
Total	100.00	1,912	100.00	980	100.00	2,130

Notes: Patents are classified manually using patent claims. ♮ Equivalents with the USPTO and SIPO patents are weighted with the respective sample share.

Table A-4: Variable Description

Variable	**Type**	**Description**
Patents		
SIPO (Table 4)	dummy	=1 if firm has a SIPO innovation patent
USPTO (Table 4)	dummy	=1 if firm has a USPTO utility patent
SIPO (Table 5)	count	Number of firm's SIPO innovation patents
USPTO (Table 5)	count	Number of firm's USPTO utility patents
Innovation effort		
R&D per worker (observed)	continuous	Real R&D expenditure per worker
Missing R&D †	dummy	=1 if R&D expenditure data is missing
Zero R&D †	dummy	=1 if firm's R&D expenditure is zero
Firm Characteristics		
Export/Sales	continuous	Share of export value in total sales
Zero Exports	dummy	=1 if firm did not export
Export/Sales>90%	dummy	=1 if firm's export/sales are above 90% ('pure exporter')
Conglomerate †	dummy	=1 if firm is part of a conglomerate
Labour	continuous	Worker headcount
Age	continuous	Firm age since founding
Leverage	continuous	total liabilities / total assets
Liquidity	continuous	[liquid assets – liquid liabilities] / total assets
Cash flow	continuous	[net income + depreciation + R&D expenditure]/ total assets
State incentives		
Filing subsidies	categorical	=1 if fully subsidized in province i of year t, =0.5 if partly and =0 if not subsidized
Ownership type		
SOE (omitted category)	dummy	=1 if firm is SOE (ownership based on paid-in capital)
FIE (HMT)	dummy	=1 if firm is foreign-owned (HK, Macao, Taiwan only)
FIE (Other)	dummy	=1 if firm is foreign-owned (non HK, Macao, Taiwan)
Private	dummy	=1 if firm is private
Collective	dummy	=1 if firm is a collective enterprise
Other	dummy	=1 if firm has an ownership type other than the above
Additional Controls		
Year	dummies	=1 if observation is in year t
Province	dummies	=1 if firm is resident in province k
Sector	dummies	=1 if firm is in SIC2 industrial sector s

Notes: All variables marked with † are referred to as 'Controls' in the results tables.

B Data Matching

The combination of the Qin and Oriana datasets contains 371,455 unique firm names which are matched with the assignee names of SIPO and USPTO patent filings. The SIPO and USPTO patent files contain 168,359 and 3,580 unique assignee names (with Chinese residency) respectively. The assignees contain a large range of different assignee types, including private individuals, police, military, universities, and public research institutes (e.g., the Chinese Academy of Sciences and other not-for-profit organisations). As a first step in the matching process, we attempt to keep only private and state-owned companies (or some hybrid form) because none of the other assignee types is contained in Qin and Oriana. After dropping any assignees that are not private or state-owned companies, cleaning/standardizing assignee names, and keeping only patents applied for between 1985-2006, we obtain 67,157 and 1,454 unique names in the SIPO and USPTO patent files respectively. These two files are then matched with the 371,455 names contained in Qin and Oriana. The main challenge in matching the two datasets is the fact that names in PATSTAT as well Qin and Oriana might still differ according to whether they have simply been transcribed using pinyin or (partly) translated. As manual matching is unfeasible due to the large number of Chinese patents, we create a matching algorithm that copes with this difficulty. As part of this algorithm, we clean and standardize names in both datasets to a maximum possible to avoid the occurrence of 'false negatives'. In a third step, we define equivalent groups.[24] We then verify whether the matched sample contains the corresponding equivalents; for example, if a SIPO patent was matched and we find it to have a USPTO equivalent, we check whether the USPTO patent was also matched. If it was not matched, we verify the USPTO patent's assignee name and add it to the matched sample if it coincides with the assignee name of the SIPO patent. This step ensures consistency between the USPTO and SIPO matches and adds a number of patents to our matched sample. Finally, we check all matched and unmatched USPTO patents manually. Due to the considerably larger number of SIPO patents, we only checked a random 10% subsample of matched and unmatched patents. As shown in Table B-1 We successfully match 52 percent and 41 percent of all USPTO and SIPO patents filed between 1985 and 2006, respectively.

[24]We apply a definition that assigns patents into the same equivalent group if patents share the same priority documents.

Table B-1: Benchmarking the matching outcome (1985-2006)

	Assignee names				Patents		
	Raw Data♮	Cleaned Data§	Matched	Match Success (percent)	Patents	Matched	Match Success (percent)
SIPO	168,359	67,157	4,907	7.31	162,259	66,741	41.13
USPTO	3,580	1,454	319	21.93	4,541	2,358	51.92

Notes: SIPO and USPTO patents extracted from PATSTAT version October 2010. ♮ The data contain patent applications between 1985 and 2006. § Only for-profit companies are kept in the sample.

C Data Cleaning

The merged Qin/Oriana-ASIE sample contains 1,307,118 firm-year observations from 358,032 individual firms spanning the period of 1999-2006 (see Table C-1), [25] around 87% of the full ASIE sample of 1,501,263 observations from 472,871 firms. Given the importance of innovation effort for patenting our regression analysis is constrained by the R&D expenditure measure which is only available in four years, namely 2001, 2002, 2005 and 2006. The sample used in the regression analysis therefore contains 804,766 firm-year observations from 374,257 firms: this is the full ASIE sample for these four years, again we account for selection into the smaller integrated Qin/Oriana-ASIE sample which covers only 732,036 firm-year observations from 315,968 firms (final two columns of Table C-1). All variables employed in the regression analysis are defined in Table A-4 and discussed in detail in Section 3 in the main text. Note that for our descriptive analysis of patenting in Section 4, we make use of the entire data span for which we have patent data which covers the period 1985 to 2006.

Table C-1: ASIE-Qin/Oriana-PATSTAT dataset

	ASIE		Qin/Oriana-ASIE		Share	R&D Sample	
Year	observations	percent	observations	percent	percent	observations	percent
1999	134,879	8.98	75,912	5.81	56.28		
2000	136,119	9.07	89,324	6.83	65.62		
2001	146,311	9.75	122,202	9.35	83.52	122,202	16.69
2002	157,128	10.47	146,828	11.23	93.44	146,828	20.06
2003	175,548	11.69	167,024	12.78	95.14		
2004	249,601	16.63	242,822	18.58	97.28		
2005	237,725	15.84	232,048	17.75	97.61	232,048	31.70
2006	263,952	17.58	230,958	17.67	87.50	230,958	31.55
Total	1,501,263	100.00	1,307,118	100.00		732,036	100.00

Notes: 'Share' indicates the number of observations in the integrated Qin/Oriana-ASIE data as a proportion of all observations in ASIE.

[25] There were 1,467 firms that are contained in Qin or Oriana but not in ASIE with most of these firms in non-manufacturing industries and we dropped these observations prior to computing the above sample size. Similarly, we cleaned the dataset by dropping firms in non-manufacturing industries contained in ASIE (two digit GB/T code >43 or <13).

D USPTO vs SIPO

This appendix section examines differences between the patent systems in the U.S. and China which may have implications for the ability and motivation of Chinese firms to seek patent protection in each country. Since our analysis focuses on invention (SIPO) and utility (USPTO) patents, our discussion here is limited to these types of patents.

China's first patent law came into force in 1985 and was since amended three times (in 1992, 2000, and 2008). The second comprehensive amendment, adopted on 25th August 2000 and effective from 1st July 2001, was necessary to bring China's patent law in line with the WTO Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS), which China adopted with WTO entry in November 2001 (Yu, 2001).[26] For our purposes, an important change brought about by the amendment regards the deletion of the requirement to obtain official permission before a Chinese resident is allowed to file for patent protection abroad. Another important change was equal treatment of state- and privately-owned companies as well as the introduction of preliminary injunctions in case of patent infringement.

Regarding the application process, most importantly for our analysis, SIPO until recently granted patents for inventions that were not necessarily 'new-to-the-world': before the third amendment to the Chinese Patent Law in 2008, Article 22.2 defined prior art excluding inventions known to the public or in public use outside of China. For example, while a patent publication in the U.S. did represent prior art preventing the granting of a patent in China, if in contrast the invention had been known or used by someone other than the inventor (without obligation of secrecy) in the U.S., it would still have been patentable in China. Yang (2008) points out that different emphasis is put on the 'industrial applicability' criterion during the examination process:[27] whereas the USPTO has a broad interpretation of the potential practical purpose an invention might serve, SIPO requires some form of demonstrable industrial applicability. This is related to a broader issue regarding patentable subject matter. The U.S. patent system allows for a broader range of patentable subject matter, including software and business methods (van Pottelsberghe, 2010).[28] In contrast, SIPO officially applies a narrower definition of patentable subject matter more in line with the stance of the European Patent Office (EPO). Finally, the fee structure differs substantially between the USPTO and SIPO (see below), with numbers suggesting that obtaining and maintaining patent protection in the U.S. is considerably more expensive in the U.S. than China.

[26] Yu, X. 2001. The Second Amendment of the Chinese Patent Law and the Comparison between the New Patent Law and TRIPS. *The Journal of World Intellectual Property* 4(1): 137-55.

[27] Yang, D. 2008. Pendency and grant rations of invention patents: A comparative study of the U.S. and China. *Research Policy* 37(6-7): 1035-46.

[28] van Pottelsberghe de la Potterie, Bruno. 2010. The Quality Factor in Patent Systems. ECARES Working Paper 2010-27.

We exploit these differences in cost as well as novelty threshold between the USPTO and SIPO to infer the type, degree of innovativeness, and potential value of the inventions created and patented by Chinese companies. During our sample period, patent filings by Chinese entities with the USPTO had to jump a higher novelty threshold than with SIPO and given the higher associated costs, we expect to see only the most valuable inventions — both from a technological and strategic management point of view — to be patented with the USPTO. Hence, we can learn about the type and quality of SIPO patents by comparing them with the USPTO patents held by firms registered in China. Our integrated dataset allows us to look not only at the characteristics of the inventions underlying USPTO and SIPO patents, but also at the characteristics of the firms that hold these patents. This enables us, not only to look at patent distributions across industries, but also within industries across firms.

In China, a patent application costs CNY 900 (at the time around US$ 110), there is an additional examination fee of CNY 2,500 (US$ 300) and maintenance fees of CNY 300 (US$ 35) every five years. At the USPTO the basic application fee is US$ 330 and examination fees amount to US$ 220. At the USPTO, renewal fees are not payable annually: at 3.5 years, the maintenance fees due amount to US$ 980, at 7.5 years to US$ 2,480 and at 11.5 years to US$ 4,110. Additional costs for Chinese firms arise from the need to translate the application into English. If a Chinese applicant employs the services of a U.S. patent attorney, although not formally required by the USPTO, substantial additional costs arise. Hence, the numbers suggest that obtaining and maintaining patent protection in the U.S. is considerably more expensive than in China.

E State incentives for patenting

We adopt the data for patent subsidy programs reported in Dang and Motohashi (2015),[29] which were collected by these authors from official government documents, news reports and telephone interviews with local officials. Dang and Motohashi (2015) devise a points system whereby subsidies related to the 'filing' (application) for a patent carries a value (i) equal to 1 if it is fully subsidised; (ii) equal to 0.5 if there is partial subsidy; and (iii) equal to 0 if there is no subsidy. The overview of the provincial incentive scheme is provided in Table E-1, while Table E-2 summarises the evolution of the patent subsidy schemes — in the right panel we compute the share of points in total potential points across all provinces.

[29] Dang, J. and K. Motohashi. 2015. Patent Statistics: A good indicator for innovation in China? Patent Subsidy program impacts on patent quality. *China Economic Review*, Vol.35: pp. 137-55.

Table E-1: Patenting incentives

Province	Start year	Subsidy
Shanghai	1999	Full
Beijing	2000	Full
Chongqing	2000	Full
Guangdong	2000	Partial
Jiangsu	2000	Full
Tianjin	2000	Full
Guangxi	2001	Full
Hainan	2001	Partial
Heilongjiang	2001	Full
Sichuan	2001	Partial
Zhejiang	2001-2005	None
	2006	None
Fujian	2002-2005	Full
	2006	Full
Guizhou	2002	Full
Henan	2002	Partial
Inner Mongolia	2002	Full
Jiangxi	2002	Partial
Xinjiang	2002	Partial
Anhui	2003	None
Shaanxi	2003	Full
Shandong	2003	Partial
Shanxi	2003	Full
Yunnan	2003	Partial
Hunan	2004-2006	Partial
	2007	None
Jilin	2004	Partial
Tibet	2004	Full
Yunnan	2004	Partial
Hebei	2005	Partial
Liaoning	2006	Full
Qinghai	2006	Full
Hubei	2007	None

Notes: We present the chronology of provincial patent subsidies adapted from Dang and Motohashi (2015). Following these author's classification, a filing subsidy is classified as 'Full' if the subsidy is equal to the fees charged by SIPO, and 'Partial' if the amount is unclear or less than the fee charged. Our empirical analysis in the main section of the paper covers 2001, 2002, 2004 and 2005.

Table E-2: Patenting incentive evolution

year	Subsidy 'points'	Potential points share
1999	1	3%
2000	5.5	18%
2001	**8.5**	**27%**
2002	**13**	**42%**
2003	16	52%
2004	18	58%
2005	**18.5**	**60%**
2006	**20.5**	**66%**

Notes: We adopt the classification system by Dang and Motohashi (2015): filing subsidies are equal to 1 if the filing or examination fee is fully subsidized in the province where the applicant is located in year t, 0.5 if partly, 0 if not. In the left panel we tally up these points, in the right column we indicate the share of full subsidies implemented across provinces (i.e. *not* merely the share of provinces which adopted any subsidy scheme). We highlight the four sample years for our regression analysis in bold.

F Additional empirical results

Table F-1: Binary Choice Models — Linear Probability Models

	[1] LPM	[2] LPM	[3] IV-LPM	[3] IV-LPM	[4] IV-LPM	[4] IV-LPM	[5] IV-LPM	[5] IV-LPM
Dep.variable	SIPO	USPTO	SIPO	USPTO	SIPO	USPTO	SIPO	USPTO
Instruments			1st lag		1st & 2nd lags		1st lag – incl. R&D	
Innovation effort								
ln(R&D pw)	**0.0101**	**0.0010**	**0.0101**	**0.0010**	**0.0105**	**0.0009**	**0.0216**	**0.0017**
	[0.001]***	**[0.000]*****	**[0.001]*****	**[0.000]*****	**[0.001]*****	**[0.002]*****	**[0.002]*****	**[0.001]*****
ln(R&D pw)^2	**0.0032**	**0.0003**	**0.0032**	**0.0003**	**0.0033**	**0.0003**	**0.0119**	0.0003
	[0.000]***	**[0.000]****	**[0.000]*****	**[0.000]****	**[0.000]*****	**[0.000]****	**[0.002]*****	[0.001]
Export behaviour								
Export/Sales	**-0.0078**	-0.0004	**-0.0163**	-0.0004	**-0.0146**	0.0002	**-0.0143**	-0.0002
	[0.002]***	[0.000]	**[0.002]*****	[0.001]	**[0.003]*****	[0.001]	**[0.002]*****	[0.001]
>90% Export/Sales	0.0006	-0.0001	**0.0047**	-0.0001	**0.0043**	-0.0006	**0.0041**	-0.0001
	[0.001]	[0.000]	**[0.001]*****	[0.001]	**[0.002]****	[0.001]	**[0.002]*****	[0.001]
Zero Exports	**-0.0055**	0.0001	**-0.0101**	0.0000	**-0.0105**	0.0001	**-0.0089**	0.0001
	[0.001]***	[0.000]	**[0.001]*****	[0.001]	**[0.001]*****	[0.000]	**[0.001]*****	[0.000]
Size and age								
ln(Workers)	**0.0026**	**0.0004**	**0.0026**	**0.0004**	**0.0029**	**0.0004**	**0.0027**	**0.0004**
	[0.000]***	**[0.000]*****	**[0.000]*****	**[0.000]*****	**[0.000]*****	**[0.001]*****	**[0.000]*****	**[0.000]*****
ln(Firm age)	0.0001	0.0001	0.0001	0.0001	-0.0001	0.0000	0.0002	0.0000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.001]	[0.000]
Financial constraints								
Liquidity	**0.0010**	0.0002	**0.0016**	0.0010	-0.0007	0.0009	0.0005	0.0009
	[0.000]***	[0.000]	**[0.001]***	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Leverage	**-0.0009**	0.0001	-0.0010	0.0007	**-0.0024**	0.0006	**-0.0014**	0.0007
	[0.001]**	[0.000]	[0.001]	[0.000]	**[0.001]*****	[0.001]	**[0.001]***	[0.001]
Cash flow	**-0.0021**	0.0001	**-0.0018**	0.0001	0.0000	0.0000	**-0.0027**	0.0000
	[0.000]***	[0.001]	**[0.001]****	[0.001]	[0.001]	[0.001]	**[0.001]*****	[0.001]
Patent subsidies								
Filing subsidy	**0.0017**	0.0000	0.0028	-0.0046	**0.0221**	-0.0042	0.0022	-0.0046
	[0.000]***	[0.000]	[0.005]	[0.006]	**[0.006]*****	[0.006]	[0.005]	[0.006]
Ownership type								
FIE (other)	0.0001	0.0002	-0.0006	0.0007	**-0.0047**	0.0007	-0.0008	0.0007
	[0.001]	[0.000]	[0.001]	[0.001]	**[0.002]*****	[0.001]	[0.001]	[0.001]
FIE (HMT)	-0.0005	-0.0002	-0.0008	0.0004	**-0.0037**	0.0005	-0.0006	0.0004
	[0.001]	[0.000]	[0.001]	[0.001]	**[0.001]*****	[0.001]	[0.001]	[0.001]
Private	-0.0004	**-0.0005**	-0.0005	**-0.0006**	-0.0004	**-0.0005**	-0.0003	**-0.0006**
	[0.000]	**[0.000]*****	[0.000]	**[0.000]*****	[0.001]	**[0.000]*****	[0.000]	**[0.000]*****
Collective	**-0.0009**	**-0.0005**	**-0.0010**	-0.0003	**-0.0019**	-0.0002	-0.0007	-0.0003
	[0.000]**	**[0.000]*****	**[0.000]****	[0.000]	**[0.001]*****	[0.000]	[0.000]	[0.000]
Other	0.0011	0.0001	0.0010	0.0000	0.0010	0.0002	0.0010	-0.0001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Observations	804,766	804,766	637,557	637,557	459,613	459,613	637,557	637,557
Firms	374,257	374,257	300,379	300,379	240,967	240,967	300,379	300,379

Notes: The table presents results from standard and IV linear probability models (LPM). The specifications in [1] and [2] correspond to those in the same columns in Table 4 in the main text, while those in [3]-[5] above correspond to columns [4]-[6]. Statistically significant coefficients and their standard errors appear in bold. We further highlight the covariates for which there is a statistically significant difference between the coefficients in the SIPO and USPTO equations. Standard errors are clustered at the firm level.