Export, Ownership, and Innovation, Evidence from Chinese Firms' Patents Filings

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This version April 3, 2017

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Abstract

We provide micro-firm evidence how global trade promotes corporate innovation in China. Firms with high level of foreign export innovate more than firms relying on domestic sales. The difference in patents for firms with high vs. low level of foreign exports is significant in magnitude and increases drastically over time. Such difference is more pronounced in non-SOE subsample. A battery of endogeneity tests including RMB policy change or bilateral treaties show that export has a causality effect on innovations. Within industries evidence suggests that Chinese multinationals catch up on patents where US peers retreat. Firms with export enjoy technology spill-over from US innovation in low-tech industries but not high-tech. Our research suggests that global export improves technology spill-over into Chinese multinationals especially non-SOEs and low-tech firms.

Key words: Emerging multinationals, Global trade, Foreign sales, China, Innovation, Patent, US, Technology spill-over

JEL Codes: F13; F15, O14, O31

1. Introduction

According to the Global Agenda Forum of the World Economic Forum in 2012, innovative emerging multinationals become an important force in the global markets and start to successfully compete with well-established multinationals from developed countries. Emerging multinationals especially Chinese firms have made impressive progress in innovation activities. For example, The Economist has series of coverage to describe[1] how Huawei, the giant emerging telecom private firm in Shenzhen invests heavily in innovations, makes breakthrough innovations and grows to be a leader from a follower in the global market. The phenomenon of emerging multinationals on innovations and competitive advantage has fuelled wide concern among academic circles, market participants and policy makers. A large literature emerges to analyse the impact of emerging Chinese manufacturing firms on US and Europe corporations. For example, Bernard, Jensen and Schott (2006), Pierce and Schott (2015), Acemoglu et al. (2016), and Autor et al. (2014) all study how Chinese rising manufacturing multinationals affect labour market in the US. Bloom et al (2016) and Autor et al (2016) look at the impacts of China's trade on European and US corporate innovation, respectively. The trade threat of Chinese emerging manufacturing firms may be transitory if they rely only on cheaper labour without core innovation edge.

Aw, Roberts and Xu (2011) theoretically model export and innovation and consider both are endogenous choices to promote growth. We follow their framework and try to identify a causal relationship between export and innovation using China as the context. China offers an ideal setting to study the effect of export and innovation

[1] The Economist has continuously covers Huawei's growth in the global telecom market to be a leader. Reports can be found in the magazines on September 24th 2009, August 4th, 2012, September 20th 2014, May 30th, 2015.

since export has been an important impetus for promote economic growth. On the other hand, innovation has increasingly become a national strategy for Chinese government to advance industrialization and development. Hu, Zhang and Zhao (2017) show that China overtook U.S. in 2011 to become the country filing the largest number of patent applications. Liu and Qiu (2016) find that input tariff cut because of China's WTO accession results in less innovation undertaken by Chinese domestic firms. Different from these studies, we study whether corporate export propels firms to innovate in order to compete globally.

Paunov (2016) find that corruption smothers corporate patents but has no impacts on exporters using a global data. His finding suggests that exporters may behave differently from other corporations in their relationship with innovation. We thus take a systematic examination the causal effect of export on corporate innovation. Specifically, we try to answer the following questions. How does rising export of Chinese multinationals enhance their innovation? Are they gaining ground in innovations that just meet the needs of domestic consumers, or are they catching up with their global peers or even starting to replace them? With firm level data on exporting and patents, this paper provides concrete micro-evidence on these questions by relating corporate global trading activities and to firm level innovation activities.

Our main hypothesis is that emerging multinationals have more incentives to innovate and they innovate more than other firms with less participation in global trading. We measure Chinese emerging multinationals with the weight of foreign sales in total sales. Those firms with greater exposure to foreign trades and competition, e.g., more foreign sales, will have to compete globally for market share. To achieve this, they need to build up competitiveness in the global scale and through the fundamental approach of innovations. Although there is consensus in the media and press that Chinese corporations start to have a significant presence in investing in and promoting innovation, it remains unclear what firms are driving innovation waves in China. Our prior is that Chinese corporations that are participating global trading and competition become the emerging force to drive the innovation waves in China.

The second hypothesis posits that Chinese non-SOEs with active global export participations or trade exposures are innovation drivers. Although SOEs have a heavy presence in China's economy, they are often found to be inefficiently managed (Megginson, Nash, Randenborgh, 1994). Many consider SOEs big but not strong or competitive because the government allows SOEs to operate in monopolistic domestic sectors or regulated industries. As the environment lack of fierce competition, SOEs do not have a strong incentive to innovate. SOEs are notorious for being afflicted with severe agency problems and moral hazard problems. Executives of SOEs in general do not invest in long-term projects such as innovation due to unique political incentives and short career horizon (Cao, Leng, Julio and Zhou, 2016). SOEs often enjoy the benefits of low cost of capital. On the other hand, firms especially non-SOEs with great participation in global market need to compete in global scales. The only approach is to innovate to build product and market competitiveness.

The third hypothesis is that Chinese emerging multinationals innovate more in areas or industries where their US peers are retreating. Despite of a popular view that Chinese manufacturing firms largely carry out reverse engineering in high-tech sectors, Chinese firms have significantly increased corporate expenditures on research and development (R&D) on technological innovations. Chinese multinationals are not only exporting low value-added products but also high-technology products in IT and telecommunications sectors. We therefore relate patenting activities of Chinese manufacturing multinationals to their US peers, and empirically test whether Chinese firms are able to benefit from technology spillover via trading activities. Falvey, Foster, Greenaway (2004), Fernandes (2007), Keller (1998), Liu and Buck (2007), Lumenga-Neso, Olarreaga, and Schiff (2005), and Madsen (2007) all show that trades serve as an important channel for knowledge transmission with macro evidence. Mancusi (2008) proposes that knowledge spillovers depend on a country's absorptive capacity of innovative performance. We further their question by providing micro firm evidence how exports work as a channel for knowledge transmission and the effect of trade on innovation spillovers varies across firm ownership type, industries and exports.

We find that Chinese multinationals, firms with great foreign sales have significant more patents than other firms with low foreign sales do. Difference between firms with more foreign sales and no/low foreign sales is more pronounced in non-SOEs than in SOE subsample. The evidence suggests that Chinese multinationals especially non-SOEs improve their innovative performance from technology spillovers through channels of foreign exports. Furthermore, there is a significant and negative relationship between corporate patents of Chinese multinationals and sample average patents of their US peers at the industry level for high tech firms while the effect becomes positive for low-tech firms. This evidence suggests that Chinese multinationals are improving in innovative performance. There are intra-industry technology spillovers from US to China but only in low-tech sectors, consistent with Mancusi (2008)'s hypothesis.

One major concern of our empirical findings is the endogeneity problem– reverse causality, since innovative firms may export more products and thus they experience more foreign sales than less innovative firms do. We address this concern with tests including a Difference-in-Difference (DiD) approach on RMB policy reform and instrumental variable regressions with bilateral treaties signed between China and foreign nations. The policy reform on RMB exchange regime initiated by the Chinese government in 2005[2]. The RMB policy change provides a quasi-natural experiment since it affected foreign sales greatly but not corporate innovation performance. The DiD tests show that foreign sales have a causal effect on corporate innovation. Secondly, we collect data on Chinese government's bilateral investment treaties[3] (BITs) signed over years and use them as instrumental variables for foreign exports. Signing BITs is shown to affect foreign sales and foreign trade exposures (Dixit, 2012). We report robust results that instrumented foreign sales have positive and significant effect on corporate patents. Lastly, we run the test with the quasi-natural experiment with control firms selected from the propensity score matching.[4] The results remain robust.

The paper is organized as follows. Section 2 summarizes the data and summary statistics. Section 3 describes the main empirical results. Section 4 represents the detailed cross-sectional tests and Section 5 concludes the paper.

2. Data, Variable Construction, and Descriptive Statistics

The sample we used in the paper includes Chinese listed corporations during the period of 2002 to 2013. We start our sample from year 2002 since fewer firms report their international market sales before year 2001, the time when China joined

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[2]Chinese central government unexpectedly implemented a policy change allowing RMB to deviate from a pegging rate to the US dollar alone to float with to a basket of currencies. As a result, RMB started to appreciate right after the reform starting in 2005 against major currencies especially US dollar.

[3]Bilateral Investment Treaty is an important international legal mechanism to improve enforcement of contracts and property rights in order to remove impediments to foreign investment. BITs require countries to protect the property rights of foreign firms and allow international bodies, such as the International Convention on the Settlement of Investment Disputes (ICSID), a member of the World Bank, to arbitrate any foreign investment disputes.

[4] For each multinational firm, we match it with another firm having no foreign sales. The matching score controls for size, industry, growth potential, leverage, profitability and other firm characteristics.

the World Trade Organization (WTO). We construct our sample from several sources. Corporate financial data is obtained from the China Stock Market & Accounting Research (CSMAR) Database. The foreign sales data come from the Wind Database (a major data vendor on listed firms in China) and is manually checked by segments files from CSMAR.

We collect firm ownership data manually combined from CSMAR, RESSET Financial Research Database (RESSET/DB) and Wind Database, as well as official websites of listed companies. All the patent data is hand collected from the State Intellectual Property Office of China (SIPO) before year 2014, which is directly affiliated to China State Council and is responsible for registering intellectual properties including patents. For each patent, we obtain the assignee names from SIPO and manually match it with the name of the listed company both in Shanghai Stock Exchange (SSE) and in Shenzhen Stock Exchange (SZSE).

Considering the impact of extreme values and outliers, we winsorize all firm characteristics at the 1st and 99th percentiles. We drop off listed firms under special treatment (ST) because they have different regulation requirement by CSRC (China Security Regulation Committee).[5] We exclude firms belonging to financial and utility industry since they have different financial disclosure regulations and their liquidity positions are different from others. Similarly, we drop listed firms with class B shares since such shares are only eligible for foreign investors with a discount on A shares (Sun, Tong and Tong, 2002). The final sample consists of 2,251 firms and 17,710 firm-year observations with non-missing foreign sales and patent data, including 825 (36.65%) of these companies never having any foreign sales and 1,426 of these firms

[5]ST firms are those in financial distress and under warning by the stock exchanges.

having record of foreign sales. According to ownership type, 938 (41.67%) firms are SOEs and the rest of the firms are non-SOEs.

2.1 Innovation Measurement

The voluminous literature on the economics of innovation, such as Seru (2012) for publicly traded firms and Lerner, Sorensen, and Stromberg (2011) for privately held firms, widely accepts patent as a primary measure of innovative output. The second reason for using the patent data as the innovation is the data availability. This patent data is available from the year 1985, long before the R&D expense[6] (research expense or development expense). We use patent innovation data from the manually collected database, which covers all patents filed and granted by the State Intellectual Property Office of China (SIPO). The database provides detailed information on patent assignee (owner) names, the patent number, application year and grant year. For specifying the year of the patent, we use the patent's application year instead of grant year, following Griliches et al (1988).

Comparing with the United States Patent and Trademark Office (USPTO), the SIPO has its own classifications on patents. According to Chinese Patent Law, the Chinese patents are categorized into three groups, invention patents, utility model patents and design patents. These three types of patents cover different innovation areas. Invention patents are for the new technological solutions that would have substantial and fundamental improvements on products or applications, while utility model patents are associated with improvements on shapes or structures of products. Design patents only focus on the innovation of art and design of the industrial products, including new art layout, new shape creation and new colour improvements.

[6]The R&D expense is part of intangible assets before 2007. After 2007 accounting reform, it becomes an independent item in the balance sheet.

To better identify the different areas of innovation as well as innovation quality in Chinese SIPO system, we construct two innovation variables. First, *PatentAll* is the number of patent applications filed in a given year eventually granted. This total number of patent granted captures overall quantity of innovation output. However, patent counts do not distinguish ground breaking inventions from incremental technological discoveries. To address this, we construct *Patent1* variable, which is the number of invention patent applications filed in a given year eventually granted. Invention patents are associated with high quality of innovation among three groups of patents in the SIPO system. Under the Chinese Patent Law, to successfully file the patent as invention patents (Type 1 patent), it would take three years to review and examine in order to make sure that these invention patents are making substantial and original contributions to the field. Since the data from SIPO is lack of the citations received to measure innovation quality (Hall et al., 2001; Harhoff, Narin, Scherer, & Vopel, 1999), we take the number of invention patents, which is high quality innovation, as the proxy of innovation quality.

As for US market, we use patent data of all listed firms from Harvard University's patent database. This database includes all patents filed and granted by the United States Patent and Trademark Office (USPTO) from 1990 to 2010. Similarly, we match patent assignee (owner) names, the patent number with the ticker names in Compustat and manually check with the errors (Griliches et al., 1988, Cao et al., 2016). We construct industry level patent of U.S. by taking the average number of patents[7] by each industry under the Global Industry Classification Standard (GICS) by MICS and S&P Global. GICS is a four-tiered, hierarchical industry classification system. It consistent of 11 sectors, 24 industry groups, 60 industries and 157 sub-

[7]We also construct the median patent of each industry for the robustness check in unreported tables. The results are upon request.

industries (GSECTOR, GGROUP, GIND, GSECTOR in Compustat respectively). The detailed industry classifications are in Appendix B. The China Security Index Company adopted the GICS classification to develop a Chinese Security Industry Classification (CSIC) and made the industry comparable. We match the U.S. industry level patent with the corresponding CSIC as the proxy for the dynamic innovation environment coming from US industry peers.

2.2 Foreign Sales Measurement

We gather information on firm’s foreign sales based on the Supplement Information on Sales in the annual report starting from 2002. Our main measure of *foreign sales ratio* is the proportion of a firm’s total foreign sales divided by the total revenue. This variable is a proxy for how much the firms rely on the foreign market. Firms generally provide a regional breakdown of their sales. If a firm does not disclose its segment sales, we code the firm’s foreign sales as zero.

In China, the stock exchanges recommend firms to disclose their foreign sales starting from 2000 but, after 2007, require all listed firms to disclose if the foreign sales ratio is more than 10%. Thus, we also define a dummy variable, *MNC10*, for Chinese multinational corporations, which is one if the foreign sales ratio is greater than 10% and zero if the company does not have any foreign sales.[8]We use 10 percent cut-off for potential censored issue as described. Besides, this threshold is widely used in past literature (eg. Jorion, 1990; He & Ng, 1998; Pinkwitz, Stulz, Williamson, 2012). However, there are other researches using different thresholds of foreign sales ratio to differ the firms. Shaked (1986) and Tallman & Li (1996) define MNCs as ones when firms having 20 percent of sales abroad. Fernandes & Gonenc (2016) use

[8]We treat firms with foreign sales between zero to ten percent as missing.

25 percent above as the standard. Following both strands of literature, we employ two different thresholds in paper: *MNC10* (if more than 10%) and *MNC25* (if more than 25%) and use them alternatively.

2.3 Construct control variables

We use controls suggested by previous literature (e.g., Hall and Ziedonis, 2001; Aghion, et al. 2005; Aghion, Reenen and Zingales, 2013). The main control variable is Tobin's Q, defined as the book value of total assets minus book value of equity plus market value of equity scaled by book value of total assets. We also use two measurements of Q since the non-tradable share is an important issue in China.[9] Size is the natural logarithm of the book value of total assets. Return on Asset (ROA) is defined as operating income before depreciation divided by total assets. Age is also the natural logarithm of the fiscal year minus the time when firm go public. Cash flow is measured as EBIT plus depreciation and amortization minus interest expense and taxes scaled by lagged total assets. Leverage here is the sum of the short-term borrowings plus the long-term debts and divided by the lagged total assets. Firm-level investment is the capital expenditures which includes the net cash payments from the acquisition of fixed assets, intangible assets and other long-term assets from the cash flow statement divided by the lagged book value of total assets. Due to the limitation of R&D Expense, we use tangibility instead.[10]Tangibility is the ratio of tangible assets divided by total assets.

2.4 Descriptive Statistics

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[9] Chen and Xiong (2002), Bai et al. (2004) discuss the issue of non-tradable shares in China and consider them to be an important issue in measuring Q. We obtain other measurement of Tobin's Q as well and find a similar result.

[10]New Accounting Standards for Enterprises No.6 Segment- Intangible Assets require firms to identify, quantify and disclose the R&D expense. The R&D expense is disclosed as independent item afterwards. These standards are effective on Jan 1st 2008. Before 2008, the R&D expense was reported in the tangible assets item.

Table 1 shows the descriptive statistics for the firm-years observations with non-missing data on foreign sales and patent information. There are 17,710 firm-year observations within the period from 2002 to 2013. We winsorize all variables at 1% and99% level.

[Insert Table 1]

Panel A of Table 1 describes summary statistics for the main dataset of the empirical analysis. We start by listing the innovation variables: *ln(1+Patent1)* and *ln(1+Patent All)*. Each year, the average number of invention patents and total patents for each firm are 8.19 and 17.81, respectively. For the key independent variables, we use the foreign sales ratio and two foreign sales dummy variables. The average foreign sales ratio for each firm each year is more than 10% in despite of the median foreign sales ratio is still zero. Then, our firm level controls include total assets, firm age, a measure of firm profitability (ROA), a measure of growth opportunity (Tobin's Q), a measure of investment(CAPEX), tangibility, leverage and cash flow.; After excluding observations with missing financial information, our final sample consists of only 14,608 firm-year observations.

Panel B of Table 1 describes the innovation variables and firm characteristics for firms with foreign sales and purely domestic firms. 53.65% of our firm-year observations are domestic firms. For these companies, they have fewer patent numbers, smaller size and lower ROA. However, the univariate tests indicate that firms without foreign sales are more mature, have higher Tobin's Q and more tangible assets. The univariate tests show that the firms with foreign sales and domestic firms have little difference in terms of leverage and cash flow. In order to show that our sample is not unbalanced in terms of different industries, Panel C of Table 1 combined CSIC with GICS into the ten industry sectors and reports the industry distribution of the number of firms with foreign sales and domestic firms. While all industries have firms with foreign sales, the industries in which more firms do so, according to the percentage, are Industrials, Materials and Consumer Discretionary. Not surprisingly, these are industries in which the global competition and scientific knowledge may play important roles.

3. Empirical Results

The objective of our study is to compare the innovation output of multinationals and pure domestic firms. In the baseline analysis, we examine the innovation output of multinationals and domestic firms and report the results in Section 3.1. In Section 3.2, to further show the causal effect of foreign sales we perform a quasi-natural experiment using the exchange rate reform as the exogenous shock to corporate foreign sales but not to firm patents directly. We use different-in-difference approach to draw the causality relationship between foreign sales and corporate innovations.

3.1 Baseline Regression Result

We start by examining the innovation output of firms with foreign sales and firms without foreign sales. The model we used is as following,

$$LnPatent_{i,t+1} = \beta_0 + \beta_1 Fsales_{i,t} + \gamma ' X_{i,t} + \varphi_t + \alpha_i + \omega_j + \varepsilon_{i(j),t} \quad (1)$$

Where i, j, and t refer to firm i, industry j, year t, respectively. The dependent variables in Equation (1) captures firm innovation outcomes: *Ln(1+Patent1)* is the natural logarithm of one plus the number of invention patents granted by the company in year $t+1$ to capture innovation quality while *Ln(1+Patent_all)* is the natural logarithm of one plus the total number of patents granted by the company in year *t+1* to capture innovation quantity. We measure the foreign sales *(FSales)* in year *t* by using both continuous and discrete variables: foreign sales ratio, dummy of 10% cut-off *(MNC10)* and dummy of 25% cut-off *(MNC25)*. X is a vector of controls that includes firm-level total assets, firm age, ROA, Tobin's Q, leverage, investment and tangibility; all are measured in year *t*, except for firm age (t+1). Various specifications include year fixed effects (φ) firm fixed effects (α) or industry fixed effects (ω). In all regressions, robust standard errors adjusted for firm-level clustering are reported in parentheses.

There are two econometric techniques commonly used to ruled out potentially unobserved individual effect and variable yearly economic cycles: the pooled ordinary least squares (OLS) regression controlling for industry and year fixed effects, and the panel regression controlling for firm and year fixed effects. Notwithstanding firm effects play more accurate firm level individual effect; it does have some shortcoming. As shown in the table 1, more than half of firms are without foreign sales so it is difficult to distinguish the invariant firm effect from the foreign sales dummies. Thus, we also choose pooled OLS regression fixed by industry to avoid potential multicollinearity problem existing between the MNC dummies and the firm identity. In Table 2, for column 2, 3, 5 and 6, when involving MNC dummies, industry fixed effect rather than firm fixed effect are used for better explaining the coefficient of the MNC dummies.

[Insert Table 2]

Panel A of Table 2 reports the result from pooled OLS regression between the number of invention patents and foreign sales. The coefficient estimates of foreign sales ratio, MNC10, MNC25 are all positive and significant at the 5% level across all specifications, suggesting multinational firms innovate more than those domestic firms. The economic effect is sizable. The coefficient estimate in column1, for example, suggests that a one standard deviation increase in foreign sales promotes a 33.6%[11] increase in the number of invention patents in the following year. In column 4, a coefficient estimate of 0.264 suggests that a one standard deviation increase in foreign sales is associated with a 30.2% increase in the total number of patents in the following year. As for the case of MNC dummies, their magnitude is much larger. Those multinational firms (with 10% or more foreign sales) produce 38.3% more invention patents, 50.7% more total patents than firms without foreign sales, and the multinational firms (with 25% more foreign sales) generally have 33.8% and 41.2% more invention patents and total patents, respectively than those without foreign sales.

Regarding control variables, we find that their coefficient estimates are consistent with findings in earlier work. Larger firms and firms with higher capital expenditures are associated with more patents. Firms with higher growth opportunities are more innovative. Further, the debt ratio or leverage is negatively associated with patents. Financial constraints are also negatively related to patent counts. Firm age matters; young firms have more patents.

Overall, our baseline regression results suggest a positive association between foreign sales and firm innovation, consistent with our first hypothesis that the foreign sales enhance firm innovation. We also want to study whether the ownership of the companies would influence the association between foreign sales and firm innovation. As we suggest, the companies with more foreign sales need to compete in global market and have more competition pressures; this competition pressure forces the

[11] Exp(0.290)-1=33.6%

firm to output more innovations. However, state owned enterprises (SOEs) face less competitive pressure, so foreign sales or global market does not affect their patents or innovations. Table 3 helps us to explain the results.

In Table 3, we perform a regression analysis where we augment our baseline specification above by including the SOE interaction term. The model we use is as following:

$$\begin{aligned} LnPatent_{i,t+1} = \beta_0 + \beta_1 SOE \times Fsales_{i,t} + \beta_2 NonSOE \times Fsales_{i,t} \\ + \beta_3 SOE_{i,t} + \gamma' X_{i,t} + \varphi_t + \alpha_i + \omega_j + \varepsilon_{i(j),t} \end{aligned} \quad (2)$$

We report the results in the columns (1) to (6) of Table 3. We include the same control variables as in regression specification of Equation (1), but we add the interaction term of SOE indicator and non-SOE indicator with foreign sales to identify the influence related to ownership type. We also control for the level of ownership may influence the innovation output as Tan et al. (2015) argued. To demonstrate the time invariant result, we still control for aggregate trends by including year fixed effects. Additionally, since our main variable of interest is the interaction term of SOE indicator and foreign sales, we include firm level SOE indicators to control the level of ownership's effect suggest by Tan et al. (2015).

[Insert Table 3]

We find that foreign sales' effect on corporate patents is majorly coming from private firms (non-SOE). In terms of economic magnitude, one standard deviation increase in the foreign sales for non-SOEs increase the number of invention patents and the number of total patents by 49.0% and 64.0%, respectively. In the contrast, for SOEs it only results in an increase by 30.7% and 6.3%, respectively. Meanwhile, the significance also drops for the interaction of SOEs with foreign sales, suggesting foreign sales or global market competition may not affect SOEs regarding their innovative activity. When MNC25 dummy variables are employed alternatively, the interaction term between foreign sales dummy and non-SOE remain positive and significant while interaction terms between foreign sales dummy and SOE have less significance. This suggests that foreign sales only affect non-SOEs' innovation activities.

After checking the ownership structure, to examine the competitive theory, we compare the innovation outputs of Chinese companies with their corresponding industries company in the U.S. First, we add the average number of patents in each industry in the US to check the relationship of US innovation and Chinese innovation. The model we use is as following:

$$\begin{aligned} LnPatent_{i,t+1} = \beta_0 + \beta_1 US\_Patent_{j,t} \times Fsales_{i,t} + \beta_2 US\_Patent_{j,t} \\ + \beta_3 Fsales_{i,t} + \gamma' X_{i,t} + \varphi_t + \alpha_i + \omega_j + \varepsilon_{i(j),t} \end{aligned} \quad (3)$$

We form an interaction term by using the foreign sales times the US patent. We want to know that, within one specific industry, when the innovation output in the US is dropping, how the innovation of Chinese companies' response and how the foreign sales help the innovation. For the US patent information, we use patent innovation data on publicly listed US corporations from Harvard University's patent database. This database includes all patents filed and granted by the United States Patent and Trademark Office (USPTO) from 1990 to 2010. The database provides detailed information on patent assignee (owner) names and the patent number. We combine the patent database with COMPUSTAT to get the companies' innovation output data; then we aggregate the firm level data to industry level by using the GICS, 24 groups classification. We manually match the Chinese Security Industry Classification with the GICS 10 sectors and 24 groups. (The matching details are in

Appendix B). Thus, the variable, *USPatent*, is calculated by average the number of patents in the corresponding industry. Due to the limitation of U.S. patent database, the period of matched sample is dropped to the year before 2009 and the number of observation decreases to 9143.

[Insert Table 4]

We report the results estimating equation (3) in Table 4. In the regression, the signs of the interaction term and the US patent variables are negative. This negative association means in the industry where US innovation is decreasing, the increase of foreign sales in Chinese firms would help to increase the firms' innovations. For example, in column (1), one standard deviation decreases of average number of patents among US corresponding industry with one standard deviation increase in Chinese firm's foreign sales would leads to 0.113 patents for each company. This negative relationship also implies that when the US companies are retreating in an industry and the US companies decrease the innovation output in industry level, Chinese firm's innovation can increase more by increasing their foreign sales. When the US companies are not actively competing in an industry, the Chinese firms have more incentive to capture the market. The result is also consistent with competing theory. For multinationals with high foreign sales ratio, they are more relying on the global market. When US industry peers lower the innovation output in the industry, Chinese multinationals have more incentives to step into the industry, and increase their innovations to win the competitiveness.

To further examine our hypothesis, we consider the sub-sample regression analysis between different industries. According to our theory, the pressure of competition is much severer in the industries that US companies are also devoting to innovate, for example, high tech industries. So, the competition phenomenon is more obvious among these industries. Similarly, for the traditional industries, US companies are outsourcing the operations so that the Chinese multinationals face less competition. Low competitions generate the complementary effect. Being the follower, the Chinese multinationals are mimicking the innovation of US companies through the foreign sales. In Table 5, we present the results for different industries.

[Insert Table 5]

In Table 5, we find the consistent result of the significant effect for different industries. We define the company as high-tech companies through the definition of tax deduction policy from the Chinese government. We group the companies having high-tech tax deduction into the high-tech category and the rest companies as the low-tech category. The results show that with high tech group, the coefficient of interaction terms of US patent and foreign sales are negative, meaning the competition relationship between the US companies and Chinese multinationals. However, for the low-tech group, all the coefficients are positive, which demonstrate the complementary relationship between the US companies and Chinese multinationals.

In this section, the results of our baseline regression analysis are consistent with our initial hypothesis. Assumed by the competition theory, non-SOE multinationals in high tech industry have more innovation outputs since they face high competition pressure both domestically and internationally.

3.2 The Difference-in-difference Approach

Our baseline analysis utilizes the pooled ordinary least squares (OLS) regressions. However, there is a plausible concern that these regression results may suffer from endogenous problems, that is, firms with better growth prospects or with anticipation in innovation may be more attractive in global market and have more foreign sales. This could also explain the positive association between foreign sales and innovation output, leading to concerns on reverse causality.

To test a causal effect of foreign sales and innovation and rule out the possibility of reverse causality, we perform a quasi-natural experiment using the Exchange Rate Reform in China as the exogenous shock to corporate foreign sales. This Exchange Rate Reform in 2005 was an unexpected event to corporations and the market. Since 1997, People's Bank of China (PBOC), the Chinese central bank, had effectively pegged the CNY to the USD at rate of 8.28 yuan/dollar. However, on July 21, 2005, PBOC announced that CNY would be managed to float with reference to a basket of currencies. On August 9, 2005, the Governor of PBOC disclosed a list of 11 reference currencies, which made the CNY appreciated for 2% suddenly. The sudden shock for the currency due to this unexpected exchange policy reform provides a quasi-natural experiment that generates plausibly exogenous variation in corporate foreign sales for exporting firms in our sample. To control for unobserved firm heterogeneity and remove potential bias due to time-invariant firm-level omitted variables, we run regressions with firm fixed effects and industry fixed effects. This allows our analysis to be free from unobserved firm individual effects that may explain their patents.

We employ a difference-in-difference (DiD) regression to compare the innovation output of the treatment firms and control firms three years before (2003-2005) and three years after (2006-2008) the announcement of the Exchange Rate Reform. Treatment group includes the firms with foreign sales and influenced by the exchange rate reform in 2005. Control group is the firms without foreign sales and not influenced by the exchange rate reform. The number of observations in treatment group is 3,781 while the number of observations in control group is 3,162. We perform the DiD tests in a multivariate regression framework by estimating the following regression model:

$$\begin{aligned} LnPatent_{i,t+1} = \beta_0 + \beta_1 ExPolicy_{i,t} \times Fsales_{i,t} + \beta_2 ExPolicy_{i,t} \\ + \beta_3 Fsales_{i,t} + \gamma' X_{i,t} + \varphi_t + \alpha_i + \omega_j + \varepsilon_{i(j),t} \end{aligned} \quad (4)$$

Where the dependent variable captures firm innovation outcomes. *ExPolicy* is a dummy variable that equals one for period after 2005 (2006-2008) and zero for period (2002-2005). X consists of a vector of control variables used in Equation (4); $\varphi_t, \alpha_i, \omega_j$ capture year fixed effects, firm fixed effect and industry fixed effect. The coefficient estimate of $ExPolicy \times Fsales$ is the DiD estimator that captures the causal effect of firm with foreign sales and influenced by the Exchange Rate Reform on firm innovation.

[Insert Table 6]

Table 6 reports the regression results estimating Equation (3) with standard errors clustered at the firm level. In column 1 to column 3, the dependent variable is *Ln (1+Patent1)*, the number of invention patents; for column 4 to column 6, the dependent variable is *Ln (1+Patent All)*, the total number of patents. The interactions of *ExPolicy* with foreign sales are significant and positive at 1% level. The innovation driven is mainly caused by the multinational firms after the passage of Exchange Rate Reform. Our identification tests based on the DiD approach suggest that there appears to be a positive, causal effect of foreign sales on firm innovation. The evidence is consistent with our first hypothesis that foreign sales enhance firm innovation.

To exclude the selection bias problem, we approach on propensity score matching (PSM) method to control for any potential bias. For each year we match multinational firms with firms without foreign sales but having similar firm characteristics on the right sides such as size, growth opportunity, leverage and profitability. The distance (caliber distance) of matching we used is 0.05 by each year and the treatment groups are those multinational firms we defined as *MNC10* and *MNC25*. In Figure 1, we present the level of innovation output (*Patent 1* as well as *Patent All*) of two types of firms after PSM. The left panel shows the number of invention patents while the right panel of figures are using the total number of patents. In this univariate analysis, we show that difference between multinationals and domestics is larger after the passage of exchange policy reform.

We then approach the DiD multivariate analysis after the PSM procedure and present the results in Table 6. The number of observation drops since we only keep data within distance of treatment groups with control groups. *TMNC10* and *TMNC25* measure the foreign sales in the treatment groups after matching the sample with PSM, changing the cut-off ratio from 10% to 25%.

[Insert Table 7]

As shown in Table 7, the regressions estimated coefficients of the interaction term between foreign sales dummy and policy dummy are still positive, with slightly drop of significance. We also show that after 2005, the influence from foreign sales on innovations becomes much stronger, which is consistent with the univariate tests in Figure 1. The greater coefficients on TMNC10 and TMNC25 after the exchange reform suggest that the increase in innovation output is larger for the treatment groups than for the control groups after the exchange reform.

The evidence from the DiD tests suggests that multinationals experience a larger increase in their innovation output compared to the pure domestic companies after the exchange reform. The reform can be used as a shock since it is only influences the foreign sales and relatively unrelated with the innovation output. This quasi natural experiment confirms that the change of foreign sales proportion can have a positive effect on the output of innovation in Chinese firms.

3.3 Robust Test on Endogeneity Problem with Bilateral Treaties

We further address the endogeneity concern by using the Bilateral Investment Treaties (BIT) signed between China and another country as an instrument for foreign sales, since signing more BITs encourages more exports.

Bilateral Investment Treaty is an important international legal mechanism to improve enforcement of contracts and property rights to remove impediments to foreign investment. BITs require countries to protect the property rights of foreign firms and allow international bodies, such as the International Convention on the Settlement of Investment Disputes (ICSID), a member of the World Bank, to arbitrate any foreign investment disputes. While BITs were designed to encourage the capital flows to foreign countries, signing BITs affects the foreign sales and the foreign exposures (Dixit, 2012), as two signed nations often have favored treatment on sales of products (Dolzer and Stevens, 1995).

Thus, using the BITs as the instrument variable helps to measure the influence of foreign sales on innovation not due to firm's innovations. We show that the exogenous increase in foreign sales due to new BITs has a positive effect on innovation, suggesting that the correlation between foreign sales and innovation is not primarily due to self-selection. We consider the inclusion of number of signed BITs as an instrumental variable for foreign sales. BIT would encourage export for several reasons. Prior literatures have demonstrated the close relationship between the foreign exposures and signature of new BITs (Dunning, 1998; Busse, Königer and Nunnenkamp, 2010; Berger, Busse, Nunnenkamp and Roy, 2011). Furthermore, BIT provides protection of foreign operations which often results in sharp increase of foreign sales. We thus first show that the number of the BITs and the weighted export by the number of BITs are significant positively correlated with companies' foreign sales, which is one of the requirements for number of BITs to be a valid instrument. BIT is between two nations which does not influence any company's R&D or innovation. It allows us to take out any firm specific factors related to innovation and identify the causal effect of foreign sales.

We collect the BITs data from the ICSID website. The data contains the signatory states, the particular treaty and year of signature. We only look at the data that one signatory nation is China. The data on BIT covers from 2001 to 2012. After merged with our innovation and financials database, there will be 13,257 year-firm observations remaining. We use the cumulative number of BITs that China signed with other countries as the instrumental variable in the first stage (Tobin and Rose-Ackerman, 2005). Alternative instrumental variable is the increase in number of BITs, weighted by the share of changing export to the region signed BIT with China accounts for relative to the total changing export of China (Neumayer and Spess, 2005). The weighting is to account for differences in the size of exporting a country makes for via signing a BIT. Figure 2 shows the cumulative number of BITs signed by China per year and the increase number of BITs weighted by changing export. When we measure the time of signed BITs, since we need to compare the influence of BITs to the company's foreign sales, we consider the BITs signed before June having the influence on the same year but the BITs signed after June having the effect on the next following year.

[Insert Figure 2]

We report the IV regressions in Table 8. We present the weak instrument variable test and Hausman based test to examine the validity of the BITs as instrumental variables, and report two-stage least squares (2SLS) results in the following section. The first column reproduces the baseline regression; columns 2 and 4 present the first stage where we regress the foreign sales on the cumulative number of BITs and the exporting weighted number of BITs and all other controls. As expected, the instrument is positive and highly significant. It is clear that signing new BITs lead to increase the foreign sales. In the column 3 and column 5, we present the results of using the forecasted foreign sales as the explanatory variable and remain the same control variable. Interestingly, the foreign sales variable remains highly significant with a coefficient that is much larger than column 1. The BITs instrument shows that instrumented foreign sales increase patent counts. The one standard deviation increase in the foreign sales, which is caused by the increase of the cumulative signed BITs, would, on average, increase the number of type 1 patent and the number of all patent by 140 and 321, respectively.

[Insert Table 8]

Thus, by using the increase of BITs as the instrumental variable, we show that the influence of foreign sales on the innovation becomes much stronger. Adding the BITs into the regression helps us to identify the increase of foreign sales irrelevant to the firm performance and other factors that would also influence the innovation. These isolated increases of foreign sales give a sharp surge on innovation. Because of the sharp rise in the magnitude and the significance for the coefficients, we are confident about the causality between the foreign sales and innovation. As shown in Table 8, after excluding other factors' influence on sales, the significant and positive effect of foreign sales on innovation becomes very robust.

5. Conclusion

This paper studies how Chinese multinationals are emerging to innovate more and become competitive globally. We show that Chinese firms with greater foreign sales exhibit more patents than other firms with no or less foreign sales. Cross sectional tests show that the difference in patents is more pronounced in firms with greater incentives to innovate, e.g., firms with low degree of agency problem, firms operating in competitive product market, and firms of high-tech sectors. Further, the effect of difference in patents only exists in non-SOE firms, suggesting that non-SOE firms with more foreign sales are the driving force for the increase in corporate innovations. Chinese emerging multinational corporations innovate more when their US industry peers are retreating in patents. This evidence suggests that the participation in the foreign market is positively associated with more innovation activities.

We utilize several tests to show our results are not caused by the endogeneity problem which states that innovative firms are more competitive and export more goods, resulting in higher foreign sales. We first use propensity score matching method to compare the difference in patents between firms with greater foreign sales and those with no/less foreign sales. Second, we utilize a quasi-natural experiment when Chinese government reformed its RMB regime from fixed rate to floating rate which causes an exogenous shock to corporate foreign sales. The difference-in-difference approach yields consistent and robust results. Corporate foreign sales have a casual effect on corporate patents. The combined evidence suggests that non-SOE firms with great participation in global trading activities drive corporate innovations.

Our research has the important and general implication for policy makers, market participants and academic circles. It highlights the importance of the success of Chinese trading activities in global scales that has greatly fuelled corporate innovation activities. Chinese emerging multinationals are becoming more innovative and they starting to catch up or even replace some of innovation activities dominated by their US peer firms. Participation in global trading activities serves an important drive for innovations that are pivotal for economic growth.

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Appendix: Variable Definition and Construction

Variables	Definitions	Source
Innovation		
Patent 1	The total number of invention patent applications filed (and eventually granted) by a firm in a given year. All missing variables are replaced by zero.	Hand Collected
Patent All	The total number of patents filed (and eventually granted) by a firm in a given year. All missing variables are replaced by zero.	Hand Collected
Foreign Sales		
Fsales	The ratio of foreign sales to the total sales and missing foreign sales are checked with the annual reports and equals to zero if a firm do not export.	Wind
MNC10	Dummy variable set equal to one if foreign sales is more than 10% of total sales and equal to zero if foreign sales is zero.	Wind
MNC25	Dummy variable set equal to one if foreign sales is more than 25% of total sales and equal to zero if foreign sales is zero.	Wind
Key Variables		
Ln(Total Assets)	The logarithm of the book value of total assets measured at the end of fiscal year t.	CSMAR
Ln(Age)	Natural logarithm of one plus the number of years since the firm has its listed price.	CSMAR
ROA	Return on assets, defined as operating income before depreciation divided by total assets, measured at the end of the fiscal year t-1.	CSMAR
Tobin's Q	Book value of total assets minus book value of equity plus market value of equity scaled by book value of total assets at the end of fiscal year t.	CSMAR
CAPEX	Capital expenditure divided by book value of total assets measured at the end of the fiscal year t-1.	CSMAR
Tangibility	Book value of tangible assets scaled by book value of total assets, at the end of fiscal year t-1.	CSMAR
Leverage	Ratio of total debt to total assets, measured at the end of fiscal year t-1.	CSMAR
Cash Flow	EBIT plus depreciation and amortization minus interest expense and taxes divided by book value of assets, measured at the end of fiscal year t-1.	CSMAR
SOE Dummy	Indicator whether the largest shareholder or the ultimate owner of the listed firms is state-owned at the end of year t.	CSMAR, Wind, Hand Collected
HHI	Herfindahl index of GICS industries classifications to which the firm belongs, measured at the end of the fiscal year t-1.	CSMAR
KZ	The KZ index measured at the end of fiscal year, calculated as -1.002 × Cash flow [(Income before extraordinary items + Depreciation and Amortization)/Lagged net property, plant and equipment] + 0.283 × Q [Market value of equity + book value of total assets-book value of equity-balance sheet deferred tax] + 3.139×Leverage[Total debt/Total assets] - 39.368 × Dividends [(Dividends)/Lagged net property, plant and equipment] - 3.315 × Cash holdings [(Cash and short-term investment)/(Lagged net property, plant and equipment)].	CSMAR
High Tech Dummy	Indicator equals to one when firms are qualified as the high-tech requirement made by government and thus received benefits like tax deduction at the end of year t.	CSMAR
US Patent	The industry-level average number of patents in the U.S. market; this number was matched through corresponding industry (GICS four levels) to Chinese firms.	Harvard US Patent Database

Appendix B: Global Industry Classification Standard (GICS): China vs. U.S.[12]

The Chinese Securities Industry Classification (CSIC)provided by China Security Index Co. Ltd (CSI) is widely used in China. It follows similar classification rules according to the Global Industry Classification Standard (GICS) by MICS and S&P Global.

Industry Name	**CSIC**	**GICS**
Level 1	CSIClv1	Gsector
Energy	00	10
Materials	01	15
Industrials	02	20
Consumer Discretionary	03	25
Consumer Staples	04	30
Health Care	05	35
Financials	06	40
Information Technology	07	45
Telecommunication Services	08	50
Utilities	09	55
Real Estate		60
Level 2	CSIClv2	Ggroup
Energy	0001	1010
Materials	0101	1510
Capital Goods	0201	2010
Commercial Services & Supplies	0202	2020
Transportation	0203	2030
Automobiles & Components	0301	2510
Consumer Durables & Apparel	0302	2520
Consumer Services	0303	2530
Media	0304	2540
Retailing	0305	2550
Food & Staples Retailing	0401	3010
Food, Beverage & Tobacco	0402	3020
Household & Personal Products	0403	3030
Health Care Equipment & Services	0501	3510
Pharmaceuticals, Biotechnology & Life Sciences	0502	3520
Banks	0601	4010
Diversified Financials	0602	4020
Insurance	0603	4030
Real Estate	0604	4040
Software & Services	0701	4510
Technology Hardware & Equipment	0702	4520
Semiconductors & Semiconductor Equipment	0703	4530
Telecommunication Services	0801	5010
Communications Equipment	0802	
Utilities	0901	5510

[12]Detailed information can be found here: https://www.msci.com/gics.

Figure 1: Propensity Score Matching for DiD Test

The figure below plots the change in the number of patents that a firm file measured in the log scale, following the exchange reform policy in 2005.Foreign sales data is only available from year 2002, year after China joined the WTO. The top panel of the figure presents relationship between the control group and treatment group of MNC10 while the bottom panel of the figure presents relationship between the control group and treatment group of MNC25. The left panel of figures are using the number of invention patents while the right panel of figures are using the total number of patents. To exclude potential selection bias issue, treatment groups are using propensity score matching (PSM). For each year, we select multinational firms with domestic firms by choosing similar characteristics, such as size, growth opportunity, leverage and profitability, as control variables in the multivariate analysis. We use caliper matching procedure that each firm have a matching distance with a 0.05 using *psmatch2* in Stata. The results are robust whatever caliper parameters are chosen.

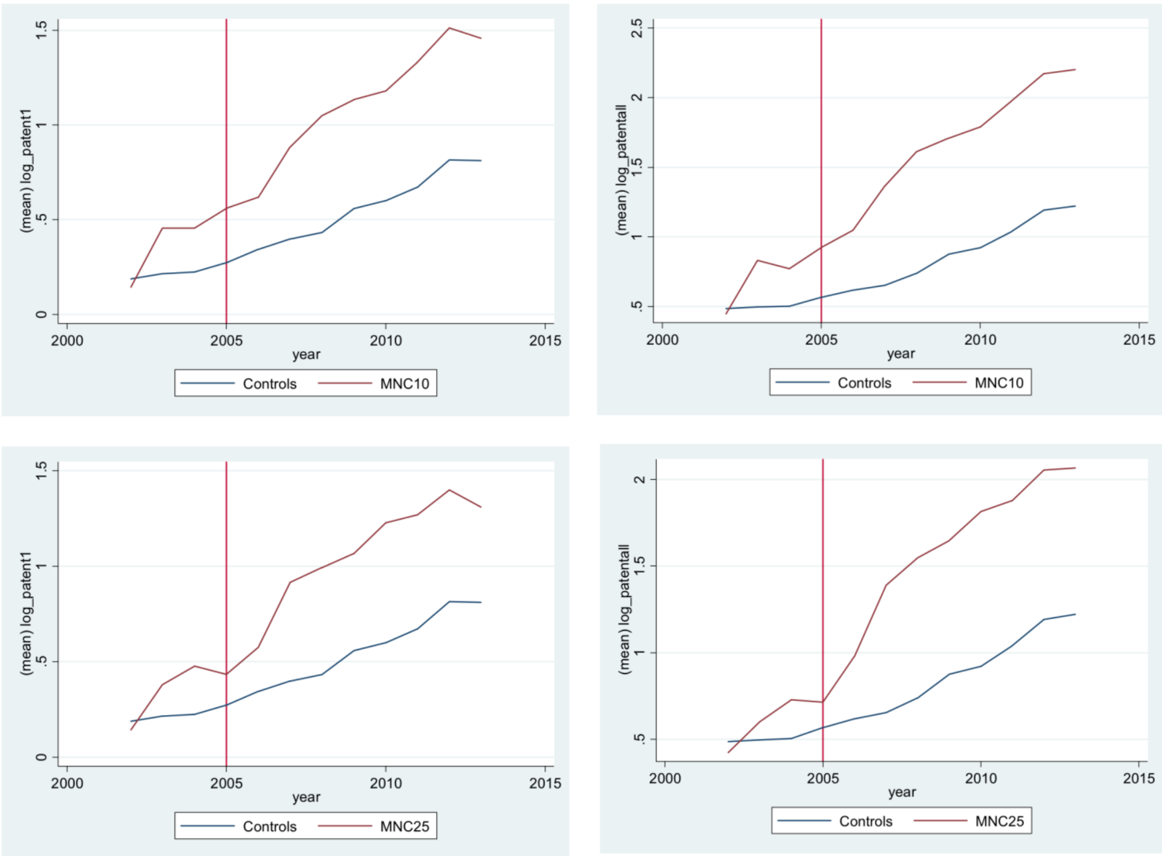

Figure 2: Time Trend for Treaty

This figure shows the time trend of the cumulative number of Treaties which is signed by China in each year and the weighted change of export from 2001 to 2011. The weighted change of export is the calculated by using the number of treaties signed between specific country and China multiplied by the percentage of the change of export from China to this country proportional to the total changed of Chinese export.

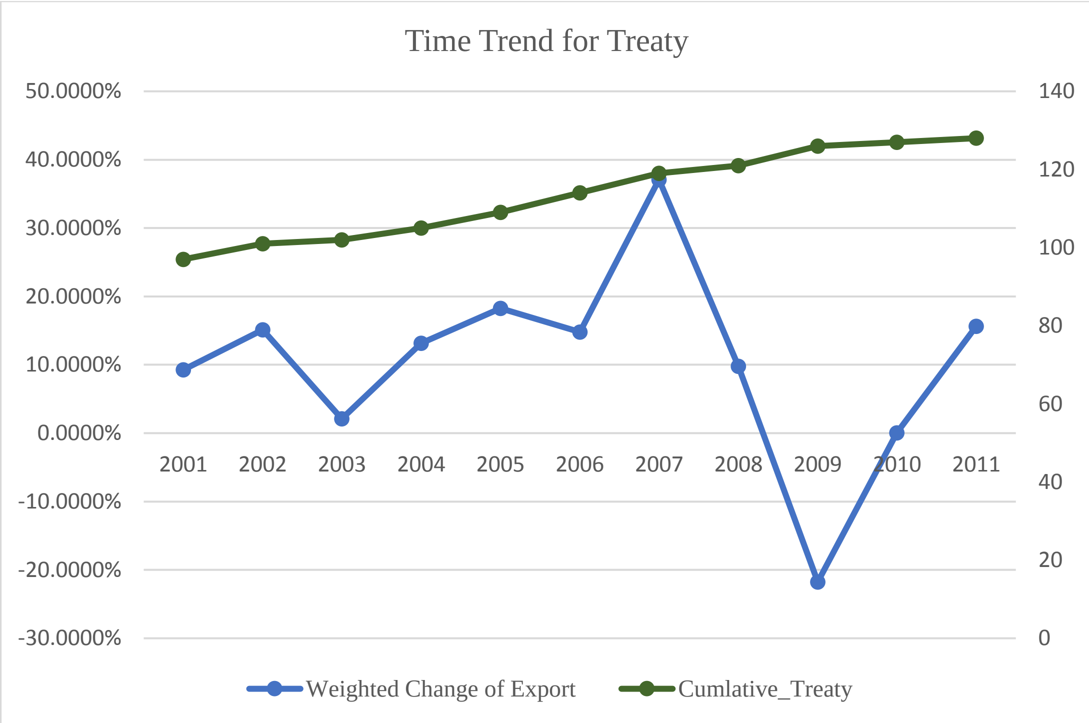

Table 1: Descriptive Statistics

This table reports descriptive statistics for our sample firms during the period 2002-2013. All variables are defined in Appendix A. We start with the patent data and control variables. Panel A presents the summary statistics for firms' innovation output and other control variables. Panel B presents the comparisons between the firms without foreign sales and firms with foreign sales. The last column reports the difference in mean between the two types of firms. ***, **, and * indicate significance at 1%,5% and 10% levels, respectively using robust standard errors for two-tailed tests. Panel C reports the industry distribution of the number of firms with foreign sales and domestic firms. The industry classifications are using the China Securities Industry Classification (CSIC) consistent with Global Industry Classification Standard (GICS).

Panel A: Summary Statistics

Variables	N	Mean	S.D.	Min.	Median	Max.
ln(1+Patent1)	17,710	0.7646	1.1453	0.0000	0.0000	8.6618
ln(1+Patent All)	17,710	1.2252	1.4956	0.0000	0.6931	8.7513
Fsales	17,710	0.1048	0.1974	0.0000	0.0000	0.9927
MNC10	14,313	0.3361	0.4724	0.0000	0.0000	1.0000
MNC25	12,147	0.2177	0.4127	0.0000	0.0000	1.0000
Ln(Total Assets)	16,328	21.3892	1.1678	17.8078	21.2391	26.1661
Ln(Age)	17,696	2.3123	0.5324	0.0000	2.3979	3.3322
ROA	16,328	0.0460	0.1023	-0.5795	0.0376	1.2596
Tobin's Q	17,161	2.1322	1.6042	0.6692	1.6573	24.2719
CAPEX	16,328	0.0740	0.0884	-0.2640	0.0486	0.7397
Tangilibity	16,328	0.3144	0.2148	0.0000	0.2728	2.2896
Leverage	16,263	0.2287	0.2154	0.0000	0.1993	2.2463
Cash Flow	15,951	0.0810	0.1142	-0.5159	0.0686	1.8419
SOE Dummy	17,661	0.4733	0.4993	0.0000	0.0000	1.0000

Panel B: Mean Comparison

Variables	Without FSales (0)		With FSales (1)		(0)-(1)
	Obs	Mean	Obs	Mean	Mean Diff
ln(1+Patent1)	9,502	0.4918	8,208	1.0804	-0.5886***
ln(1+Patent All)	9,502	0.8160	8,208	1.6989	-0.8829***
Ln(Total Assets)	8,859	21.2712	7,469	21.5293	-0.2581***
Ln(Age)	9,492	2.3244	8,204	2.2982	0.0262***
ROA	8,859	0.0439	7,469	0.0484	-0.0045***
Tobin's Q	9,191	2.2244	7,970	2.0259	0.1985***
CAPEX	8,859	0.0684	7,469	0.0807	-0.0123***
Tangilibity	8,859	0.3188	7,469	0.3092	0.0097***
Leverage	8,816	0.2296	7,447	0.2276	0.002
Cash Flow	8,562	0.0808	7,389	0.0811	-0.0003
SOE Dummy	9,471	0.5177	8,190	0.4220	0.0957***

Panel C: Industry Distribution						
Industry Names	**Without FSales**		**With FSales**		**Total**	
	Obs	**Percent**	**Obs**	**Percent**	**Obs**	**Percent**
Consumer Discretionary	2,000	21.05	1,479	18.02	3,479	19.64
Consumer Staples	1,007	10.6	503	6.13	1510	8.53
Energy	416	4.38	216	2.63	632	3.57
Health Care	782	8.23	533	6.49	1315	7.43
Industrials	2,480	26.1	2,193	26.72	4,673	26.39
Information Technology	779	8.2	982	11.96	1761	9.94
Materials	1,805	19	2,070	25.22	3,875	21.88
Telecommunication Services	233	2.45	232	2.83	465	2.63
Total	**9,502**	**100**	**8,208**	**100**	**17,710**	**100**

Table 2: Baseline Regression

This table reports the regressions of firm innovation on firm foreign sales. The dependent variable is the natural logarithm of one plus the number of invention patents filed (and eventually granted) by a firm in a given year in panel A. In panel B, the dependent variable is natural logarithm of one plus total number of patents filed (and eventually granted) by a firm in a given year. The main variables of interest are foreign sales ratios, 10% cut-off foreign sales ratio dummy and 25% cut-off foreign sales ratio dummy. The foreign sales ratio is calculated as the percentage of revenue from foreign countries on the total revenue. The 10% cut foreign sales ratio dummy equals to one if the foreign sales ratio is greater than 10% and equals to zero if the firm doesn't have foreign sales. The 25% cut foreign sales ratio dummy equals to one if the foreign sales ratio is greater than 25% and equals to zero if the firm doesn't have foreign sales. The set of control variables includes the natural logarithm of firm assets, the natural logarithm of one plus firm age at the IPO year, return on assets, Tobin's Q, firm leverage, firm investment measured by capital expenditure scaled by firm assets, tangibility measured by PPE scaled by firm assets. All regressions include firm (industry), year fixed effect. Robust standard errors are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Panel A: Ln(1+Patent1)			**Panel B: Ln(1+Patent All)**		
	(1)	(2)	(3)	(4)	(5)	(6)
lag(Fsales)	0.290**			0.264**		
	(0.113)			(0.124)		
lag(MNC10)		0.324***			0.410***	
		(0.047)			(0.061)	
lag(MNC25)			0.291***			0.345***
			(0.062)			(0.076)
lag(Ln(Total Assets)	0.239***	0.342***	0.306***	0.258***	0.421***	0.387***
	(0.036)	(0.038)	(0.041)	(0.039)	(0.042)	(0.044)
Ln(Age)	0.462***	-0.228***	-0.231***	0.649***	-0.377***	-0.378***
	(0.114)	(0.048)	(0.047)	(0.130)	(0.064)	(0.063)
lag(ROA)	-0.136*	0.278**	0.238*	-0.092	0.491***	0.464***
	(0.076)	(0.135)	(0.139)	(0.096)	(0.172)	(0.175)
lag(Tobin's Q)	0.016**	0.065***	0.057***	0.015*	0.071***	0.067***
	(0.007)	(0.012)	(0.013)	(0.008)	(0.016)	(0.017)
lag(Leverage)	-0.109**	-0.452***	-0.399***	-0.131*	-0.773***	-0.711***
	(0.055)	(0.082)	(0.081)	(0.071)	(0.117)	(0.116)
lag(CAPEX)	0.022	0.597***	0.611***	0.073	0.802***	0.851***
	(0.092)	(0.148)	(0.151)	(0.114)	(0.194)	(0.197)
lag(Tangibility)	0.077	-0.060	-0.045	0.079	0.002	0.008
	(0.061)	(0.095)	(0.096)	(0.077)	(0.127)	(0.130)
Constant	-5.498***	-6.627***	-5.873***	-5.850***	-7.665***	-6.966***
	(0.748)	(0.801)	(0.865)	(0.835)	(0.898)	(0.938)
Firm FE	Y	N	N	Y	N	N
Industry Lv2 FE	N	Y	Y	N	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	14608	12078	10420	14608	12078	10420
adj. R-sq	0.158	0.285	0.265	0.147	0.311	0.291

Table 3: Baseline Regression of SOE Ownership

This table reports the regressions of firm innovation on firm foreign sales and adds the SOEs interaction term. The dependent variable is the natural logarithm of one plus the number of invention patents filed (and eventually granted) by a firm in a given year in panel A. In panel B, the dependent variable is natural logarithm of one plus total number of patents filed (and eventually granted) by a firm in a given year. The SOE indicator equals to one if the largest shareholder is government or related parties otherwise equals to zero. The main variables of interest are foreign sales ratios interacted with SOE indicator, 10% cut-off foreign sales ratio dummy interacted with SOE indicator and 25% cut-off foreign sales ratio dummy interacted with SOE indicator. The foreign sales ratio is calculated as the percentage of revenue from foreign countries on the total revenue. The 10% cut foreign sales ratio dummy equals to one if the foreign sales ratio is greater than 10% and equals to zero if the firm doesn't have foreign sales. The set of control variables includes the natural logarithm of firm assets, the natural logarithm of one plus firm age at the IPO year, return on assets, Tobin's Q, firm leverage, firm investment measured by capital expenditure scaled by firm assets, tangibility measured by PPE scaled by firm assets. All regressions include firm (industry), year fixed effect. Robust standard errors are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Panel A: Ln(1+Patent1)			Panel B: Ln(1+Patent All)		
	(1)	(2)	(3)	(4)	(5)	(6)
SOE*lag(Fsales)	0.268*			0.061		
	(0.161)			(0.209)		
nonSOE*lag(Fsales)	0.399***			0.495***		
	(0.131)			(0.163)		
SOE*lag(MNC10)		0.354***			0.390***	
		(0.068)			(0.090)	
nonSOE*lag(MNC10)		0.285***			0.416***	
		(0.060)			(0.076)	
SOE*lag(MNC25)			0.223***			0.183*
			(0.084)			(0.109)
nonSOE*lag(MNC25)			0.336***			0.462***
			(0.079)			(0.095)
SOE Dummy	-0.028	-0.064	-0.054	-0.022	-0.067	-0.054
	(0.042)	(0.044)	(0.045)	(0.057)	(0.058)	(0.059)
lag(Ln(Total Assets)	0.364***	0.349***	0.318***	0.444***	0.432***	0.401***
	(0.036)	(0.040)	(0.043)	(0.040)	(0.044)	(0.046)
Ln(Age)	-0.240***	-0.227***	-0.223***	-0.384***	-0.371***	-0.364***
	(0.046)	(0.048)	(0.048)	(0.062)	(0.064)	(0.063)
lag(ROA)	0.180	0.275**	0.215	0.394**	0.464***	0.419**
	(0.127)	(0.137)	(0.140)	(0.164)	(0.174)	(0.177)
lag(Tobin's Q)	0.050***	0.064***	0.058***	0.049***	0.071***	0.068***
	(0.011)	(0.012)	(0.013)	(0.015)	(0.016)	(0.017)
lag(Leverage)	-0.510***	-0.472***	-0.422***	-0.847***	-0.806***	-0.749***
	(0.080)	(0.083)	(0.082)	(0.114)	(0.117)	(0.115)
lag(CAPEX)	0.650***	0.598***	0.589***	0.862***	0.796***	0.817***
	(0.149)	(0.149)	(0.152)	(0.191)	(0.195)	(0.198)
lag(Tangibility)	-0.031	-0.042	-0.027	0.057	0.025	0.029
	(0.093)	(0.096)	(0.098)	(0.125)	(0.128)	(0.131)
Constant	-6.969***	-6.721***	-6.092***	-8.045***	-7.865***	-7.264***
	(0.755)	(0.835)	(0.907)	(0.847)	(0.927)	(0.970)
Industry Lv2 FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	14557	12035	10378	14557	12035	10378
adj. R-sq	0.269	0.285	0.267	0.294	0.312	0.295

Table 4: Baseline Regression of Comparing with Innovation in the U.S.

This table reports the regressions of firm innovation on firm foreign sales and adds the US patent as interaction term. The dependent variable measures the number of invention patents in panel A. In panel B, the dependent variable measures total number of patents. The main variables of interest are interaction of foreign sales with US patent number. The US patent number is the industry level average of total number of patents in the U.S. for level 2 GICS, 24 sectors. The foreign sales ratio is calculated as the percentage of revenue from foreign countries on the total revenue. The MNC10 equals to one if the foreign sales ratio is greater than 10% and equals to zero if the firm doesn't have foreign sales. The measure is the same as MNC25. The set of control variables includes the natural logarithm of firm assets, the natural logarithm of one plus firm age at the IPO year, return on assets, Tobin's Q, firm leverage, firm investment measured by capital expenditure scaled by firm assets, tangibility measured by PPE scaled by firm assets. All regressions include firm (industry), year fixed effect. Robust standard errors are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

`	**Panel A: Ln(1+Patent1)**			**Panel B: Ln (1+Patent All)**		
	(1)	(2)	(3)	(4)	(5)	(6)
lag(Fsales)* lag(log(1+USPatent))	-0.113*			-0.105		
	(0.067)			(0.079)		
lag(Fsales)	0.472**			0.462**		
	(0.187)			(0.213)		
lag(MNC10)* lag(log(1+USPatent))		-0.030			-0.030	
		(0.031)			(0.046)	
lag(MNC10)		0.311***			0.380***	
		(0.077)			(0.111)	
lag(MNC25)*lag(log(1+USPatent))			-0.012			-0.023
			(0.038)			(0.056)
lag(MNC25)			0.266***			0.319**
			(0.095)			(0.135)
lag(log(1+USPatent))	-0.121***	-0.177***	-0.186***	-0.147***	-0.229***	-0.242***
	(0.024)	(0.029)	(0.030)	(0.029)	(0.038)	(0.040)
lag(Ln(Total Assets)	0.198***	0.300***	0.272***	0.197***	0.410***	0.385***
	(0.041)	(0.039)	(0.039)	(0.046)	(0.046)	(0.046)
Ln(Age)	0.273**	-0.201***	-0.198***	0.486***	-0.304***	-0.293***
	(0.122)	(0.053)	(0.051)	(0.142)	(0.073)	(0.069)
lag(ROA)	0.064	0.346**	0.315*	0.201*	0.568***	0.570***
	(0.089)	(0.163)	(0.167)	(0.113)	(0.208)	(0.212)
lag(Tobin's Q)	0.011	0.067***	0.059***	0.006	0.087***	0.082***
	(0.008)	(0.013)	(0.013)	(0.009)	(0.019)	(0.020)
lag(Leverage)	-0.030	-0.270***	-0.210***	-0.018	-0.570***	-0.502***
	(0.056)	(0.081)	(0.076)	(0.076)	(0.125)	(0.121)
lag(CAPEX)	-0.038	0.351**	0.324**	0.116	0.512**	0.517**
	(0.096)	(0.154)	(0.153)	(0.125)	(0.209)	(0.208)
lag(Tangibility)	0.021	-0.053	-0.013	-0.016	-0.051	-0.014
	(0.059)	(0.094)	(0.094)	(0.082)	(0.134)	(0.137)
Constant	-4.135***	-5.456***	-4.859***	-4.121***	-7.135***	-6.631***
	(0.844)	(0.825)	(0.833)	(0.987)	(0.985)	(0.984)
Firm FE	Y	N	N	Y	N	N
Industry Lv2 FE	N	Y	Y	N	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	9143	7905	6998	9143	7905	6998
adj. R-sq	0.136	0.251	0.237	0.119	0.265	0.251

Table 5: Regression of Competition with U.S. Innovative Environment

This table reports the estimation of baseline regression after adding innovative environment from U.S. industry. The main interested variable here is the interaction of foreign sales measurement with the U.S. industry level innovation. The U.S. industry average number of patents is defined in the Appendix and we are using the level 2 GICS/CSIC matching procedure to identify the same industry. To avoid potential endogenous concerns, we lagged one year of the US patent. The High-Tech Dummy equals to one if a firm qualified the high-tech requirement made by government and thus received benefits like tax deduction in China. The dependent variables are measures of innovation productivity including the number of invention patents and the total number of patents. The main explanatory variables are foreign sales ratios, 10% cut-off foreign sales ratio dummy and 25% cut-off foreign sales ratio dummy. The set of control variables includes the natural logarithm of firm assets, the natural logarithm of one plus firm age at the IPO year, return on assets, Tobin's Q, firm leverage, firm investment measured by capital expenditure scaled by firm assets, tangibility measured by PPE scaled by firm assets. All regressions include firm (industry), year fixed effect. Robust standard errors are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Panel A: Ln(1+Patent1)					
	(1)		(2)		(3)	
	High-Tech	Low-Tech	High-Tech	Low-Tech	High-Tech	Low-Tech
lag(Fsales)*lag(USPatent)	-0.140	0.202***				
	(0.094)	(0.076)				
lag(Fsales)	0.462**	0.102				
	(0.232)	(0.150)				
lag(MNC10)*lag(USPatent)			-0.082*	0.069*		
			(0.043)	(0.038)		
lag(MNC10)			0.319***	0.158*		
			(0.107)	(0.086)		
lag(MNC25)*lag(USPatent)					-0.097*	0.104**
					(0.054)	(0.047)
lag(MNC25)					0.326**	0.106
					(0.137)	(0.098)
lag(USPatent)	-0.210***	-0.040	-0.198***	-0.052	-0.257***	-0.035
	(0.053)	(0.033)	(0.060)	(0.035)	(0.063)	(0.035)
lag(Ln(Total Assets)	0.357***	0.286***	0.350***	0.267***	0.334***	0.229***
	(0.041)	(0.051)	(0.043)	(0.054)	(0.044)	(0.056)
Ln(Age)	-0.099	-0.151**	-0.110	-0.164***	-0.101	-0.168***
	(0.066)	(0.062)	(0.067)	(0.062)	(0.068)	(0.059)
lag(ROA)	0.396	0.065	0.394	0.158	0.435	0.127
	(0.270)	(0.159)	(0.282)	(0.166)	(0.293)	(0.170)
lag(Tobin's Q)	0.075***	0.053***	0.094***	0.060***	0.083***	0.053***
	(0.023)	(0.015)	(0.024)	(0.015)	(0.024)	(0.016)
lag(Leverage)	-0.372***	-0.203**	-0.352***	-0.167**	-0.252*	-0.131*
	(0.132)	(0.082)	(0.136)	(0.080)	(0.140)	(0.075)
lag(CAPEX)	0.476*	0.214	0.368	0.241	0.379	0.192
	(0.246)	(0.183)	(0.254)	(0.178)	(0.261)	(0.170)
lag(Tangibility)	-0.241*	0.150	-0.216	0.073	-0.176	0.098
	(0.139)	(0.103)	(0.141)	(0.101)	(0.149)	(0.101)
Constant	-6.582***	-5.628***	-6.531***	-5.211***	-6.080***	-4.445***
	(0.918)	(1.052)	(0.971)	(1.111)	(0.995)	(1.145)
Industry Lv2 FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	4172	4740	3533	4175	3040	3774

adj. R-sq	0.266	0.230	0.288	0.238	0.282	0.226

	Panel B: Ln(1+Patent All)					
	(1)		(2)		(3)	
	HighTech	LowTech	HighTech	LowTech	HighTech	LowTech
lag(Fsales)*lag(USPatent)	-0.233*	0.298**				
	(0.121)	(0.122)				
lag(Fsales)	0.596**	-0.149				
	(0.285)	(0.247)				
lag(MNC10)*lag(USPatent)			-0.118*	0.128**		
			(0.060)	(0.062)		
lag(MNC10)			0.435***	0.111		
			(0.144)	(0.139)		
lag(MNC25)*lag(USPatent)					-0.163**	0.165**
					(0.071)	(0.078)
lag(MNC25)					0.470***	0.013
					(0.176)	(0.164)
lag(USPatent)	-0.340***	0.012	-0.303***	-0.021	-0.374***	-0.010
	(0.069)	(0.048)	(0.075)	(0.053)	(0.080)	(0.053)
lag(Ln(Total Assets)	0.462***	0.406***	0.446***	0.390***	0.429***	0.361***
	(0.050)	(0.059)	(0.052)	(0.063)	(0.052)	(0.065)
Ln(Age)	-0.170*	-0.195**	-0.203**	-0.202**	-0.182**	-0.204**
	(0.093)	(0.087)	(0.092)	(0.088)	(0.088)	(0.086)
lag(ROA)	0.620*	0.407*	0.495	0.438*	0.543	0.462*
	(0.346)	(0.218)	(0.339)	(0.233)	(0.347)	(0.239)
lag(Tobin's Q)	0.060**	0.078***	0.090***	0.095***	0.078***	0.095***
	(0.029)	(0.022)	(0.029)	(0.025)	(0.030)	(0.027)
lag(Leverage)	-0.611***	-0.523***	-0.567***	-0.510***	-0.462**	-0.472***
	(0.186)	(0.141)	(0.184)	(0.145)	(0.187)	(0.145)
lag(CAPEX)	0.680**	0.353	0.553*	0.411*	0.630*	0.372
	(0.313)	(0.243)	(0.319)	(0.243)	(0.322)	(0.235)
lag(Tangibility)	-0.382**	0.275*	-0.405**	0.190	-0.360*	0.198
	(0.186)	(0.157)	(0.185)	(0.158)	(0.197)	(0.161)
Constant	-7.887***	-7.921***	-7.673***	-7.555***	-7.214***	-6.971***
	(1.094)	(1.247)	(1.139)	(1.328)	(1.137)	(1.380)
Industry Lv2 FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	4172	4740	3533	4175	3040	3774
adj. R-sq	0.309	0.223	0.329	0.234	0.324	0.221

Table 6: Difference-in-Difference (DiD) Multivariate Regression

This table reports the diagnostics and results of the DiD regressions designed for testing on how a plausibly exogenous shock to foreign sales due to the passage of the Exchange Rate Reform in 2005 affects firm innovation. Sample selection begins with all firms with non-missing variables and observation outcomes in the three years before exchange rate reform (2003-2005) and three years after exchange rate reform (2006-2008). Treatment group includes the firms with foreign sales and influenced by the exchange rate reform. Control group is the firms without foreign sales thus would not influenced by the exchange rate reform. We run the multivariate DiD test results with standard errors adjusted for firm-level clustering. All regressions include firm (industry), year fixed effect. Robust standard errors are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Panel A: Ln(1+Patent1)			Panel B: Ln(1+Patent All)		
	(1)	(2)	(3)	(4)	(5)	(6)
ExPolicy*lag(Fsales)	0.317***			0.392***		
	(0.122)			(0.149)		
lag(Fsales)	0.057			0.054		
	(0.139)			(0.160)		
Expolicy*lag(MNC10)		0.162***			0.267***	
		(0.057)			(0.078)	
lag(MNC10)		0.144**			0.144*	
		(0.056)			(0.086)	
Expolicy*lag(MNC25)			0.228***			0.402***
			(0.077)			(0.102)
lag(MNC25)			0.103			0.017
			(0.069)			(0.097)
ExPolicy	0.105**	0.051	0.046	0.089	0.027	0.010
	(0.051)	(0.047)	(0.050)	(0.064)	(0.065)	(0.069)
lag(Ln(Total Assets)	0.196***	0.311***	0.289***	0.195***	0.432***	0.412***
	(0.044)	(0.048)	(0.050)	(0.053)	(0.053)	(0.055)
Ln(Age)	0.237	-0.201***	-0.190***	0.466**	-0.286***	-0.271***
	(0.154)	(0.065)	(0.064)	(0.182)	(0.086)	(0.084)
lag(ROA)	-0.007	0.238	0.217	0.093	0.424*	0.437*
	(0.108)	(0.171)	(0.173)	(0.144)	(0.232)	(0.236)
lag(Tobin's Q)	-0.001	0.080***	0.074***	-0.012	0.106***	0.102***
	(0.010)	(0.017)	(0.018)	(0.013)	(0.023)	(0.024)
lag(Leverage)	-0.101	-0.287***	-0.227**	-0.153*	-0.641***	-0.576***
	(0.068)	(0.093)	(0.090)	(0.089)	(0.137)	(0.134)
lag(CAPEX)	0.045	0.355**	0.304*	0.236	0.527**	0.520**
	(0.116)	(0.170)	(0.175)	(0.161)	(0.238)	(0.245)
lag(Tangibility)	0.047	-0.094	-0.065	0.091	-0.115	-0.079
	(0.070)	(0.101)	(0.104)	(0.102)	(0.146)	(0.150)
Constant	-4.297***	-5.856***	-5.461***	-4.454***	-7.885***	-7.533***
	(0.909)	(0.979)	(1.035)	(1.131)	(1.119)	(1.153)
Firm FE	Y	N	N	Y	N	N
Industry Lv2 FE	N	Y	Y	N	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	6009	5254	4669	6009	5254	4669
adj. R-sq	0.089	0.225	0.212	0.070	0.245	0.235

Table 7: Difference-in-Difference (DiD) Regression after Adding Propensity Score Matching

This table reports the diagnostics and results of the Propensity Score Matching (PSM) and DiD regressions designed for testing on how a plausibly exogenous shock to foreign sales due to the passage of the Exchange Rate Reform in 2005 affects firm innovation. We only keep the sample by using the PSM method by selecting purely domestic firms with similar characteristics with multinational firms by each year. TMNC10 and TMNC25 measure the foreign sales in the treatment group after selecting and matching the sample with the rest. TMNC10 equals to one if the firm in the treatment group have more than 10% foreign sales ratio and equals to zero if the firm is in the control group without any foreign sales; same as TMNC25, changing the cut-off ratio from 10% to 25%. We run the subsample test results with standard errors adjusted for firm-level clustering. All regressions include industry and year fixed effect. The controls remain the same. Robust standard errors are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Pre-ExPolicy (ExPolicy=0)				**Post-ExPolicy (ExPolicy=1)**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ln(1+Patent1)		**Ln(1+Patent All)**		**Ln(1+Patent1)**		**Ln(1+Patent All)**	
TMNC10	0.177***		0.174**		0.274***		0.380***	
	(0.056)		(0.086)		(0.058)		(0.077)	
TMNC25		0.133*		0.043		0.301***		0.388***
		(0.070)		(0.098)		(0.077)		(0.099)
lag(Ln(Total Assets)	0.307***	0.288***	0.452***	0.433***	0.317***	0.308***	0.425***	0.404***
	(0.055)	(0.061)	(0.063)	(0.066)	(0.046)	(0.054)	(0.053)	(0.058)
Ln(Age)	-0.092	-0.066	-0.104	-0.109	-0.324***	-0.350***	-0.489***	-0.504***
	(0.062)	(0.061)	(0.084)	(0.084)	(0.087)	(0.089)	(0.113)	(0.112)
lag(ROA)	0.169	0.100	0.209	0.198	0.513**	0.597**	0.758**	0.950***
	(0.235)	(0.218)	(0.363)	(0.337)	(0.227)	(0.256)	(0.316)	(0.350)
lag(Tobin's Q)	0.127***	0.121***	0.146***	0.147***	0.058***	0.052***	0.086***	0.076***
	(0.031)	(0.031)	(0.047)	(0.046)	(0.017)	(0.019)	(0.026)	(0.026)
lag(Leverage)	-0.318***	-0.207**	-0.709***	-0.534***	-0.268**	-0.158	-0.585***	-0.442***
	(0.105)	(0.103)	(0.176)	(0.174)	(0.120)	(0.129)	(0.159)	(0.166)
lag(CAPEX)	0.377	0.387	0.542	0.535	0.394	0.211	0.519	0.484
	(0.248)	(0.244)	(0.333)	(0.330)	(0.251)	(0.257)	(0.337)	(0.349)
lag(Tangibility)	-0.067	-0.114	-0.022	-0.073	-0.136	-0.074	-0.206	-0.150
	(0.123)	(0.123)	(0.170)	(0.170)	(0.118)	(0.128)	(0.171)	(0.185)
Constant	-6.108***	-5.774***	-8.799***	-8.414***	-5.564***	-5.375***	-7.128***	-6.717***
	(1.145)	(1.263)	(1.335)	(1.403)	(1.013)	(1.163)	(1.180)	(1.269)
Industry Lv2 FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	2408	2150	2408	2150	2739	2314	2739	2314
adj. R-sq	0.180	0.165	0.193	0.187	0.223	0.226	0.258	0.257

Table 8: 2SLS regression result for two instrumental variables

This table reports the comparison of the OLS regressions and 2SLS regression result. There are two instrumental variables using, one is the cumulative number of BITs (Bilateral Investment Treaty), another one is the change of percentage export weighted by number of new sign BITs. The main interested variable is still the foreign sales ratio. Panel A reports the result for dependent variable used as patent type 1 and Panel B reports the result for dependent variable used as all patent types. We run the subsample test results with standard errors adjusted for firm-level clustering. All regressions include industry and year fixed effect. The controls remain the same. Robust standard errors are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A: Ln(1+Patent1)

	OLS	2SLS_Cumlative Number of BITs		2SLS_Export Weighted Number of BITs	
	(1)	(3)	(4)	(6)	(7)
	Ln(1+Patent1)	lag(Fsales) (First Stage)	Ln(1+Patent1)	lag(Fsales) (First Stage)	Ln(1+Patent1)
lag(Fsales)	0.290**				
	(0.113)				
Num_Treaty		0.484***		0.051***	
		(0.025)		(0.019)	
lag(Fsales)_*Hat*			4.955***		5.776***
			(0.392)		(1.257)
lag(Ln(Total Assets)	0.240***	-0.009***	0.386***	0.000	0.386***
	(0.036)	(0.002)	(0.035)	(0.002)	(0.035)
Ln(Age)	0.461***	-0.042***	-0.041	-0.002	-0.033
	(0.114)	(0.005)	(0.043)	(0.004)	(0.042)
lag(ROA)	-0.148**	0.065***	0.052	0.090***	-0.013
	(0.075)	(0.025)	(0.150)	(0.025)	(0.201)
lag(Tobin's Q)	0.016**	-0.009***	0.091***	-0.003***	0.093***
	(0.007)	(0.001)	(0.009)	(0.001)	(0.012)
lag(Leverage)	-0.106*	0.032***	-0.494***	0.014	-0.513***
	(0.055)	(0.011)	(0.078)	(0.011)	(0.082)
lag(CAPEX)	0.023	0.039	0.234	0.067***	0.165
	(0.093)	(0.024)	(0.154)	(0.025)	(0.179)
lag(Tangibility)	0.080	-0.022**	0.086	-0.032***	0.125
	(0.061)	(0.009)	(0.093)	(0.009)	(0.099)
Constant	-5.518***	-1.908***	-8.107***	0.086**	-8.198***
	(0.750)	(0.104)	(0.712)	(0.040)	(0.778)
Industry Lv2 FE	Y	N	Y	N	Y
Year FE	Y	N	Y	N	Y
Hausman Test (P-value)		0.000		0.000	
N	14598	10784	10792	10784	10792
adj. R-sq	0.158	0.039	0.248	0.004	0.223

Panel B: Ln(1+PatentAll)					
	OLS	2SLS_Cumlative Number of BITs		2SLS_Export Weighted Number of BITs	
	(1)	(3)	(4)	(6)	(7)
	Ln(1+PatentAll)	**lag(Fsales) (First Stage)**	**Ln(1+PatentAll)**	**lag(Fsales) (First stage)**	**Ln(1+PatentAll)**
lag(Fsales)	0.264**				
	(0.124)				
Num_Treaty		0.484***		0.051***	
		(0.025)		(0.019)	
lag(Fsales)_*Hat*			6.326***		4.492***
			(0.549)		(1.600)
lag(Ln(Total Assets)	0.259***	-0.009***	0.496***	0.000	0.495***
	(0.039)	(0.002)	(0.040)	(0.002)	(0.039)
Ln(Age)	0.647***	-0.042***	-0.102*	-0.002	-0.095*
	(0.130)	(0.005)	(0.056)	(0.004)	(0.056)
lag(ROA)	-0.116	0.065***	0.284	0.090***	0.465*
	(0.091)	(0.025)	(0.195)	(0.025)	(0.249)
lag(Tobin's Q)	0.015*	-0.009***	0.109***	-0.003***	0.101***
	(0.008)	(0.001)	(0.012)	(0.001)	(0.015)
lag(Leverage)	-0.126*	0.032***	-0.854***	0.014	-0.840***
	(0.072)	(0.011)	(0.116)	(0.011)	(0.119)
lag(CAPEX)	0.075	0.039	0.369*	0.067***	0.473**
	(0.114)	(0.024)	(0.200)	(0.025)	(0.231)
lag(Tangibility)	0.084	-0.022**	0.154	-0.032***	0.114
	(0.076)	(0.009)	(0.129)	(0.009)	(0.135)
Constant	-5.881***	-1.908***	-10.035***	0.086**	-9.851***
	(0.835)	(0.104)	(0.793)	(0.040)	(0.867)
Industry Lv2 FE	Y	N	Y	N	Y
Year FE	Y	N	Y	N	Y
Hausman Test (P-value)		0.000		0.000	
N	14598	10784	10792	10784	10792
adj. R-sq	0.147	0.039	0.268	0.004	0.245