The Impact of Foreign Direct Investment on Innovation: Evidence from Patent Filings and Citations in China

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Abstract: This paper studies how foreign direct investment (FDI) affects innovation in the host country, using matched firm-level patent data of Chinese firms. The data contain multidimensional information about patent counts and citations which, together with an identification strategy based on Lu et al. (2017), allows us to measure innovation comprehensively and to uncover the causal relationship. Our empirical analysis shows that FDI has positive intra-industry effects on the quantity and quality of innovation by Chinese firms. We show that these positive effects are driven by increases in competition, rather than by knowledge spillover from FDI which is measured by patent citations between domestic firms and foreign invested enterprises (FIEs). We further investigate the inter-industry effects of FDI and find that FDI has positive vertical effects on innovation in upstream sectors.

Keywords: FDI; Innovation; Patent; Competition; Spillover

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1. Introduction

One of the kernel intentions for developing countries to attract foreign direct investment (FDI) is to promote the growth of domestic industries by absorbing foreign investors' advanced technology. A considerable body of research has examined FDI's impact on productivity in developing countries, finding some evidence that the presence of FDI indeed facilitates technology transfer through spillovers and enhancements of domestic firms' productivity (e.g., Blomström and Sjöholm, 1999; Javorcik, 2004; Kugler, 2006; Blalock and Gertler, 2008; Burstein and Monge-Naranjo, 2009).[1] The long-term productivity growth of a country, however, depends also on the innovation of its domestic firms. Innovation will become increasingly important for many developing countries as they grow further and narrow the gap with the developed world (e.g., Chen and Puttitanum, 2005). With the continued rise of foreign direct investment to developing countries, an important question for both economists and policy makers is: How will FDI impact the innovation of host-country firms?

From a theoretical perspective, the influx of FDI may either positively or negatively impact domestic firms' innovation: while the potential knowledge spillover from advanced foreign firms is likely beneficial, the business stealing effect of increased competition may reduce domestic firms' innovation (e.g., Aghion et al., 2005; Bloom et al., 2019). Empirical research on the relationship between FDI and innovation is relatively sparse. The few existing studies for developed countries have produced mixed results.[2] Studies for developing countries have focused on China (Hu and Jefferson, 2009; Cheung and Lin, 2004; Zhang, 2017). As the largest developing country, China has in the past few decades experienced large increases in both FDI and innovation (Figure 1), providing a natural setting for research that has broad implications for developing countries. These studies find a positive relationship between FDI and innovation

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[1] However, as indicated by Havranek and Irsova (2011), results vary broadly across methods and countries. Some studies have also found negative effects of FDI on firms' productivity (e.g., Haddad and Harrison, 1993; Aitken and Harrison, 1999).

[2] García et al. (2013) find that FDI inflows into Spain are negatively associated with the ex-post innovation of local manufacturing firms, whereas Crescenzi et al. (2015) find that domestic firms in sectors with more FDI have stronger innovative performance in the UK.

in China, but their measurement of innovation is largely limited to patent counts and lacks quality metrics that account for the heterogeneity in patent quality. More importantly, these studies primarily contain correlation results, without adequately addressing potential problems associated with omitted variables and reverse causality. This issue is especially concerning in light of the surprising finding of Lu et al. (2017). Using a novel identification strategy, Lu et al. (2017) find evidence that inward FDI *negatively* impacts Chinese firms' productivity. One wonders whether FDI may also negatively affect Chinese firms' innovation once the *causal* relationship is identified.

This paper conducts an empirical study of inward FDI's impact on Chinese firms' innovation, using new firm-level matched data on firms' operations and patents in China.[3] The newly available data set on patent applications by Chinese firms allows us to construct comprehensive measures of firms' innovation quantity and quality, including patent counts and patent citations, using the methodology in the innovation literature (e.g., Hall et al., 2001, 2005). Following the identification strategy put forward by Lu et al. (2017), we further construct an instrument for FDI that utilizes a plausibly exogenous change of FDI regulations in China, the revisions to the *Catalogue for the Guidance of Foreign Investment Industries* in 2002. We are then able to compare firms' innovation performance between the treatment group (i.e., FDI-encouraged industries) and the control group (i.e., FDI-unchanged industries) before and after the changes in FDI regulation. Our research thus overcomes the two main difficulties in the existing studies on FDI and innovation, namely the comprehensive measurement of innovation and the identification of a causal relationship.

We find positive intra-industry effects of FDI on firms' innovation quantity and quality, measured respectively by the number of patents and by patent citations (number, generality, and originality). Moreover, the positive impact of FDI appears to be more pronounced for more important innovations (i.e., for invention patents than for utility model and design patents). Further evidence backs up these positive effects when considering "radical innovation". The

[3]As discussed in more detail later, we merge the firm-level data from the Annual Survey of Industrial Firms with the comprehensive patent data obtained from the China National Intellectual Property Administration in China.

results remain valid with respect to various robustness tests, including the addition of multiple controls. The comprehensive data further allow us to examine the possible mechanisms for FDI's effects. In particular, based on the patent citations made by domestic firms to foreign invested enterprises (FIEs), we construct a direct measurement of knowledge spillover from FDI, and we quantify competition intensity not only through market concentration but also through a measure of technology competition using the patent data. We find evidence that the influx of FDI intensifies market competition and pressures domestic firms in the same industry to innovate for technological upgrades, leading to an overall positive impact, but no evidence of a significant horizontal knowledge spillover effect of FDI on firm innovation. This is surprising, in contrast to the finding of Lu et al. (2017) that FDI has negative competition but positive spillover effects on firm productivity. The competition and spillover effects of FDI for innovation and for productivity can thus be very different.[4] Furthermore, we find that the effects of FDI on innovation are heterogenous across different types of domestic firms. Specifically, the effects are smaller for larger firms and for state-owned enterprises (SOEs), and they are larger for firms less distanced from the technology frontier.

FDI can also potentially affect innovation through vertical linkages. We find that the presence of FDI in downstream sectors has positive effects on the innovation of firms in the upstream industries, whereas the presence of FDI in upstream sectors has negative effects on the innovation of downstream firms. The literature has suggested that vertical knowledge spillover is a major source of the vertical effects of FDI on productivity (Javorcik, 2004; Javorcik and Spatareanu, 2008; Blalock and Gertler, 2008), but it does not separately identify the knowledge spillover. Our comprehensive patent data allow us to construct direct measures of both backward and forward knowledge spillovers, based on the patent citation network. We demonstrate that there are significant knowledge spillovers through backward but not forward linkages which, together with other factors in vertical relations, provide explanations to the different effects of backward and forward FDI on Chinese firms' innovation.

[4] Productivity may depend more than innovation on factors such as sales, know-how, and management practices for which FDI is likely to have (more) positive spillover effects but may also have stronger business-stealing effects.

The rest of the paper is organized as follows. Section 2 describes the data for our study and also provides some institutional background. Section 3 presents the identification strategy and the underlying assumptions. Section 4 reports the main empirical results on the (intra-industry) effects of FDI on innovation, explains the results by analyzing the potential competition and knowledge spillover mechanisms, and further examines the heterogeneity of the innovation effects of FDI. Section 5 conducts additional analysis, using various controls and considering alternative assumptions, to confirm the robustness of our main results. Section 6 examines the vertical effects of FDI and the underlying mechanisms of backward vs. forward knowledge spillovers. Section 7 concludes.

2. Data

First, this section describes our constructions of a firm-level panel data set and a patent data set of Chinese firms. We then describe the process of matching these two data sets. Measures of innovation are then discussed. Finally, we describe the (exogenous) changes in FDI regulations to be considered for our analysis.

2.1. Firm-level panel data

We construct annual firm-level data for the 1998–2007 period that cover all firms, including SOEs and non-SOEs, based on the Annual Survey of Industrial Firms (ASIF) conducted by the National Bureau of Statistics of China (NBS). Firms in the ASIF data account for around 95% of total Chinese industrial output and 98% of total Chinese industrial exports (Tan and Peng, 2003), spanning 37 two-digit manufacturing industries and 31 provinces or province-equivalent municipal cities. In 2003, a new classification system for industry codes (GB/T 4754-2002) was adopted in China to replace the old classification system (GB/T 4754-1994) that had been used from 1995 to 2002. Following the concordance table constructed by Brandt et al. (2012), we link the two classifications and develop consistency in the industry codes over our entire sample period (1998–2007). To further clean the sample, we implement screening to remove potentially problematic observations. As in Cai et al. (2018), we drop observations where firm identifiers, county code, sector ID, or year of establishment are missing, as well as observations that have total sales below 5 million RMB or fewer than eight employees. Additionally, observations are dropped if total assets are less than liquid assets or total fixed assets. Since we are interested in the impact of FDI on domestic firms, we exclude from our sample all foreign firms (i.e., any firm with more than 25% of its equity owned by foreign investors, according to *China's Foreign Investment Law*).

2.2. Patent data

The Chinese patent data for our study, obtained from the China National Intellectual Property Administration (CNIPA), cover all published patent applications since 1985 when CNIPA started to accept patent applications. The data contain all the records of patent applications and approvals as of June 2017, including around 6.77 million invention patents, 6.26 million utility model patents, and 4.17 million design patents. We divide the information of each patent into three parts: (1) Patent information: patent name, application number, application date, publishing number, publishing date, and International Patent Classification (IPC). (2) Applicant information: Applicant's name, applicant's address, applicant's ZIP code, and applicant's country (or province). (3) Patent rights information: inventor's name, priority number, priority day, agent, agency, legal status information, summary, claim book, and citation information.

2.3. Data matching

Based on the matching methodology in He et al. (2018), we match the ASIF data and the patent data for Chinese firms. The assignee names of Chinese patents are matched to the names of manufacturing firms through exact matching, approximate matching, and manual checks. Details are reported in Appendix B. After the matching procedures, we merge the aggregate patent data to the ASIF data set at a firm-year level.

2.4. Innovation measures

Patent counts are widely used as a basic measure of innovation (Hall et al., 2001). This study uses four metrics to capture patent counts: number of all patents, number of invention patents, number of utility model patents, and number of design patents. We further use another set of metrics to gauge the quality of patents: the number of citations a patent receives following its approval, the generality index, and the originality index. The number of citations a patent receives is a direct measure of its importance. A patent that cites a broader array of technology classes is viewed as having greater originality, while a patent that is cited by a more technologically varied array of patents is viewed as having greater generality (Trajtenberg et al., 1997). Specifically, the originality and the generality of a patent is measured respectively by the Herfindahl index of the patents it cites and the Herfindahl index of its citing patents.

Because citation rates and patent counts vary over time and across technologies (e.g., using a patent's citation number to measure its innovation quality could have the bias of favoring earlier rather than later patents), we will define scaled variables that adjust for such variations. Specifically, following Hall et al. (2001), we scale the innovation measures by IPC technology class and year. A technology class is a detailed classification of International Patent Classification. We use IPC one-digit figure as the technology class. To compute a scaled measure, we divide the measure by the average value of the measure in the same year and technology class. This allows us to obtain scaled number of patents, scaled citations, scaled generality, and scaled originality. We will use the scaled measures to conduct robustness checks for our results.

2.5. FDI and its regulations in China

FIEs virtually did not exist in China before its reform and opening-up in 1978. After the Law on Sino-Foreign Equity Joint Ventures was passed in 1979, a series of laws and regulations were enacted to attract FDI, accompanied by various policies such as tax reduction, land usage, and subsidies. Among the regulations concerning FDI, *Catalogue for the Guidance of Foreign Investment Industries* (henceforth, the Catalogue) is the most important one, becoming the government's guidelines for regulating the inflows of FDI in 1997. To comply with China's commitments for entry to the WTO, China substantially revised the Catalogue in March 2002 (China also revised the Catalogue in November 2004, but only with minor revisions). As proposed by Lu et al. (2017), the substantial changes in the Catalogue can be considered as exogenous, because China's WTO accession was commonly regarded as exogenous and the revisions of the Catalogue in 2002 were part of China's agreement on WTO's accession. In this study, we use the plausibly exogenous changes in FDI regulations (i.e., changes in the Catalogue) to identify the effects of FDI on domestic firms' innovation.

To obtain information about changes in FDI regulations, we first identify whether there was a change in the FDI policies for each product in the Catalogue, where products were classified into four categories: (1) FDI is encouraged; (2) FDI is permitted; (3) FDI is restricted; (4) FDI is prohibited. We compare the 1997 and 2002 versions of the Catalogue and classify each product into one of three possible outcomes: (1) FDI became more welcome; (2) FDI became less welcome; (3) no change in FDI regulation.

We next aggregate the changes in FDI policies for individual products at the industry level. We use the Industrial Product Catalogue to map the product-level classifications of the Catalogue into the four-digit Chinese Industry Classification (CIC) of 2003. Following this aggregation process, all the four-digit CIC industries are classified into four categories: (1) FDI encouraged industry; (2) FDI discouraged industry; (3) FDI no change industries; (4) mixed industry. The detailed classification process is listed in Appendix C.

From the data classification process above, 117 four-digit CIC industries are classified as the FDI encouraged industries; 297 are FDI unchanged industries; five are FDI discouraged industries, and six are FDI mixed industries.[5] The latter two groups are excluded from the analysis.

3. Estimation Strategy

In this section, we first describe our econometric specification, followed by a discussion of the validity of our identification strategy.

[5] In Lu et al. (2017), 112 are FDI encouraged industries, 300 are FDI no change industries, seven are FDI discouraged industries, and five are FDI mixed industries. While we follow the same procedure as theirs, our classification of the industries is slightly different, reflecting some small difference in the subjective judgement of assigning an industry to one of the four categories. Our regression results are robust with respect to this difference.

3.1. Econometric specification

To study the impact of FDI on firms' innovation, we estimate the following benchmark model:

$$Innovation_{fit} = \alpha_0 + \delta FDI\_Industry_{it} + \mathbf{X}'_{fit}\lambda + \alpha_f + \gamma_t + \varepsilon_{fit}. \tag{1}$$

where $Innovation_{fit}$ is the innovation performance of firm f in four-digit industry i and year t, measured respectively by the number of all patents, the number of invention patents, the number of utility model patents, the number of design patents, the number of patent citations, generality, and originality. $\mathbf{X}_{fit}$ is a vector of time-varying firm and industry characteristics, including firms' output, firms' capital labor ratio, firms' export status, and a dummy variable indicating whether a firm is an SOE. The summary statistics of the main variables are presented in Table 1. The firm and year fixed effects and the constant term are denoted respectively by α_f, γ_t and α_0. $FDI\_Industry_{it}$ is our regressor of interest and is defined as:

$$FDI\_Industry_{it} = \frac{\sum_{f\in\Omega_{it}} FDI\_Firm_{fit} \times Output_{fit}}{\sum_{f\in\Omega_{it}} Output_{fit}} \times 100\%,$$

where $Output_{fit}$ measures the output of firm f in industry i in year t. FDI_Firm_{fit} is defined as firms' foreign equity share. Ω_{it} is the set of firms in industry i in year t. $FDI\_Industry_{it}$ is an industry level FDI variable that captures the presence of FDI in industry i in year t. Innovation metrics are likely to be autocorrelated over time. Thus, we allow the standard errors to have arbitrary heteroskedasticity and autocorrelation by clustering standard errors at firm-level (Blanco and Wehrheim, 2017).

Our specific interest lies in δ, the parameter that captures the effects of FDI on innovation of firms in the same sector. A positive value of δ indicates that the presence of FDI has positive intra-industry effects on firms' innovation. To obtain an unbiased estimate of δ in the benchmark model, an important assumption is that, conditional on all of the control variables, the regressor $FDI\_Industry_{it}$ is uncorrelated with the error term. However, there are concerns that this assumption might be violated. For example, the more innovative firms are likely to be in industries that attract more FDI.

To tackle the identification problem, we use variation across industries in the change of FDI regulation as an instrument for $FDI\_Industry_{it}$ to identify the impact of FDI on the innovation of Chinese firms, following Lu et al. (2017) in their study of FDI's effects on productivity. Specifically, we compare firm innovation performance in the treatment group (i.e., FDI encouraged industries) with firm innovation performance in the control group (i.e., FDI no change industries) before and after the implementation of the Catalogue in 2002. This is an instrumental variable (IV) estimation based on a difference-in-difference (DID) strategy. The first stage of the IV estimation is

$$FDI\_Industry_{it} = \alpha_0 + \eta Treatment_i \times Post02_t + \mathbf{X}'_{fit}\psi + \alpha_f + \gamma_t + \zeta_{fit} \tag{2}$$

where $Treatment_i$ indicates whether industry i belongs to the treatment group; and $Post02_t$ is a dummy indicating the period after implement of Catalogue 2002, namely $Post02_t = 1 \ if \ t > 2002, \ Post02_t = 3/4 \ if \ t = 2002, \ and \ Post02_t = 0 \ if \ t < 2002$.[6]

3.2. Validity of DID based instrumental variable

The above DID based instrument is valid under two conditions. First, the relevance condition: the share of FDI increased more in the encouraged industries than in the no change industries. This relevance condition is confirmed by the significance of η in Equation (2), which is shown in Panel B in Table 2.

Second, the instrument should also satisfy the exclusion restriction condition. That is, variations across industries from the change in FDI regulation do not affect firms' innovative behavior through channels other than the share of FDI. Specifically, conditional on all the controls, our instrumental variable $Treatment_i \times Post02_t$ is uncorrelated with the error term ε_{fit} in Equation (1), namely $\text{cov}\left(Treatment_i \times Post02_t, \varepsilon_{fit} \mid \mathbf{W}_{fit}\right) = 0$, where $\mathbf{W}_{fit}$ summates all of the controls in the regression. Since our instrument is DID based, there are only two possible sources of violation of this identifying assumption: $\text{cov}\left(Post02_t, \varepsilon_{fit} \mid \mathbf{W}_{fit}\right) \neq 0$ or $\text{cov}\left(Treatment_i, \varepsilon_{fit} \mid \mathbf{W}_{fit}\right) \neq 0$.

[6] $Post02_t = 3/4$ for 2002 in our empirical analysis, as the Catalogue 2002 was implemented on April 1, 2002. The results (available upon request) remain robust when $Post02_t = 1$ for 2002.

One concern is that the post-treatment period indicator $Post02_t$ and the second-stage error term ε_{fit} are possibly correlated when the timing of the FDI regulation change was non-random. However, the regulation revision in 2002 resulted from a lengthy negotiation between China and 150 WTO member countries upon China's accession into WTO. Since the result of the negotiation was uncertain prior to 2001, the timing of FDI regulation change in 2002 was plausibly random and Chinese firms would not have anticipated the change of FDI regulations in 2002. Nevertheless, to deal with the possible non-random selection of timing, we control for other ongoing policy reforms during that time that might affect our results. Since one crucial policy reform in the early 2000s was the privatization of SOEs, in a similar way to Lu et al. (2017), we add the interaction between year dummies and industry SOE share in 2001 into X_{fit}. We also include the year fixed effects, which controls for all the macro shocks that might have correlated with the timing of FDI regulations in China.

Another concern is that the treatment status $Treatment_i$ and the second-stage error term ε_{fit} might be correlated, which would mean that the selection of FDI encouraged industries upon China's accession to WTO is non-random. To alleviate this concern, we control for the potential factors that might affect the selection of the treatment group. First, following Gentzkow (2006), we carefully characterize the potential determinants, Z_{i1998}, of the changes in FDI regulations upon the WTO accession. We identify three determinants at the four-digit industry level: new product intensity, number of firms, and average age of firms (Appendix Table A1). We then add interactions between γ_t and these three determinants Z_{i1998} in X_{fit} to control for the plausible predeterminants of the selection of industries for the change in FDI regulation. Second, we also control for time-varying firm characteristics in X_{fit} that might affect the selection of our treatment group, including firms' output, firms' capital–labor ratio, firms' ownership structure, and firms' export status.

4. Effects of FDI on Innovation

This section presents our results on how FDI inflows impact firms' innovation in China. Subsection 4.1 contains our main results, concerning how FDI impacts the quantity and quality of innovation by firms within the same industry. Subsection 4.2 provides further evidence on the impact of FDI on the quality of innovation by considering radical innovation. Subsection 4.3 explains the mechanisms behind our main results. The heterogeneity of the innovation effects of FDI is explored in subsection 4.4.[7]

4.1. Main results

For the dependent variable in our regressions in this subsection, we use in turn: (i) the number of all patents of a firm to measure innovation quantity; (ii) the numbers of invention patents, utility model patents, and design patents each as an additional innovation measure; (iii) the number of citations, the generality, and the originality of patents of a firm to measure innovation quality.

The distribution of patent measures in the pooled sample is right-skewed, with approximately the 95th percentile of the distribution being zero. We tackle this problem of the dependent variable with two methods. First, the natural logarithm of each innovation measure is used. To avoid losing firm-year observations with zero patents or citations per patent, we add one to the actual values when calculating the natural logarithm (Liu et al., 2021). Second, following Hu et al. (2017), we take the original innovation measures as dependent variables and use the conditional fixed effects Poisson model, in which the zero value of an innovation measure is replaced with the logarithm of 0.01.

Table 2 reports the baseline results of estimating Equation (1). The results in columns (1)–(3) come from the 2SLS (two stage least square) estimation. In column (1), we control for firm and year fixed effects, as well as the interactions between year dummies and FDI regulation determinants. The result of the second-stage regression shows that the impact of FDI is positive and both economically and statistically significant at the 1% level, implying that a 10 percentage points increase in FDI leads to a 0.41% increase in the number of all patents. The first-stage estimation shows that the instrument $Treatment_i \times Post02_t$ has a positive and statistically significant effect on $FDI\_Industry_{it}$, confirming that the relaxation of FDI

[7] While our main analysis concerns the intra-industry effects of FDI, we will also study the vertical effects of FDI later in Section 6.

regulations triggers inflows of FDI. The Cragg-Donald Wald F-statistic (2700.857) is much larger than the critical value at the 10% significance level (Stock and Yogo, 2005), rejecting the null hypothesis that our IV for FDI is subject to the weak IV problem.

In column (2), we add interactions between year dummies and SOE share to control for the privatization of SOEs. The coefficient of the second-stage regression shows that the impact of FDI on patent counts is statistically significant at the 1% level. In column (3), we further control for firm characteristics. The coefficient of the second-stage regression again shows that the impact of FDI on patent counts is statistically significant at 1%, implying that the number of all patents rises by 3% after increasing FDI by ten percentage points. The results reported in column (4) come from a conditional fixed effects Poisson estimation. After being instrumented, this model shows that FDI consistently generates a positive and statistically significant effect on the number of all patents.

In column (5), we further report the reduced-form estimation results. The estimated coefficient of the instrumental variable is positive and statistically significant, consistent with our aforementioned findings. In column (6), we present the OLS estimation results, which shows the impact of FDI is negative but not statistically significant. There can be a severe endogenous problem in OLS estimations, such as the issues of omitted variables and reverse causality.

We next investigate whether the positive effect of FDI on innovation varies for different categories of patents. There are three categories of patent in China: invention patents, utility model patents, and design patents. The invention patent corresponds to a more substantial invention due to its requirement of novelty, inventiveness, and practical applicability. The utility model patent requires that some significant improvement be made to an existing product. The design patent is more about some modification to the product appearance.

With the number of each of these three categories of patents as the dependent variable, Table 3 reports the estimation results. The estimated coefficient in column (1) shows that FDI exerts a positive and statistically significant impact on invention patents. As for the magnitude, a ten percentage points increase in FDI results in invention patents increasing by 0.35%. The Poisson estimation result in column (2) further supports the positive effect. The estimation results in columns (3) and (4) show that there is no statistically significant impact of FDI on utility model patents. The estimated coefficients in columns (5) and (6) show that FDI has a positive impact on design patents but the relationship is not statistically significant. Together, these results show that the inflows of FDI benefit the more innovative invention patents, compared with the less innovative utility model and design patents.

We next examine the impact of FDI on the quality of innovation, measured respectively by patent citations, generality, and originality. Table 4 reports our findings. The estimated coefficient for the 2SLS in column (1) shows that FDI has a positive and statistically significant impact on the number of patent citations, and a ten percentage points increase in FDI leads to a 0.48% increase in the number of citations. The Poisson estimation in column (2) bears out this result. In addition, the 2SLS and Poisson estimation results for generality are reported in columns (3) and (4) respectively, indicating that FDI has a positive and statistically significant impact on generality. Moreover, the 2SLS and Poisson estimation results for originality are reported in columns (5) and (6) respectively, also indicating a positive and statistically significant impact.

Overall, our baseline results show that FDI has a positive impact on firms' innovation. On the one hand, FDI contributes to a significant increase in the quantity of innovation. In particular, the inflows of FDI exert a larger impact on the rise of invention patents, which are the most inventive patents, than on the growth of utility model and design patents. On the other hand, FDI leads to a noticeable improvement in the quality of innovation. It is also evident that, with the inflows of FDI, firms not only produce more influential patents but also generate more original patents.

Finally, we use the seven scaled measures of innovation as dependent variables and run the regressions of the benchmark setting. In Table 5, columns (1)–(7) report the 2SLS estimation results. We find that the estimated coefficients are qualitatively the same after scaling the innovation measures. Specifically, the inflows of FDI still have a positive and statistically significant impact on both the scaled measures of innovation quantity and on the scaled measures of innovation quality. Poisson estimation results in columns (8)–(14) are in support of the above results, except that the coefficients in columns (13) and (14) are not statistically significant.

4.2. Radical innovation

The numbers of patents and patent citations are the most basic measures of innovation output in literature. However, these measures do not distinguish between breakthrough innovation and incremental innovation (e.g., Griliches, 1990). From our main results, FDI has a significant impact on invention patents but not on utility model patents or design patents, suggesting that the positive effects of FDI on innovation are more pronounced for more substantial innovations. Is this still true for innovations that break new technology ground, or "radical innovations"? This question has its independent interest, and the answer can provide further evidence on how FDI affects innovation in the quality dimension. We report our results below, considering in turn four alternative measures of radical innovation that have been used in the literature.

Tail innovation. Following Acemoglu et al. (2014), let $s_{ft}(p)$ denote the number of the patents of a firm that are above the p^{th} percentile of the distribution in year t according to citations. Then, the tail innovation index is defined as:

$$Tail_{ft}(p) = \frac{s_{ft}(p)}{s_{ft}(0.5)}$$

where p should be greater than 50%. This is of course also equivalent to the ratio of the number of patents by firm f in year t with citations above the p^{th} percentile divided by the number of patents by firm f in year t with citations above the median (it is not defined for firms that have no patents with citations above the median). We assign two values to p, 99% and 95%. The results reported in columns (1) and (2) in Table 6 show that the presence of FDI increases tail innovation significantly.

Best patent. Enlighted by Bernstein (2015), the most cited patent for firm f at year t can be regarded as the best patent which is unlikely to be affected by low-quality innovation activities. We then examine the generality and originality of the best patent since the number of the best patent is always 1 for innovative firms. The results reported in columns (3) and (4) in Table 6 show that FDI has significantly positive effects on the generality and originality of the best patent.

Breakthrough innovation. Following Balsmeier et al. (2017) and Guo et al. (2019), the breakthrough innovation is computed as the (natural logarithm of one plus) number of patents of a firm with citations in the top 5% (10%) in the distribution of citations, where the distribution is constructed with all the patents applied in the same technology class in the same year. The results reported in columns (5) and (6) in Table 6 show that the effects of FDI on breakthrough innovation are positive and statistically significant.

New technology innovation. We construct new technology innovation as the (natural logarithm of one plus number of patents that is filed in technology classes previously unknown to the firm (Balsmeier et al., 2017; Guo et al., 2019). We make use of two technology class criteria: one-digit IPC code and three-digit IPC code. Columns (7) and (8) in Table 6 show that the effects of FDI on new technology innovation are also positive and statistically significant, suggesting that the inflows of FDI bring to firms entirely new innovation from other technology fields.

Using four alternative measures of radical innovation, we find that the intra-industry impact of FDI is consistently positive and significant for radical innovation. This also reinforces the finding in our main results that the positive effects of FDI on innovation are more pronounced for more substantial innovations (represented by invention patents), relative to less substantial ones (represented by utility model patents and design patents).

In the rest of the paper, in order to be concise, we focus on three innovation measures, including the number of all patents, the number of invention patents, and the number of patent citations, as dependent variables and report only the 2SLS estimation results. The estimation results using other innovation measures are available upon request.

4.3. Examining the mechanisms: competition vs. spillovers

So far, we have established that FDI causes increases in innovation quantity and quality for firms in the same sector. In principle, FDI can affect the innovation of host-country firms through two main channels: the competition effect and the knowledge spillover effect (e.g., Aitken and Harrison, 1999; Javorcik, 2004). We next investigate these possible underlying economic mechanisms.

4.3.1. Competition effect

The entry of foreign rivals enhances competition in host country. The impact of competition on innovation is theoretically ambiguous (e.g., Bloom et al., 2019) and can exhibit an inverted-U shape (Aghion et al., 2005). While competition might discourage innovation by reducing the rents that reward new innovation (the business-stealing effect), it can also provide the competitive pressure that encourages innovation.

Following Degryse and Ongena (2005), we measure product market competition intensity based on the Herfindahl–Hirschman index:

$$Product\ market\ competition_{it} = 1 - \sum_{f \in \Omega_{it}} \left(\frac{Output_{fit}}{Output_{it}} \right)^2$$

The second-stage and first-stage results of 2SLS regression are reported in Table 7 and Appendix Table A2 Panel A, respectively. The results of column (1) in Table 7 show that the horizontal FDI increased product market competition significantly. The interactions between horizontal FDI and product market competition of columns (2)–(4) show that FDI inflows boost the quantity and quality of innovation through enhancing product market competition.

Firms compete not only in the product market, but also in the technology space. When there are more competing technologies in the industry, a firm potentially has a higher innovation incentive for two reasons. First, a firm's innovation may cannibalize its own existing technology, but a higher number of technologies in the industry (provided by other firms) weakens the firm's incentive to avoid the cannibalization (e.g., Jungbauer et al., 2021). Second, more competing technologies may directly pressure the firm to increase innovation in order to stay competitive. Thus we also evaluate the competition effect of FDI on innovation through its impact on technology competition.

We measure technology competition of a firm by the number of invention patents (taking the logarithm) on the market that are in the same three-digit IPC code, the same four-digit industry and the same year, weighted by the firm's invention patent counts in that year (Jungbauer et al., 2021). The second-stage results of 2SLS regression are reported in Table 8, and the first-stage estimation results are shown in Appendix Table A2 Panel B. In Table 8, the results in column (1) show that the presence of horizontal FDI does strengthen competition significantly. From columns (2)–(4), we find that the estimated coefficients of interactions between horizontal FDI and technology competition on three measures of innovation are positive and statistically significant, implying that FDI is able to stimulate innovation quantity and quality through increased technology competition.

These findings indicate that the presence of FDI in China strengthens competition, both in product market and in technology, which in turn promotes innovation. This is consistent with the existing empirical evidence suggesting that competition typically increases innovation, especially in markets with an initially low level of competition (Shu and Steinwender, 2019).

4.3.2. Horizontal knowledge spillovers

Domestic firms may benefit from the presence of FDI through the knowledge spillovers of foreign entrants. Foreign parent firms have incentives to directly transfer knowledge to their affiliates in host countries. Meanwhile, local firms may learn from foreign entrants by observing, imitating, and reverse-engineering their new products and technology. Our unique patent citation data enable us to develop a direct and novel measure of the knowledge spillovers of FDI, which allows us to directly evaluate the knowledge spillovers of FDI on the firms in the same sector.

Our patent data indicate the linkages of different patents through citations (i.e., a specific patent cites other patents or is cited by other patents), which reveals the source of knowledge. Thus, the patent citations allow us to directly measure the knowledge spillovers from FIEs to local firms. We construct metrics of knowledge spillovers based on the concept of citation network, following the methodology in the literature (Bloom et al., 2013; He, 2015; and Acemoglu et al., 2016). Specifically, we construct two variables, $\textit{Horizontal Spillover Dummy}_{fit}$ and $\textit{Horizontal Spillover Intensity}_{fit}$, to measure the horizontal knowledge spillovers. Dependent variable $\textit{Horizontal Spillover Dummy}_{fit}$ indicates whether a domestic firm cites any patent owned by FIEs, and $\textit{Horizontal Spillover Intensity}_{fit}$ indicates the ratio of citations to patents owned by FIEs to all citations. The regression results reported in columns (1) and (2) in Table 9 show that the coefficients of horizontal FDI are negative, but small in magnitude and statistically insignificant. Therefore, there is no evidence for a significant knowledge spillover effect of horizontal FDI on Chinese firms' innovation.

4.3.3. Overall effect

The combination of a positive competition effect and a negligible knowledge spillover effect within the sector explains the overall positive intra-industry effect of FDI on innovation. Intriguingly, Lu et al. (2017) demonstrate that FDI has a negative competition effect and a positive spillover effect, resulting in an overall negative intra-industry effect on Chinese firms' productivity. Possibly, more intense competition due to FDI would reduce domestic firms' revenue, and such business stealing has a stronger and more direct negative impact on productivity than on innovation. At the same time, there could be more ways for technology/knowledge transfers to affect productivity than to affect innovation. These differences might explain the different intra-industry effects of FDI on productivity and on innovation for Chinese firms.

4.4. Heterogeneity of effects

Our baseline analysis shows that inflows of FDI cause higher innovation by Chinese firms. Because firms differ in many dimensions, it is also interesting to learn whether the effect of FDI differs across firm types. We investigate the heterogeneous effects in this subsection and present the second-stage regression results of 2SLS in Table 10. The first-stage results are shown in Appendix Table A3.

Firm size. We capture firm size with a dummy variable, $Size_{fit}$, which equals 1 for large-medium sized firms (firms with more than 300 employees and 20 million-yuan sales) and otherwise 0, in accordance with the *Standards for Small and Medium-Sized Enterprises* in China. The regression results are presented in Table 10 Panel A. The coefficients of FDI are still positive and statistically significant, but the coefficients of interaction terms are negative. This suggests that the positive effects of FDI on innovation are weaker for larger firms, contrary to the prior finding that small firms lack the necessary absorptive capacity to benefit from FDI spillovers (Girma, 2005).

Ownership. Lu et al. (2017) find that the effect of FDI on productivity differs for firms with different ownership structures. To see whether this is also the case with innovation, we add the dummy variable (which equals 1 if the firm is an SOE and 0 if not), SOE_{fit}, and the interaction between SOE and fitted FDI. Table 10 Panel B shows that the impacts of FDI remain positive. The ownership of SOE has a positive and statistically significant effect on firm innovation, but it attenuates the positive effects of FDI on innovation.

Alliance. Interfirm linkages or cooperative alliances may benefit firms by helping them, for example, develop new technology, improve technical skills, and explore innovative products (Dowling and McGee, 1994; Grenadier and Weiss, 1997). We define a dummy variable, $Alliance_{fit}$, which indicates whether the firm has an alliance with foreign investment, and report the estimation results in Table 10 Panel C. We find that the impact of FDI on innovation remains positive. However, the coefficients of interaction terms are significantly negative, suggesting that alliance with foreign investment weakens the positive effect of FDI on firms' innovation. Conceivably, a domestic firm that is not partnered with FDI has a stronger desire to innovate and to be more competitive.

Technological distance. A domestic firm that is far from the technological frontier could benefit more from knowledge transfer but may also have less ability to learn. To investigate the possible role of technological distance, we follow Aghion et al. (2005) to construct the technological distance variable:

$$Technological\ distance_{fit} = (TFP\ maximum_{it} - TFP_{fit}) / TFP\ maximum_{it},$$

where TFP_{fit} is the total factor productivity (TFP) of firm f in industry i in year t, and $TFP\ maximum_{it}$ is the highest TFP level in industry i in year t, where the TFP of a firm is calculated using the method from Ackerberg et al. (2015). The regression results in Table 10 Panel D show that FDI still has a positive and significant effect on firm innovation. The coefficient of technological distance is positive, suggesting that being far from the technological frontier benefits a firm's innovation, which is consistent with findings in the literature (e.g., Haskel et al., 2007). However, the coefficients of the interaction between FDI and technological distance are negative, indicating that technological distance weakens the positive impact of FDI on innovation. Plausibly, firms closer to the technological frontier face more head-to-head competition with the FIEs and are more motivated to innovate by the competition from FIEs.

5. Robustness Analysis

In this section, we examine the robustness of our baseline regression results. In the first set of robustness tests, we add controls for several factors that might confound the relationship between FDI and innovation and address some additional empirical issues. In the second set of robustness tests, similar to Lu et al. (2017), we consider some factors that might affect FDI inflows or the change in FDI regulations.

5.1. Robustness tests – set 1

Based on the existing literature, some other factors might influence and make these results biased. To tackle these problems, we conduct some more robustness tests to bear out our findings.

Controlling for systematic changes. In DID specifications, there are potential systematic changes in the influence of controls on innovation after the switch of FDI regulations, which may coincide with the changes in FDI. To test whether our results are sensitive to this issue, we control for systematic changes in time-varying firm controls by estimating:

$$Innovation_{fit} = \alpha_0 + \delta FDI\_Industry_{it} + X'_{fit}\lambda + Post_{02} \times Controls'_{fit}\zeta + \alpha_f + \gamma_t + \varepsilon_{fit} \quad (3)$$

Specifically, we further add the interactions between the dummy of Catalogue changing time and time-varying firm controls. The results in Table 11 Panel A suggest that the positive and statistically significant effects of FDI on firm innovation quantity and quality is unlikely driven by systematic changes from DID misspecification.

Controlling for patent policy changes. Researchers have found that the increasing enforcement and protection of intellectual property rights contribute to the patent explosion in China (Hu and Jefferson, 2009; Ang et al., 2014; Fang et al., 2017). We manually collect enforcement schedule of patent protection policy of each province in China (shown in Appendix Table A4). We include a dummy indicating the period after enforcement of patent protection policy (i.e., it equals 1 after enforcement and 0 otherwise) as an additional control. The estimation results are reported in Table 11 Panel B. We find that the impact of FDI on innovation quantity and quality is still positive and statistically significant. Also, the estimated coefficients of patent protection policy indicates that the increased protection of intellectual property rights (IPRs) in China positively impacts innovation output, consistent with the findings in the literature that strengthening IPRs increases innovation in developing countries (Chen and Puttitanum, 2005).

Controlling for high-tech zones. Tian and Xu (2018) demonstrate that the establishment of national high-tech zones has a positive effect on the innovation of local firms. We collect the establishment time of high-tech zones of each city and merge it with ASIF data. Similarly, we include a dummy indicating the period after establishment of the high-tech zone for the first time (i.e., it equals 1 after enforcement and equals 0 otherwise) as an additional control. The estimation results reported in Table 11 Panel C suggest that this additional control is statistically insignificant, while the coefficients of FDI remain robust.

Controlling for subsidies. Some literature indicates that subsidies from Chinese government catalyze firms' innovation (Howell, 2017; Fang et al., 2018). To control for this potential influence, we include subsidy level (the natural logarithm of one plus the subsidies amount) as a control to isolate the effect of FDI. The estimation results reported in Table 11 Panel D show that the findings of baseline results remain robust. And results confirm the findings in the literature that the government subsidies do indeed boost firms' innovation activities.

Firm entry and exit. One might be concerned that the presence of FDI could crowd out firms with low innovation capability while increasing firms' innovation quantity and quality on average. To address this concern, we use a sample in which all firms are present during the whole sample period to eliminate the potential influence of firm entry and exit. The estimation results reported in Table 11 Panel E show that with only such firms, the effects of FDI on innovation quantity and quality are still positive and statistically significant.

Two-way clustered standard errors. The standard errors in baseline regressions are clustered at firm-level. For robustness test, we cluster the standard errors at firm and industry-year level, as our interest of regressor is an industry-level measurement and varies across years. The results in Table 11 Panel F suggest that our findings are not driven by a particular clustering level of standard errors.

5.2. Robustness tests – set 2

We conduct this set of robustness tests as in Lu et al. (2017), and the results are reported in Appendix Table A5.

Exclusion of exports. The regressor of interest for our analysis, $FDI\_Industry_{it}$ is constructed using firms' total output. This could potentially overestimate the presence of FDI, as foreign multinationals export a large portion of their output. For the robustness test, we exclude the exports in the variable construction. The estimation results are reported in Appendix Table A5 Panel A. We continue to find positive and statistically significant effects of FDI on innovation quantity and quality, with the magnitudes becoming even larger.

Composition of foreign multinationals. There are two types of FDI in China, wholly foreign-owned and joint ventures. The two forms of FDI may play different roles in affecting firm innovation in China. To address this issue, we control the percentage of wholly foreign-owned multinationals in all foreign multinationals. The estimation results are reported in Appendix Table A5 Panel B, showing that the effects of FDI on innovation remain valid.

Controlling for special economic zones. Due to policy preference or regional subsidies, the special economic zones are more likely to attract FDI. To address this issue, we control the percentage of industrial output from the special economic zones to isolate the effect of FDI. The estimation results reported in Appendix Table A5 Panel C show that the effects of FDI on the quantity and quality of firm innovation remain positive and statistically significant. However, the coefficients of additional control are all statistically insignificant.

Alternative values of determinants. We include the interactions between year dummies and determinants of treatment selection Z_{i1998} measured in 1998 to address the possible non-random selection issue. However, using the determinants measured in 1998 is somewhat arbitrary. Therefore, we also consider the determinants measured in 2002. The estimation results reported in Appendix Table A5 Panel D show that the results with the alternative measurements are consistent with the baseline results.

Nonlinearity of the first-stage outcome. The fitted value of the first-stage outcome, $\widehat{FDI\_Industry_{it}}$, ranges from 0 to 1. We set the baseline regression model as linear, and employ the 2SLS estimation. There might be a concern that this could result in bias from misspecification. To address this concern, we employ the Logit model for the first-stage estimation to predict the fitted value. The estimation results are shown in Appendix Table A5 Panel E. The results suggest that our findings of baseline regression are robust to nonlinearity of the first-stage regression.

6. The Vertical Effects of FDI on Innovation

FDI inflows may affect not only the innovation of firms within the same industry, but also the innovation of firms in the upstream or downstream industries. Javorcik (2004) demonstrates that the intra-industry effects of FDI are different from the inter-industry effect of FDI. We now turn to the vertical, or inter-industry, effects of FDI on Chinese firms.

6.1. Vertical effects of FDI

Following Javorcik (2004), we construct the domestic firm's backward FDI and forward FDI. Specifically, for domestic firm f in sector s in year t, its backward FDI, is constructed as:

$$FDI\_Sector_{st}^{backward} = \sum_{k \text{ if } k \neq s} \alpha_{sk} \times FDI\_Sector_{kt}$$

where FDI_Sector_{kt} denotes the extent of FDI in sector k and year t, α_{sk} is the proportion of sector (two-digit CIC code) s 's output supplied to sector k. Backward FDI captures the foreign presence in the sectors that are supplied by domestic firms in sector s.

The forward FDI is calculated as:

$$FDI\_Sector_{st}^{forward} = \sum_{m \text{ if } m \neq s} \beta_{sm} \times \frac{\sum_{j \in \Omega_{mt}} FDI\_Firm_{jt} \times (Output_{jt} - Export_{jt})}{\sum_{j \in \Omega_{mt}} (Output_{jt} - Export_{jt})}$$

where β_{sm} is the share of inputs purchased by sector s from sector m. $Export_{jt}$ is firm j's export in year t; $Output_{jt} - Export_{jt}$ is the size of firm j's output for the domestic market. Forward FDI is a measure of the presence of FDI in upstream industries of sector s. Note that as only the intermediate inputs sold in domestic markets are relevant, the exports are excluded. The values of α_{sk} and β_{sm} are both taken from the 2002 input–output table. The instruments for $FDI\_Sector_{st}^{backward}$ and $FDI\_Sector_{st}^{forward}$ are $\sum_{k \text{ if } k \neq s} \alpha_{sk} \times Treatment_k \times Post02_t$ and $\sum_{m \text{ if } m \neq s} \beta_{sm} \times Treatment_m \times Post02_t$, respectively.

The second-stage results of the 2SLS estimation are shown in Table 12 (The results of the first stage are reported in Appendix Table A6). The estimated coefficients in column (1) show that the effect of FDI on the number of all patents within the same sector remain significantly positive, consistent with our earlier finding. For the effects of vertical FDI, backward FDI shows a positive and statistically significant effect on the number of all patents, while forward FDI shows a negative and statistically significant effect. In column (2), we find the similar effects of horizontal and vertical FDI on the number of invention patents, though the effect of forward FDI is not statistically significant. In column (3), we also find that both the horizontal FDI and backward FDI have a positive and statistically significant effect on the number of patent citations, while the forward FDI has a negative and statistically significant effect.

These results consistently show that the presence of FDI in the downstream sectors has positive effects on the innovation of upstream firms, which might take place through the backward linkages (i.e., contacts between foreign invested enterprises and local suppliers). Yet, the presence of FDI in the upstream sectors exerts negative effects on firms' innovation, though the impact of forward FDI on the number of invention patents is insignificant. Next we examine potential backward and forward knowledge spillovers that may explain these vertical effects.

6.2. Explaining the vertical effects: vertical knowledge spillovers

There might be backward knowledge spillovers through contacts between foreign entrants and their local suppliers in the upstream industries or forward knowledge transfers through contacts between foreign entrants and their local buyers in the downstream industries. To explore these possibilities, similar to the metrics of horizontal knowledge spillovers, we construct variables to measure backward and forward knowledge spillovers. Dependent variable $\textit{Backward Spillover Dummy}_{fit}$ indicates whether a firm in industry i cites the patent owned by firms from the downstream industries, and $\textit{Backward Spillover Intensity}_{fit}$ indicates the ratio of citations citing patents from downstream firms to all citations. Similarly constructed are the $\textit{Forward Spillover Dummy}_{fit}$ and the $\textit{Forward Spillover Intensity}_{fit}$. Columns (1) and (2) in Table 13 show positive and statistically significant knowledge spillovers from a downstream sector to its upstream domestic suppliers. This provides a plausible explanation for the positive effect of backward FDI on innovation.

In columns (3) and (4), the coefficients of forward FDI are insignificant, though positive, suggesting a negligible knowledge spillover from foreign investment to domestic firms in the downstream industries. The presence of FDI in the upstream industries is likely to exert opposing effects on downstream firms' innovations. On the one hand, upstream FIEs provide intermediate goods of more variety and higher quality at lower costs. This can reduce the pressure for downstream firms to innovate. On the other hand, downstream firms may benefit from upstream foreign suppliers by learning the technology embedded in the intermediate goods supplied by foreign investors. This type of knowledge spillover could promote the innovation of downstream firms. However, because we find no significant knowledge spillovers of forward FDI, it appears that the negative impact of forward FDI on innovation is due to the weakened incentive for the downstream firms to innovate when they could do well from the improvement of input supply even without innovation. Interestingly, Liu and Qiu (2016) also find that the inflows of intermediate goods with high quantity and quality reduce firms' innovation in China. Notice that cheaper/better inputs from upstream foreign suppliers may have different impacts on productivity and innovation. The availability of high-quality inputs can clearly raise productivity, but it may reduce innovation incentives. This might explain the difference between our finding of the negative effect of forward FDI on innovation and the positive effect of forward FDI on TFP in Lu et al. (2017).

7. Conclusion

This paper has studied the impact of foreign direct investment inflows on the innovation of Chinese firms. Our analysis uses more comprehensive measures of innovation quantity and quality than those used in the literature and adopts a research design that enables us to identify the causal impact of FDI on innovation. We find that FDI has positive intra-industry effects on firms' innovation in China and show that the positive effects are due to increased competition instead of knowledge spillover from FDI. We also find that FDI positively impacts innovation in upstream industries through backward vertical knowledge spillovers.

The conventional wisdom is that knowledge spillovers from FDI facilitate the technological upgrading of firms in a developing country. Surprisingly, we find no significant positive effect on innovation from intra-industry knowledge spillover. This is in contrast to the result stated in the literature that FDI has a positive knowledge spillover effect on productivity. On the other hand, we find that FDI inflows intensify competition, and the increased competitive pressure leads to more innovation by domestic firms, contrary to findings in the literature that FDI has a negative competition effect on firm productivity. These results suggest that the effects of FDI on host-country firms are subtle, being rather different for innovation and for productivity.

Innovation is a key driver of economic growth and prosperity. As developing countries raise technological capabilities and income levels, they will increasingly rely on innovation to achieve sustained economic growth and development. Many developing countries suffer from severe market imperfections and the lack of effective market competition. A broad lesson for developing countries from the experience in China is that attracting foreign direct investment and creating a competitive market environment can play complementary roles in promoting innovation.

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Figures and Tables

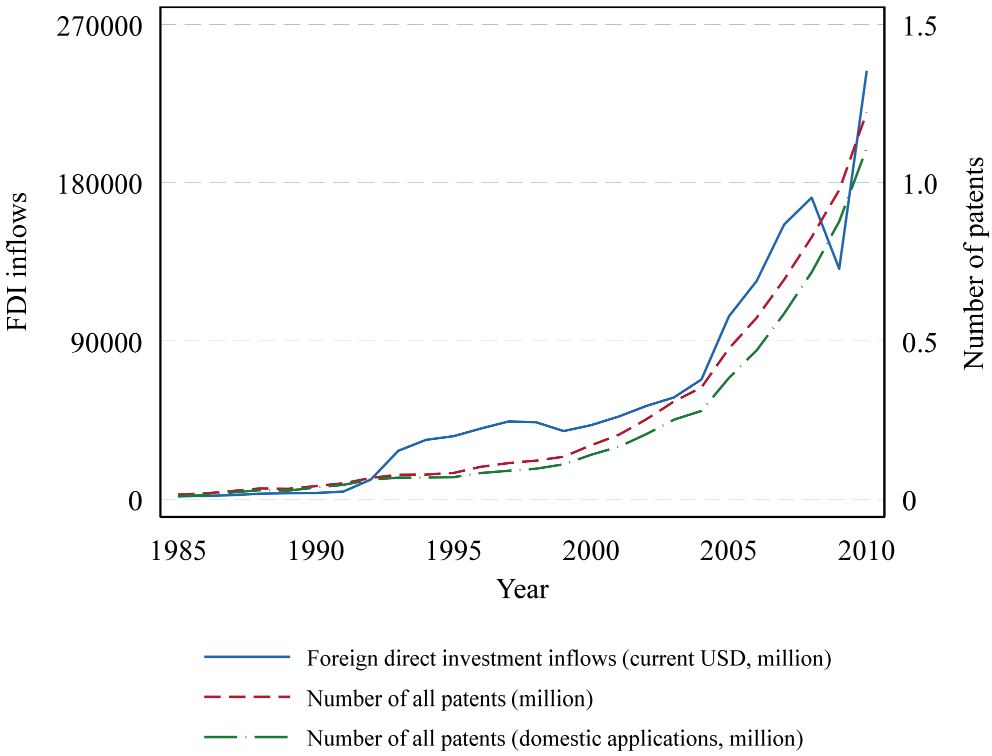

Figure 1 FDI and domestic patents (1985-2010)

Data resource: FDI from World Development Indicators Database. Number of patents recorded from China National Intellectual Property Administration Yearly Statistics.

Table 1 Summary statistics

Firm-level variables	Observations	Mean	Standard Deviation
Output	1,256,810	72.502	587.365
Capital–labor ratio	1,256, 810	56.551	194.850
Exporter status	1,256, 810	0.206	0.404
SOE status	1,256, 810	0.087	0.281
Number of all patents	1,256, 810	0.214	10.869
Number of invention patents	1,256, 810	0.064	9.347
Number of citations	1,256, 810	0.228	30.838
Generality	1,256, 810	0.021	0.117
Originality	1,256, 810	0.021	0.114
Scaled number of all patents	1,256, 810	0.055	1.398
Scaled number of invention patents	1,256, 810	0.014	0.789
Scaled number of citations	1,256, 810	0.070	9.926
Scaled generality	1,256, 810	0.037	0.352
Scaled originality	1,256, 810	0.035	0.317

Table 2 Innovation quantity – all patents

Model	2SLS	2SLS	2SLS	Poisson	Reduced-form	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Second-stage estimation. Dependent variable:	Log Allpatent	Log Allpatent	Log Allpatent	Allpatent		
FDI industry (instrumented)	0.041***	0.038***	0.030***	1.385**		
	(0.008)	(0.009)	(0.009)	(0.629)		
Panel B. First-stage estimation. Dependent variable:	FDI industry	FDI industry	FDI industry	FDI industry		
Treatment × Post02	0.184***	0.164***	0.164***	0.164***		
	(0.005)	(0.005)	(0.005)	(0.005)		
Cragg-Donald Wald F-statistic	2700.857	2134.102	2131.760	2131.760		
Kleibergen-Paap Wald F-statistic	1669.369	1301.328	1298.858	1298.858		
Panel C. Reduced-form and OLS estimation. Dependent variable:					Log Allpatent	Log Allpatent
Treatment × Post02					0.005***	
					(0.002)	
FDI industry						-0.0004
						(0.0005)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
FDI determinants × year dummies	Yes	Yes	Yes	Yes	Yes	Yes
SOE privatization × year dummies	No	Yes	Yes	Yes	Yes	Yes
Time-varying firm controls	No	No	Yes	Yes	Yes	Yes
Observations	1,256,810	1,256,810	1,256,810	1,256,810	1,256,810	1,256,810

Note: A constant term is included but not reported. Robust standard errors in parentheses are clustered by firm. Determinants of changes in FDI regulations include new product intensity, number of firms, and average age of firms at the four-digit industry level in 1998. Time-varying firm controls include firm output, export status, capital-labor ratio, and SOE dummy. ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 3 Innovation quantity – three categories of patent

Model	2SLS	Poisson	2SLS	Poisson	2SLS	Poisson
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Log Invention	Invention	Log Utility	Utility	Log Design	Design
FDI industry (instrumented)	0.035***	1.782***	-0.006	0.408	0.001	1.359
	(0.005)	(0.558)	(0.006)	(0.513)	(0.006)	(1.075)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
FDI determinants × year dummies	Yes	Yes	Yes	Yes	Yes	Yes
SOE privatization × year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,256,810	1,256,810	1,256,810	1,256,810	1,256,810	1,256,810

Note: A constant term is included but not reported. Robust standard errors in parentheses are clustered by firm. Determinants of changes in FDI regulations include new product intensity, number of firms, and average age of firms at the four-digit industry level in 1998. Time-varying firm controls include firm output, export status, capital-labor ratio, and SOE dummy. ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 4 Innovation quality

Model	2SLS	Poisson	2SLS	Poisson	2SLS	Poisson
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Log Citation	Citation	Log Generality	Generality	Log Originality	Originality
FDI industry (instrumented)	0.048***	1.420**	0.022***	0.314*	0.023***	0.366**
	(0.008)	(0.575)	(0.005)	(0.177)	(0.005)	(0.180)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
FDI determinants × year dummies	Yes	Yes	Yes	Yes	Yes	Yes
SOE privatization × year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,256,810	1,256,810	1,256,810	1,256,810	1,256,810	1,256,810

Note: A constant term is included but not reported. Robust standard errors in parentheses are clustered by firm. Determinants of changes in FDI regulations include new product intensity, number of firms, and average age of firms at the four-digit industry level in 1998. Time-varying firm controls include firm output, export status, capital-labor ratio, and SOE dummy. ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 5 Scaled index

Model	2SLS						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	Log Scaled Allpatent	Log Scaled Invention	Log Scaled Utility	Log Scaled Design	Log Scaled Citation	Log Scaled Generality	Log Scaled Originality
FDI industry (instrumented)	0.012**	0.017***	-0.005	-0.001	0.032***	0.019***	0.022***
	(0.005)	(0.003)	(0.004)	(0.003)	(0.005)	(0.005)	(0.005)
Model	Poisson						
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Dependent variable:	Scaled Allpatents	Scaled Invention	Scaled Utility	Scaled Design	Scaled Citation	Scaled Generality	Scaled Originality
FDI industry (instrumented)	1.207**	1.677***	0.418	1.011	1.550***	0.082	0.102
	(0.519)	(0.396)	(0.468)	(0.772)	(0.518)	(0.287)	(0.293)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FDI determinants × year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SOE privatization × year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,256,810	1,256,810	1,256,810	1,256,810	1,256,810	1,256,810	1,256,810

Note: A constant term is included but not reported. Robust standard errors in parentheses are clustered by firm. Determinants of changes in FDI regulations include new product intensity, number of firms, and average age of firms at the four-digit industry level in 1998. Time-varying firm controls include firm output, export status, capital-labor ratio, and SOE dummy. ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 6 Radical innovation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Dependent variable:	Tail patents (99%)	Tail patents (95%)	Generality of the best patent	Originality of the best patent	Breakthrough patent (top 5%)	Breakthrough patent (top 10%)	New technology (one-digit)	New technology (three-digit)
FDI industry (instrumented)	0.013***	0.014***	0.013***	0.016***	0.003**	0.005***	0.018***	0.020***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)	(0.003)	(0.004)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FDI determinants × year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SOE privatization × year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,256,810	1,256,810	1,256,810	1,256,810	1,256,810	1,256,810	1,256,810	1,256,810

Note: A constant term is included but not reported. Robust standard errors in parentheses are clustered by firm. Determinants of changes in FDI regulations include new product intensity, number of firms, and average age of firms at the four-digit industry level in 1998. Time-varying firm controls include firm output, export status, capital-labor ratio, and SOE dummy. ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 7 Product market competition effect

	(1)	(2)	(3)	(4)
Dependent variable:	Product market competition	Log Allpatent	Log Invention	Log Citation
FDI industry (instrumented)	0.008***	-0.044***	-0.008	-0.025*
	(0.001)	(0.015)	(0.008)	(0.013)
Product market competition		-0.043	0.043**	0.042
		(0.040)	(0.021)	(0.034)
FDI industry × Product market competition (instrumented)		0.077***	0.045***	0.076***
		(0.017)	(0.010)	(0.015)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
FDI determinants × year dummies	Yes	Yes	Yes	Yes
SOE privatization × year dummies	Yes	Yes	Yes	Yes
Time-varying firm controls	Yes	Yes	Yes	Yes
Observations	1,256,810	1,256,810	1,256,810	1,256,810

Note: The interaction term between industry-level FDI and product market competition is instrumented with the interaction between FDI regulation change and product market competition. A constant term is included but not reported. Robust standard errors in parentheses are clustered by firm. Determinants of changes in FDI regulations include new product intensity, number of firms, and average age of firms at the four-digit industry level in 1998. Time-varying firm controls include firm output, export status, capital-labor ratio, and SOE dummy. ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 8 Technology market competition effect

	(1)	(2)	(3)	(4)
Dependent variable:	Technology market competition	Log Allpatent	Log Invention	Log Citation
FDI industry (instrumented)	0.159***	0.070*	0.061*	0.116*
	(0.010)	(0.041)	(0.031)	(0.062)
Technology market competition		-1.243**	-0.941**	-1.955**
		(0.529)	(0.415)	(0.813)
FDI industry × Technology market competition (instrumented)		2.305***	1.808***	3.544***
		(0.723)	(0.567)	(1.110)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
FDI determinants × year dummies	Yes	Yes	Yes	Yes
SOE privatization × year dummies	Yes	Yes	Yes	Yes
Time-varying firm controls	Yes	Yes	Yes	Yes
Observations	1,256,810	1,256,810	1,256,810	1,256,810

Note: The interaction term between industry-level FDI and technology market competition is instrumented with the interaction between FDI regulation change and technology market competition. A constant term is included but not reported. Robust standard errors in parentheses are clustered by firm. Determinants of changes in FDI regulations include new product intensity, number of firms, and average age of firms at the four-digit industry level in 1998. Time-varying firm controls include firm output, export status, capital-labor ratio, and SOE dummy. ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 9 Horizontal spillover effect

	(1)	(2)
Dependent variable:	Horizontal Spillover Dummy	Horizontal Spillover Intensity
FDI industry (instrumented)	-0.00055	-0.00019
	(0.00066)	(0.00043)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
FDI determinants × year dummies	Yes	Yes
SOE privatization × year dummies	Yes	Yes
Time-varying firm controls	Yes	Yes
Observations	1,256,810	1,256,810

Note: A constant term is included but not reported. Robust standard errors in parentheses are clustered by firm. Determinants of changes in FDI regulations include new product intensity, number of firms, and average age of firms at the four-digit industry level in 1998. Time-varying firm controls include firm output, export status, capital-labor ratio, and SOE dummy. ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 10 Heterogeneity effects

Dependent variable:	Log Allpatent	Log Invention	Log Citation
Panel A. Firm size	(1)	(2)	(3)
FDI industry (instrumented)	0.078***	0.068***	0.092***
	(0.012)	(0.007)	(0.012)
Size	0.250***	0.166***	0.226***
	(0.022)	(0.013)	(0.021)
FDI industry × Size (instrumented)	-0.252***	-0.176***	-0.238***
	(0.024)	(0.014)	(0.022)
Observations		1,256,810	
Panel B. SOE	(1)	(2)	(3)
FDI industry (instrumented)	0.035***	0.040***	0.057***
	(0.010)	(0.005)	(0.009)
SOE	0.053*	0.062***	0.110***
	(0.030)	(0.017)	(0.029)
FDI industry × SOE (instrumented)	-0.072**	-0.077***	-0.137***
	(0.035)	(0.020)	(0.034)
Observations		1,256,810	
Panel C. Alliance with foreign capital	(1)	(2)	(3)
FDI industry (instrumented)	0.035***	0.040***	0.054***
	(0.010)	(0.005)	(0.009)
Alliance	0.119**	0.124***	0.168***
	(0.058)	(0.038)	(0.060)
FDI industry × Alliance (instrumented)	-0.097**	-0.101***	-0.135***
	(0.044)	(0.028)	(0.045)
Observations		1,256,810	
Panel D. Technological distance	(1)	(2)	(3)
FDI industry (instrumented)	0.055***	0.073***	0.095***
	(0.016)	(0.010)	(0.016)
Technological distance	0.046**	0.081***	0.100***
	(0.021)	(0.014)	(0.023)
FDI industry × Technological distance (instrumented)	-0.065**	-0.119***	-0.146***
	(0.032)	(0.022)	(0.035)
Observations		1,206,400	
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
FDI determinants × year dummies	Yes	Yes	Yes
SOE privatization × year dummies	Yes	Yes	Yes
Time-varying firm controls	Yes	Yes	Yes

Note: The interaction term in each panel is instrumented with the interaction between FDI regulation change and the corresponding firm's characteristic. A constant term is included but not reported. Robust standard errors in parentheses are clustered by firm. Determinants of changes in FDI regulations include new product intensity, number of firms, and average age of firms at the four-digit industry level in 1998. Time-varying firm controls include firm output, export status, capital-labor ratio, and SOE dummy. ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 11 Robustness tests

Dependent variable	Log Allpatent	Log Invention	Log Citation
Panel A: Control for systematic changes	(1)	(2)	(3)
FDI industry (instrumented)	0.040***	0.039***	0.055***
	(0.010)	(0.005)	(0.009)
Cragg-Donald Wald F-statistic		2131.760	
Kleibergen-Paap Wald F-statistic		1298.858	
Observations		1,256,810	
Panel B: Control for PPP	(1)	(2)	(3)
FDI industry (instrumented)	0.030***	0.035***	0.048***
	(0.009)	(0.005)	(0.008)
PPP	0.016***	0.007***	0.011***
	(0.002)	(0.001)	(0.001)
Cragg-Donald Wald F-statistic		2131.547	
Kleibergen-Paap Wald F-statistic		1298.761	
Observations		1,256,810	
Panel C: Control for high-tech zones	(1)	(2)	(3)
FDI industry (instrumented)	0.030***	0.035***	0.048***
	(0.009)	(0.005)	(0.008)
HTZ	0.012	-0.005	-0.007
	(0.017)	(0.011)	(0.016)
Cragg-Donald Wald F-statistic		2131.859	
Kleibergen-Paap Wald F-statistic		1299.320	
Observations		1,256,810	
Panel D: Control for subsidies	(1)	(2)	(3)
FDI industry (instrumented)	0.029***	0.034***	0.047***
	(0.009)	(0.005)	(0.008)
Subsidies	0.003***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)
Cragg-Donald Wald F-statistic		2126.801	
Kleibergen-Paap Wald F-statistic		1295.425	
Observations		1,255,792	
Panel E: Sample of long-standing firms	(1)	(2)	(3)
FDI industry (instrumented)	0.036***	0.051***	0.077***
	(0.014)	(0.007)	(0.013)
Cragg-Donald Wald F-statistic		935.702	
Kleibergen-Paap Wald F-statistic		798.342	
Observations		179,804	
Panel F: Two-way clustered standard errors	(1)	(2)	(3)
FDI industry (instrumented)	0.030**	0.035***	0.048***
	(0.013)	(0.009)	(0.013)
Observations		1,256,810	
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
FDI determinants × year dummies	Yes	Yes	Yes
SOE privatization × year dummies	Yes	Yes	Yes
Time-varying firm controls	Yes	Yes	Yes

Note: A constant term is included but not reported. Robust standard errors in parentheses are clustered by firm. Determinants of changes in FDI regulations include new product intensity, number of firms, and average age of firms at the four-digit industry level in 1998. Time-varying firm controls include firm output, export status, capital-labor ratio, and SOE dummy. ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 12 Horizontal FDI and vertical FDI

	(1)	(2)	(3)
	2SLS	2SLS	2SLS
Dependent variable:	Log Allpatent	Log Invention	Log Citation
FDI industry (instrumented)	0.023^{***}	0.041^{***}	0.052^{***}
	(0.005)	(0.003)	(0.005)
Backward FDI (instrumented)	0.001^{***}	0.0003^{***}	0.001^{***}
	(0.000)	(0.0001)	(0.000)
Forward FDI (instrumented)	-0.099^{***}	-0.019	-0.038^{*}
	(0.026)	(0.012)	(0.019)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
FDI determinants × year dummies	Yes	Yes	Yes
SOE privatization × year dummies	Yes	Yes	Yes
Time-varying firm controls	Yes	Yes	Yes
Observations	1,256,810	1,256,810	1,256,810

Note: A constant term is included but not reported. Robust standard errors in parentheses are clustered by firm. Determinants of changes in FDI regulations include new product intensity, number of firms, and average age of firms at the four-digit industry level in 1998. Time-varying firm controls include firm output, export status, capital-labor ratio, and SOE dummy. ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 13 Vertical spillover effect

	(1)	(2)	(3)	(4)
Dependent variable:	Backward Spillover Dummy	Backward Spillover Intensity	Forward Spillover Dummy	Forward Spillover Intensity
Backward FDI (instrumented)	0.00001**	0.00006***		
	(0.00000)	(0.00001)		
Forward FDI (instrumented)			0.00015	0.00012
			(0.00055)	(0.00041)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
FDI determinants × year dummies	Yes	Yes	Yes	Yes
SOE privatization × year dummies	Yes	Yes	Yes	Yes
Time-varying firm controls	Yes	Yes	Yes	Yes
Observations	1,256,810	1,256,810	1,256,810	1,256,810

Note: A constant term is included but not reported. Robust standard errors in parentheses are clustered by firm. Determinants of changes in FDI regulations include new product intensity, number of firms, and average age of firms at the four-digit industry level in 1998. Time-varying firm controls include firm output, export status, capital-labor ratio, and SOE dummy. ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively.

Appendix A

Table A1 Determinants of changes in FDI regulations (industry level)

	(1)	(2)	(3)	(4)
Dependent variable:	Changes in FDI regulations	Changes in FDI regulations	Changes in FDI regulations	Changes in FDI regulations
New product intensity	1.684***	1.678***	1.542***	1.585***
	(0.311)	(0.330)	(0.345)	(0.339)
Export intensity	-0.039	-0.038	-0.004	-0.013
	(0.184)	(0.184)	(0.183)	(0.183)
Number of firms	0.0002**	0.0002**	0.0002**	0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Ellison-Glaeser index	0.316	0.315	0.302	0.288
	(0.256)	(0.256)	(0.251)	(0.255)
Average age of firms	-0.004**	-0.004**	-0.004**	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
Log average employment	0.061	0.061	0.046	0.053
	(0.048)	(0.048)	(0.049)	(0.048)
Log average wage per worker	-0.051	-0.051	-0.067	-0.070
	(0.118)	(0.118)	(0.115)	(0.115)
Number of all patents		0.006		
		(0.070)		
Number of invention patents			2.521	
			(1.749)	
Number of citations				0.727
				(0.575)
Constant	-0.014	-0.014	0.084	0.055
	(0.344)	(0.345)	(0.342)	(0.339)
R^2	0.112	0.112	0.119	0.116
Observations	422	422	422	422

Note: Observations are at the four-digit industry level. Robust standard errors in parentheses are clustered by industry. ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively.

Table A2 Competition effects – first-stage estimation results

Panel A. Product market competition	(1)	(2)
Dependent variable:	FDI industry	FDI industry × Product market competition
Treatment × Post02	2.503***	-0.065
	(0.304)	(0.156)
Treatment × Post02 × Product market competition	-2.386***	0.228
	(0.309)	(0.159)
Cragg-Donald Wald F-statistic	1190.190	
Kleibergen-Paap Wald F-statistic	766.933	
Observations	1,256,810	
Panel B. Technology market competition	(1)	(2)
Dependent variable:	FDI industry	FDI industry × Technology market competition
Treatment × Post02	0.164***	-0.003
	(0.005)	(0.002)
Treatment × Post02 × Technology market competition	-0.011*	-0.100***
	(0.006)	(0.031)
Cragg-Donald Wald F-statistic	974.426	
Kleibergen-Paap Wald F-statistic	37.464	
Observations	1,256,810	
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
FDI determinants × year dummies	Yes	Yes
SOE privatization × year dummies	Yes	Yes
Time-varying firm controls	Yes	Yes

Note: A constant term is included but not reported. Robust standard errors in parentheses are clustered by firm. Determinants of changes in FDI regulations include new product intensity, number of firms, and average age of firms at the four-digit industry level in 1998. Time-varying firm controls include firm output, export status, capital-labor ratio, and SOE dummy. ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively.

Table A3 Heterogeneity – first-stage estimation results

Panel A. Firm size	(1)	(2)
Dependent variable:	FDI industry	FDI industry × Size
Treatment × Post02	0.169***	0.066***
	(0.005)	(0.002)
Treatment × Post02 × Size	-0.026***	-0.172***
	(0.007)	(0.007)
Cragg-Donald Wald F-statistic	1058.060	
Kleibergen-Paap Wald F-statistic	666.939	
Observations	1,256,810	
Panel B. SOE	(1)	(2)
Dependent variable:	FDI industry	FDI industry × SOE
Treatment × Post02	0.164***	0.025***
	(0.005)	(0.001)
Treatment × Post02 × SOE	-0.004	-0.142***
	(0.011)	(0.011)
Cragg-Donald Wald F-statistic	1007.450	
Kleibergen-Paap Wald F-statistic	508.890	
Observations	1,256,810	
Panel C. Alliance	(1)	(2)
Dependent variable:	FDI industry	FDI industry × Alliance
Treatment × Post02	0.165***	0.013***
	(0.005)	(0.001)
Treatment × Post02 × Alliance	-0.123***	-0.304***
	(0.028)	(0.028)
Cragg-Donald Wald F-statistic	1032.861	
Kleibergen-Paap Wald F-statistic	643.280	
Observations	1,256,810	
Panel D. Technological distance	(1)	(2)
Dependent variable:	FDI industry	FDI industry × Technological distance
Treatment × Post02	0.240***	0.140***
	(0.007)	(0.006)
Treatment × Post02 × Technological distance	-0.201***	-0.238***
	(0.013)	(0.017)
Cragg-Donald Wald F-statistic	978.453	
Kleibergen-Paap Wald F-statistic	583.367	
Observations	1,206,400	
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
FDI determinants × year dummies	Yes	Yes
SOE privatization × year dummies	Yes	Yes
Time-varying firm controls	Yes	Yes

Note: A constant term is included but not reported. Robust standard errors in parentheses are clustered by firm. Determinants of changes in FDI regulations include new product intensity, number of firms, and average age of firms at the four-digit industry level in 1998. Time-varying firm controls include firm output, export status, capital-labor ratio, and SOE dummy. ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively.

Table A4 Patent protection policy

Year	Province
1996	Guangdong
1997	Hebei, Sichuan
1998	Shandong, Hubei, Anhui
1999	Liaoning, Zhejiang, Guangxi
2001	Henan, Hunan
2002	Shanxi, Shanghai
2003	Ningxia, Guizhou
2004	Shaanxi, Gansu, Heilongjiang, Yunnan, Fujian, Xinjiang
2005	Beijing
2007	Chongqing
After 2007	Jiangsu, Jiangxi, Qinghai, Tianjin
No policy	Jilin, Neimenggu, Hainan, Xizang

Table A5 Robustness tests

Dependent variable	Log Allpatent	Log Invention	Log Citation
Panel A: Exclusion of exports	(1)	(2)	(3)
FDI industry (instrumented)	0.035***	0.040***	0.055***
	(0.010)	(0.006)	(0.010)
Cragg-Donald Wald F-statistic		2669.402	
Kleibergen-Paap Wald F-statistic		1398.350	
Observations		1,256,810	
Panel B: Composition of foreign multinationals	(1)	(2)	(3)
FDI industry (instrumented)	0.032***	0.037***	0.051***
	(0.010)	(0.005)	(0.009)
Share of wholly-owned FIE	0.005	0.012***	0.017***
	(0.007)	(0.004)	(0.006)
Cragg-Donald Wald F-statistic		1849.425	
Kleibergen-Paap Wald F-statistic		1123.241	
Observations		1,255,799	
Panel C: Control for special economic zones	(1)	(2)	(3)
FDI industry (instrumented)	0.036***	0.035***	0.047***
	(0.009)	(0.005)	(0.008)
Share of output of SEZ	0.013	0.003	0.002
	(0.018)	(0.009)	(0.015)
Cragg-Donald Wald F-statistic		2540.151	
Kleibergen-Paap Wald F-statistic		1390.949	
Observations		1,123,952	
Panel D: Alternative values of determinants	(1)	(2)	(3)
FDI industry (instrumented)	0.018**	0.029***	0.038***
	(0.009)	(0.005)	(0.008)
Cragg-Donald Wald F-statistic		2437.048	
Kleibergen-Paap Wald F-statistic		1618.218	
Observations		1,256,810	
Panel E: Nonlinearity of first-stage estimation	(1)	(2)	(3)
FDI industry (instrumented)	0.006***	0.003***	0.005***
	(0.001)	(0.000)	(0.001)
Observations		1,256,810	
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
FDI determinants × year dummies	Yes	Yes	Yes
SOE privatization × year dummies	Yes	Yes	Yes
Time-varying firm controls	Yes	Yes	Yes

Note: A constant term is included but not reported. Robust standard errors in parentheses are clustered by firm. Determinants of changes in FDI regulations include new product intensity, number of firms, and average age of firms at the four-digit industry level in 1998. Time-varying firm controls include firm output, export status, capital-labor ratio, and SOE dummy. ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively.

Table A6 Horizontal and vertical FDI – first-stage estimation results

Horizontal and vertical FDI	(1)	(2)	(3)
	Horizontal FDI	Backward FDI	Forward FDI
Treatment × Post02	0.708***	-0.074	-0.039***
	(0.007)	(0.070)	(0.001)
α × Treatment × Post02	0.006***	-0.823***	-0.001***
	(0.000)	(0.013)	(0.000)
β × Treatment × Post02	-0.095***	-0.989***	-0.174***
	(0.006)	(0.097)	(0.002)
Cragg-Donald Wald F-statistic		8675.223	
Kleibergen-Paap Wald F-statistic		3324.412	
Observations		1,256,810	
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
FDI determinants × year dummies	Yes	Yes	Yes
SOE privatization × year dummies	Yes	Yes	Yes
Time-varying firm controls	Yes	Yes	Yes

Note: A constant term is included but not reported. Robust standard errors in parentheses are clustered by firm. Determinants of changes in FDI regulations include new product intensity, number of firms, and average age of firms at the four-digit industry level in 1998. Time-varying firm controls include firm output, export status, capital-labor ratio, and SOE dummy. ***, ** and * denote significance at the 1%, 5%, and 10% level, respectively.

Appendix B

Based on the matching methodology put forward by He et al. (2018), our matching project steps are as followings:

Step1. Extracting patent data

In order to improve matching efficiency, we remove patents with the following characteristics: (1) Patents with application date outside the period of 1998-2007; (2) Patents assigned to individuals; (3) Patents assigned to foreign firms with an address in a foreign country.

Step2. Get full name

A set of pre-processing routines are implemented to deal with patent assignee names and ASIF firm names to get standardize “full name”:

(1) Trim all symbols and punctuation marks that are not letters, characters, or numbers. These include hyphen, parentheses, apostrophe, comma, bar mark, etc. We remove both half-width and full-width symbols such as & and ＆, and both half-width and full-width punctuation marks such as ? and ？.

(2) Convert all full-width letters into half-width ones. For example, convert Ｂ into B, Ｃ into C.

(3) Convert Chinese numbers into Arabic numbers. Specifically, convert (０，１，２，…，９) and (零或〇, 一, 二, …, 九) into (0, 1, 2, …, 9).

Step3. Get short name

Remove various designators of corporate form to obtain the so-called “short names”. A set of such designators is the so-called stemming list, which includes: (1) Affix words: 股份有限责任公司, 股份有限公司, 有限责任公司, 独立行政法人, 有限总公司, 有限分公司, 总公司, 分公司, 董事会, 集团, 有限公司, 有限责任, 株式会社, 公司, 股份, 企业, 工厂, 厂; (2) Address words: 省, 市, 自治区, 县, 镇, 乡, 村.

Step4. Exact matching

(1) Exact matching based on full name. We consider it is an exact matching pair if the full name of ASIF firm and the full name of patent assignee are identified a pair of the identical full name.

(2) Exact matching based on the short name. Similarly, we consider it is an exact matching pair if the short name of ASIF firm and the short name of patent assignee are identified a pair of the identical short name. However, in this case, some pairs are not exactly the same. We manually check each pair of exact matching based on the short name after automatically computing matching to confirm whether it is a pair of identical firms. For example, we regard 东风汽车股份有限公司 and 东风汽车公司 are the identical firm, while 安阳县钢铁厂 and 安阳钢铁集团有限责任公司 are not the identical firm although they have the identical short name.

Step5. Approximate matching

Our approximate matching divides the rest observations into two samples:

(1) Name containing sample: short name of ASIF firm contains the short name of patent assignee, or short name of patent assignee contains the short name of ASIF firm. It is more likely to find an identical pair in this sample. We manually check these observations to identify pairs of identical firms. For example, 江苏好孩子集团 and 好孩子集团 are regarded as the same firm.

(2) Name not containing sample: To conduct this work, we adopt the Levenshtein method. Levenshtein distance (Levenshtein, 1966)[1] solves the following problem: given two names, how to convert one name into the other with the minimum cost of a sequence of editing steps including character insertion, character deletion, character substitution, and transposition of two adjacent characters, each of which has a nonnegative cost. To calculate the Levenshtein distance, one has to assign a cost to each edit operation. Based on the Levenshtein distance, we define the Levenshtein similarity between two names X and Y as follows:

$$Name\ Similarity = 1 - Levenshtein\ Distance = 1 - d / \left(N_x + N_y\right)$$

where d is the number of edits needed to transform one name into the other, N_x is the length of name X, and N_y is the length of name Y.

[1] Levenshtein, V. I., 1966. Binary Codes Capable of Correcting Deletions, Insertions, and Reversals. In *Soviet Physics Doklady*, 10(8), 707-710.

We set the threshold at 0.75 based on prior work. Towards this part of observations, we carry out manual checks to identify pairs of identical firms. In total, 476,942 patents are matched up to ASIF data. Detailed specification is in Appendix Table B1.

Table B1 Matching result

Year	Invention	Utility	Design	Total
1998	741	3,275	5,645	9,661
1999	1,112	4,344	7,606	13,062
2000	1,785	5,482	8,891	16,158
2001	2,876	7,021	10,145	20,042
2002	6,691	10,510	13,664	30,865
2003	11,679	14,342	15,114	41,135
2004	16,752	18,979	21,714	57,445
2005	23,853	23,092	25,277	72,222
2006	33,797	30,832	31,184	95,813
2007	44,992	39,603	35,944	120,539
Total	144,278	157,480	175,184	476,942

Appendix C

First, we compare the 1997 and 2002 versions of the Catalogue for the Guidance of Foreign Investment Industries. According to the changes in the FDI policies for each product. we classify each product into one of four possible outcomes:

(1) FDI became more welcome. For example, fruit and vegetable beverage, protein beverage, and coffee beverage were listed in the supported category in 2002, while in the permitted category in 1997. We designate these products as FDI encouraged products.

(2) FDI became less welcome. For example, Hepatitis B diagnostic reagent, and Hepatitis C diagnostic reagent were listed in the permitted category in 2002, while in the encouraged category in 1997. We designate these products as FDI discourage products.

(3) No change in FDI regulation. For example, styrene butadiene rubber was listed in the permitted category in both 1997 and 2002. We designate this product as the FDI no change product.

Second, we aggregate the changes in FDI regulations from the product level to the industry level. It is worth noting that the product classifications of the Catalogue are generally more disaggregated than the four-digit CIC industry classifications. Thus, two or more products from the Catalogue may be sorted into the same four-digit CIC industry. According to this aggregation process, all the four-digit CIC industries are classified into four categories:

(1) FDI encouraged industry. For all the possible Catalogue products in a four-digit CIC industry, there was either an improvement in FDI regulations or no change in FDI regulations. For example, two products tea beverage (CIC sub-code: 15390100) and coffee beverage (CIC sub-code: 15399901) in Tea and Other Beverages Manufacturing Industry (CIC code: 1539) experienced an improvement in FDI regulations (listed in the supported category in 2002, while in the permitted category in 1997), and there was no change in FDI regulations for other products in this industry. We designate Tea and Other Beverages Manufacturing Industry as an FDI encouraged industry.

(2) FDI discouraged industry. For all of the possible Catalogue products in a four-digit CIC industry, there was either a deterioration in FDI regulations or no change in FDI regulations. For example, two products monocrystalline silicon (CIC sub-code: 26650202) and polycrystalline silicon (CIC sub-code: 26650203) in Information Chemical Manufacturing

Industry (CIC code: 2665) experienced a deterioration in FDI regulations (listed in the permitted category in 2002, while in the supported category in 1997), and there was no change in FDI regulations for other products in this industry. We designate Information Chemical Manufacturing Industry as an FDI discouraged industry.

(3) FDI no change industries: There was no change in FDI regulations for any of the possible Catalogue products under a four-digit CIC industry. For example, there was no change in FDI regulations for all products in Metal Structure Manufacturing Industry (CIC code: 3411). We designate Metal Structure Manufacturing Industry as an FDI no change industry.

(4) Mixed industry: Some of the possible Catalogue products in a four-digit CIC industry experienced an improvement in FDI regulations, but some other products worsened in FDI regulations. For example, in Auto Parts and Accessories Manufacturing Industry (CIC code: 3725), two products vehicle radiator (CIC sub-code: 37250108) and airbag device (CIC sub-code: 37250203) experienced an improvement in regulations (listed in the supported category in 2002, while in the restricted category in 1997), but window lifter (CIC sub-code: 37250204) experienced a deterioration in FDI regulations (listed in the permitted category in 2002, while in the supported category in 1997). We designate Auto Parts and Accessories Manufacturing Industry as an FDI mixed industry.