The reverse China shock on innovations and spillover: evidence from manufacturing industries

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November 18, 2025

Abstract

We provide a theoretical framework to separately illustrate the innovation efforts of "High-end" and "Low-end" firms in response to international market access from the perspective of developing countries. By aggregating the firms into the regional level, a broader model is developed that shows the relationship between regional innovations and exports, based on the micro-level choices of individual firms. Then, in the empirical section, we adopt a new IV to investigate how trade affects patents and innovations from a broader perspective in manufacturing sectors from 1998 to 2015, with a Double Debiased Machine Learning (DDML) robustness check. We then demonstrate that higher trade exposure in a city surprisingly leads to lower innovation, as measured by granted patents, although knowledge intensity typically has spatial spillover effects on nearby cities. Further analysis reveals that this interesting phenomenon stems from a human capital "squeeze-out" channel: driven by the export boom, skilled labor was reallocated to more profitable sectors with a comparative advantage (manufacturing production) rather than innovation-intensive activities (R&D) in China. Contrary to common beliefs, although human capital plays a crucial role in innovation, the channels through which it affects patents in China differ from those in developed countries. Unlike human capital, physical capital does not significantly affect Chinese regional innovations.

Keywords: International Trade; China; Innovation; Spillover
JEL Classification: F3

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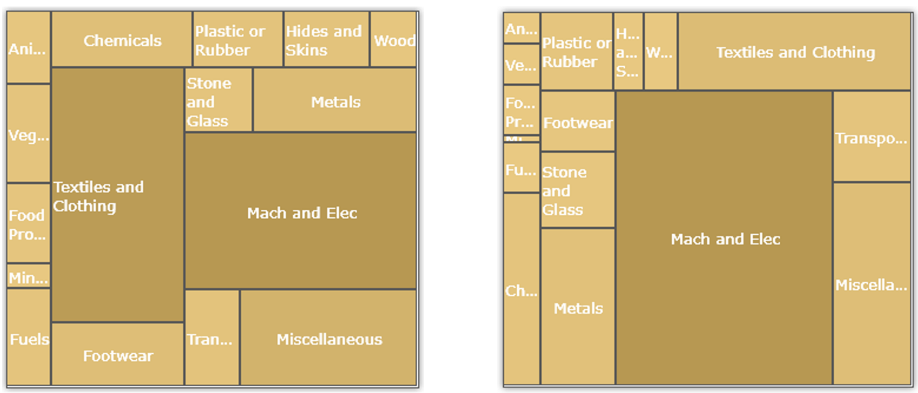
1 Introduction

Over the past two decades, globalization has profoundly restructured the global division of labor and reshaped international trade patterns. The significant transformation led to a dramatic increase in exports from developing countries, especially China, to developed countries. While this process has stimulated growth and integration into global markets, it has also generated significant distributional consequences. In advanced economies, research has extensively documented the adverse effects of Chinese import competition on labor markets, particularly within manufacturing sectors, a phenomenon widely referred to as the "China Syndrome" (Autor, Dorn, and Hanson 2013; D. H. Autor et al. 2014; Dauth, Findeisen, and Suedekum 2014; Autor, Dorn, and Hanson 2016; Pierce and Schott 2016; Bloom, Draca, and Van Reenen 2016; Dauth, Findeisen, and Suedekum 2021). However, few researchers have paid attention to the flip side of this process: how integration into global markets and the surge in external demand have changed China itself (Ouyang and Yuan 2024). Even fewer studies examine these dynamics from the perspective of innovation and technological upgrading (Brandt et al. 2017).

Over the past two decades since joining the WTO, China has experienced not

Figure 1: A comparison of Chinese export composition between 1998 and 2015



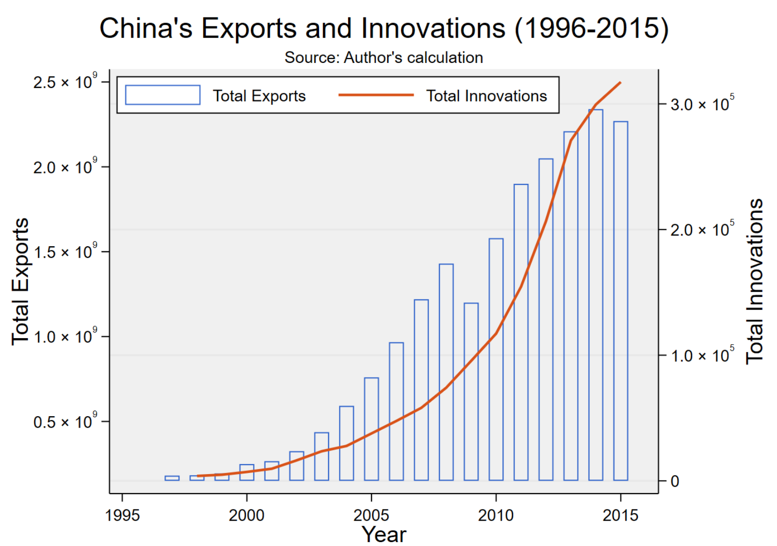
(a) Chinese Exports 1998 (b) Chinese Exports 2015

The total value of exports from China started from 183,809 million USD in 1998 to 2,273,468 million USD in 2015. It increases by more than 10 times. Also, the commodities exported from China consist mainly of raw materials, intermediate goods, and low-end consumer goods like "Textiles and Clothing" in 1998. The composition of exports changed to mainly "Machinery and Electronics" (42.11%) in 2015.

Data Sources: World Integrated Trade Solution (WITS) Data [a]

a. https://wits.worldbank.org/CountryProfile/en/Country/CHN/Year/2015/SummaryText only a surge in exports but also a transformation in the structure and composition of its exports. As shown in figure 1, China is upgrading within global value chains (GVCs) and shifting to higher-value-added segments by improving its technology. On the other hand, few researchers have paid attention to innovations driven by trade access in China, although we can see similar surge patterns for both of them.

Figure 2: Export and Innovations



In this picture, we show the correlation between the time and the Total export of China, and the total number of innovations (measured by the authorized patents) from 1996 to 2015. The bar chart with the measurement on the left indicates the total value of Chinese exports to the world in 1,000 USD. The line chart with the measurement on the right represents the total granted patents [a] in China.

Data Source: World Integrated Trade Solution (WITS) Data; China National Intellectual Property Administration

a. A granted patent, also known as an issued patent, means that a patent application has successfully undergone examination by the relevant intellectual property office (such as the USPTO, EPO, or SIPO) and has been formally conferred as an exclusive legal right. This right permits the patent holder to exclude others from commercially making, using, selling, offering for sale, or importing the invention for a limited period, typically in exchange for a public disclosure of the invention.

This paper examines the impact of export exposure on regional innovation in China's manufacturing industries from 1998 to 2015, offering a brief overview of how globalization has influenced innovation capacity in a large emerging economy. From a model perspective, this paper adapts the firm-level frame-

work from Akcigit and Melitz (2022) and aggregates it to the regional level to examine the relationship between market expansion through trade and local innovation incentives. Empirically, we adopt the classic measure of region-level export exposures and employ a robust instrumental variable strategy based on ASEAN trade flows to address concerns about endogeneity. Double Debiased Machine Learning (DDML) is implemented both as the second identification strategy and as a robustness test to prove the consistency of the results. The baseline and secondary analysis results reveal several key findings. First, in contrast to conventional expectations, greater export exposure is associated with significant declines in the number of local granted patents. Additionally, we include foreign direct investment in our study, which consistently exerts a positive effect on innovation, similar to previous studies. Third, spatial econometric analysis reveals that while trade exposure reduces innovations locally, it fosters positive spillovers in neighboring regions, underscoring the importance of knowledge diffusion across nearby regions. One step ahead, the interaction with human capital suggests a reallocation of skilled labor away from high-end manufacturing toward sectors of comparative advantage, offering a channel through which international trade may crowd out local innovations by squeezing out high-skilled or high-educated workers — a human-capital form of Dutch Disease. By integrating trade, FDI, human capital, and spatial spillovers into a unified framework, this study provides new evidence for the literature on globalization and innovation and shows how the Chinese case diverges from previous experiences in advanced economies.
This paper will proceed as follows. Section 2 is the conceptual theoretical framework. Section 3 is how we measure the trade exposure and other control variables. Additionally, we provide the regression function, along with the identification strategy and explanations of the instrumental variable used in this research. Section 4 provides detailed information about the data sets and how they are matched with each other. Section 5 shows the baseline result table. We will also provide illustrations to support the explanation. Section 6 shows the secondary analysis, including the spatial econometric method. Together with direct and indirect results, the spatial spillover results will be presented using different spatial models. The results for human capital are also included for comparison with those for physical capital. Section 7 is the conclusion. Appendices are provided to illustrate the detailed mathematical progress, along with some robustness checks.

2 Literature Review

When we started to ask about the relationship between trade exposure and local innovations, many papers provide both theoretical and empirical evidence showing that opening to trade lead to higher innovation from different perspectives including Market size (Jones 1995a, 1995b, 1999; Aghion, Bergeaud, Lequien, and Melitz 2024), Product Market Competition (Nickell 1996; Aghion et al. 2005; Aghion et al. 2004, 2009), Comparative Advantage (Acemoglu and Ventura 2002; Uy, Yi, and Zhang 2013), and Knowledge Spillovers (Melitz and Redding 2021). But, most of the studies focus on developed countries; only Redding (1999) mentions that developing countries may face a trade-off between comparative advantages and the "*entering sectors in which they currently lack a comparative advantage, but may acquire such a comparative advantage in the future as a result of the potential for productivity growth (in high technology goods)*". But the paper is too old to explain the current situation. We can see from the figure 2 that the number of patents in China is increasing at the same pattern as exports from China during the period. In addition, although the patterns of export and innovation appear similar, there is no evidence to indicate a significantly positive relationship between the two. China faces the same trade-off mentioned by Redding (1999), where long-run welfare is higher when focusing on high technology rather than showing comparative advantage in trade opening.

This omission is surprising, given the central role of innovation in sustaining long-term economic growth and the long-standing theoretical argument — dating back to Adam Smith (1776) and formalized by Krugman (1979) and Krugman et al. (1980) - that market expansion can stimulate technological progress. Yet empirical findings remain inconclusive. Some of the papers emphasize the positive effects of trade liberalization on innovation via scale extension and by showing comparative advantages (Melitz and Redding 2021; Cai, Li, and Santacreu 2022), while others highlight diminishing returns to research productivity (Jones 1995b, 1999; Bloom et al. 2020) or the possibility that import competition may crowd out innovative effort (Hombert and Matray 2018; D. Autor et al. 2020; Yang, Li, and Lorenz 2021). Moreover, the channels through which trade liberalization interacts with human capital, foreign direct investment (FDI), and spatial spillovers remain poorly understood (Aghion, Bergeaud, Lequien, Melitz, and Zuber 2024). This lack of systematic evidence on how the "reverse China shock" has affected domestic innovation, and through what mechanisms, constitutes an important research gap that this study seeks to address.

With the expansion of trade and the development of global supply chains, the international division of labor has become increasingly clear. Driven by trade and foreign direct investment (FDI) through the global value chain, technology transfer and knowledge spillover have been considered major drivers of innovation. The theory of FDI technology spillover has been proposed by MacDougall (1975) and followed by a large number of similar studies. Some researchers believe that countries have a higher capability to innovate when they host FDI, and consider it as one of the most economical and effective channel through which the new technologies (mostly from the developed countries) has been introduced to developing countries (Blomström and Kokko 1998; Blomstrom and Kokko 2001), and show that FDI may yield positive impacts on the domestic technology (Tan, Zhang, and Cao 2023; Morita and Nguyen 2021). Blomström and Persson (1983) show the existence of the technology spillover effect by providing empirical evidence from Mexico.

On the other hand, Hu and Jefferson (2003) reached similar conclusions using data from China. On the other hand, some researchers have proposed the contradictory view that FDI does not have significant effects on technological innovation in host countries, or even negative effects (Behera and Dash 2017). Romijn and Albaladejo (2002) proves that the promotion effect of FDI in the host country is weak by testing the hypothesis of spillover from FDI, and De Backer and Sleuwaegen (2003) shows that the domestic investment can be crowded out by FDI and the domestic competition is intensified which leads to inhibition of the innovation capacity of local technologies. Hu and Jefferson (2003) provide some reasons, including research methods, firm characteristics, and inconsistency in national environments.

Beyond trade, our paper also provides empirical evidence of a significant positive relationship between innovation and FDI. The difference is that we integrate measures of human capital, discovering that FDI squeezes out local investment and pushes the educated labor force from innovation to the industries with comparative advantages. From another perspective, Baranson (1970) and Schrader (1991) mentioned the importance of firms in international technology transfer, while Martínez-Zarzoso and Chelala (2021) provides empirical evidence that regional trade agreements (RTA) also contribute to the technology transfer in trade. Previous papers focus on different fields of technology transfer and knowledge diffusion, like agriculture (Dalampira et al. 2022), labor market and wage inequality (Wang, Findlay, and Thangavelu 2021), defense (Moretti, Steinwender, and Van Reenen 2025), information technology (Han, Chang, and Hahn 2011) and sustainable development (Pandey, Coninck, and Sagar 2022; Huang and Lv 2021). The diffusion of international technology can affect the domestic economy by advancing the technology frontier (Melitz and Redding 2021) and has been shown to positively contribute to efficiency and technology absorption in developing countries (Henry, Kneller, and Milner 2009). Bloom, Schankerman, and Van Reenen (2013) identifies technology spillovers and shows that the social return is at least twice the private return using US firm-level data. And Moretti, Steinwender, and Van Reenen (2025) find evidence of international spillover of the R&D when a particular industry and country raise private R&D. In order to specify how technology transfer is promoted by trade, Alvarez, Buera, Lucas, et al. (2013) shows the "selection effect" of trade, which means that the inefficient producer will be replaced by firms with more efficient technology, while Atkeson and Burstein (2010)developed a general equilibrium model to show that the reduction of marginal trade costs could lead to relatively higher innovation at the firm level. Taking advantage of trade, producers are being exposed to higher productivity and frontier knowledge through dynamic selection, as shown by Sampson (2016) and Perla, Tonetti, and Waugh (2021). This paper follows the same logic and provides empirical evidence from a broader perspective, showing that greater trade exposure can lead to higher patent and innovation activity. Different from most of the empirical research which focuses on the developed countries, this paper focuses on China, which is widely considered as a producer as in Feng and Li (2021).

Technology diffusion can occur not only between countries but also within a country, which is a phenomenon known as the geometric spatial spillover effect. After the theoretical framework and application methods provided by Paelinck et al. (1979) and the early version of Anselin (2013), Moreno and Trehan (1997) and LeSage and Pace (2009) provided empirical evidence for economic growth using spatial spillovers and distinguishing between direct and indirect effects. While most of the researchers focus on developed countries like Spain (Cabrer-Borras and Serrano-Domingo 2007), Europe (Moreno, Paci, and Usai 2005) and the US (Ó hUallacháin and Leslie 2005; Audretsch and Feldman 2004, 1996; Giroud, Liu, and Mueller 2024; Lim 2003), fewer studies focus on developing areas like Brazil (Gonçalves and Almeida 2009) and China (Bai, Ma, and Pan 2012; Rho and Moon 2014; Song Wang et al. 2023). Most of the studies recently regarding China discuss topics related to the environment and pollution (Peng et al. 2021; Liu 2018; Fu et al. 2022; Zhang et al. 2022) or regional development (Li, Chai, and Ren 2023; Shuai Wang et al. 2022; Tian and Wang 2018), while this paper fills the gap by providing a wider picture of city-level innovation driven by trade exposure for the whole nation. We make specific contributions to empirical applications of Instrumental Variable methodology in spatial econometrics using the Spatial Durbin model with panel data. In addition, empirically, we are able to show how trade exposure affects innovation for neighborhoods through spatial spillover compared to the local city.

Furthermore, our research extends the secondary analysis by including the impacts of human capital. Previous researches show that how human capital plays the role as the driver of innovations (Lenihan, McGuirk, and Murphy 2019; Lee, Florida, and Gates 2010; Costa, Pádua, and Moreira 2023). At the firm level, some researchers provide empirical evidence on how human capital triggers the firm-level innovation from different perspectives (Sun, Li, and Ghosal 2020; Fonseca, Faria, and Lima 2019; Capozza and Divella 2019; Van Uden, Knoben, and Vermeulen 2017; Bornay-Barrachina et al. 2012). At the country level, some studies investigate the perspectives on immigration and innovation by showing the creativity triggered by diverse socio-cultural backgrounds (Burchardi et al. 2020; Ozgen, Nijkamp, and Poot 2012; Kerr 2010). But, in contrast, China is usually not considered as a developed country where immigrants are welcomed, which means most of the studies linking innovation with human capital in China focus on the environment (Lin et al. 2021; Wang and Wu 2021; Khan et al. 2020), or provide a broad research on using provincial data (Xu and Li 2020; Fleisher, Li, and Zhao 2010). All the studies mentioned discussed the causality of how human capital drives innovation; a few of them also explored how innovations impact human capital from a broader perspective, providing some evidence from the spatial spillover effect aspect. Related studies previously show the role of the spatial spillover conceptually (Acs 2013) or empirically, mostly in the US or the Silicon Valley (Acs, Anselin, and Varga 2002; Almeida and Kogut 1999; Anselin, Varga, and Acs 1997). A few of the works mentioned China (Baycan, Nijkamp, and Stough 2017; Wen, Yang, and Huang 2023; Lao et al. 2021) from different perspectives. Our research tells a similar story from the perspective of trade. In addition, by combining the findings with human capital in secondary analysis, we contribute to the literature by applying spatial spillover methods to identify the channel through which trade exposure affects regional innovation. We provide new insights into how innovation triggered by trade exposure can spur the reallocation of human capital in surprising ways.

3 Theoretical background

China is widely recognized as a geographically extensive and demographically large country. Substantial heterogeneity in geography, ethnic traditions, and cultural environments has led the central government to organize the country into a large number of provincial- and municipal-level administrative units. The significant economic and cultural disparities across these jurisdictions give rise to region-specific consumer preferences and consumption patterns. From a theoretical perspective, it is therefore natural to approximate each administrative unit as a small closed economy [1], which provides a convenient starting point for our modeling. Also, according to the research scope, only the manufacturing industry is considered.

3.1 Firm level

We are using the model from Akcigit and Melitz (2022) and adapting it to fit in our case. Let's start from the closed economy. Consider the firms in region i are going to produce two different types of the final products Y_{1t} and Y_{2t} in a perfectly competitive market. The Y_{1t} represents the 'high-end' products that require higher quality, innovation-driven, and higher costs. On the other hand, Y_{2t} denotes the 'low-end' products that need to be cheap, have low costs, and require no innovations in quality improvement. The labor in region i used to produce Y_{1t} and Y_{2t} are L_{1it} and L_{2it}, respectively. And $L_{1it} + L_{1it} = L_{it}$ is the total labor market in the region. Let's assume that the market size of high-end products Y_1 in region i is L_{1i} while the market size of low-end products Y_2 in region i is also L_{2i}. Then we start from the production function of the firms:

$$Y_{1t} = \frac{L_{1it}^{\beta}}{1-\beta} \int_0^{N_1} q_{jt}^{\beta} k_{jt}^{1-\beta} dj, \tag{1}$$

where the i is set for the region. The quantity of intermediate commodity j is denoted as k_{jt} at time t, and q_{jt} denotes the firm-level quality. The price of the

1. The persistence of relatively segmented regional economies has hindered the development of a fully integrated national economy. In 2022, the Chinese central government initiated the establishment of a "Unified National Market" with the explicit objective of dismantling such segmentation. A suite of policy measures, including the relaxation of firm relocation constraints, the reduction of interregional entry barriers, and the discouragement of self-contained "small-cycle" development strategies, has been deployed to eliminate institutional frictions impeding nationwide market integration and to enhance the conditions for fair competition. (https://www.gov.cn/zhengce/2022-04/10/content_5684385.htm; https://www.ndrc.gov.cn/wsdwhfz/202408/t20240812_1392356.html)

final good is normalized to 1. $\beta \in (0,1)$ is both the share of the fixed factor in production and the inverse elasticity of substitution between the intermediate varieties j. And the second part is the industries that produce low-end products and gain profits from reducing the costs:

$$Y_{2t} = \frac{L_{2it}^{\beta}}{1-\beta} \int_0^{N_2} q_{jt}^{\beta} k_{jt}^{1-\beta} dj, \tag{2}$$

According to Akcigit and Melitz (2022), the results remain consistent if we assign two different variables to those separate concepts. For simplicity, we drop the time index. And now the maximization of profits of the final good producer is:

$$\begin{aligned} &\max_{L_{1i},k_j} \left\{ \frac{L_{1i}^{\beta}}{1-\beta} \int_0^{N_1} q_j^{\beta} k_j^{1-\beta} dj - p_j k_j - L_{1i} w_1 \right\} \\ &\max_{L_{2i},k_j} \left\{ \frac{L_{2i}^{\beta}}{1-\beta} \int_0^{N_2} q_j^{\beta} k_j^{1-\beta} dj - p_j k_j - L_{2i} w_2 \right\}, \end{aligned} \tag{3}$$

respectively.
Then, the first order condition shows that the optional wage and the price of intermediate good j should be:

$$\begin{cases} w_1 & = \frac{\beta}{1-\beta} L_{1i}^{\beta-1} \int_0^{N_1} q_j^{\beta} k_j^{1-\beta} dj, \\ p_{1j} & = L_{1i}^{\beta} q_j^{\beta} k_j^{-\beta}, \end{cases} \begin{cases} w_2 & = \frac{\beta}{1-\beta} L_{2i}^{\beta-1} \int_0^{N_2} q_j^{\beta} k_j^{1-\beta} dj, \\ p_{2j} & = L_{2i}^{\beta} q_j^{\beta} k_j^{-\beta}. \end{cases} \tag{4}$$

We assume that each variety j is produced by a regional monopolist at marginal cost $\eta_j > 0$. But, the 'high-end' firms focus on quality improvement can maximize their profit by:

$$\pi_{1j} = \max_{p_{1j},k_j} \{p_{1j} k_j - \eta_j k_j\} \quad \text{subject to (4)}, \tag{5}$$

and the equilibrium quantity and price become:

$$\begin{aligned} k_{1j} &= \left[\frac{1-\beta}{\eta_j} \right]^{\frac{1}{\beta}} L_{1i} q_j, \\ p_{1j} &= \frac{\eta_j}{(1-\beta)}. \end{aligned} \tag{6}$$

And, by substituting the optimal k and p into the profit maximization problem, we can show that profit is proportional to the quality:

$$\pi_{1j} = \Upsilon L_{1i} q_j \eta_j^{\frac{\beta-1}{\beta}}, \quad \Upsilon \equiv (1-\beta)^{\frac{1-\beta}{\beta}} \beta \tag{7}$$

on the other hand, for the 'low-end' firms focus on cost reduction, their profit maximization problem is:

$$\pi_{2j} = \max_{p_{2j},k_j} \{p_{2j} k_j - \eta_j k_j\} \quad \text{subject to (4)}, \tag{8}$$

And the equilibrium quantity and price are:

$$
\begin{aligned}
k_{2j} &= \left[\frac{1-\beta}{\eta_j}\right]^{\frac{1}{\beta}} L_{2i} q_j, \\
p_{2j} &= \frac{\eta_j}{(1-\beta)}.
\end{aligned}
\tag{9}
$$

Similarly, we can show:

$$
\pi_{2j} = \Upsilon L_{2i} q_j \eta_j^{\frac{\beta-1}{\beta}}, \quad \Upsilon \equiv (1-\beta)^{\frac{1-\beta}{\beta}} \beta \tag{10}
$$

In order to measure the innovation incentives of the firms, we also assume that the firms are myopic, which means they only maximize the instantaneous profit (one-step ahead profit) rather than the discounted sum of all potential profits in the future. Following the model setting by Akcigit and Melitz (2022), we also consider the stochastic outcome of the innovation. For the 'high-end' firms, we implement the same settings, meaning that when the innovation is successful, the firms can increase their quality by one step, $\lambda_1 > 0$, from q_j to $(1+\lambda_1)q_j$. And the innovation cost should be:

$$
C_1 = \theta_1 q_j x_j^2, \quad \text{where} \quad \theta_1 > 0. \tag{11}
$$

But the difference is that, when we consider the manufacturing industry in China, which is still widely recognized as a labor-intensive, developing country, the increase in quality should not be the only driver of producer innovation. Some papers already show that the cost-innovation of Chinese firms, especially the manufacturing industry, can improve productivity, and increase the competitive advantages from many perspectives (Liu, Wang, and Yi 2022; Le and Lei 2018; Liefner and Losacker 2020; Zeng and Williamson 2007; Zhang and Wang 2008). Cost-saving innovation has been a dominant strategy for many Chinese manufacturers over the past two decades. So, we set the marginal cost of production to decrease by a step $\lambda > 0$ if the innovation is successful. It will decrease from η_j to $(1-\lambda)\eta_j$ in the next period or keep constant as η_j otherwise. Also, we set the innovation cost function as:

$$
C_2 = \theta_2 \frac{1}{\eta_j} x_j^2, \quad \text{where} \quad \theta_2 > 0. \tag{12}
$$

The function is not linear in the firm's production cost η_j because the innovation effort x_j has a diminishing marginal effect. Let's assume that all the firms choose $x_j < 1$. We also set an exogenous probability of entry, $z_j \in [0,1]$, which indicates that the firm's entry will permanently replace the regional incumbent. It means each good j is produced by only one firm at a time within this region. For clarification, we are providing two circumstances where $\beta > 0.5$ and $\beta \leq 0.5$. Then, a 'high-end' firm earning $\pi_{1j} = \Upsilon L q_j \eta_j^{\frac{\beta-1}{\beta}}$ with innovation efforts in improving quality q_j is expected to earn next period profit with innovation effort choice x_{1j} as:

$$
\mathbb{E}\pi_{1j} = (1-z_j)\left[x_{1j}\pi_{1j}(1+\lambda_1) + (1-x_{1j})\,\pi_{1j}\right] + \theta_1 q_j x_{1j}^2. \tag{13}
$$

While for the 'low-end' firms which focus on cost saving,

$$\mathbb{E}\pi_{2j} = (1 - z_j)\left[x_{2j}\pi_{2j}(1-\lambda_2)^{\frac{\beta-1}{\beta}} + (1 - x_{2j})\,\pi_{2j}\right] - \theta_2 \frac{1}{\eta_j} x_{2j}^2. \tag{14}$$

By maximizing the expected profit, the equilibrium innovation choice for the two types of firms should be:

$$\begin{cases} x_{1j} &= \frac{(1-z_j)}{2\theta_1}\lambda_1 \Upsilon L_{1i}\eta_j^{\frac{\beta-1}{\beta}} \\ x_{2j} &= \frac{(1-z_j)L_{2i}q_j\Upsilon}{2\theta_2}\left[(1-\lambda_2)^{\frac{\beta-1}{\beta}} - 1\right]\cdot \eta_j^{\frac{2\beta-1}{\beta}} \end{cases} \tag{15}$$

We can find that, actually, the innovation effort choices made by 'high-end' and 'low-end' firms differ because of the different directions of profit-gaining.
So, by substituting the optimal x_j into the equation, the expected maximized profit next period is:

$$\mathbb{E}\pi_{1j} = (1 - z_j)\,\Upsilon L_{1i} q_j \eta_j^{\frac{2\beta-1}{\beta}}\left(1 + \frac{\lambda_1^2(1-z_j)\Upsilon L_{1i}}{4\theta_1}\eta_j^{\frac{2\beta-1}{\beta}}\right) \tag{16}$$

for the 'high-end' firms, and for the 'low-end' firms:

$$\begin{aligned} \mathbb{E}\pi_{2j} = &\frac{(1-z_j)^2}{2\theta_2}\left[(1-\lambda_2)^{\frac{\beta-1}{\beta}} - 1\right](L_{2i}q_j\Upsilon)^2\cdot\eta_j^{\frac{3\beta-2}{\beta}}(1-\lambda_2)^{\frac{\beta-1}{\beta}} - \theta_2\frac{1}{\eta_j}x_{2j}^2 \\ &- \frac{(1-z_j)^2}{2\theta_2}\left[(1-\lambda_2)^{\frac{\beta-1}{\beta}} - 1\right](L_{2i}q_j\Upsilon)^2\cdot\eta_j^{\frac{3\beta-2}{\beta}} + (1-z_j)\left[L_{2i}q_j\Upsilon\eta_j^{\frac{\beta-1}{\beta}}\right], \\ \Rightarrow = &(1-z_j)\Upsilon L_{2i}q_j\eta_j^{\frac{\beta-1}{\beta}}\left\{\frac{(1-z_j)L_{2i}q_j\Upsilon}{2\theta_2}\left[(1-\lambda_2)^{\frac{\beta-1}{\beta}} - 1\right]^2\cdot\eta_j^{\frac{2\beta-1}{\beta}} + 1\right\} \\ &- \theta_2\frac{1}{\eta_j}\left\{\frac{(1-z_j)L_{2i}q_j\Upsilon}{2\theta_2}\left[(1-\lambda_2)^{\frac{\beta-1}{\beta}} - 1\right]\cdot\eta_j^{\frac{2\beta-1}{\beta}}\right\}^2 \end{aligned} \tag{17}$$

So, we can approach the results by comparing the optimal innovation choice here with the static result:
Result 1.1 *Innovation effort does not depend on quality for the 'high-end' firms as:*

$$\frac{\partial x_{1j}}{\partial q_j} = 0. \tag{18}$$

Result 1.2 *Innovation effort increases when the marginal cost of the producer decreases, with a low share of fixed factors in the production:*

$$\frac{\partial x_{2j}}{\partial \eta_j} \begin{cases} > & 0, \quad \text{if} \quad \beta > \frac{1}{2} \\ \leq & 0, \quad \text{if} \quad \beta \leq \frac{1}{2} \end{cases}, \quad \beta \in (0,1) \tag{19}$$

The results show that the 'low-end' firms show their innovation efforts are affected by production costs conditioned on the β level. As what we stated previously, β is both the share of the fixed factors in production and the inverse elasticity of substitution between the intermediate varieties j. So, for the 'low-end' firms that rely mostly on fixed factors in production, lower production costs lead to greater innovation efforts, and vice versa.

Result 2. *Innovation effort increases with market size for both 'high-end' and 'low-end' firms:*

$$\frac{\partial x_{1j}}{\partial L_{1i}} > 0, \quad \text{and} \quad \frac{\partial x_{2j}}{\partial L_{2i}} > 0. \tag{20}$$

Then let's try to set up a simple 'two-country' model to clarify the effects of export exposure for both the 'high-end' and 'low-end' firms. In the closed economy, the domestic country has a labor market L^D while the foreign country has a labor market L^F. Let's assume that the domestic country shows a comparative advantage in labor-intensive industries while the foreign country has a comparative advantage in technology-intensive industries. And both countries have a relatively similar size of population where $L^D > \tau^{-\frac{(1-\beta)}{\beta}} L^F$. According to the Stolper-Samuelson Theorem, the labor-intensive domestic country will focus on 'low-end' manufacturing, while the technology-intensive foreign country will focus on 'high-end' industries after opening to trade, as they are more profitable. Assume that the "iceberg" transport cost of $\tau \geq 1$ to access the foreign market L^F. So, for the domestic country, the market size for the 'low-end' firms is obviously higher than the 'high-end' firms, where $L_2 \equiv L_2^D + \tau^{-\frac{(1-\beta)}{\beta}} L_2^F > L_2^D$. Now, we can clearly see that 'low-end' exporters will achieve higher profits by accessing foreign markets (according to 17). So, by getting access to export, they increase their innovation by:

$$\Delta x_{2j} = \frac{(1-z_j)L_2^F q_j \Upsilon}{2\theta_2} \left[(1-\lambda_2)^{\frac{\beta-1}{\beta}} - 1 \right] \cdot \eta_j^{\frac{2\beta-1}{\beta}} \cdot \tau^{-\frac{(1-\beta)}{\beta}} > 0. \tag{21}$$

On the other hand, the 'high-end' firms that focus on innovation and quality improvement are facing a loss of market size after opening to trade as 'high-end' firms in a foreign country, which is technology-intensive, will benefit more from innovation and beat the domestic 'high-end' firms in the global competition. Let's assume that the market size is kept balanced after the trade opening, which means the market size loss for the 'high-end' firms in the domestic country is $\mathcal{L}_1 - L_1^F - \tau^{-\frac{(1-\beta)}{\beta}} L_2^F$. Then the 'high-end' firms in the domestic country are going to reduce their innovation efforts by:

$$\Delta x_{1j} = \frac{(1-z_j)}{2\theta_1} \lambda_1 \Upsilon \eta_j^{\frac{\beta-1}{\beta}} \cdot \left\{ L_{1i} - \tau^{-\frac{(1-\beta)}{\beta}} L_2^F \right\} < 0. \tag{22}$$

The optimal innovation effort chosen by the firms is the same whether we assume the market is in monopolistic competition, since incumbent leaders make their innovation decisions before this entry outcome is revealed. The incumbent firms will wipe out their profits when they foresee the entry.

3.2 Region level

In this research, we focus only on the relatively 'high-end' manufacturing firms in China that are innovating by improving quality. So, the change of innovation effort could be described as:

$$\Delta x_{jt} = \psi_{jt} \cdot \Delta L_{it}, \quad \psi_{jt} = \frac{(1-z_j)}{2\theta} \lambda \Upsilon \eta_j^{\frac{\beta-1}{\beta}}. \tag{23}$$

Then we can aggregate the firm-level results into the regional level.

$$\Sigma_j \Delta x_{jt} = \Sigma_j \psi_{jt} \cdot \Delta L_{it}, \quad \psi_{jt} = \frac{(1-z_j)}{2\theta} \lambda \Upsilon \eta_j^{\frac{\beta-1}{\beta}}. \tag{24}$$

And so, by simplification:

$$\Delta X_{it} = \Psi_{it} \cdot \Delta L_{it}, \quad \Psi_{it} = \frac{(1-z_j)}{2\theta} \lambda \Upsilon \eta_j^{\frac{\beta-1}{\beta}}. \tag{25}$$

From here, we could reach an equation where Ψ measures the relationship between regional innovation and the regional labor force. Different from the firm-level result, where we assume the market is a monopoly and there exists only one firm producing all the output in sector j, the regional-level market follows a monopolistic competition rather than a monopoly. Obviously, there does not exist a small region in a country where all of the products needed are produced inside. Instead, the small regions in the country produce similar but not identical products, which perfectly fit the structure of a monopolistic competition market. Also, we follow the model setting of Autor, Dorn, and Hanson (2013) where a structure of "gravity" of trade is assumed as in Arkolakis, Costinot, and Rodríguez-Clare (2012). The regions produce both tradable and non-tradable goods, which could be considered as consumption of leisure. The hats over L_{Ti} denote log changes ($\hat{x} \equiv dlnx$). To do a reverse work against Autor, Dorn, and Hanson (2013), we consider that the world's increasing demand and the falling trade cost are going to affect the region i in China through two different channels: (1) The access to the large global market and the increasing of external demand which could be captured by the change in China's export capability in each industry j ($\hat{A}_{Cj}$) and, (2) the decreasing internal demand for goods produced within China as are some more substitutes from the foreign market. It could be denoted as $\hat{E}_{Cj}$ for each industry j, and it's also considered as exogenous. So, the impacts of export-demand and import-supply shocks to China on region i's employment are:

$$\hat{L}_{Ti} = \rho_i \sum_j c_{ij} \frac{L_{ij}}{L_{Ti}} \left[\sum_k \theta_{ijk} \phi_{Cjk} \hat{A}_{Cj} - \theta_{ijC} \hat{E}_{Cj} \right], \tag{26}$$

The employment outcomes are the sum of the increases in demand for region i's shipments to all markets where China has greater access and competes with the rest of the world. It's been measured by the growth in China's export capability ($\hat{A}_{Cj}$) times the initial share of output by region i that is shipped to each market k ($\theta_{ijk} \equiv X_{ijk}/X_{ij}$) and the initial imports from the rest of the world in total purchases by each market k ($\psi_{Cjk} \equiv M_{kjC}/E_{kj}$); and on the other hand, the decrease in demand for region i from the domestic market where we choose to ignore. Because China, widely considered as the "world factory", has an imbalanced trade and breaks the "traded vs non-traded" symmetry. So the model from Autor, Dorn, and Hanson (2013) could be adopted and simplified [2] as:

$$\hat{L}_{Ti} = \alpha \sum_j \frac{L_{ij}}{L_{Ti}} \frac{X_{ijC}}{X_{ij}} \frac{M_{Cj}}{E_{Cj}} \hat{A}_{Cj} \approx \tilde{\alpha} \sum_j \frac{L_{ij}}{L_{Cj}} \frac{M_{Cj}\hat{A}_{Cj}}{L_{Ti}}. \tag{27}$$

In this equation, we have the traded-sector employment in region i depends on the growth of the Chinese total export multiple by the growth in Chinese export-supply capability $M_{Cj}\hat{A}_{Cj}$. Then it's been scaled by i's regional labor force L_{Ti} and weighted by the industry level share of region i in Chinese employment L_{ij}/L_{Cj}.
Now we have both sides of the model and let's bring equation 27 into equation 25, and we can approximate the relationship between the regional innovation efforts and the regional export exposure as follows:

$$\Delta X_{it} \approx \Psi_I \cdot \left[\tilde{\alpha} \sum_j \frac{L_{ij}}{L_{Cj}} \frac{M_{Cj}\hat{A}_{Cj}}{L_{Ti}} \right]. \tag{28}$$

As we have concluded previously at equation 20, although accessing the larger foreign market can increase the profit of manufacturing firms in China that specialize in cost-reduction innovation, it will decrease the innovation effort of the firms. So we will test the theory and see whether the data tell the same story in the following empirical sections.

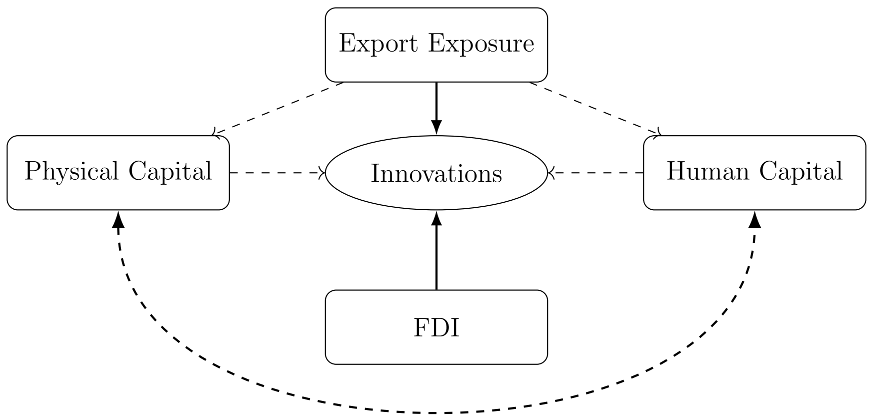
3.3 Illustration

After the theoretical framework, we also include a figure to briefly illustrate the work presented in this paper. This research mainly focuses on how regional exports affect regional innovation. But we should also include FDI which is widely considered as the major channel of technology spillover and so we could compare the results. In addition, we also want to compare how exports affect innovation through human capital versus physical capital. The two channels can bring us completely distinguished results. The baseline results include how the Export exposure and FDI affect the local innovations. Then, a detailed secondary analysis about the human capital, including the micro level separation, together with the comparisons with physical capital, is implemented in the following sections.

4 Empirical Approach

This study aims to examine the causal relationship between trade exposure and innovation at the regional level. In order to measure regional trade exposure,

2. The detailed simplification process could be find from Autor, Dorn, and Hanson (2013)



we follow the logic of Autor, Dorn, and Hanson (2013) and do a flip-side work. Empirically,

$$\Delta Innovation_{it} = \beta \cdot \Delta EPW_{it} + error_{it}, \quad \Delta EPW_{it} = \Sigma_j \frac{L_{ijt}}{L_{cjt}} \frac{\Delta M_{cjt}}{L_{it}}. \tag{29}$$

By using this methodology, the Chinese regional exposure to external demand is measured using labor-force apportioned export exposure per worker in this region.

$$\Delta EPW_{it} = \Sigma_j \frac{L_{ijt}}{L_{cjt}} \frac{\Delta M_{cjt}}{L_{it}}. \tag{30}$$

In this equation, ΔEPW_{it} represents the change of export exposure of the city i in time t to the world. On the right hand, L_{ijt} is the employment in city i at time t in sector j; the L_{cjt} is the employment at time t in sector j of China; the L_{it} is the employment in the city i time t, and the ΔM_{cjt} is the change of Chinese export to the whole world in sector j during period t. In other words, the change in export exposure is measured by the region-time-average change in Chinese exports to the world, multiplied by the ratio of city-level employment in specific sectors for a given period, and then aggregated by sector.

The simple regression leads to several endogenous problems. First of all, although we aim to determine the causal impact of trade exposure on innovations in China, innovations can also significantly lead to changes in trade exposure through changes in industry productivity, a phenomenon known as reverse causality. Second, some researchers suggest that China could intensively depreciate the CNY currency, as well as significantly increase its national reserve of US dollars, to promote financial stability and enhance exports (Goldstein 2004; Ogbonna, Gbadebo, and Ibenta 2020; Chou 2000; Leightner 2010). This type of preference leads to unexpectedly high exports from China to the world, particularly to developed countries. The tradable-commodity preference leads to biased high investment in specific industries preferred for export, with an undervalued CNY. So in order to solve the endogenous problems, we adopt the instrumental variable strategy to clear the identification. We instrument for growth in Chinese exports to the world using the ASEAN [3] countries' total export to the world. There are several reasons the IV has been chosen. First, geographical proximity. ASEAN countries and China are neighbors really close to each other. Also, in the first half of 2020, ASEAN surpassed the EU for the first time to become China's largest trading partner [4], while China has been the largest trading partner for ASEAN countries since 2009 [5]. Intimate communication and close commercial collaboration underscore the strong relationship between China and ASEAN countries. Second, structural similarity of industries. Most of the ASEAN countries are labor-intensive and developing countries similar to China, while a few of them have technology-intensive industries and high-tech exports such as Singapore and Malaysia. By aggregating exports across industries from all ASEAN countries, it can serve as a good substitute for comprehensive exports from China. Third, obviously, the mathematical tests, in addition to the principles we follow to choose the IV, including weak-identification and underidentification tests, are implemented, and the results will be shown in the result tables.

By implementing the IV as an identification, we can eliminate the endogeneities of Chinese productivity shock caused reversely by patents and innovations in industries. In addition, the potential impacts of the Chinese government's fiscal and financial policies on trade can be ignored at the same time. So, we instrument the measured export exposure variable ΔEPW_{it} with an ASEAN countries export exposure variable ΔEPW_{Ait} which is constructed by casting the ASEAN export to the city level with the proportion measured using the industry-level employment in different cities of China:

$$\Delta EPW_{Ait-1} = \Sigma_j \frac{L_{ijt-1}}{L_{cjt-1}} \frac{\Delta M_{Ajt-1}}{L_{it-1}}. \tag{31}$$

The IV is processed through two steps. The first is that we are substituting the change in industry-level Chinese export ΔM_{cjt} to the world with ASEAN countries industry-level export ΔM_{Ajt}. Second, the IV is lagged as there is a lag between the trade exposure and the observable outcomes on the job markets as well as the innovations. So, by adopting the IV as the identification strategy, we are able to eliminate the endogenous problems mentioned before including the reverse causality together with the policies made by the Chinese government which can potentially affect the Chinese trade exposure and the regional innovations at the same time. But, in addition, there are still some potential threats to the strategy. Firstly, the productivity shock affecting China may also

3. The Association of Southeast Asian Nations (ASEAN), including Brunei Darussalam, Burma, Cambodia, Indonesia, Laos, Malaysia, the Philippines, Singapore, Thailand, and Vietnam.
4. https://www.gov.cn/xinwen/2020-03/23/content_5494368.htm
5. https://www.mfa.gov.cn/web/gjhdq_676201/gjhdqzz_681964/lhg_682518/zghgzz_682522/

have an impact on the ASEAN countries. On the one hand, ASEAN countries have sometimes been considered as part of the Chinese export supply chain (Tham, Kam, and Abdul Aziz 2016; Bi 2021) because they started to build the free-trade area from 2002[6]. In this case, the export shock driven by Chinese innovations shows a strong positive correlation with exports in ASEAN countries. On the other hand, ASEAN countries and China could be competitors in the global market to some extent. Just as what's been discussed by Tongzon (2005), the free-trade agreement ACFTA and the similarity in the manufacturing industry can lead to competition between ASEAN countries and China. This means that export shocks in Chinese exports can capture the market share and decrease the competitiveness of similar tradable industries in ASEAN countries. In other words, Chinese exports can be negatively correlated with those of ASEAN countries. So, in order to solve this problem, the results from using another country as a substitute will be shown in the appendix in the robustness checks. Additionally, we are not excluding the ASEAN countries from the Chinese export as the explanatory variable, just as we do not limit the export to the world without China when we adopt exports from ASEAN countries as an IV. As a good complementary region, including trade with each other, can describe the trade pattern more precisely.

The second threat to the identification strategy is the productivity shock in the developed countries. Similar to China, ASEAN countries are predominantly labor-intensive economies that are primarily destinations for technology diffusion from developed countries. The technology breakthrough and productivity shock in the developed countries can cause an increase in innovations in the developing countries through technology transfer via FDI (Tan, Zhang, and Cao 2023; Morita and Nguyen 2021). On the other hand, technological innovation in developed countries also leads to industrial transformation and upgrading, while squeezing out labor-intensive industries and transferring these sectors to developing countries, such as China and ASEAN. Then, industrial clustering and comparative advantages lead to even higher exports from China and ASEAN countries, meaning that innovations in China and exports from both China and ASEAN countries can rise simultaneously in response to a technological shock in developed countries. For example, when there is a new technology breakthrough in manufacturing in the US, the US can invest more in the advanced manufacturing industries like the "Semiconductor Manufacturing Industry" and transfer the low-profit furniture manufacturing sector to China and ASEAN, where both export in furniture manufacturing and innovations related to furniture manufacturing will increase. Although we can not rule out the possibility, there are evidence shows that China has already surpassed the US in intellectual property application in 2012, and patents authorized has outnumbered US from 2020 [7]. Also, many studies show that the developed countries started to tranfer their

6. The negotiation of ASEAN-China Free Trade Area (ACFTA) started from 2002 and was established in 2010. http://www.asean-cn.org/index.php?m=content&c=index&a=show&catid=267&id=84
7. https://www.wipo.int/web-publications/world-intellectual-property-indicators-2024-highlights/en/patents-highlights.html

technology from a long time ago (Baranson 1970; Kojima 1977), and now the technology diffusion does not play an important role in the Chinese innovation compared to he inner incentives of China. What's more, our results show that there is a negative relationship between export exposure and innovation, which is in conflict with the possibility mentioned above, and that's another reason we ignored it.

4.1 Data source and Measurement

This section provides detailed information on the database used in this research and the measurements of various variables, as well as the data construction.
For the explanatory variables, we utilize China's annual firm-level industry survey data, officially known as the "All state-owned and all above-scale non-state owned industrial enterprise database", from 1998 to 2015. This dataset also encompasses the period preceding and following China's accession to the WTO. The National Bureau of Statistics revised the coverage of the annual survey in 1998 to include all state-owned and all above-scale non-state-owned firms, rather than all firms with independent accounting, as was the case in 1992. Therefore, this research only includes data from 1998 for data consistency. Similar to the Longitudinal Research Database (LRD) maintained by the US, the Chinese firm-level data unit of observation is based on the legal units of a firm. However, unlike some other similar databases from other countries, the Chinese firm-level database employs a different sampling criterion (Brandt, Van Biesebroeck, and Zhang 2014). Only the industrial firms that are 'above-scale' will be included in the dataset. Before 2011, the non-state-owned firms with sales exceeding 5 million CNY[8] (around 605,000 USD based on the exchange rate between 1997 and 2005), and the criteria for firm-selection became 20 million CNY (3.1 million USD based on the USD/CNY average exchange rate) in 2011. The Chinese firm-level dataset includes not only the sales and employment amounts, but also the salaries from the total/main business of each year. According to the precise locations of the manufacturing firms, so we could aggregate it to the city- and county-level[9] employment (And total salaries paid) of specific sectors in a year. There will be 6063 observations in total in the city-level[10] aggregated mapping. In addition, in the census year 2004, the state-owned and above-scale non-state-owned firms reported their detailed employment data broken down by five different education levels[11], and three non-exhaustive technical titles[12] separated by total and female employment. However, the problem is that there is only one census during the period covered, and therefore, the analysis using the subsamples cannot be implemented due to the lack of data. The above-scale

8. All of the state-owned firms will be included, no matter how much the sales are.
9. 'County' could also be understood as 'district' or 'prefecture'.
10. The Chinese municipalities, including Beijing, Tianjin, Shanghai, and Chongqing, are also included in the city-level aggregation, even they are at the province-level.
11. Postgraduate, university, college, high school, primary or less
12. Senior, intermediate, junior

sample grew from 165,118 observations in 1998 to 327,853 in 2008, and 305,504 in 2015.

On the other hand, the variable of trade exposure is measured using the trade data from the World Integrated Trade Solution (WITS) database. The trade data is at the six-digit Harmonized System (HS) product level using the ISICRev3 code. The ISICRev3 code was being adjusted to ISICRev3.1 in 2002 and then been revised to ISICRev4 from 2008. We adjusted the codes to ensure consistency in production codes during the covered period. The IV used follows the same logic but a reverse work compared to Autor, Dorn, and Hanson (2013), the gross exports reported by China is been substituted by gross exports reported by ASEAN countries to the world. For the controls, city-level controls are from the Annual Statistic Yearbook for the cities from 1998 to 2015 [13]; In constructing the independent variable by using the total population as the denominator, the total population in the administrative area at the end of the year will be used. We also refer to the China National Intellectual Property Administration (CNIPA) for the patent data in order to measure the innovations. The patents authorized are chosen instead of the number of patent applications to measure the true amount of innovations that have happened. The patents have been aggregated into the city level to match the trade exposure based on their locations. In addition, some cities that do not have patents for certain years will be deleted to ensure the strict balanced panel data for the following spatial econometrics analysis.

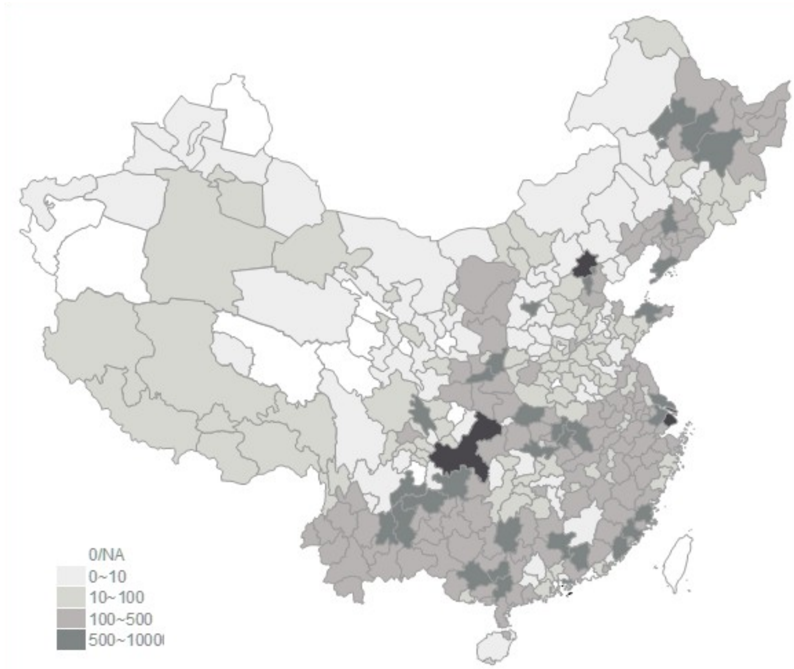
5 The impacts of trade exposure on regional innovation

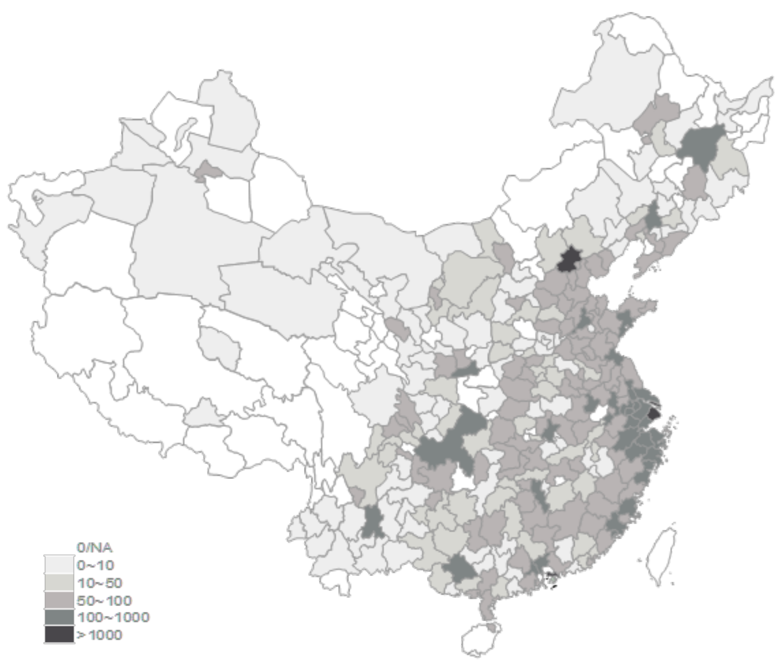
The identification strategy we implemented is specified in 4.

This figure 5 shows the prefecture-level city mapping the number of patent authorized in 2015. There are six levels of assorted colours. The first colour is white which represents 0 patent authorized, or no data available. On the contrary, the darkest color, black, represents cities with more than 1000 patents authorized in 2015, including Beijing, Shanghai, and Shenzhen. We could easily tell that some cities in the west of China, especially the ethnic Autonomous Regions in Tibet and Xinjiang Uyghur Autonomous Region (XUAR), usually have fewer innovations measured by patents and are considered as less developed in many studies. Compared to cities in the West and Southwest China, cities in the coastal areas are relatively more developed and perform better in the competition of innovations. As we can see, the region near Shanghai where we usually called the "Yangtze River Delta" including Shanghai, Jiangsu, and Zhejiang, is a main economic hub of the country and so the innovations are

13. Some of the cities changed their names, changed the city code by the government, or the administrative divisions were altered. These cases are renamed or recoded to maintain data consistency.

Figure 3: Population compared to Innovations





The upper map shows the city-level population in China in 2015. The lower map represents the number of innovations. The maps only cover cities in mainland China, including four municipalities (Beijing, Tianjin, Shanghai, and Chongqing).

intensive around. Additionally, another characteristic of the innovation is that the capital of the province where universities and resources are concentrated tends to have more innovations. On the other hand, we can see that cities with intensive innovation have an impact on the regions nearby over a considerable distance. Not only the "Yangtze River Delta" in the east, but also the group of cities near Shenzhen and Hong Kong, the group of cities near Beijing, the capital of China, and the cities near Chongqing & Chengdu in the Southwest. We will also provide empirical evidence through spatial spillovers to statistically demonstrate the phenomenon in the following sections, following the baseline results.

5.1 Empirical estimation

We are using the 2SLS estimation method to estimate the relationship between the regional trade exposure and the innovations measured by the number of patents. So we apply the model in the following form:

$$\Delta\frac{INNV_{it}}{Pop_{it}} = \beta_0 + \beta_1\Delta EPW_{it} + X'_{it}\beta_2 + \epsilon_{it}. \tag{32}$$

In this equation, we use the change of the city-level innovations on top of the population of the city to measure the innovation intensity in the region. And on the right-hand side, we include the city-level trade exposure, and also the control variables represented by X'_{it} where i represents cities and t means time. In the control variables, we include the GDP per capita of the place, the area of the administrative region, and the population at the end of the year. All of the controls have been first-stage differentiated to measure the change instead of the value. Also, the error term is included as ϵ_{it}. Besides this, the time fixed effects and the regional fixed effects are been taken into consideration in the results table shown as follows: This is the baseline result table by the model and the 2SLS estimation method and IV identification strategy applied. Columns 1, 4, and 7 are simple regressions without taking regional fixed effects, the time trends, and even the controls into consideration. Columns 2, 5, and 8 are regression specifications with fixed effects, and columns 3, 6, and 9 are specifications with everything included. The first three columns estimate the causal effect of export exposure on the innovations. As we can see, trade exposure has a significant negative impact on innovation, as measured by the average number of granted patents. For every unit of increase in trade exposure, there is around a 0.2 unit decrease in the average number of patents in the city. The finding is, to some extent, contrary to the common perception, as most studies, such as Melitz and Redding (2021) and Damijan and Kostevc (2015), show that trade and knowledge diffusion stimulate innovation. Besides robustness, the FDI is included in the specification in columns 4-6 to verify consistency with previous studies. As what we have mentioned in Section 1, FDI usually shows positive impacts on innovations through technology diffusion. The results in columns 4 to 6, which include both trade exposure and FDI, show that the impact of FDI on

Table 1: Baseline Results

Dependent Variable: Granted Patents (averaged)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔEPW	-0.171***	-0.174***	-0.227***	-0.144***	-0.166***	-0.238***	-0.161***	-0.170***	-0.224***
	(-3.37)	(-5.75)	(-5.97)	(-3.58)	(-5.51)	(-5.38)	(-3.14)	(-5.41)	(-5.84)
ΔFDI				0.263***	0.214***	0.117**			
				(3.22)	(3.23)	(2.44)			
$\Delta No.Researchers$							0.255***	0.137*	0.0821
							(2.80)	(1.73)	(1.50)
N	3841	3841	3817	3641	3641	3625	3841	3841	3817
Underidentification	6.873	12.66	10.71	7.893	12.70	10.01	6.855	12.59	10.70
Weak identification	6.298	15.27	14.26	9.183	18.71	15.64	6.305	15.24	14.23
Region FE:	N	Y	Y	N	Y	Y	N	Y	Y
Time Trend:	N	Y	Y	N	Y	Y	N	Y	Y
Controls:	N	N	Y	N	N	Y	N	N	Y

† ΔEPW is the change of Export Exposure per capita, measured by the formula 30. Results of $\Delta FDI \times 100,000$ based on Unit; Results of $\Delta No.Researchers \times 10,000$; We allow the heteroskedasticity and cluster the observations on the province level. The control variables include GDP per capita, Total population, administrative area, and some local characteristics. The Underidentification test uses the 'Kleibergen-Paap rk LM statistic' and the Weak identification test uses the 'Cragg-Donald Wald F statistic', critical values for that is 8.96 (15% maximal IV size); No Over-identification test required as the equation is exactly identified.t statistics in parentheses;

*** Significance at the 1 percent level.
** Significance at the 5 percent level.
* Significance at the 10 percent level.

innovations is significantly positive, consistent with many previous studies. The impact of export exposure remains consistent with the specifications in columns 1 to 3. The results reinforce the evidence indicating the negative impact of trade exposure on innovation in China. This is an interesting but tricky result as the impact of FDI shows here is similar to the previous studies, but the result of trade exposure does not follow the common perception. A possible explanation could be the characteristics of the country: we are studying China, which is considered a labor-intensive rather than a technology-intensive country (in other words, a developing country), where most studies are conducted. So, in order to clarify the reasons why trade exposure has negative impacts on innovation and the channels through which this phenomenon occurs, human resources are also considered, measured by the number of researchers in the region, in addition to FDI. The results of columns 7 to 9 for trade exposure remain consistent with the specifications before, with statistical significance. Additionally, the human resources show evidence of positive impacts on innovation, which is similar to the FDI mentioned earlier. But, before showing the following analysis, a spatial spillover effect is taken into consideration and the results are shown first.

5.2 Robustness Check

We are providing several ways for the robustness checks. First of all, Angrist and Pischke (2009) gives the number 42 as the minimum number of clusters for which the cluster works. Since our study focuses on mainland China which has 32 province-level administration regions, the number of clusters is significantly lower than 42. We will also provide baseline results without the cluster to ensure robustness. Here is the robustness table 2

As we can see from the table 2, the negative relationship between regional innovations and export exposure remains significant. Also, the positive impacts of FDI and the number of researchers on regional innovation are even more significant than the baseline results indicate. Additionally, the underidentification and weak identification show higher significance compared to the baseline. Obviously, the significance increases without applying clustering strategies, but the significance and robustness demonstrate the consistency of the results.

From another perspective, we are using the Double Debiased Machine Learning (Ddml) method to re-check our identification strategy. In our empirical regression equation 32, we assume that the controls affect the change in regional innovation per capita in a linear manner. But is this true? The controls, including GDP per capita, the coverage of the administrative area, and population, could significantly affect the results in a non-linear manner. When a city is small and has a limited number of residents, innovation may increase as the population grows. However, when a city becomes a metropolitan area with a large population, it becomes more attractive to individuals with high educational backgrounds and is home to numerous higher education institutions. Innovations in the region can experience exponential growth. In the DDML model we set, LassoCV is a method that combines the Lasso and cross-validation. It's

Table 2: Robustness for Baseline Results

Dependent Variable: Granted patents (averaged)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔEPW	-0.171**	-0.174***	-0.227***	-0.144**	-0.166***	-0.238***	-0.161**	-0.170***	-0.224***
	(-2.10)	(-3.41)	(-3.98)	(-2.18)	(-3.50)	(-4.30)	(-2.04)	(-3.37)	(-3.95)
ΔFDI				0.263***	0.214***	0.117***			
				(5.64)	(5.48)	(3.36)			
$\Delta No.Researchers$							0.255***	0.137***	0.0821***
							(9.73)	(5.17)	(2.98)
N	3841	3841	3817	3641	3641	3625	3841	3841	3817
Underidentification	16.57	40.92	35.31	24.01	48.93	39.68	16.64	40.89	35.10
Weak identification	16.63	41.00	35.28	24.15	49.15	39.70	16.70	40.96	35.07
Region FE:	N	Y	Y	N	Y	Y	N	Y	Y
Time Trend:	N	Y	Y	N	Y	Y	N	Y	Y
Controls:	N	N	Y	N	N	Y	N	N	Y

† ΔEPW is the change of Export Exposure per capita, measured by the formula 30. Results of $\Delta FDI \times 100,000$ based on Unit; Results of $\Delta No.Researchers \times 10,000$; We don't allow the heteroskedasticity in this table. The control variables include GDP per capita, Total population, administrative area, and some local characteristics. The Underidentification test uses the 'Kleibergen-Paap rk LM statistic' and the Weak identification test uses the 'Cragg-Donald Wald F statistic', critical values for that is 8.96 (15% maximal IV size); No Over-identification test required as the equation is exactly identified.t statistics in parentheses;

*** Significance at the 1 percent level.
** Significance at the 5 percent level.
* Significance at the 10 percent level.

more easily interpreted and it can recognize the significant variables. And so, we are applying the double machine learning, with partial linear IV using LassoCV, like this:

$$\begin{aligned} Y - D\theta_0 = g_0(X) + \zeta, \quad \mathbb{E}(\zeta|Z, X) = 0 \\ Z = m_0(X) + V, \quad \mathbb{E}(V|X) = 0. \end{aligned} \tag{33}$$

The model is similar to the IV model which we use in the baseline section where the D represents the export exposure in China ΔEPW_it while Z represents the export exposure in ASEAN countries with lag ΔEPW_{Ait}. And we are showing the results here:

Table 3 presents the various specifications of double-debiased machine learning.

Table 3: Double Debiased Machine Learning

Dependent Variable: Granted Patents (averaged)				
	(1)	(2)	(3)	(4)
ΔEPW	-0.473*	-0.282**	-0.516*	-0.318**
	(0.269)	(0.117)	(0.280)	(0.127)
N	3831	3831	3831	3831
Time trend:	N	Y	N	Y
Region FE:	N	N	Y	Y

† ΔEPW is the change of Export Exposure per capita, measured by the formula 30. The controls include GDP per capita, Area of administrative region, and population at the end of the year. There are 42 seeds and five k-folds. The observations are clustered. St.d in the parentheses.

*** Significance at the 1 percent level.
** Significance at the 5 percent level.
* Significance at the 10 percent level.

As we can see from the columns in the table, the results follow the same pattern as our baseline model, where the export exposure had a significant negative impact on the regional innovation. Other robustness checks are shown in the appendix.

5.3 Spatial Spillover

Spatial spillover effect is always considered as one of the main reasons for technology diffusion not only internationally but also within countries among different regions. Not only can the regional innovations affect the innovations spatially nearby, but also other 'local' factors including the trade exposure can affect the innovations. Given the significant negative impact on local innovations, we need to see whether trade exposure has similar effects on innovations in nearby regions. Technically, in order to clarify the spatial spillover effects of the regional innovations and the trade exposure, we employ spatial econometrics in our analysis. Two different kinds of spatial models are applied. One of them is the spatial autoregression model (SAR), where only the spatial lag of the dependent variable is included in order to provide explanations for how the dependent variable nearby affects the local dependent variable. The equation 36 represents the SAR model. The second is the spatial durbin model (SDM) where both the spatial lag of dependent and independent variables are included to measure a more comprehensive picture of the spatial spillover effect. The equation 37 represents the SDM model.

$$Y = \rho WY + X\beta + \epsilon \tag{34}$$
$$Y = \rho W_1 Y + X\beta + W_2 X\theta + \epsilon \tag{35}$$

W is the spatial weighting matrix that measures the relationships between the regions nearby. There are several kinds of the spatial weighting matrix that could be considered, including the Contiguity matrix, Distance matrix, and Nest (combined) matrixes. The matrixes can be replaced by different types in order to measure the different types of relationships between the regions. As what we mentioned previously, the explanatory variable included as Chinese export exposure to the world faces some strict endogenous problems. Most previous empirical studies either consider the IV strategy in the SAR model or use the SDM model with panel data, without considering the IV strategy. What we are doing is applying the IV strategy to the SAR and the SDM models with panel data by the 2SLS estimator. Meanwhile, the fixed effects should be taken into consideration. The Spatial Durbin panel model under the 2SLS and Maximum Likelihood estimation is identified by Lee and Yu (2016), and empirical tools including the fixed effects are provided by Belotti, Hughes, and Mortari (2017). By adopting the method with our own model, we have:

$$\Delta\frac{INNV_{it}}{Pop_{it}} = \rho W \Delta\frac{INNV_{it}}{Pop_{it}} + \beta_1 \Delta EPW_{it} + X'_{it}\gamma + \epsilon_{it} \tag{36}$$

$$\begin{aligned}\Delta\frac{INNV_{it}}{Pop_{it}} &= \rho W_1 \Delta\frac{INNV_{it}}{Pop_{it}} + \beta_1 \Delta EPW_{it} + X'_{it}\gamma \\ &\quad + \theta_1 W_2 \Delta EPW_{it} + W_2 X'_{it}\zeta + \epsilon_{it} \qquad (37)\\ w_{ij} &= 1/d_{ij}^{\alpha}\ if\ i \neq j\end{aligned}$$

And the Instrument variable is the same as the identification strategy mentioned in equation 31. In addition, as currently there is no STATA package designed for the IV strategy with panel data applied in the SAR and SDM model, we are doing the 2SLS manually by regressing the export exposure on the IV and other controls. And then doing the main regression using the predicted value from previous first stage. But, mathematically, the standard error is biased, and we adjust the standard deviation by the mathematical process provided in Appendix 8. In both of the equations, ρ represents the impacts of innovations of nearby regions cast on the local region, which is also the spatial lag of the dependent variable. Here, we use the Inverse distance matrix which is the reverse of the distance between the regions in order to measure the geometrical closeness. The diagonal elements of the inverse distance matrix are set to zero and not computed. And the results are shown in table 4:

Table 4 shows the results of spatial spillover effects of the regional innovations

Table 4: Spatial Spillover Results

Dependent Variable: Granted Patents (averaged)

	Without matrix		SAR Model		SDM Model	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔEPW	-0.078***	-0.277***	-0.206***	-0.177***	-0.246***	-0.216***
	(0.0247)	(0.0888)	(0.0157)	(0.0108)	(0.0305)	(0.0172)
Spatial (Wx)					0.157***	0.137***
					(0.0305)	(0.0186)
ρ			0.528***	0.564***	0.657***	0.650***
			(0.183)	(0.157)	(0.177)	(0.175)
N	3502	3502	3502	3296	3502	3296
R^2	0.156	-0.196	0.0864	0.0855	0.0903	0.0922
Individual FE:	N	Y	N	Y	N	Y

† ΔEPW is the change of Export Exposure per capita, measured by the formula 30. *Spatial* (Wx) here represents the spatially lagged dependent variable; ρ represents the spatially lagged explanatory variable. The controls include GDP per capita, Area of the administrative region, population at the end of the year, number of researchers, and total road freight volume. St.d in the parentheses.

*** Significance at the 1 percent level.
** Significance at the 5 percent level.
* Significance at the 10 percent level.

and the trade exposure using the SAR and SDM model. By comparison, we also include the first two columns of results which do not consider the spatial weighting matrix and the spatial lags. Only the coefficients of interest are included. The controls are included but the results are not shown in the table here. Columns 3 and 4 are results for the SAR model so only the item of autoregression is included and the coefficient is shown as ρ. And columns 5 and 6 are for the SDM model which includes both the spatial lag for the explanatory variables but also the dependent variable. The differences between the two columns of results across the three specifications are whether individual fixed effects have been considered. The three different specifications consistently show the negative impacts on the innovations by trade exposure, which is also consistent with the baseline results provided. In the SAR model with the spatial lag of the innovation as the dependent variable, the spatial lag shows a positive impact on local innovations, with statistical significance. It means that the innovations in the regions nearby can positively affect the innovations locally, which is consistent with the technology diffusion theory in most of the previous papers. It demonstrates the diffusion of technology across regions in China, especially in the manufacturing sector. Also shows the benefits of industrial agglomeration and the advantages of vertical industry integration in China. What's more, the results of the SDM model also show a similar phenomenon. The difference is that we found contradictory negative impacts of trade exposure in nearby regions on local innovation. And here are the contradictions. The remarkable finding is that trade exposure's impacts on innovations in nearby regions contradict its impacts on local innovations. It shows the phenomenon that higher export exposure in local city lead to lower innovations locally, but, contribute to higher innovations somewhere else even with the condition of positive technology diffusion between the regions. It's very interesting to dig into the question and figure out the specific channels through which the phenomenon will occur. There must be some factors that could affect both innovations and local trade exposure simultaneously, causing this contradictory phenomenon across regions close to each other. As a developing country, one of the most notable differences between China and developed countries is the level of human capital intensity. We are taking that into consideration and provide empirical evidence to show how the human capital affect the trade exposure and the innovations simultaneously, then discuss about the channels through which human capital cast impacts on the innovations locally and remotely on opposite sides, respectively.

5.4 Human Capital

The human capital is measured in three different ways. First, the number of students in the colleges. Compared to students at the junior high school level, those at the senior high school level (or universities) may relocate from their hometowns to big cities or economically developed areas. Also, some evidence shows that students with better educational backgrounds prefer to remain in the city where they attend university rather than return to their birthplace (Liping and Kunfeng 2014). So we believe that including students with a high level of education can better reflect the local human capital situation. Second, the number of researchers is considered. The innovations are measured by the number of local patents granted, which means most of the innovations should be considered contributions by researchers at local research institutes. Researchers are different from the professors at local universities, which is the third way of measurement; they are working in research institutes where they may not have students enrolled. The difference between the researchers and the professors is not only about the students but also about the systems they work in. Most researchers are focusing on Manufacturing, Geology, Hydraulic Engineering, or Environmental Science, and there are government-funded research programs in these areas. But professors could focus not only on these natural sciences but also on the social sciences, maintaining a balance between research and teaching. So, in order to figure out the impact of human capital using the three different measurements, we take the interaction of the human resources with the trade exposure in the identification specifications. And the models become this by adopting the strategy:

$$\Delta \frac{INNV_{it}}{Pop_{it}} = \beta_0 + \beta_1 \Delta EPW_{it} + \beta_2 \Delta HR_{it} + \beta_3 \Delta EPW_{it} \cdot \Delta HR_{it} + X'_{it}\beta_4 + \epsilon_{it}. \tag{38}$$

In this equation, ΔHR_{it} represents the human capital mentioned previously and the data comes from the China City Statistical Yearbook. The IV strategy is also implemented here with not only the trade exposure, but also the interaction with human capital taken into consideration. The export exposure is instrumented using the IV mentioned in section Identification strategy **??**. According to the statistics applied, the interaction between export exposure and the human resource is instrumented by the interaction of the IV and the human resource $\Delta EPW_{Ait-1} \cdot \Delta HR_{it}$. And the results are shown in the following table 5. In this table, we provide the results of export exposure, as in the previous table. In addition, the interaction between export exposure and human capital is shown below with the coefficients of human capital itself.

The table 5 has 6 columns with three different specifications where the measurements for the human capitals are different. The difference between the 2 columns for each specification is whether the controls are being considered as all the regressions have already considered the regional fixed effect and also the time trend as in the previous tables. The results in the table are very interesting here. As we can see from the first line, which shows that the export exposure has a statistically significant impact on the regional innovations. This is consistent with the results shown in the previous tables with different specifications. This consistency also proves the robustness of our result in the baseline model. Before checking the interaction item results, we can first examine the coefficients for the human capital items. Although not all results are statistically significant, the results provide some evidence that human capital has a positive, significant impact on innovation, consistent with the literature mentioned earlier (Lenihan, McGuirk, and Murphy 2019; Lee, Florida, and Gates 2010; Costa, Pádua, and Moreira 2023). Also, we provide a similar table of specifications A.4 for the robustness check where the results are similar, and even more significant. But when we turn to the interaction item of export exposure and human capital, we can see that it surprisingly shows a significantly negative impact on innovation. Columns 5 and 6 do not provide evidence with 5% significance[14], but we can still notice the sign and the significance is around 12%. The negative coefficients of the interaction items indicate that export exposure will have increasingly negative impacts on innovation as local human capital increases. This kind of causality could be shown by the following picture:

Human capital acts as a Moderator Variable here, moderating the impact of export exposure on local innovations in China. By analyzing the results from the export exposure, FDI, spatial spillover of both local innovations and export

14. The table of robustness also provides similar results with even higher significance.

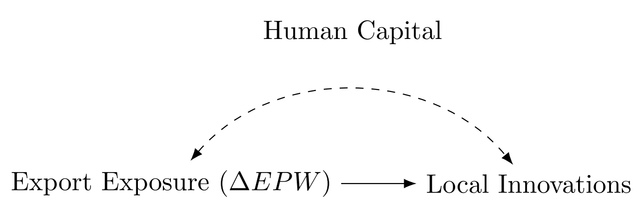
Table 5: Interaction with Human Capital

Dependent Variable: Granted Patents (averaged)

	(1)	(2)	(3)	(4)	(5)	(6)
ΔEPW	-0.237***	-0.232***	-0.139***	-0.196***	-0.140***	-0.205***
	(-3.89)	(-4.67)	(-4.69)	(-4.94)	(-3.69)	(-5.04)
$\Delta EPW \times \Delta No.Student$	-0.263**	-0.266**				
	(-2.04)	(-2.29)				
$\Delta EPW \times \Delta No.Researcher$			-0.178***	-0.164**		
			(-3.02)	(-2.22)		
$\Delta EPW \times \Delta No.Prof$					-0.131	-0.0933
					(-1.55)	(-1.44)
$\Delta No.Student$	-0.0469	0.0703				
	(-0.18)	(0.28)				
$\Delta No.Researcher$			0.548***	0.466**		
			(3.45)	(2.29)		
$\Delta No.Prof$					0.266	0.161
					(1.33)	(1.08)
N	3698	3681	3841	3817	3689	3672
$adjR^2$	-1.196	-0.933	-0.468	-0.445	-0.739	-0.609
Underidentification	8.415	9.346	12.50	10.80	12.29	10.12
Weak-identification	3.661	4.683	7.308	6.946	7.136	6.421
Region FE:	Y	Y	Y	Y	Y	Y
Time Trend:	Y	Y	Y	Y	Y	Y
Controls:	N	Y	N	Y	N	Y

† ΔEPW is the change of Export Exposure per capita, measured by the formula 30. Results of $No.Student \times 10,000$, $and\ No.Prof \times 1,000$; We allow the heteroskedasticity and cluster the observations on the province level. The control variables include GDP per capita, Total population, administrative area, and some local characteristics. The Underidentification test uses the 'Kleibergen-Paap rk LM statistic' and the Weak identification test uses the 'Cragg-Donald Wald F statistic', critical values for that is 8.96 (15% maximal IV size); No Over-identification test required as the equation is exactly identified. t statistics in parentheses;
*** Significance at the 1 percent level.
** Significance at the 5 percent level.
* Significance at the 10 percent level.

Figure 4: The causality with Human Capital



exposure in the neighborhoods, as well as the moderating effect by taking the local human capital into consideration, we can finally answer the question by providing a more detailed picture of channels through which the export exposures affect the innovations in China, in the manufacturing industries. And we propose explanations here.

Compared to the developed countries where technologies and capital are intensive, export exposure has a negative impact on local innovations in China, especially in the manufacturing sectors. The international diffusion of technology and the relocation of production from developed countries bring technological and managerial expertise to labor-intensive host countries like China. The FDI from the capital-intensive countries and the export to the world from the country that hosts the production offshoring help bring the technology from the technology-intensive regions and also stimulate the local innovations through production upgrading. But as a labor-intensive country, labor-intensive industries can be more profitable than skill- or technology-intensive industries. It may be better for talented people with higher educational backgrounds or stronger skill certificates who are supposed to contribute to patents and innovations to relocate to industries with a comparative advantage. There are several possible explanations for this phenomenon. First, this is a "squeeze out" of the talented worker from innovation-oriented industries to the labor-intensive industries in the manufacturing sectors, where working with an assembly line and low-end manufacturing is more profitable. Or, it's a "squeeze out" of the employees in the manufacturing sectors to the services sectors or other sectors not closely related to the export.

6 Secondary Analysis

6.1 Grouping

Then we are going to dig deeper and discuss the differences between different industries with varying levels of educational and skill intensity. As what we have discussed in the previous sections, the educational intensity and human capital play an important role in the regional innovations by acting as a moderator in the impacts from export exposure. So we continue to separate the observations and divide them into different groups with contradictory backgrounds with levels of intensity and make comparisons between. In order to measure intensity, we focus on the proportion of workers with higher educational backgrounds or better skill certifications among all workers at the end of the year. We focus on the top 30% and bottom 30% for the comparison and the results are shown here in table 6:

In this table 6, we compare the education-intensive and skill-intensive sectors against the labor-intensive sectors using both Panel A and Panel B. The first three columns are a comparison between education-intensive sectors and labor-intensive sectors. Meanwhile, columns 4 to 6 are a comparison between

Table 6: Education and Skill Level Grouping Results

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: High education and skill						
	High education			High skill		
ΔEPW	-0.0590*	-0.0882**	-0.0659***	-0.0267**	-0.0467***	-0.0362***
	(-1.85)	(-2.54)	(-3.29)	(-2.50)	(-3.42)	(-3.47)
N	3633	3633	3612	3637	3637	3616
Underidentification	2.815	4.226	5.597	5.813	8.508	9.007
Weak identification	2.923	4.730	6.892	9.032	13.79	18.17
Panel B: Low education and skill						
	Low education			Low skill		
ΔEPW	-0.00215**	-0.00346**	-0.00429***	-0.00467***	-0.00649***	-0.00837***
	(-2.26)	(-2.67)	(-2.78)	(-3.76)	(-4.98)	(-5.29)
N	3609	3609	3588	3652	3652	3630
Underidentification	8.339	8.435	8.117	16.12	17.43	17.25
Weak identification	19.89	21.72	20.53	48.05	65.31	70.37
Region FE:	N	Y	Y	N	Y	Y
Time Trend:	N	Y	Y	N	Y	Y
Controls:	N	N	Y	N	N	Y

† ΔEPW is the change of Export Exposure per capita, measured by the formula 30. We allow the heteroskedasticity and cluster the observations on the province level. The control variables include GDP per capita, Total population, administrative area, and some local characteristics. The Underidentification test uses the 'Kleibergen-Paap rk LM statistic' and the Weak identification test uses the 'Cragg-Donald Wald F statistic', critical values for that is 8.96 (15% maximal IV size); No Over-identification test required as the equation is exactly identified.t statistics in parentheses;

*** Significance at the 1 percent level.
** Significance at the 5 percent level.
* Significance at the 10 percent level.

skill-intensive sectors and labor-intensive sectors. Although we can see that the group with high educational backgrounds cannot pass the Weak Identification test, where the critical value of the Stock-Yogo weak ID test at a 15% maximal IV size is 8.96. But, by taking columns 4 to 6 into consideration, we can still find some evidence from comparing the two panels, respectively. First, we can observe that export exposure has a more pronounced negative impact on innovation in the skill-intensive and education-intensive sectors compared to the labor-intensive sectors. The results are consistent with not only the baseline results, but also the human capital part where we conclude that the education background and skill certificates act like a moderator and play an important role in the channel. It provides some supporting evidence. The results shown here demonstrate that employees with stronger skill sets who are expected to work in innovation-oriented sectors are more easily transitioned into more profitable but less technology-oriented sectors. Second, if we check the result table from another perspective, by comparing the education-intensive versus the skill-intensive sectors, the gap between the different education groups is larger than the gap between the groups with different skill levels. The differences show the flexibility of education where the employees with better educational grounds can easily relocate to more profitable industries or even quit the manufacturing sectors and find a job in finance or service sectors which is beyond the scope of this study. Compared to education, skill certificates are somewhat rigid, making it difficult for skilled workers to switch to other industries. In general, the table provides supporting evidence where export exposure casts negative impacts on local innovations through the squeeze-out effect of the talented employees who were supposed to contribute to the innovations if they were in the developed countries.

6.2 Privatization and Foreign Ownership

To take one step further, we proceed to examine the type and ownership of the firms. The "squeeze out" effect is evident not only from a personal perspective, but also from the employer's and firm's perspectives. We are categorizing the observations into two groups using two distinct criteria. First, we categorize the items into "Public" versus "Private" based on the shareholding structure of the firms. If the firm is a state-owned enterprise (SOE), then consider it as "Public". If the firm is privately held, or Foreign-controlled holding, a Collective holding, or an HK-Macau-Taiwan holding, then consider it as "Private". We consider the regions where private firms take more than 50% share as "High Privatization" while the rest of the regions as "Low Privatization" [15]. Similarly, following the same logic, we separate the firms based on their level of internationalization. There are 24 different types of firms in total, which are summarized in Table

15. "Low Privatization" regions have public firms take more, or equal to 50 percent of the total firms. So the number of "Low Privatization" regions is significantly higher than the "High Privatization" regions shown in table 7 and table A.5.

A.9. Similarly, the regions where firms have access to foreign owners and management account for more than 50% of the total firms counted, are noted as "High foreign ownership rate" and vice versa. The grouping results are shown in the following table 7.

The main table of the results is shown here[16]. The comparisons between Panel A and Panel B vividly illustrate the distinct characteristics of human capital affected by privatization and foreign ownership rates. First, there is some evidence in columns 1 and 2 indicating that employees from sectors and enterprises with a higher privatization rate exhibit slightly higher flexibility and are more easily

Table 7: Privatization and Foreign Ownership Rate Grouping Results

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: High privatization and foreign ownership rate						
	High privatization			High foreign ownership rate		
ΔEPW	-0.193***	-0.205***	-0.149**	-0.202***	-0.228***	-0.259***
	(-4.64)	(-4.84)	(-3.09)	(-4.91)	(-5.67)	(-4.81)
N	748	745	680	712	712	679
Underidentification	2.808	3.594	3.320	3.021	3.506	2.923
Weak identification	15.02	29.36	39.35	65.07	37.38	135.9
Panel B: Low privatization and foreign ownership rate						
	Low privatization			Low foreign ownership rate		
ΔEPW	-0.0557	-0.124**	-0.184**	-0.0469**	-0.0804***	-0.132***
	(-0.82)	(-2.48)	(-2.71)	(-2.23)	(-3.57)	(-2.91)
N	2541	2541	2410	2880	2880	2810
Underidentification	12.66	15.78	10.73	14.09	14.45	8.574
Weak identification	7.708	12.66	7.561	11.57	13.31	6.481
Region FE:	N	Y	Y	N	Y	Y
Time Trend:	N	Y	Y	N	Y	Y
Controls:	N	N	Y	N	N	Y

† ΔEPW is the change of Export Exposure per capita, measured by the formula 30. We allow the heteroskedasticity and cluster the observations on the province level. The control variables include GDP per capita, Total population, administrative area, and some local characteristics (road freight volume, and number of hospitals). The Underidentification test uses the 'Kleibergen-Paap rk LM statistic', so all the regressions passed with Chi-sq(1) $P - val < 0.1$. And the Weak identification test uses the 'Cragg-Donald Wald F statistic'; the critical value is 8.96 (15% maximal IV size). No Over-identification test required, as the equation is exactly identified. t statistics in parentheses;

*** Significance at the 1 percent level.
** Significance at the 5 percent level.
* Significance at the 10 percent level.

16. Additional results with other controls, including FDI and the number of researchers, are also provided in Table A.5 in the Appendix.

to be squeezed out. In other words, easier to flow to other sectors and firms. According to the special characteristics of State-owned Enterprises (SOEs) in China, these firms typically have relatively lower employee mobility compared to private firms. This result provides some evidence about how privatization affects human capital. Second, we observe a similar result from the comparison between the "High" and "Low" foreign ownership rates. The regions with higher shares of foreign-owned and -controlled enterprises cast significantly more negative impacts from export exposure on the local innovations. The international division of labor driven by the fragmentation of production provides some explanations for this phenomenon. This international division of labor is often illustrated by the 'Smiling Curve' concept. It posits that multinational enterprises (MNEs) from developed nations dominate the high-value-added segments of the value chain—such as R&D, design, marketing, and brand management—which are located in their home countries. The lowest-value-added segment, manufacturing and assembly (the bottom of the curve), is frequently offshored to emerging economies. So, it's easy to provide explanations for this phenomenon. When the MNEs come into China with capital and management experience driven by vertical specialization within Global Value Chains (GVCs), they intensively focus on "low-end" manufacturing and assembly which is the most profitable part in the labor-intensive countries. That's why we can see an even more pronounced negative impact on innovations from export exposure in regions with higher "international access". And we can come to a conclusion where the international vertical specialization in the global supply chain does not encourage innovation in developing countries. The talented people, or human capital in innovation in other words, will be squeezed out to more profitable sectors.

7 Physical Capital

After discussing the human capital in the previous sections, we also examine the results of physical capital, using interactions to compare the impacts of the two. Similar to human capital, we also treat three factors as distinct measures of physical capital. They are gross assets, fixed assets, and current assets[17]. In this study, we aggregate the three factors from the firm level to the city level.

$$\Delta\frac{INNV_{it}}{Pop_{it}} = \beta_0 + \beta_1\Delta EPW_{it} + \beta_2\Delta K_{it} + \beta_3\Delta EPW_{it}\cdot\Delta K_{it} + X_{it}'\beta_4 + \epsilon_{it}. \quad (39)$$

Where the K_{it} represents the city-level physical capital.

Following the same logic as the Human capital, we also apply the IV for not only the export exposure, but also the interaction item $\Delta EPW_{it}\cdot\Delta K_{it}$ where the identification is consistent with the strategy mentioned in section **??**. And then, the results are shown in table **??** which have the same arrangement as

17. The gross assets do not include only fixed assets and current assets, but also intangible assets and long-term investments.

table 5.

As we can see from the table 8, the coefficients for the impacts of export

Table 8: Interaction physical capital

Dependent Variable: Granted Patents (averaged)						
	(1)	(2)	(3)	(4)	(5)	(6)
ΔEPW	-0.178***	-0.185***	-0.186***	-0.216***	-0.186***	-0.223***
	(-3.69)	(-3.27)	(-4.68)	(-5.22)	(-5.03)	(-5.53)
$\Delta EPW \times \Delta Gross\ Asset$	-1.39e-09	-1.86e-09				
	(-0.86)	(-0.99)				
$\Delta EPW \times \Delta Fixed\ Asset$			2.25e-10	8.87e-10		
			(0.21)	(1.01)		
$\Delta EPW \times \Delta Current\ Asset$					3.46e-10*	5.92e-10***
					(1.73)	(2.87)
$\Delta Gross\ Asset$	3.99e-09*	2.37e-09*				
	(1.88)	(1.90)				
$\Delta Fixed\ Asset$			-7.49e-10	-1.26e-09***		
			(-1.41)	(-2.94)		
$\Delta Current\ Asset$					-1.30e-10	-3.41e-10
					(-0.24)	(-0.69)
N	3560	3537	3560	3537	3560	3537
$adjR^2$	-0.710	-0.462	-0.568	-0.390	-0.546	-0.417
Underidentification	12.89	11.11	6.536	6.704	12.89	11.79
Weak identification	9.076	9.099	3.426	4.020	9.003	9.775
Region FE:	Y	Y	Y	Y	Y	Y
Time Trend:	Y	Y	Y	Y	Y	Y
Controls:	N	Y	N	Y	N	Y

† ΔEPW is the change of Export Exposure per capita, measured by the formula 30. We allow the heteroskedasticity and cluster the observations on the province level. The control variables include GDP per capita, Total population, administrative area, and some local characteristics (road freight volume and number of hospitals). Gross assets include fixed assets, current assets, and other intangible assets (Intellectual Property, Virtual Assets). The Underidentification test uses the 'Kleibergen-Paap rk LM statistic', so all the regressions passed with Chi-sq(1) $P - val < 0.1$. And the Weak identification test uses the 'Cragg-Donald Wald F statistic'; the critical value is 8.96 (15% maximal IV size). No Over-identification test required, as the equation is exactly identified. t statistics in parentheses;

*** Significance at the 1 percent level.
** Significance at the 5 percent level.
* Significance at the 10 percent level.

exposure casts on the local innovations are statistically significant which keep consistent with all our results mentioned previously. There is some evidence from columns 5 and 6 indicating that higher current assets have a significant positive impact on the effects of innovation coming from export exposure. Current Assets including Cash and Cash Equivalents, Receivables and Prepayments, Inventories and so on. Regions with higher current asset intensity can better sponsor the creation and innovations, which obviously lead to more innovations after opening to trade, although the gross impact is negative. This phenomenon confirms our prior conclusion about "squeeze out" in the human capital part, thereby providing further evidence for this mechanism from a different perspective on physical capital. However, when we come to the gross assets and fixed assets, neither physical capital nor the interaction between capital and export

exposure has a significant impact on innovation. This finding can be explained by two aspects. Firstly, fixed assets do not significantly affect the innovation, or even hinder that. Cash flow can be a budget constraint for firms and investment in fixed capital for future production can lead to "Crowding out" of resources in R&D. Especially the manufacturing firms in developing countries where following the path of global vertical industry segmentation and focus on "Low-end" production. Second, the impacts of gross assets can come from the counteracting effects of both current assets and fixed assets, which offset each other. So we can conclude from these that, compared to human resources, physical capital does not significantly impact innovations, especially the fixed assets. One step further, in order to maintain consistency with human capital, we also separate the sectors into different groupings, applying asset ratios as criteria. First, we take the asset per capita into consideration. We select the asset per capita based on the industry level and group the top 30% versus the bottom 30% of them. The criteria are good for capturing asset intensity and identifying which industries are considered knowledge-intensive. On the other hand, we also use the asset sale ratio as the second measurement for the grouping standard. The sales-over-gross-asset ratio is always considered a measurement of the efficiency of the company and how much revenue the firm can generate based on the total assets it has. It is also called the assist turnover ratio. We take the inverse of the asset turnover ratio here and calculate it at the industry level within a city, rather than at the firm level, to measure a broader level of efficiency.
As we can see from the table, by comparing the first three columns with Panel A versus Panel B, we can easily observe that the export exposure leads to more recession in innovation in asset-intensive regions. We keep our argument which says the talented workers with better educational backgrounds and skill certificates are being squeezed out into other, more profitable sectors, which means the labor-intensive sectors, instead of the asset-intensive sectors, in China. The results and phenomena shown here are consistent with the previous results in section 5.4. In addition, columns 4 to 6 show a different story. The reverse asset-sales ratio indicates regional efficiency, and we observe that innovations in regions with a high asset-to-sales ratio have a more pronounced negative impact from export exposure. Obviously, regions with rigid bureaucracies and inefficient systems exhibit a lack of creativity and innovation. The reverse asset turnover ratio can capture the characteristics and how regional innovations are affected by efficiency. The findings here provide cross-validation with the results shown in table 7. Systems with higher efficiency and flexibility are more conducive to innovation activities.

At this point, our analysis achieves a logical closure. Throughout the secondary analysis, we initially posited that "high-educated" and "high-skilled" employees — particularly in developing nations like China — are more prone to being channeled by the vertical specialization of global value chains into roles that, while relatively lucrative, are focused on "manufacturing" rather than "creation". This proposition is further reflected in the classification results based on "type" and "ownership" of the firms, aggregated into the region

Table 9: Fiscal Capital Grouping Results

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: High Fiscal Capital						
	High Asset per capita			High Asset to Sales		
ΔEPW	-0.0424***	-0.0692***	-0.0770***	-0.0335**	-0.0370***	-0.0642**
	(-3.29)	(-5.39)	(-6.26)	(-2.45)	(-3.34)	(-2.69)
N	3832	3832	3808	3306	3306	3285
Underidentification	5.242	7.324	7.363	7.294	10.42	8.689
Weak identification	7.121	12.50	13.23	7.754	12.07	9.289
Panel B: Low Fiscal Capital						
	Low Asset per capita			Low Asset to Sales		
ΔEPW	-0.0184***	-0.0177***	-0.0194***	-0.0223**	-0.0202**	-0.0311***
	(-2.88)	(-3.12)	(-3.09)	(-2.31)	(-2.56)	(-3.46)
N	3807	3807	3783	3231	3231	3214
Underidentification	12.32	13.25	12.81	6.437	8.158	7.618
Weak identification	29.57	34.83	32.33	14.17	24.23	22.29
Region FE:	N	Y	Y	N	Y	Y
Time Trend:	N	Y	Y	N	Y	Y
Controls:	N	N	Y	N	N	Y

† ΔEPW is the change of Export Exposure per capita, measured by the formula 30. We allow the heteroskedasticity and cluster the observations on the province level. The control variables include GDP per capita, Total population, administrative area, and some local characteristics (road freight volume and number of hospitals). The Underidentification test uses the 'Kleibergen-Paap rk LM statistic', so all the regressions passed with Chi-sq(1) $P - val < 0.1$. And the Weak identification test uses the 'Cragg-Donald Wald F statistic'; the critical value is 8.96 (15% maximal IV size). No Over-identification test required, as the equation is exactly identified. t statistics in parentheses;

*** Significance at the 1 percent level.
** Significance at the 5 percent level.
* Significance at the 10 percent level.

level. Theoretically, multinational enterprises (MNEs) are expected to facilitate a certain degree of technology transfer through technology diffusion and FDI. However, our empirical results indicate that regions with a higher share of foreign ownership actually experienced greater innovation suppression following trade liberalization. This finding validates the hypothesis presented in our earlier theoretical model: compared to their "low-end" counterparts, Chinese "high-end" manufacturing firms are more significantly impacted by industrial chain transfers from developed countries. Consequently, for these firms, innovation fails to leverage comparative advantage and does not yield substantial profits. Similarly, the preceding discussion regarding physical capital substantiates this point: Chinese manufacturing firms that are more labor-intensive, and thus better able to exploit their comparative advantage, are less susceptible to the impacts of global value chain integration and the "unprofitability of innovation". It is possible that only by maintaining high levels of current assets for R&D investment and ensuring the efficiency of both the enterprise and the broader regional system can firms sustain their innovative capacity in the wave of globalization.

8 Conclusion

This study provides a comprehensive analysis of the complex relationship between export exposure and regional innovation within China's manufacturing sector from 1998 to 2015, a period defined by rapid global economic integration. By investigating the "reverse China shock," we reveal how the surge in external demand has reshaped domestic innovation. Integrating trade, foreign direct investment (FDI), human capital, and spatial spillovers into a unified framework, our analysis challenges conventional wisdom and offers a new perspective from the developing country.

Our theoretical framework adapts firm-level models to the regional level, demonstrating that how access to international markets may affect the cost-reducing innovations in "low-end" firms compared to quality-improving innovations in "high-end" firms due to intensified competition from technologically advanced foreign counterparts. This theoretical prediction is robustly supported by our empirical findings. Contrary to expectations and previous studies based on developed economies, we find that greater export exposure is associated with a significant decline in local innovations mostly provided by "high-end" firms, measured by granted patents. This negative effect contrasts sharply with the consistently positive impact of FDI, which highlights foreign capital inflows as a distinct and effective channel for technology diffusion.

Furthermore, our spatial econometric analysis uncovers a complex geographic dynamic: while increased trade exposure suppresses innovation within a specific city, it generates positive spillovers for neighboring regions. This suggests a spatial reallocation of innovative activities. We identify human capital dynamics as the primary mechanism driving these results. Human capital acts as a moderating variable, amplifying the negative local impact of export exposure on innovation. This supports a "squeeze-out" hypothesis, where China's comparative advantage in labor-intensive industries leads to the reallocation of skilled labor from R&D - intensive roles to more immediately profitable manufacturing activities like assembly. This effect is particularly pronounced in education- and skill-intensive sectors, further validating our proposed mechanism. On the other hand, physical capital does not appear to play a significant moderating role. The significance of this study lies in its solid findings of the trade-off between short-term gains from leveraging comparative advantages and long-term sustainable growth driven by domestic innovation. From a policy perspective, our findings suggest that promoting exports alone is insufficient for fostering technological upgrading. Policymakers must recognize the potential crowding-out effects of export-led growth on domestic innovation. To counteract the "squeeze-out" effect, targeted policies are essential for retaining and effectively utilizing skilled human capital in innovation-oriented sectors. Such measures could include R&D subsidies, tax incentives for high-tech firms, and strengthened bridges between industries and universities. Additionally, given the positive spatial spillovers observed, promoting regional innovation clusters could maximize knowledge diffusion and create resilient innovation networks less susceptible to localized pressures from export competition.

This paper contributes to the literature by offering one of the first comprehensive analyses of how export-led growth has influenced innovation in the manufacturing sectors in a major emerging economy. By employing a novel instrumental variable strategy, complemented by spatial econometric models and robustness checks using machine learning, we provide fresh evidence on the mechanisms linking trade, globalization, human capital, and technological diffusion progress. Future studies could extend this analysis by examining heterogeneous effects across different firm types, exploring the role of global value chain integration, and investigating the evolution of these dynamics in the post-2015 era of shifting global trade patterns under a new set of geopolitical circumstances.

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Appendix

Theory Appendix

In section 3.1, we have discussed the firm-level relationship between innovation and market size, assuming that all the firms in manufacturing sectors are focusing on cost-saving innovations instead of quality improvement in developing countries. We are providing an adjusted model based on alternative scenarios here, which still yields similar results to the model we previously presented.
We also start from the firms in closed economy with a perfectly competitive market based on the production function 2. The difference is, we do not simplify the quality index q_j as an exogenous constant value. Instead, we are introducing another factor $\mathbb{A} \in [0,1]$, which is a factor the firms choose how much 'share' of their innovations intend to improve the quality of final products while $1-\mathbb{A}$ shows how much share the firms choose to focus on 'cost-saving' innovations. So, when the firms are going to maximize their profit:

$$\pi_j = \max_{p_j,k_j} \{p_j k_j - \eta_j k_j\} \quad \text{subject to (3),} \tag{A.1}$$

and achieve the equilibrium quantity and price:

$$\begin{aligned} k_j &= \left[\frac{1-\beta}{\eta_j}\right]^{\frac{1}{\beta}} L_i q_j, \\ p_j &= \frac{\eta_j}{(1-\beta)}. \end{aligned} \tag{A.2}$$

And the profit become:

$$\pi_j = \Upsilon L_i q_j \eta_j^{\frac{\beta-1}{\beta}}, \quad \Upsilon \equiv (1-\beta)^{\frac{1-\beta}{\beta}} \beta \tag{A.3}$$

Then, based on the Myopic Firms assumption, in order to calculate the expected next period profit, we should consider two different types of costs. First, the cost of quality improvement. In order to improve the quality by step λ_1, the cost should be $C_1 = \theta_1 q_j x_j^2$. And on the other hand, reduce the cost by step λ_2, the cost should be $C_2 = \theta_2 \frac{1}{\eta_j} x_j^2$. So, the firm earning $\pi_{ij} = \Upsilon L q_j \eta_j^{\frac{\beta-1}{\beta}}$ with marginal cost η_j and quality q_j is expected to earn next period profit with innovation effort choice x_{ij} as:

$$\begin{aligned} \mathbb{E}\pi_j =& \mathbb{A}\left\{(1-z_j)\left[x_j\pi_j(1+\lambda_1) + (1-x_j)\pi_j\right] - \theta_1 q_j x_j^2\right\} + \\ & (1-\mathbb{A})\left\{(1-z_j)\left[x_j\pi_j(1-\lambda_2)^{\frac{\beta-1}{\beta}} + (1-x_j)\pi_j\right] - \theta_2\frac{1}{\eta_j}x_j^2\right\} \end{aligned} \tag{A.4}$$

So, firms can maximize this expected profit, leading to the equilibrium innovation choice:

$$
\begin{aligned}
x_j &= \frac{\mathbb{A}\pi_j\lambda_1 - \mathbb{A}z_j\pi_j\lambda_1 + (1-\mathbb{A})(1-z_j)\left[\pi_j(1-\lambda_2)^{\frac{\beta-1}{\beta}} - \pi_j\right]}{2\left[\mathbb{A}\theta_1 q_j + (1-\mathbb{A})\theta_2\frac{1}{\eta_j}\right]} \\
&= \frac{(1-z_j)\left\{\mathbb{A}\lambda_1 + (1-\mathbb{A})\left[(1-\lambda_2)^{\frac{\beta-1}{\beta}} - 1\right]\right\}\pi_j}{2\left[\mathbb{A}\theta_1 q_j + (1-\mathbb{A})\theta_2\frac{1}{\eta_j}\right]}.
\end{aligned} \tag{A.5}
$$

And by simplifying $\mathbb{A}$ to 0 or 1, we can reach the same results as equation 15 in our model. Then we try to focus on $\mathbb{A}$ here, we can see that:

$$
\frac{\partial x_j}{\partial \mathbb{A}} = \frac{2\pi_j\left\{\lambda_1\theta_2\frac{1}{\eta_j} - (1-z_j)\left[(1-\lambda_2)^{\frac{\beta-1}{\beta}} - 1\right]\theta_1 q_j\right\}}{4\left[\mathbb{A}\theta_1 q_j + (1-\mathbb{A})\theta_2\frac{1}{\eta_j}\right]^2}
$$

As we can see from the equation, the impact of $\mathbb{A}$ on the innovation effort depends on the relative costs of the 'quality-improvement' versus the 'cost-saving' innovations.

On the other hand,

$$
\frac{\partial x_j}{\partial \eta_j} = \frac{\Upsilon L_i q_j \eta_j^{\frac{-1}{\beta}}\frac{\beta-1}{\beta}\cdot\left\{\mathbb{A}\lambda_1 + (1+\mathbb{A})\left[(1-\lambda_2)^{\frac{\beta-1}{\beta}} - 1\right]\right\}}{4\left[\mathbb{A}\theta_1 q_j + (1-\mathbb{A})\theta_2\frac{1}{\eta_j}\right]^2} < 0.
$$

Similar to the model shown in the main text, when we consider the possibility that the firms can choose between the different types of innovation, production cost still has a negative relationship with innovation.

Technical Appendix

Mathematics Here, we provide the mathematical proof for the standard error adjustment for 2SLS manually.

$$
\left\{
\begin{aligned}
y &= X \cdot b + u, \\
X &= Z \cdot b_1 + u \\
\hat{X} &= Z \cdot b_{1OLS} = Z \cdot [(Z'Z)^{-1} \cdot (Z'X)] = P_z \cdot X,\ where\ P_z = Z \cdot (Z'Z)^{-1} \cdot Z' \\
y &= X \cdot b + u \\
b_{2SLS} &= (\hat{X}'X)^{-1} \cdot (\hat{X}'y) = (X'P_zX)^{-1} \cdot X'P_zy \\
Var(b_{2SLS}) &= E(\hat{\beta^2_{2SLS}}) - E(\hat{\beta_{2SLS}})^2 \\
&= E\{[(X'P_zX)^{-1} \cdot X'P_z(X\beta_{2SLS} + u)]^2\} - \beta^2_{2SLS} \\
&= E\{[\beta_{2SLS} + (X'P_zX)^{-1}X'P_zu]^{-1}\} - \beta^2_{2SLS} \\
&= [(X'P_zX)^{-1}X'P_z]^2 \cdot E[u^2] \\
&= \{(X'Z(Z'Z)^{-1}Z'X)^{-1} \cdot X'Z(Z'Z)^{-1}Z' \cdot (X'Z(Z'Z)^{-1}Z'X)^{-1} \cdot X'Z(Z'Z)^{-1}Z'\} \cdot \sigma^2 \\
&= \{(X'Z(Z'Z)^{-1}Z'X)^{-1} \cdot Z(Z'Z)^{-1}Z'\} \cdot \sigma^2 \\
&= (X'Z(Z'Z)^{-1}Z'X)^{-1} \cdot \sigma^2 \\
&= \sigma^2 \cdot (X'P_zX)^{-1} \\
\sigma^2 &= e'e/N,\ e = y - x \cdot b_{2SLS}
\end{aligned}
\right\}
$$

Robustness and Additional Tables

In this section, we will provide robustness checks for not only the baseline table in the empirical analysis part, but also for additional tables in the secondary analysis, including alternative specifications that cannot be included in the main text. We will focus on the baseline robustness tables first, then include some additional tables for the following secondary analysis and spatial econometrics parts.

Table A.1: Robustness for Baseline Results in Appendix 1

Dependent Variable: Granted patents (averaged)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔEPW	-0.405**	-0.252***	-0.342***	-0.354***	-0.235***	-0.356***	-0.395**	-0.247***	-0.338***
	(-2.54)	(-4.06)	(-3.88)	(-3.66)	(-5.18)	(-3.81)	(-2.53)	(-4.01)	(-3.85)
ΔFDI				0.167**	0.127**	0.163***			
				(2.49)	(2.20)	(2.79)			
$\Delta No.Researcher$							0.140	0.155*	0.0692
							(1.54)	(1.86)	(1.16)
N	3817	3817	3817	3625	3625	3625	3817	3817	3817
Underidentification	3.435	8.873	4.432	4.881	10.06	4.744	3.393	8.831	4.404
Weak identification	3.334	10.000	4.634	5.899	16.02	5.661	3.290	9.937	4.601
Region FE:	N	N	Y	N	N	Y	N	N	Y
Time Trend:	N	Y	N	N	Y	N	N	Y	N
Controls:	Y	Y	Y	Y	Y	Y	Y	Y	Y

† ΔEPW is the change of Export Exposure per capita, measured by the formula 30. Results of $\Delta FDI \times 100,000$ based on Unit; We allow the heteroskedasticity in this table and the observations are clustered on a province level. The control variables include GDP per capita, Total population, administrative area, and some local characteristics (road freight volume, and number of hospitals). The Underidentification test uses the 'Kleibergen-Paap rk LM statistic' and the Weak identification test uses the 'Cragg-Donald Wald F statistic', critical values for that is 8.96 (15% maximal IV size); No Over-identification test required as the equation is exactly identified. t statistics in parentheses;

*** Significance at the 1 percent level.
** Significance at the 5 percent level.
* Significance at the 10 percent level.

Table A.2: Robustness for Baseline Results in Appendix 2

Dependent Variable: Granted patents (averaged)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔEPW	-0.171***	-0.248***	-0.249***	-0.144***	-0.220***	-0.246***	-0.161***	-0.246***	-0.247***
	(-3.37)	(-4.55)	(-5.55)	(-3.58)	(-5.77)	(-5.91)	(-3.14)	(-4.51)	(-5.53)
ΔFDI				0.263***	0.150***	0.100**			
				(3.22)	(3.62)	(2.32)			
$\Delta No.Researcher$							0.255***	0.0395	0.0378
							(2.80)	(0.87)	(0.68)
N	3841	3841	3817	3641	3637	3621	3841	3841	3817
Underidentification	6.873	9.166	9.533	7.893	11.36	9.628	6.855	9.145	9.509
Weak identification	6.298	9.350	11.68	9.183	13.85	14.50	6.305	9.294	11.61
Region FE:	N	Y	Y	N	Y	Y	N	Y	Y
Time Trend:	N	Y	Y	N	Y	Y	N	Y	Y
Controls:	N	N	Y	N	N	Y	N	N	Y

† ΔEPW is the change of Export Exposure per capita, measured by the formula 30. Results of $\Delta FDI \times 100,000$ based on Unit; In this table, the region fixed effect is changed from province-level to city-level. We allow the heteroskedasticity in this table and the observations are clustered on a province level. The control variables include GDP per capita, Total population, administrative area, and some local characteristics (road freight volume, and number of hospitals). The Underidentification test uses the 'Kleibergen-Paap rk LM statistic' and the Weak identification test uses the 'Cragg-Donald Wald F statistic', critical values for that is 8.96 (15% maximal IV size); No Over-identification test required as the equation is exactly identified. t statistics in parentheses;

*** Significance at the 1 percent level.

** Significance at the 5 percent level.

* Significance at the 10 percent level.

Table A.3: Robustness for Baseline Results in Appendix 3

Dependent Variable: Granted patents (averaged)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔEPW	-0.248***	-0.331***	-0.223***	-0.227***	-0.336***	-0.230***	-0.241***	-0.326***	-0.220***
	(-4.21)	(-4.30)	(-6.14)	(-5.32)	(-4.16)	(-5.39)	(-4.14)	(-4.24)	(-5.98)
ΔFDI				0.125**	0.156***	0.115**			
				(2.16)	(2.76)	(2.37)			
$\Delta No.Researcher$							0.159**	0.0726	0.0864
							(1.96)	(1.26)	(1.61)
N	3831	3831	3831	3637	3637	3637	3831	3831	3831
Underidentification	9.302	4.858	11.11	10.53	5.359	10.48	9.292	4.852	11.15
Weak identification	10.62	5.141	15.09	17.76	6.695	17.32	10.57	5.118	15.09
Region FE:	N	Y	Y	N	Y	Y	N	Y	Y
Time Trend:	Y	N	Y	Y	N	Y	Y	N	Y
Controls:	Y	Y	Y	Y	Y	Y	Y	Y	Y

† ΔEPW is the change of Export Exposure per capita, measured by the formula 30. Results of $\Delta FDI \times 100,000$ based on Unit; In this table, the region fixed effect is at the province-level. We allow the heteroskedasticity in this table and the observations are clustered on a province level. The control variables include GDP per capita, Total population, administrative area, and some local characteristics. The Underidentification test uses the 'Kleibergen-Paap rk LM statistic' and the Weak identification test uses the 'Cragg-Donald Wald F statistic', critical values for that is 8.96 (15% maximal IV size); No Over-identification test required as the equation is exactly identified. t statistics in parentheses;

*** Significance at the 1 percent level.
** Significance at the 5 percent level.
* Significance at the 10 percent level.

Table A.4: Interaction Human Capital Robustness

Dependent Variable: Granted Patents (averaged)

	(1)	(2)	(3)	(4)	(5)	(6)
ΔEPW	-0.182***	-0.185***	-0.114***	-0.179***	-0.0980***	-0.160***
	(-3.55)	(-4.70)	(-4.36)	(-4.98)	(-3.33)	(-4.30)
$\Delta EPW \times No.Student$	-0.0494**	-0.0556**				
	(-2.31)	(-2.40)				
$\Delta EPW \times No.Researcher$			-0.0478***	-0.0394***		
			(-3.39)	(-3.65)		
$\Delta EPW \times No.Prof$					-0.113***	-0.107***
					(-2.90)	(-3.01)
$No.Student$	0.191***	0.0951**				
	(6.88)	(2.34)				
$No.Researcher$			0.120***	0.0567*		
			(2.81)	(2.02)		
$No.Prof$					0.384***	0.263***
					(5.57)	(3.58)
N	3741	3721	3841	3817	3724	3704
Underidentification	7.341	7.769	13.16	10.47	11.12	8.910
Weak-identification	4.007	4.838	7.615	7.171	7.645	5.995
Region FE:	Y	Y	Y	Y	Y	Y
Time Trend:	Y	Y	Y	Y	Y	Y
Controls:	N	Y	N	Y	N	Y

† ΔEPW is the change of Export Exposure per capita, measured by the formula 30. Results of $No.Student \times 10,000$, *and* $No.Prof \times 1,000$ based on Units. We allow the heteroskedasticity and cluster the observations on the province level. The control variables include GDP per capita, Total population, administrative area, and some local characteristics (road freight volume, and number of hospitals). The Underidentification test uses the 'Kleibergen-Paap rk LM statistic', so all the regressions passed with Chi-sq(1) $P - val < 0.1$. And the Weak identification test uses the 'Cragg-Donald Wald F statistic'; the critical value is 8.96 (15% maximal IV size). No Over-identification test required, as the equation is exactly identified. t statistics in parentheses;

*** Significance at the 1 percent level.

** Significance at the 5 percent level.

* Significance at the 10 percent level.

The table shown here is a supplement to the previous results presented in Table 5. We present the results of interactions between export exposure and human capital, without taking the first-order difference. Both the interaction items and human capital themselves exhibit statistically significant positive impacts on local innovation, as measured by granted patents. The results here are consistent with, and provide even more obvious evidence to, our conclusion previously.

Table A.5: Privatization and Foreign Ownership Rate Grouping Results Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: High privatization and foreign ownership rate						
	High privatization			High foreign ownership rate		
ΔEPW	-0.164**	-0.187**	-0.142**	-0.202***	-0.227***	-0.257***
	(-2.47)	(-2.71)	(-2.95)	(-4.24)	(-5.13)	(-4.97)
ΔFDI	0.128	0.131	0.0555	0.266**	0.234*	0.0638
	(1.15)	(1.03)	(0.72)	(2.11)	(1.92)	(0.63)
$\Delta No.Researchers$	1.244	1.176	0.733	0.224**	0.130	0.0628
	(1.53)	(1.41)	(1.19)	(1.98)	(1.27)	(0.78)
N	748	745	680	712	712	679
Underidentification	3.046	3.732	3.415	3.047	3.548	2.950
Weak identification	16.80	27.55	41.06	61.95	35.00	121.8
Panel B: Low privatization and foreign ownership rate						
	Low privatization			Low foreign ownership rate		
ΔEPW	-0.0325	-0.106**	-0.184***	-0.0466**	-0.0710***	-0.142**
	(-0.49)	(-2.10)	(-2.76)	(-2.03)	(-3.30)	(-2.60)
ΔFDI	0.232*	0.191**	0.0949	0.124*	0.137*	0.132
	(1.90)	(2.12)	(1.26)	(1.81)	(1.77)	(1.68)
$\Delta No.Researchers$	0.209**	0.0938	0.0553	0.100***	0.103***	0.0462
	(2.41)	(1.69)	(0.93)	(2.77)	(2.88)	(1.20)
N	2364	2364	2241	2683	2683	2621
Underidentification	12.66	15.30	14.18	15.11	15.65	11.04
Weak identification	11.55	16.51	10.33	15.39	17.73	6.662
Region FE:	N	Y	Y	N	Y	Y
Time Trend:	N	Y	Y	N	Y	Y
Controls:	N	N	Y	N	N	Y

† ΔEPW is the change of Export Exposure per capita, measured by the formula 30. Results of $\Delta FDI 10,000$ based on Units. We allow the heteroskedasticity and cluster the observations on the province level. The control variables include GDP per capita, Total population, administrative area, and some local characteristics (road freight volume, and number of hospitals). The Underidentification test uses the 'Kleibergen-Paap rk LM statistic', so all the regressions passed with Chi-sq(1) $P - val < 0.1$. And the Weak Identification test uses the 'Cragg-Donald Wald F statistic'; the critical value is 8.96 (15% maximal IV size). No Over-identification test required, as the equation is exactly identified.t statistics in parentheses;

*** Significance at the 1 percent level.
** Significance at the 5 percent level.
* Significance at the 10 percent level.

Table A.6: Spatial Results Robust

Dependent Variable: Granted Patents (averaged)

	Contiguity Matrix				Reverse Economics Matrix				Nest Matrix			
	SAR		SDM		SAR		SDM		SAR		SDM	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔEPW	-0.221***	-0.1898***	-0.188***	-0.171***	-0.248***	-0.225***	-0.211***	-0.195***	-0.231***	-0.1996***	-0.268***	-0.236***
	(0.0150)	(0.0098)	(0.0099)	(0.0061)	(0.0148)	(0.0097)	(0.0185)	(0.0126)	(0.0214)	(0.0147)	(0.0393)	(0.0231)
Spatial (Wx)			-0.0084	0.0057			-0.0752***	-0.05995***			0.149***	0.132***
			(0.0361)	(0.0220)	(0.0305)	(0.0186)	(0.0081)	(0.0061)	(0.0859)	(0.0768)	(0.0374)	(0.0242)
ρ	0.423***	0.4795***	0.479***	0.492***	0.148*	0.142*	0.161***	0.157***	0.146*	0.171**	0.202**	0.206**
	(0.148)	(0.112)	(0.091)	(0.087)	(0.0874)	(0.0855)	(0.0511)	(0.0515)	(0.0786)	(0.0685)	(0.0998)	(0.0892)
N	3502	3502	3502	3296	3502	3296	3502	3296	3502	3296	3502	3296
R^2 -within	0.0864	0.203	0.0864	0.0945	0.0867	0.0872	0.0928	0.0929	0.0887	0.0891	0.0913	0.0927
Individual FE:	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y

† ΔEPW is the change of Export Exposure per capita, measured by the formula 30. *Spatial* (Wx) here represents the spatially lagged dependent variable; ρ represents the spatially lagged explanatory variable. The control variables include GDP per capita, Total population, and administrative area. The standard error is adjusted using the mathematical process shown in Technical Appendix 8. t statistics in parentheses;

*** Significance at the 1 percent level.
** Significance at the 5 percent level.
* Significance at the 10 percent level.

Table A.7: Physical Capital No interaction for robustness

Dependent Variable: Patents authorized (averaged)						
	(1)	(2)	(3)	(4)	(5)	(6)
ΔEPW	-0.134***	-0.180***	-0.208***	-0.248***	-0.205***	-0.245***
	(-4.13)	(-4.63)	(-4.74)	(-5.17)	(-4.71)	(-5.23)
$\Delta Depreciation_t$	2.40e-08***	2.16e-08***				
	(3.49)	(3.19)				
$\Delta Inventory$			6.35e-09***	4.77e-09***		
			(3.16)	(3.47)		
$\Delta Finished\ Goods$					1.94e-08**	1.42e-08***
					(2.70)	(2.92)
N	3818	3794	3818	3794	3818	3794
Underidentification	10.76	9.327	11.68	10.22	11.56	10.10
Weak identification	13.46	12.83	13.97	13.74	13.95	13.73
Region FE:	Y	Y	Y	Y	Y	Y
Time Trend:	Y	Y	Y	Y	Y	Y
Controls:	N	Y	N	Y	N	Y

† ΔEPW is the change of Export Exposure per capita, measured by the formula 30. We allow the heteroskedasticity and cluster the observations on the province level. The control variables include GDP per capita, Total population, and administrative area. The Underidentification test uses the 'Kleibergen-Paap rk LM statistic'. The Weak identification test utilizes the 'Cragg-Donald Wald F statistic'; the critical value is 8.96 (15% maximal IV size). No Over-identification test required, as the equation is exactly identified. t statistics in parentheses;

*** Significance at the 1 percent level.
** Significance at the 5 percent level.
* Significance at the 10 percent level.

Alternative measurements for the physical capital are applied in these tables. $\Delta Depreciation_t$ here represents the total depreciation of the firms at time t and has been aggregated to the regional level. We use the total depreciation of all firms within the region to calculate the physical capital consumed in period t. $\Delta Inventory$ represents the change in the total inventory of all the manufacturing firms within the region. $\Delta Finished\ Goods$ here refers to the change of manufactured items that have completely passed through all stages of a firm's production process and are immediately available for sale to external customers within the region. Usually been classified as "Current Asset" on the balance sheets.

Table A.8: Interaction Physical Capital Robustness 2

Dependent Variable: Granted Patents (averaged)

	(1)	(2)	(3)	(4)	(5)	(6)
ΔEPW	-7.390	-3.076	-0.188***	-0.224***	-0.188***	-0.224***
	(-0.07)	(-0.15)	(-5.02)	(-5.56)	(-5.03)	(-5.60)
$\Delta EPW \times \Delta Depreciation_t$	0.00000552	0.00000211				
	(0.07)	(0.14)				
$\Delta EPW \times \Delta Inventory$			2.35e-09***	3.09e-09***		
			(3.18)	(4.66)		
$\Delta EPW \times \Delta Finished\ Goods$					4.73e-09**	5.87e-09**
					(2.06)	(2.63)
$\Delta Depreciation_t$	-0.0000128	-0.00000484				
	(-0.07)	(-0.14)				
$\Delta Inventory$			-8.88e-10	-1.91e-09		
			(-0.42)	(-1.01)		
$\Delta Finished\ Goods$					-2.40e-09	-5.15e-09
					(-0.43)	(-1.02)
N	3560	3537	3560	3537	3560	3537
Underidentification	0.00519	0.0200	12.83	11.77	13.13	11.86
Weak identification	0.00248	0.00947	8.903	9.747	9.180	9.794
Region FE:	Y	Y	Y	Y	Y	Y
Time Trend:	Y	Y	Y	Y	Y	Y
Controls:	N	Y	N	Y	N	Y

† ΔEPW is the change of Export Exposure per capita, measured by the formula 30. We allow the heteroskedasticity and cluster the observations on the province level. The control variables include GDP per capita, Total population, and administrative area. The Underidentification test uses the 'Kleibergen-Paap rk LM statistic'. The Weak identification test utilizes the 'Cragg-Donald Wald F statistic'; the critical value is 8.96 (15% maximal IV size). No Over-identification test required, as the equation is exactly identified. t statistics in parentheses;

*** Significance at the 1 percent level.
** Significance at the 5 percent level.
* Significance at the 10 percent level.

We switch to different measurements of the Physical Assets, and the results remain consistent with the table 8 shown previously in the Secondary analysis.

Table A.9: Details of the types of firms

(1) Type	(2) Foreign Owner
State-owned Enterprise (SOE)	NO
Collectively-owned Enterprise (COE)	NO
Sino-foreign Equity Joint Venture (EJV)	YES
Hong Kong, Macao, or Taiwan Sole Proprietorship Enterprise	YES
Equity Joint Venture (Hong Kong, Macao or Taiwan-invested)	YES
Hong Kong, Macao, or Taiwan-invested Joint Stock Company Ltd.	YES
Wholly Foreign-owned Enterprise (WFOE)	YES
Private Sole Proprietorship	NO
Private Limited Liability Company (Private LLC)	NO
Joint Stock Company Ltd. (or Stock Corporation)	NO
State-collective Joint Enterprise	NO
Other Limited Liability Company [a]	NO
State-owned Joint Enterprise	NO
Cooperative Joint Venture (Hong Kong, Macao or Taiwan-invested)	YES
Collectively-owned Joint Enterprise	NO
Other Joint Enterprises	NO
Other Enterprises	NO
Private Partnership	NO
Foreign-invested Joint Stock Company Ltd.	YES
Sino-foreign Cooperative Joint Venture (CJV)	YES
Shareholding Cooperative Enterprise	NO
State-owned Sole Proprietorship Company[b]	NO
Private Joint Stock Company Ltd.[c]	NO

a. This is often used interchangeably with "State-owned Enterprise" but is more specific. "State-owned Sole Proprietorship" is also a literal translation.
b. This is a more specific legal term under the Company Law, often simply grouped under SOE in economic analysis.
c. Or Private Stock Corporation

AI Statement

This paper benefits from AI translation, information retrieval, and academic paper searching. However, all the results and writings have been created by the authors themselves, without any assistance from AI. The authors are responsible for the accuracy and the academic integrity of this research.