# Real Exchange Rate and Innovation: Firm-Level Evidence from China

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**Abstract**: This paper examines how exchange rate movement affects firms' innovation activities using a panel dataset of Chinese manufacturing firms. We construct firm-specific effective real exchange rate (RER) to measure the exchange rate shocks faced by each firm according to its composition of trading partners. Our empirical results report that a 10% increase in effective RER (i.e. depreciation) increase the share of new product sales in total sales by about 0.2 percentage points. Our result is robust to 1) the inclusion of firm- and industry-specific control variables, firm-specific fixed effects and year effects; and 2) the use of alternative weighting in constructing effective RER and alternative estimation methods. Nonetheless, there is no evidence showing that firm-specific RER shocks affect patent application, which suggests that the quality of innovation brought by RER fluctuations is limited. We further show that a better export opportunity is the main channel through which a depreciation of exchange rate promotes innovation activities. A better export opportunity leads to a higher revenue from export, which in turn, we argue that, relaxes the financial constraint faced by firms to conduct innovation activities.

**Keywords:** Exchange Rate, Innovation, Patent, Financial Constraint

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## 1. Introduction

Innovation is known to be important for productivity gains and economic growth (Aghion and Howitt, 2009; Aw, Roberts, and Xu, 2011). Nonetheless, developing countries often lack funding and knowledge to pursue innovation. Thus, many governments in developing countries have been embracing globalization in order to accumulate funding and knowledge through trading with foreign countries.[1] A challenge for trading globally is that policy makers need to understand how the level of real exchange rate (RER), which determines the relative price of traded domestic and foreign goods, affects domestic firms' incentives and capabilities to innovate.

In theory, the effect of RER movement on firms' innovation is ambiguous. Consider a firm which simultaneously sell their output in both foreign and domestic markets, and import intermediates. On one hand, a depreciation of domestic currency would make its goods more attractive for foreigners (export opportunity) and make products of its foreign competitors less attractive in the domestic market (import competition). A higher demand for a firm's product increases the firm's incentives to innovate because it increases the potential rents from innovation (Acemoglu and Linn, 2004; Aghion and Howitt, 2009). On the other hand, a depreciation of domestic currency would raise the cost of domestic firms to access overseas' knowledge (access to imported inputs), discouraging innovation by firms (Coe and Helpman, 1995; Acharaya and Keller, 2008). Moreover, Aghion et al. (2018) document a skewed innovation response to an export demand shock between more and less productive firms; firms respond to an increased export demand by patenting more and this response is entirely driven by the subset of initially more productive firms.

Essentially, the nexus between RER and innovation is an empirical question. To shed a light on this issue, we examine how RER fluctuations affect firms' innovation activities using a panel dataset of Chinese manufacturing firms. We construct effective RER at the firm level as our dataset reports exports by destination and imports by source country for each firm. The firm-specific exchange rate allows us to measure the RER fluctuations faced by each firm

[1] Shu and Steinwender (2019) provide a comprehensive review on the effects of trade liberalization on innovation. They consider a variety of measures of innovation, including research and development (R&D) spending (input into innovation), patents (output of innovation), product mix (e.g., number of products, product quality, and product differentiation), and survey responses on adoption of new technologies, new management practices, or product or process innovations.

according to its composition of trading partners. For innovation activities, we measure them with new product sales and patent applications. To identify the channels through which RER affects innovation activities, we construct export-, import- and import penetration-weighted RER in order to disentangle the following three channels, namely export opportunity, imported intermediate inputs and import competition.

Our empirical results report that a 10% depreciation in effective RER increase the share of new product sales by about 0.2 percentage points. Our result is robust to 1) the inclusion of firm-specific control variables, firm-specific fixed effects, non-linear time trends of several innovative sectors and year effects; and 2) the use of alternative weighting in constructing effective RER and alternative empirical specifications. Nonetheless, there is no evidence showing that effective RER fluctuations affect patent applications. It suggests that the effective RER fluctuations are more able to affect commercialization of innovation than basic research. Further, we show that export opportunity is the main channel through which a depreciation of effective RER promotes innovation activities. Finally, we use a theoretical model to explain how a better export opportunity promotes innovative activities. We suggest that increased profits from more exports induced by a RER depreciation are used to overcome financial constraint for innovation.

Our paper contributes to the literature analyzing how RER fluctuations affect firms' innovation activities.[2] Based on 360 U.S. manufacturing firms over the period 1975-1987, Zietz and Fayissa (1994) document that firms in R&D intensive industries increase R&D spending following a RER appreciation, suggesting that import competition (driven by a RER appreciation) drives innovation. Funk (2003) examines 269 U.S. manufacturing firms for the period 1979-1994, finding that following a real depreciation R&D investment of firms with foreign sales increases while R&D investment of firms with no foreign sales does not change significantly. These results suggest a real depreciation increases export opportunity, which in turn encourages innovation. Alfaro et al. (2018) estimate a structural dynamic model of R&D investment of heterogeneous firms that self-select into exporting their output and/or importing intermediate inputs, and find that firms in export-orient (import-orient) countries are more (less) likely to engage in R&D in response to a RER depreciation. Our work is most

[2] For analysis using industry-level data, see Becker and Pain (2008) and Tabrizy (2020), and for cross-country analysis, see Chen (2017).

related to Kaiser et al. (2018), who find that a RER appreciation reduces R&D activities of Swiss firms. These results are more in line with the decline in export opportunity and the rise of import competition, but not a cheaper access to imported intermediate inputs. The previous works rely on aggregate or industry level RER. Our work differs from theirs in using firm-specific effective RER, which better captures the differential effects of exchange rate movements on firms with different composition of trade partners.[3]

Further, our paper contributes to the literature that examines the impact of exchange rate movement on behaviors of Chinese firms. Li, Ma, and Xu (2015) find that exporters do not change much of their export price and their export volume is only reduced moderately when RMB appreciates. Xu, Mao, and Tong (2016) extend the former work by not only analyzing the responses of export price and volume, but also showing exporters adjust their product scope and export duration in response to exchange rate fluctuations. Dai and Xu (2017) find that a RER appreciation reduces the relative employment growth in firms more reliant on exports, increase the relative employment growth in firms more reliant on imported intermediate inputs, and reallocate labor across firms with different export destinations and import source countries. In a closer relationship to our work, Dai, Yu, and Zhao (2018) exploit the exchange rate appreciation of RMB during 2005–2007 as a quasi-experiment and show that the appreciation imposes greater competitive pressure on exporters relative to non-exporters. In response, exporters increase innovation activities more than non-exporters. However, they model the exchange rate shock common to all firms, which limits the control for aggregate shocks. Our work differs from theirs in constructing the firm-specific effective RER that captures more closely the real exchange rate faced by each firm. Our work also provides evidence that currency depreciation relaxes financial constraint, which in turn promotes innovation activities.

Finally, our paper contributes to a recent literature that investigates the impact of opening external sector on innovation of Chinese firms. Previous studies use China's accession to the World Trade Organization (WTO) in 2001 as a quasi-natural experiment. Liu and Qiu (2016) find that a reduction in intermediate input tariff hinders innovation activity of Chinese firms, which is consistent with the use of foreign technology at the expense of own innovation for

[3] Another benefit of using firm-specific effective RER is the increased precision of the estimation due to more variation in the firm-level RER.

production. Bombardini, Li, and Wang (2017) and Liu, Lu, and Luong (2021) employ a reduction of input tariff as a measure of increased import competition of foreign products on domestic Chinese firms. The former reports that a stronger import competition in previous years leads to more innovation activities of Chinese firms, while the latter finds a negative effect of contemporaneous import competition on firm innovation. Liu and Ma (2020) show that a reduction of trade policy uncertainties in destination markets promotes innovation activities of Chinese firms. Our work differs from the previous papers in examining and explaining how innovative activities are affected by exchange rate fluctuations, which is partly driven by exchange rate reforms.

The remaining parts of this paper are organized as follows. Sections 2 provides background information. Section 3 presents the empirical methodology. Sections 4 and 5 discuss the empirical findings. Section 6 concludes.

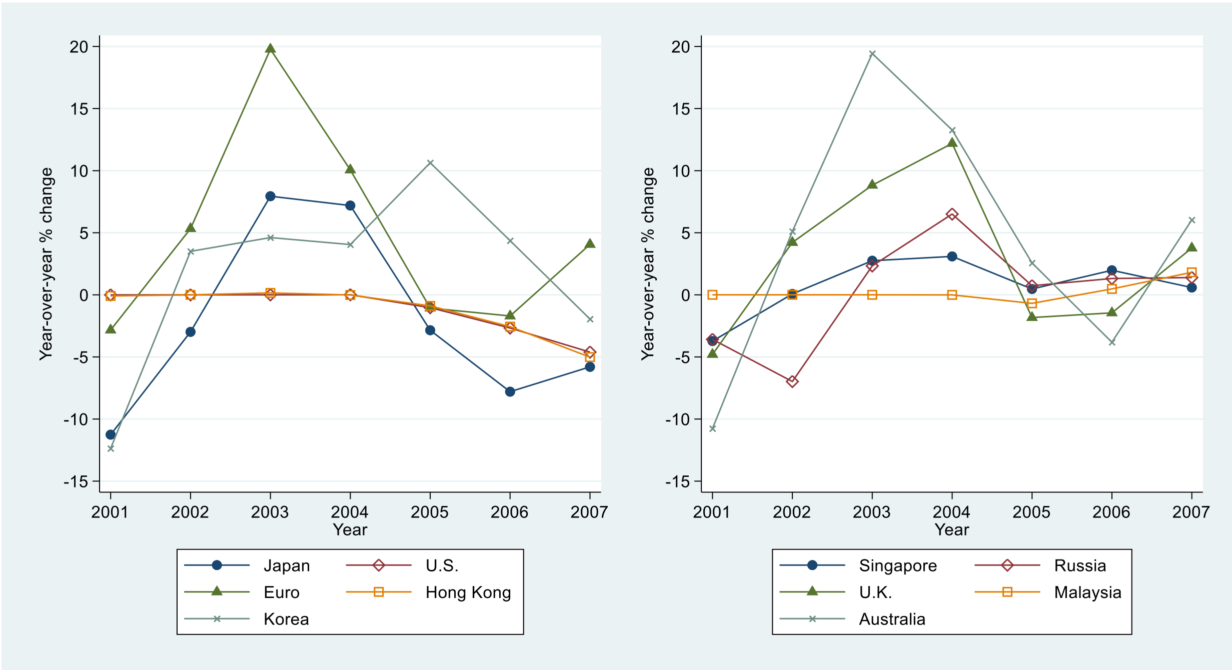
## 2. Background

This section provides a brief discussion on China's exchange rate regime and describes the exchange rate fluctuations over our sample period.

On 21 July 2005, the People's Bank of China (PBOC) announced a major reform of the exchange rate regime, abandoning the decade-long strict peg against the U.S. dollar (USD) and adopting a managed floating regime. Prior to the reform, the Chinese currency, renminbi (RMB), had been pegged to the USD at the rate of 8.28 RMB/USD since 1997. Figure 1 depicts the year-over-year percentage change in exchange rates of the RMB against the currencies of China's ten largest trading partners over the period 2001-2007. It confirms that, before 2005, while there was almost no fluctuation between RMB and USD, RMB fluctuated against other currencies.

Under the new regime, the exchange rate target was set with reference to a basket of currencies and more fluctuations of the exchange rate were allowed. Specifically, each day the PBOC announced its target (the central parity, also known as the 'fix') for the following trading day based on that day's closing price of the USD against the RMB. The following day, the RMB/USD rate would be allowed to fluctuate within a band of ±0.3 percent around the announced central parity. The trading prices of the non-USD currencies against the RMB would be allowed to move within a wider band of ±1.5 percent.[4] In September 2005, the trading band for non-USD currencies was widened to ±3 percent. In May 2007, the daily band around the central RMB/USD parity was widened to ±0.5 percent (Das, 2019). Figure 1 depicts that, after 2005, while RMB appreciated against USD, RMB fluctuations against other currencies muted.

Figure 1. Year-over-year percentage change of nominal exchange rates of the RMB, 2001–07




*Note:* This figure shows the year-over-year percentage change in exchange rates of the RMB against currencies of China's ten largest trading partners for the period 2001-2007. According to data from World Integrated Trade Solutions (WITS), those ten trading partners are Japan, United States, Euro area, Hong Kong, South Korea, Singapore, Russia, United Kingdom, Australia, and Malaysia. A positive value represents a depreciation of the RMB.

Our empirical strategy exploits two dimensions of variation in exchange rates, namely the variation over time as shown in Figure 1 and the variation across firms due to changes in composition of trading partners, to examine how RER fluctuations affect innovation.

[4] See PBOC's announcement on "Reforming the RMB Exchange Rate Regime," July 21, 2005. www.pbc.gov.cn/english/130721/2831438/index.html

## 3. Empirical Strategy

This section first presents the empirical model, and then describes the data sources and the construction of our key variables.

### 3.1 Empirical Model

Denote firms by $i$, industry by $j$, and year by $t$. We estimate the following equation:

$$y_{ijt} = \beta \ln(RER_{it}) + \boldsymbol{X}'_{it}\boldsymbol{\gamma} + \boldsymbol{Z}'_{jt}\boldsymbol{\delta} + \lambda_i + \lambda_t + \epsilon_{ijt}, \quad (1)$$

where $y_{ijt}$ is the share of new product sales (i.e., sales of new products over total sales) of firm $i$ in industry $j$ in year $t$, $RER_{it}$ is trade-weighted effective RER for firm $i$ in year $t$ (see a later sub-section for its construction), $\boldsymbol{X}_{it}$ is a vector of firm $i$'s characteristics in year $t$, $\boldsymbol{Z}_{jt}$ is a vector of industry $j$'s characteristics in year $t$, $\lambda_i$ is the firm-specific fixed effects, $\lambda_t$ is the year fixed effects, and $\epsilon_{ijt}$ is the error term.

Following the previous studies on firm-level innovation (Gorodnichenko and Schnitzer, 2013; Liu and Qiu, 2016; Dai, Yu, and Zhao, 2018), we include the following time-varying firm characteristics ($\boldsymbol{X}_{it}$):

$Age$: Number of years since a firm is established.

$Age^2$: Square term of $Age$. This is to capture the potential life cycle of innovation.

$\ln(Size)$: Log of the firm size measured by the number of employees. Potentially, large firms are less likely to be financial constrained, and enjoy scale economies in R&D.

$\ln(Fixed)$: Log of fixed assets.

$Current$: Current ratio, i.e. Current Assets / Current Liabilities.

$Debt$: Debt-Asset ratio, i.e. Total Debt / Total Assets. The above three variables relate to financial constraint. Physical assets can help relaxing financial constraint; for example, physical assets can be used as collateral for bank loans. Firms with a higher current ratio and less debt are less likely to be financially constrained.

$\ln(TFP)$: Log of total factor productivity (TFP). Productive firms are likely to be innovative.

$Foreign$: Equity share owned by foreign investors.

We include the firm fixed effects ($\lambda_i$) which control for all time-invariant characteristics of firms (as well as industries and regions). We also include year fixed effects ($\lambda_t$) to capture shocks common to all firms, such as interest rates, fiscal policy, and regulatory changes. The analysis of Liu and Qiu (2016) and Liu and Ma (2020) demonstrate the importance of accounting for differential trends in innovation activities across sectors. In a specification, instead of including year fixed effects, we include industry-year fixed effect ($\lambda_{jt}$) to take into account industry-specific non-linear trends.

The coefficient of interest is $\beta$, which captures the impact of effective RER on the share of new product sales. The identification of $\beta$ comes from the variation in effective RER across firms and over time, which relates to the variation in the share of trading partners and exchange rates. The identification also requires that the error term $\epsilon_{ijt}$ (a firm's idiosyncratic shock in innovation) is uncorrelated with the effective RER conditional on a large set of control variables and fixed effects. A similar assumption is made in previous studies, such as Amiti, Itskhoki, and Konings (2014), Dai and Xu (2017), and Kaiser et al. (2018).

### 3.2 Data

Our empirical analysis is based on firm-level datasets on production, trade, and innovation.

***Firm-Level Production Data:*** The firm-level data on production come from the Annual Survey of Industrial Production (ASIP), complied by China's National Bureau of Statistics (NBS). This dataset covers all state-owned enterprises (SOEs) and non-SOEs with annual sales above RMB 5 million (about $US 600,000 at the exchange rate of 2001) over the period 2001-2007. The sample firms span 37 two-digit manufacturing industries and 31 provinces or province-equivalent municipal cities.[5]

The ASIP production data contains detailed information on firms, including official name, address, phone number, postal code, time of establishment, industry classification, sales,

[5] The dataset is representative. Based on the census of industrial firms conducted by the NBS, in 2004 firms included in the ASIP account for 90% of industrial output, 97.5% of exports, and over 70% of industrial employment (Brandt, van Biesebroeck, and Zhang, 2012).

profits, exports, total assets, number of employees, capital stock, equity share owned by foreign investors, and many other financial-statement variables. In particular, we employ this dataset to construct the main measure of innovation activities (i.e., share of new product sales), and time-varying firm characteristics in our empirical model.[6]

***Firm-Product-Level Trade Data***: The transaction-level data on trade come from the General Administration of Customs of China (GACC), which covers the universe of China's importers and exporters for the period 2001-2007. It contains data on the export and import values at the firm level by month, by product (HS 8-digit) and by destination or source country. It also contains information on firms (e.g., official name, address, phone number, postal code) and trade mode.[7]

In particular, we employ this dataset to construct the trade-weighting for firm-specific trade-weighted effective RER.

***Firm-Level Patent Data:*** The firm-level data on patent come from China National Intellectual Property Administration (CNIPA).[8] This dataset contains detailed information on all patent filings since 1985, including the date of filing, the official name and address of the applicant, and the name and type of the patent.[9] In particular, we employ this dataset to construct firm-level patent counts.

We merge the three firm-level datasets as follows. Following Yu (2015), we merge the ASIP production data and the GACC trade data in two steps. First, we merge the two datasets using firm name and year.[10] Second, we match the remaining un-merged samples by postal

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[6] Following Cai and Liu (2009) and subsequent studies such as Feenstra, Li, and Yu (2014), Yu (2015), and Dai and Xu (2017), we clean the ASIP production data as follows. First, guided by the basic rules of the Generally Accepted Accounting Principles (GAAP), we drop observations for which any of the following is observed: (1) the firm's identification number is missing or not unique, (2) the firm's established time is invalid (opening year is after 2007 or the opening month is later than December or earlier than January), (3) liquid assets are greater than total assets, (4) total fixed assets are greater than total assets, (5) the net value of fixed assets is greater than the value of total assets, (6) current depreciation is greater than accumulated depreciation, or (7) exports are greater than sales. Second, we exclude firms with fewer than eight workers because they fall under a different legal regime (Brandt, van Biesebroeck, and Zhang, 2012). Finally, observations with missing or negative values on any of the key variables (such as sales, exports, capital stock, and number of employees) are deleted.

[7] We defer a discussion of trade mode until we describe the measure of vertical specialization in Section 4.

[8] CNIPA is responsible for all patent-related work and regulations. Following a government restructuring, the former State Intellectual Property Office of China (SIPO) was reorganized into CNIPA on 28 August 2018.

[9] We defer a discussion of patent type until we describe the measure of innovation activities in the next subsection.

[10] We aggregate the monthly GACC trade data to the annual level to be consistent with the annual ASIP production data.

code and the last seven digits of the firm's phone number. Then, we match the merged ASIP-GACC data with the CNIPA patent data using firm name and address. Our merged dataset has 246,686 observations.

**Data on Exchange Rates and Prices**: To construct the firm-specific effective RER, we use data on nominal exchange rates and consumer price indices coming from the International Financial Statistics (IFS) of the International Monetary Fund (IMF) and the Bank of International Settlements (BIS).

### 3.3 Key Variables of Interest

***Firm-level Innovation:*** We employ a variety of measures for firm-level innovation activities. First, we employ the share of new product sales in total sales. This measure is also used in Dai, Yu, and Zhao (2018).[11] The advantage of this measure is that it incorporates the commercialization of innovation activities, which is more relevant to the profits of innovating firms. The disadvantage of this measure is that it may not capture high quality or original innovation, which is yet close to the stage of commercialization.

Second, following the previous studies (e.g., Liu and Qiu 2016; Bombardini, Li, and Wang, 2017; Liu and Ma, 2020; Liu, Lu, and Luong, 2021), we employ the number of patent applications as a measure of innovation activities. According to China's Patent Law, patents are classified into three types: invention, utility model, and design.[12] In general, invention patents is more innovative than utility model and design patents. To examine whether our results are robust to measures of innovation activities, we also use the number of invention, utility, and design patents as separate measures.

***Effective RER:*** Our key explanatory variable is the firm-specific effective RER. Exchange

[11] Acemoglu and Linn (2004) measures innovation of pharmaceutical firms with number of new drugs.

[12] Invention patent refers to any new technical solution relating to a product or a process. Utility model patent refers to any new solution relating to a product's shape, structure, or a combination thereof, which is fit for practical use. Design patent refers to any new design regarding the shape, pattern, or their combination thereof, which creates an aesthetic feeling and is fit for industrial application. Invention patents, which have a 20-year protection period, are substantively examined and can take three years to five years to grant. Utility model and design patents, which have a 10-year protection period, are not substantively examined and are granted after a formal examination, which generally takes about one year to 1.5 years or less.

rate movements may affect each firm to differing degrees, owing to differing composition of the firm's trade partners. Our firm-level trade transaction data allow us to construct firm-specific trade-weighted effective RER, where the weight of each partner currency (country $k$) is the share of that partner $k$ in the exports and imports of the specific firm. This measure is also used in Xu, Mao, and Tong (2016), Dai and Xu (2017), and Li, Wei, and Zhang (2018).[13] In particular, we compute the firm-specific RER as follows

$$RER_{it} = \prod \left( \frac{e_{kt}}{e_{0t}} \cdot \frac{P_t}{P_{kt}} \right)^{w_{ik,t-1}},$$

where $RER_{it}$ is trade-weighted effective RER for firm $i$ in year $t$, $e_{kt}$ and $e_{0t}$ are the nominal exchange rate for country $k$'s currency in terms of the Chinese RMB (a decline indicates that the RMB appreciates against currency $k$) in year $t$ and the base year (i.e., 2000) respectively, $P_t$ and $P_{kt}$ are the consumer price index ($2000 = 100$) for China and country $k$ in year $t$ respectively, and $w_{ik,t-1}$ is the share of country $k$ in the total exports plus imports of firm $i$ in year $t-1$. Note that all trade variables are lagged for one period to avoid potential endogeneity.

### 3.4 Descriptive statistics

Table 1 presents the definitions and summary statistics of the main variables used for our empirical analysis. On average, each firm obtains 5 percent of their sales from the new product and applies 0.09 patents per year. Turing to the firm characteristics, on average, firms established less than 9 years ago, have current assets 9 times more than current liabilities, and have debt at 55% of total assets.

## 4. Empirical Results

This section first presents our main results, and then provides a variety of robustness checks. We then explore the driving forces behind our empirical results.

[13] The use of firm-specific real effective exchange rates goes at least as far back as Funk (2003), who construct firm-specific rates using industry-level trade data combined with firm-level sales data.

### 4.1. Baseline results

Table 2 presents the results of Equation (1). We include the control variables and fixed effects block-by-block and show that the coefficients of $\ln(RER)$ are robust across specifications. We discuss the results in Column 4, which include the most extensive set of control variables and fixed effects. The coefficient of $\ln(RER)$ is 0.002, which means a 10% depreciation in effective RER leads to 0.02 percentage points increase in the share of new product sales. Among the potential channels, our results are consistent with a greater export opportunity. In contrast, our results are not consistent with the channel of less import competition and more expensive access to imported inputs by depreciation.

The coefficients of control variables are reasonable, which provides further confidence in our empirical specification. Larger, capital-intensive, and more liquid firms are more innovative. These results suggest that financial constraint may play a role in innovative activities as firm size, capital intensity and liquidity are common measures for access to finance. Productive firms are more innovative, which suggests that firms are more motivated to develop new products if they benefit more from it.

### 4.2. Robustness Checks

In this sub-section, we perform a set of robustness tests, including the number of patents as measures of innovation, alternative weights for real effective exchange rates, and alternative empirical specifications. The results are presented in Table 2-3.

#### *4.2.1 Industry-Specific Trends*

One may concern that there are different trends across industries in their innovation activities. Such differential trends may be driven by policy preference from the central government. To check this concern, we include an industry-year fixed effects, which allows us to control for unobserved industry characteristics in a flexible way. We report the results in Column 4 of Table 2, and find our results are robust to this modification.

#### *4.2.2 Alternative weights for effective RER*

In Equation (1), all trade weights in the firm-specific effective RER are lagged for one period to avoid potential endogeneity. As an alternative, we use a time-invariant trade weight by using the export and import values in 2000. We report the results based on the time-invariant trade weight in Column 1 of Table 3, and find that our results are robust to this modification.

### *4.2.3 Lagged effective RER*

Exchange rate can affect innovative activities with time lag. Here, we include the lagged $\ln(RER)$ in Equation (1) and report the results in Column 2 of Table 3. The coefficient of $\ln(RER)$ in the previous year is significant, but that in the current year is insignificant. It suggests that it take at least one year for firms adjusting their innovative activities in response to exchange rate movement. This result is reasonable because there is a time needed for developing new products.

### *4.2.4 Alternative measures of innovation activities*

To investigate whether the effect of RER on innovation is robust to the use of other innovation measures. We use the number of patent application filed by firm $i$ in industry $j$ in year $t$, $Patent_{ijt}$, as the dependent variable. Since there are zeros for the patent application filed, we estimate Equation (1) with $\ln(1 + Patent_{ijt})$ as the dependent variable, and report the results in Column 3 of Table 3.

We also follow the existing studies to model patent application as a count variable. We assume $Patent_{ijt}$ to be Poisson distributed with mean $\lambda_{ijt} > 0$. We employ the following exponential function form as the link between $Patent_{ijt}$ and the explanatory variables:

$$\begin{aligned}\lambda_{ijt} &= E\left[Patent_{ijt} \middle| \ln(RER_{it}), \boldsymbol{X_{it}}, \boldsymbol{Z_{jt}}, \lambda_i, \lambda_t\right] \\ &= \exp\left[\beta_1 \ln(RER_{it}) + \boldsymbol{X}'_{it}\boldsymbol{\gamma} + \boldsymbol{Z}'_{jt}\boldsymbol{\delta} + \lambda_i + \lambda_t\right].\end{aligned}$$

We estimate the above specification using the fixed effects Poisson estimator and report the results in Column 4 of Table 3.

Further, the Poisson estimator assumes that the conditional mean is equal to the conditional variance. However, this assumption is violated in most empirical applications, as the conditional variance is often larger than the conditional mean, leading to over-dispersion. A consequence of this violation of assumption is that the standard errors are underestimated, even though the Poisson estimates are still asymptotically consistent. To address this issue, we estimate the link between $Patent_{ijt}$ and the explanatory variables with a fixed effects negative binomial (NB) model and report the results in Column 5 of Table 3.

Interestingly, Columns 3-5 of Table 3 report that the coefficients of $\ln(RER)$ are insignificant. It suggests that RER movement does not provide enough incentives for firms to change their fundamental innovative activities. Instead, RER movement provides incentive or resources to commercialize innovative activities, which is measured by the new product sales. For the remaining parts of our paper, we focus on the share of new product sales as the innovation outcome.

### 4.3. Potential Channels

There are three potential channels through which RER can affect innovation, namely 1) export opportunity; 2) import competition; and 3) access to intermediate inputs. In this sub-section, we explore which channels are more likely to drive our main results.

To disentangle those three channels, we construct three trade-weighted effective RER. First, we construct the export- and import-weighted effective RER as follows

$$EXRER_{it} = \sum_{k} \left( \frac{e_{kt}}{e_{0t}} \cdot \frac{P_t}{P_{kt}} \right)^{w_{ik,t-1}^{EX}}$$

$$IMRER_{it} = \sum_{k} \left( \frac{e_{kt}}{e_{0t}} \cdot \frac{P_t}{P_{kt}} \right)^{w_{ik,t-1}^{IM}},$$

where $EXRER_{it}$ and $IMRER_{it}$ are export- and import-weighted effective RER for firm $i$ in year $t$, respectively, $w_{ik,t-1}^{EX}$ and $w_{ik,t-1}^{IM}$ are the shares of country $k$ in the total exports and imports of firm $i$ in year $t-1$ respectively. The export- and import-weighted effective RER capture the impact of exchange rate fluctuations on firms' innovation through export opportunity and import cost channels, respectively.

To capture the effect of exchange rate movement on domestic firms through import competition channel, we construct the industry-level import-penetration-weighted effective RER as follows,

$$IMPRER_{jt} = \sum_k \left(\frac{e_{kt}}{e_{0t}} \cdot \frac{P_t}{P_{kt}}\right)^{w^{IMP}_{jk,t-1}}$$

$$w^{IMP}_{jk,t-1} = \frac{IM_{jk,t-1}}{DS_{j,t-1} + \sum_k IM_{jk,t-1}},$$

where $IMPRER_{jt}$ is the import-penetration-weighted effective RER for industry $j$ in year $t$, $w^{IMP}_{jk,t-1}$ is the import penetration ratio from country $k$ in industry $j$ of China's domestic market, $IM_{jk,t-1}$ is the total import value from country $k$ by industry $j$ in year $t-1$, and $DS_{j,t-1}$ is total domestic sales of industry $j$ in year $t-1$.

We estimate Equation (1) with $\ln(EXRER_{it})$ and $\ln(IMRER_{it})$ instead of $\ln(RER_{it})$, and report the results in Column 1 of Table 4. Further, we estimate Equation (1) with $\ln(EXRER_{it})$, $\ln(IMRER_{it})$ and $\ln(IMPRER_{it})$ instead of $\ln(RER_{it})$, and report the results in Column 2 of Table 4..

### *4.3.1 Supplementary Evidences*

In addition to constructing three firm-specific effective RER to identify the potential channels, we supplement the previous approach with the following two analyses.

***Industry Upstreamness***: We postulate that upstream industries benefit less from the channel of accessing intermediate inputs because upstream industries rely less on intermediate inputs than downstream industries. If the access to intermediate inputs was a channel for exchange rate movement to affect innovation, we would observe firms in upstream industries benefit more from RER depreciation.

To assess whether countries are specializing in relatively upstream versus downstream stages of global production processes, Antràs et al. (2012) and Antràs and Chor (2013) propose an industry-level measure of relative production-line position. For each industry $i \in \{1, 2, \ldots, N\}$ in an $N$-industry closed economy, a measure of industry "Upstreamness" (or average distance from final use) is

$$U_i = 1 \cdot \frac{F_i}{Y_i} + 2 \cdot \frac{\sum_{j=1}^{N} d_{ij} F_j}{Y_i} + 3 \cdot \frac{\sum_{j=1}^{N} \sum_{k=1}^{N} d_{ik}\, d_{kj} F_j}{Y_i} + 4 \cdot \frac{\sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{l=1}^{N} d_{il}\, d_{lk}\, d_{kj} F_j}{Y_i} + \cdots,$$

where $Y_i$ is the total output of industry $i$, $F_i$ is the amount of industry $i$'s output used as a final good, and $d_{ij}$ is the amount of sector $i$'s output needed to produce one unit of industry $j$'s output. For an open economy, we need to replace $d_{ij}$ in the equation above with

$$\hat{d}_{ij} = d_{ij} \cdot \frac{Y_i}{Y_i - X_i + M_i}$$

where $X_i$ and $M_i$ denote exports and imports of sector $i$'s output, respectively. To construct the "Upstreamness", we supplement with the input/output table of China for 2007 taken from China's National Bureau of Statistics (NBS).

We estimate Equation (1) with the inclusion of $\ln(RER_{it}) \times (U_J - \overline{U_J})$, and report the results in Column 3 of Table 4. Since the interaction term is insignificant, these results provide no evidence that access to imported inputs is a channel through which exchange rate movement affects innovation. These results are consistent with our main results.

***Vertical Specialization (VS):*** Vertical specialized firms rely more on imported input to produce their export. A depreciation of RER would impose a more negative effect on those firms because they faced a larger cost increase in using imported inputs. If the access to intermediate input was a channel for exchange rate movement to affect innovation, we would observe vertically specialized firms benefit less from RER depreciation.

Hummels, Ishii, and Yi, (2001) propose a measure of VS, i.e. the process by which production is separated into different stages across countries, as the value share of imported intermediates in exports. Extending Hummels et al. (2001), Upward, Wang, and Zheng (2013) propose a firm-level measure of VS:

$$VS = M^p + \frac{M^0}{Y - X^p} \cdot X^0$$

where $M$ is imported intermediates, $X$ is exports, $Y$ is total output, and the superscripts $p$ and $o$ denote processing trade and ordinary trade respectively. $Y - X^p$ is the value of output minus processing exports, or equivalently domestic sales plus ordinary exports. To compute VS, we use both the ASIP and GACC data. Data on import and export are taken from the GACC trade data; all imports are considered as imported intermediates. Domestic sales are the total sales net of exports in the ASIP production data.

We estimate Equation (1) with the inclusion of $\ln(RER_{it}) \times (VS_{it} - \overline{VS_t})$ and $VS_{it}$, and report the results in Column 4 of Table 4. Since the interaction term is insignificant, these results provide no evidence that access to imported inputs is a channel through which exchange rate movement affects innovation. These results are consistent with our main results.

## 5. Mechanism: A Model and Evidence

The previous section shows that exchange rate movement affects innovation through affecting export opportunity. Here, we propose a mechanism behind such channel. Consider a depreciation in RER. We argue that it increases firm's revenue by exporting more. As a result, with more surplus from export, the firm is capable to overcome the financial constraint in conducting innovation activities. In this section, we provide a simple model to illustrate our argument and then provide supporting evidence.

### 5.1 A Model

We modify the theoretical model developed by Gorodnichenko and Schnitzer (2013) to illustrate the impact of the real exchange rate on innovation and how the impact depends on firm characteristics.

Consider a firm who can invest in innovation activities, at a fixed cost $F_I$, before engaging in production. There are two sources of funds to finance innovation and production, internal funds from cash flows and external funds from creditors. A unit of external funds costs $\gamma > 1$, while the opportunity cost of a unit of internal funds is normalized to 1. This assumption captures the idea that external funding is more costly than internal funding due to asymmetric information.

At stage 1, innovation must be financed using internal funds, since innovation is especially prone to asymmetric information problems but cannot be easily collateralized. At stage 2, production needs to be financed using either internal funds or external funds. Since internal funds is less costly than external funds, the firm only turns to external funding when there are not sufficient internal funds to finance the production. We assume that, a priori, sufficient internal funds for production will be available with probability $q$ while external finance will be required with probability $1 - q$.

We capture financial constraints by the firm's likelihood of needing external finance. Two kinds of events can increase that likelihood. First, at stage 1 the firm may choose to engage in innovation activities which must be financed using internal funds, leaving less internal funds for production at stage 2. Second, the firm may experience an appreciation of real exchange rate; this decreases profits and cash flows, reducing the probability of having sufficient internal funds by $\delta(e)$. We assume that $\delta(e) > 0$ and $\frac{d\delta}{de} > 0$.

More formally, the sequence of events is as follows. The potential exogenous real exchange rate, $e$, is realized at stage 0. At stage 1, the firm chooses whether to innovate. Let $\pi_i$ denote the profit if no innovation takes place; here $i = 0$ if production is financed with internal funds and $i = \gamma$ if it is financed externally, $\pi_0 > \pi_\gamma$. Similarly, for $i = \{0, \gamma\}$ let $\pi_i^I$ denote the profit if the firm has carried out an innovation, where $\pi_i^I > \pi_i$. We assume that the increased profit from innovation decreases as the cost of financing increases. Formally,

Assumption 1.

$$\frac{d\left(\pi_\gamma^I - \pi_\gamma\right)}{d\gamma} < 0.$$

Ex ante, the firm's expected payoff if it does not innovate is

$$E(\pi) = \left(q - \delta(\mathrm{e})\right)\pi_0 + \left(1 - q + \delta(\mathrm{e})\right)\pi_\gamma$$

If the firm chooses to engage in innovation at stage 1, then production can be financed internally at stage 2 with probability $q - \delta(\mathrm{e}) - \delta_I$; this means that external finance will be used with probability $1 - q + \delta + \delta_I$. For innovating firms, the ex-ante expected profit is

$$E(\pi|I) = (q - \delta(\mathrm{e}) - \delta_I)\pi_0^I + (1 - q + \delta(\mathrm{e}) + \delta_I)\pi_\gamma^I - F_I$$

At stage 2, production takes place and profits are realized.

We can now determine the investor's incentive to innovate at stage 1 and describe how it is affected by potential financial constraints arising from exchange rate appreciation at stage 0. The firm decides to innovate if and only if

$$\Delta\pi = E(\pi|I) - E(\pi) = (q-\delta)(\pi_0^I - \pi_0) + (1-q+\delta)\left(\pi_\gamma^I - \pi_\gamma\right) - \delta_I\left(\pi_0^I - \pi_\gamma^I\right) - F_I > 0.$$

To determine the impact of real exchange rate shocks, we take the first derivative of $\Delta\pi$ with respect to $e$:

$$\frac{\partial\Delta\pi}{\partial e} = -(\pi_0^I - \pi_0)\frac{d\delta}{de} + \left(\pi_\gamma^I - \pi_\gamma\right)\frac{d\delta}{de} < 0;$$

this follows from Assumption 1. The higher the real exchange rate, the more severely the firm is financially constrained and the less likely it is to innovate.

Now we examine how the impact of financial constraints is affected by the cost of external finance. We find that

$$\frac{\partial^2\Delta\pi}{\partial e\partial\gamma} = \delta'(e)\frac{d\left(\pi_\gamma^I - \pi_\gamma\right)}{d\gamma} < 0.$$

So, the larger is $\gamma$ (the greater is the cost of external finance), the more damaging is the effect of an appreciation on the firm's incentive to innovate.

### 5.2 Evidence for Financial Constraint

If financial constraint hindered innovative activities of firm, we would find innovative activities of firms with a weaker financial constraint are more responsive to exchange rate movement. Here, we provide evidence with several measures that relates to financial constraint.

***Fixed Assets:*** Larger firms are expected to have a weaker financial constraint because there is less information friction for creditor to examine large firms, and large firms are more able to provide collateral asking for funding. We estimate Equation (1) with an interaction term between $\ln(RER)$ and $\ln(Fixed)$, and report the results in Column 1 of Table 5. The coefficient of the interaction term is positive and significant, suggesting that innovative activities of larger firms tend to respond more strongly to exchange rate movements. This provides supporting evidence that firms that are less likely to be financially constrained are more responsive to exchange rate movements.[14]

[14] We repeat the analysis with total employment as the measure of firm size and obtain consistent results. See Column 2 of Table 5.

***State Ownership:*** Firms in China can be classified into three types by ownership structure: state-owned enterprises (SOEs), private domestic firms, and foreign invested enterprises (FIEs). State- and foreign-owned firms tend to face less severe financial constraints than private domestic firms (e.g., Poncet, Steingress, and Vandenbussche, 2010; Cull et al., 2015).

To examine whether innovation activities of firms with different ownership respond differently to exchange rate movements, we estimate Equation (1) with an interaction term between $\ln(RER)$ and $SOE$, an indicator for state-owned enterprises. The results are presented in Column 4 of Table 5.

### 5.3 RER and Financial Constraint

This sub-section examines the impact of exchange rate movement on financial condition. Financial constraint is shown to be weaken by a depreciation of RER if we find financial condition of a firm improves after the depreciation.

***Current Ratio:*** We estimate Equation (1) with current ratio (i.e. Current Assets/Current Liabilities) as the dependent variable.

***Debt-to-Asset Ratio:*** We estimate Equation (1) with debt ratio (i.e. Debt/Total Assets) as the dependent variable.

## 6. Conclusion

To be written.

## References


**Acemoglu, D. and Linn, J.,** 2004. Market size in innovation: theory and evidence from the pharmaceutical industry. *Quarterly journal of economics* 119(3): 1049-1090.

**Acharya, R.C. and Keller, W., 2008.** Estimating the productivity selection and technology spillover effects of imports. *NBER Working Paper* No. 14079.

**Alfaro, L., Cuñat, A., Fadinger, H. and Liu, Y.,** 2018. The real exchange rate, innovation and productivity: Heterogeneity, asymmetries and hysteresis. *NBER Working Paper* No. 24633.

**Antràs, P. and Chor, D., 2013.** Organizing the global value chain. *Econometrica* 81(6): 2127-2204.

**Antràs, P., Chor, D., Fally, T. and Hillberry, R.,** 2012. Measuring the upstreamness of production and trade flows. *American Economic Review* 102(3): 412-416.

**Aghion, P., Bergeaud, A., Lequien, M. and Melitz, M.J.,** 2018. The heterogeneous impact of market size on innovation: Evidence from French firm-level exports. *NBER Working Paper* No. 24600.

**Aghion, P. and Howitt, P.,** 2009. *The economics of growth*. Cambridge, Massachusetts. London, England: The MIT Press.

**Amiti, M., Itskhoki, O. and Konings, J.,** 2014. Importers, exporters, and exchange rate disconnect. *American Economic Review* 104 (7): 1942-1978.

**Autor, D., Dorn, D., Hanson, G.H., Pisano, G. and Shu, P.,** 2020. Foreign competition and domestic innovation: Evidence from US patents. *NBER Working Paper* No. 22879.

**Aw, B.Y., Roberts, M.J. and Xu, D.Y.,** 2011. R&D investment, exporting, and productivity dynamics. *American Economic Review* 101(4): 1312-44.

**Becker, B. and Pain, N.,** 2008. What determines industrial R&D expenditure in the UK?. *The Manchester School* 76(1): 66-87.

**Brandt, L., Biesebroeck, J.V. and Zhang, Y.**, 2012. Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing. *Journal of Development Economics* 97(2): 339-351.

**Cai, H. and Liu, Q.,** 2009. Competition and corporate tax avoidance: Evidence from Chinese industrial firms. *Economic Journal* 119(537): 764-795.

**Chen, S.S.**, 2017. Exchange rate undervaluation and R&D activity. *Journal of International Money and Finance* 72: 148-160.

**Coe, D.T. and Helpman, E.,** 1995. International r&d spillovers. *European Economic Review* 39(5): 859-887.

**Cull, R., Li, W., Sun, B. and Xu, L.C.,** 2015. Government connections and financial constraints: Evidence from a large representative sample of Chinese firms. *Journal of Corporate Finance* 32: 271-294.

**Dai, M. and Xu, J.,** 2017. Firm-specific exchange rate shocks and employment adjustment: Evidence from China." *Journal of International Economics* 108: 54-66.

**Dai, M., Yu, M. and Zhao, C.,** 2018. Export tightening, competition, and firm innovation: Evidence from the renminbi appreciation. *Review of Development Economics* 22(1): 263-286.

**Das, M.S.,** 2019. China's evolving exchange rate regime. *IMF Working Paper* No 19/50.

**Feenstra, R.C., Li, Z. and Yu, M.,** 2014. Exports and credit constraints under incomplete information: Theory and evidence from China. *Review of Economics and Statistics* 96(4): 729-744.

**Funk, M.,** 2003. The effects of trade on research and development. *Open Economies Review* 14(1): 29-42.

**Gorodnichenko, Y. and Schnitzer, M.**, 2013. Financial constraints and innovation: Why poor countries don't catch up. *Journal of the European Economic Association* 11(5):1115-1152.

**Hummels, D., Ishii, J. and Yi, K.M.**, 2001. The nature and growth of vertical specialization in world trade. *Journal of International Economics* 54(1): 75-96.

**Kaiser, B. and Siegenthaler, M.,** 2016. The skill-biased effects of exchange rate fluctuations. *Economic Journal* 126(592): 756-780.

**Kaiser, B., Siegenthaler, M., Spescha, A. and Wörter, M.,** 2018. The impact of real exchange rates on Swiss firms: Innovation, investment, productivity and business demography. *KOF Studies* No. 109.

**Li, H., Ma, H. and Xu, Y.,** 2015. How do exchange rate movements affect Chinese exports? - A firm-level investigation. *Journal of International Economics*, 97: 148-161.

**Li, Z., Wei, S.J. and Zhang, H.,** 2018. Production chains, exchange rate shocks, and firm performance.

**Liu Q., Lu, R. and Luong, T.A.,** 2021. Import competition and firm innovation: Evidence from China. *Journal of Development Economics* 151: 102650.

**Liu, Q. and Ma, H.,** 2020. Trade policy uncertainty and innovation: Firm level evidence from

China's WTO accession. *Journal of International Economics* 127: 103387.

**Liu, Q. and Qiu, L.D.,** 2016. Intermediate input imports and innovations: Evidence from Chinese firms' patent filings. *Journal of International Economics* 103:166-183.

**Poncet, S., Steingress, W. and Vandenbussche, H.,** 2010. Financial constraints in China: Firm-level evidence. *China Economic Review* 21(3): 411-422.

**Shu, P. and Steinwender, C.,** 2019. The impact of trade liberalization on firm productivity and innovation. *Innovation Policy and the Economy* 19(1): 39-68.

**Tabrizy, S.S.,** 2020. Industrial research and development and real exchange rate depreciation in a small open economy. *World Economy* 43(9): 2490-2523.

**Upward, R., Wang, Z. and Zheng, J.,** 2013. Weighing China's export basket: The domestic content and technology intensity of Chinese exports. *Journal of Comparative Economics* 41(2): 527-543.

**Xu, J., Mao, Q. and Tong, J.,** 2016. The impact of exchange rate movements on multi-product firms' export performance: Evidence from China. *China Economic Review* 39: 46-62.

**Yu, M.,** 2014. Processing trade, tariff reductions and firm productivity: Evidence from Chinese firms. *Economic Journal* 125(585): 943-988.

**Zietz, J. and Fayissa, B.,** 1994. The impact of exchange rate changes on investment in research and development. *Quarterly Review of Economics and Finance* 34(2): 195-211.

**Table 1. Descriptive statistics.**

| Variable | Definition | Mean | S.D. | Obs |
|---|---|---|---|---|
| *Outcome* | | | | |
| $NPS$ | New product sales share | 0.047 | 0.172 | 184,108 |
| $Patent$ | Total # of patents | 0.107 | 3.966 | 184,116 |
| $RER$ | Effective real exchange rate | 20.30 | 54.26 | 184,116 |
| EXRER | Export-weighted RER | 0.005 | 0.141 | 184,116 |
| IMRER | Import-weighted RER | 0.003 | 0.104 | 184,116 |
| | | | | |
| *Firm Controls* | | | | |
| $Age$ | Firm age | 8.928 | 8.913 | 184,116 |
| $Age^2$ | Firm age squared | 159.1 | 584.5 | 184,116 |
| $\ln(Employment)$ | Logarithm of firm employment | 5.290 | 1.159 | 184,115 |
| $\ln(Fixed)$ | Logarithm of fixed assets | 9.058 | 1.816 | 184,116 |
| Foreign | Foreign share of total equity | 0.277 | 0.409 | 184,115 |
| $Current$ | Current ratio | 7.231 | 650.7 | 182,387 |
| $Debt$ | Debt to asset ratio | 0.554 | 0.309 | 184,004 |
| $\ln(TFP)$ | Logarithm of total factor productivity | 1.644 | 0.186 | 184,082 |
| $VS$ | Measure of vertical specialization | 0.491 | 0.601 | 183,840 |
| | | | | |
| *Industry Controls* | | | | |
| $HHI$ | Herfindahl-Hirschman Index | 0.238 | 0.071 | 184,103 |
| $U$ | Measure of industry upstreamness | 3.143 | 3.865 | 184,059 |

**Table 2. Baseline Results**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | New product sales share | | | |
| $\ln(RER_{it})$ | 0.0023*** | 0.0021*** | 0.0021*** | 0.0020*** |
| | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| *Firm controls* | | | | |
| $Age_{it}$ | | -0.0000 | -0.0000 | -0.0000 |
| | | (0.0001) | (0.0001) | (0.0001) |
| $(Age_{it})^2$ | | 0.0000 | 0.0000 | 0.0000 |
| | | (0.0000) | (0.0000) | (0.0000) |
| $\ln(Employment_{it})$ | | 0.0064*** | 0.0064*** | 0.0059*** |
| | | (0.0011) | (0.0011) | (0.0011) |
| $\ln(Fixed_{it})$ | | 0.0038*** | 0.0038*** | 0.0036*** |
| | | (0.0008) | (0.0008) | (0.0008) |
| $Current_{it}$ | | 0.0000** | 0.0000** | 0.0000** |
| | | (0.0000) | (0.0000) | (0.0000) |
| $Debt_{it}$ | | -0.0002 | -0.0002 | -0.0001 |
| | | (0.0016) | (0.0016) | (0.0016) |
| $\ln(TFP_{it})$ | | 0.0085* | 0.0084* | 0.0084* |
| | | (0.0046) | (0.0046) | (0.0046) |
| *Industry controls* | | | | |
| Output $\text{tariff}_{jt}$ | | | | |
| Input $\text{tariff}_{jt}$ | | | | |
| $HHI_{jt}$ | | | -0.0227 | -1.4258 |
| | | | (0.0166) | (1.2276) |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Industry-year FE | No | No | No | Yes |
| Observations | 204,914 | 202,947 | 202,934 | 202,934 |
| $R$-squared | 0.768 | 0.770 | 0.770 | 0.770 |

*Note:* Industry-year fixed effect are the interactive fixed effects of 2-digit industries and years. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table 3. Robustness Checks.**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent Variable | NPS | NPS | ln(1+#Patents) | #Patents | #Patents |
| Method | OLS | OLS | OLS | Poisson | Neg. Bino. |
| $\ln(RER_{it})$ | | 0.0012 | -0.0005 | -0.0012 | -0.0012 |
| | | (0.0008) | (0.0008) | (0.0319) | (0.0310) |
| $\ln(RER_{i,t-1})$ | | 0.0020** | | | |
| | | (0.0009) | | | |
| $\ln(RER_{i,2000})$ | 0.0017* | | | | |
| | (0.0009) | | | | |
| <u>*Firm controls*</u> | | | | | |
| $Age_{it}$ | -0.0000 | 0.0002 | -0.0007*** | -0.0025 | -0.0025 |
| | (0.0001) | (0.0002) | (0.0003) | (0.0101) | (0.0096) |
| $(Age_{it})^2$ | 0.0000 | -0.0000 | 0.0000*** | -0.0001 | -0.0001 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0001) | (0.0001) |
| $\ln(Employment_{it})$ | 0.0065*** | 0.0076*** | 0.0066*** | 0.2675*** | 0.2675*** |
| | (0.0011) | (0.0014) | (0.0013) | (0.0619) | (0.0516) |
| $\ln(Fixed_{it})$ | 0.0038*** | 0.0033*** | 0.0013** | 0.0621 | 0.0621** |
| | (0.0008) | (0.0010) | (0.0006) | (0.0426) | (0.0312) |
| $Current_{it}$ | 0.0000** | -0.0000 | 0.0000 | 0.0011 | 0.0011 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0038) | (0.0047) |
| $Debt_{it}$ | -0.0001 | -0.0008 | -0.0022 | -0.2584 | -0.2584* |
| | (0.0016) | (0.0018) | (0.0017) | (0.1578) | (0.1381) |
| $\ln(TFP_{it})$ | 0.0086* | 0.0095* | 0.0158*** | 0.9714** | 0.9714*** |
| | (0.0046) | (0.0057) | (0.0043) | (0.4038) | (0.2672) |
| <u>*Industry controls*</u> | | | | | |
| Output $\text{tariff}_{jt}$ | | | | | |
| Input $\text{tariff}_{jt}$ | | | | | |
| $HHI_{jt}$ | -0.0227 | -0.0283 | -0.0084 | -0.0103 | -0.0103 |
| | (0.0166) | (0.0239) | (0.0206) | (1.2874) | (1.1205) |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | No | Yes | Yes | Yes | Yes |
| Observations | 202,934 | 136,057 | 244,301 | 9,221 | 9,221 |
| $R$-squared | 0.770 | 0.788 | 0.612 | | |

*Note:* Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table 4. Potential Channels.**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $\ln(EXRER_{it})$ | | | | |
| | | | | |
| $\ln(IMRER_{it})$ | | | | |
| | | | | |
| $\ln(IMPRER_{it})$ | | | | |
| | | | | |
| $\ln(RER_{it})$ | | | 0.0021*** | 0.0021*** |
| | | | (0.0007) | (0.0007) |
| $\ln(RER_{it}) \times (U_j - \overline{U_J})$ | | | 0.0001 | |
| | | | (0.0001) | |
| $\ln(RER_{it}) \times (VS_{it} - \overline{VS_t})$ | | | | -0.0001 |
| | | | | (0.0008) |
| $VS_{it}$ | | | | -0.0009 |
| | | | | (0.0021) |
| Firm Controls | Yes | Yes | Yes | Yes |
| Industry Controls | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Observations | | | 202,883 | 202,635 |
| $R$-squared | | | 0.770 | 0.770 |

*Note:* Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table 5. Mechanism.**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent variable | NPS | NPS | Current | Debt |
| Interacted variable ($K$) | $\ln(Fixed_{it})$ | $\ln(Emp_{it})$ | N/A | N/A |
| $\ln(RER_{it})$ | 0.0019*** | 0.0021*** | 10.1711 | 0.0010 |
| | (0.0007) | (0.0007) | (8.9513) | (0.0009) |
| $\ln(RER_{it}) \times (K_{it} - \bar{K}_i)$ | 0.0030*** | 0.0047*** | | |
| | (0.0008) | (0.0011) | | |
| $\ln(RER_{it}) \times SOE_i$ | | | | |
| $\ln(Fixed_{it})$ | -0.0037* | | | |
| | (0.0020) | | | |
| $\ln(Employment_{it})$ | | -0.0076** | | |
| | | (0.0030) | | |
| Firm Controls | Yes | Yes | Yes | Yes |
| Industry Controls | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Observations | 202,934 | 202,934 | 244,320 | 246,477 |
| $R$-squared | 0.770 | 0.770 | 0.439 | 0.778 |

*Note:* Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.