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Exchange Rate Expectations and Exports:

Firm-Level Evidence from China

Xiaohua Bao, Hailiang Huang, Larry D. Qiu, and Xiaozhuo Wang*

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Abstract

The notion that the exchange rate affects exports is well understood. However, whether exporters respond to the *expectations* of the exchange rate is unknown. Hence, in this study, we construct a measure of exchange rate expectations based on news articles from the Factiva database. We use machine learning to identify and classify news articles about the appreciation of the renminbi (RMB, Chinese currency). Our empirical estimation shows that from 2000 to 2006, Chinese firms reduced their exports in response to a higher expectation of RMB appreciation. They switched their sales from export to domestic markets. The responses are larger in low-productivity firms, state-owned enterprises, processing trade, and final goods trade.

Key Words: Exchange rate expectation; Exports; RMB appreciation
JEL Classification Codes: D22, F14, F31

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1. Introduction

One of the accusations made by the U.S. government against China, which led to the recent China–U.S. trade war, is that the Chinese government manipulates the exchange rate to gain advantages in international trade, leading to a large bilateral trade imbalance: surplus in China and deficit in the U.S.[1] This accusation is not new. From the end of the last century to the beginning of this century, the Chinese government was under tremendous pressure from foreign countries to revalue its currency, which is the renminbi (RMB), and reform its exchange rate system. Partly because of this pressure, people expected that RMB would eventually appreciate.[2] The question is when and by how much.[3] An interesting research question is whether exchange rate expectations affect China's exports. Answers to this question are not available in the literature on the exchange rate and trade, and this study aims to provide an answer.

In this study, we introduce a measure of exchange rate expectation and examine its effect on Chinese firms' exports from January 2000 to December 2006. Specifically, we construct a measure of expectations of RMB appreciation based on the popularity of media reports, which are drawn from the Factiva database. We rely on matching learning to identify news articles related to changes in the RMB exchange rate and classify them into two categories: (1) those with the view of RMB appreciations and (2) the others. We use the percentage of news articles having the view of RMB appreciations among all those identified news articles as a proxy for the expectation of RMB appreciations. Using monthly data, we regress Chinese firms' exports on the expectation of RMB appreciations, controlling for other factors that may influence exports, such as exchange rate volatility and spot exchange rate. The regression also includes firm-year, destination-year, and month fixed effects. We found that expectation of RMB appreciations has a negative and statistically significant effect on exports.

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[1] Those accusations, which are often a political response to ill-informed domestic concern about the causes of U.S. trade deficits and job losses, are inappropriate (Frankel, 2006). Whether an appreciation of the Chinese currency against the U.S. dollar would have an immediately noticeable effect on the overall U.S. trade deficit and employment is questionable.

[2] We will use appreciation and revaluation interchangeably in this paper because their distinction does not affect the analysis and interpretation of our results.

[3] Many people urged RMB appreciation (Goldstein, 2003, Goldstein and Lardy, 2003, and Lynch, 2004) and Frankel (2006) wrote in 2005 that "the time has probably come to allow the yuan to appreciate."

Quantitatively, a 1% increase in the expectation of RMB appreciation reduces the value of Chinese firms' exports by 6.4%. In our data, 359 news articles, on average, are related to changes in the RMB exchange rate per month, and 276 of them have the view of RMB appreciations. Thus, our estimation result implies that in each month, when four additional pieces of news support RMB appreciation, exports drop by 6.4%, which is approximately US$ 16,974. We also found that in response to a higher expectation of RMB appreciations, firms switch their sales from export to domestic markets. The negative effects on exports are larger for low-productivity firms, state-owned enterprises (SOEs), processing trade, and final goods trade.

Our main finding is interesting because it shows that a pure expectation, rather than an actual change, has real effects. The People's Bank of China (PBC), the Chinese central bank, suddenly announced on July 21, 2005, to revalue its currency from the long-time, fixed rate of 8.27 to 8.11 yuan per U.S. dollar, which is a 2.1% appreciation of RMB. Moreover, its exchange rate system is changed from a fixed rate system to a more flexible one. Hence, RMB appreciation was a pure expectation and never realized before July 2005. However, we found that the expectation has real impacts on exports.[4]

Our study is related to two strands of literature. The first one is the literature on exchange rate expectations. Maddala (1991), Takagi (1991), MacDonald (2000), and Jongen *et al.* (2007) provided reviews of the earlier literature. Most studies in this literature were motivated by the proposition that expectations play a central role in the determination of exchange rates. However, expectations are not observable. Hence, researchers construct measures of exchange rate expectations based on surveys of monetary officials, international banks, financial market experts, traders, and others.[5] Their analyses focus on the properties of survey-based exchange rate expectations.[6] Our study contributes to this literature but is differentiated from the existing studies in two ways. First, we analyze the effects of exchange rate expectations on exports, whereas the literature focused on the properties of the expectations *per se*. Second, measures of exchange rate expectations in the existing studies are based on a survey, whereas ours is based on news articles, with the help of machine learning in article search

[4] We also run a regression using data from January 2000 to June 2005 and obtain similar results.

[5] Comprehensive survey data on exchange rate expectations are also available in FX4casts: https://www.FX4casts.com.

[6] In a recent paper, Beckmann and Czudaj (2017) analyzed the effects of policy uncertainty on exchange rate expectations.

and text analysis. This approach of using the text search method, particularly based on newspaper archives, to measure certain variables and outcomes has become very popular in recent years. For example, Baker *et al.* (2016) developed an index of economic policy uncertainty through newspaper text search. They found that policy uncertainty is associated with greater stock price volatility and reduced investment. A number of other studies also found significant effects of the news content on economic outcomes. Our study shows the impacts of news reports on people's expectations of the exchange rate and firms' export decisions.

The second strand of literature that our paper belongs to is the literature on how firms respond to exchange rate changes.[7] Examples in this literature include Berman *et al*. (2012) with data on French firms and Chatterjee *et al*. (2013) with data on Brazil. Other studies used data on Chinese firms. Tang and Zhang (2012) examined the exchange rate effects on Chinese exporters' intensive and extensive margins (entry, exit, and product churning) over the period of 2000–2006. Based on data from 2000 to 2007, Li *et al*. (2015) constructed firm-specific exchange rates and found that a 10% RMB appreciation led to decreases in export price, quantity, and value by 0.5%, 2.2%–4%, and 2.5%–4.5%, respectively. Fatum *et al*. (2018) focused on the trade between China and the U.S. during 2000–2011 and found that for ordinary firms (i.e., firms without processing trade involvement), a 10% RMB appreciation against the U.S. dollar reduces Chinese exports to the U.S. by 19%. However, for the processing trade, this negative effect is not significant because the appreciation has opposite effects on imports and exports. We also analyze the effects of the exchange rate on (Chinese) firms' exports and focus on exchange rate expectations, whereas all existing studies used the realized and/or forward exchange rates. Although forward rates are related to future exchange rates, the former is not a good proxy for the latter. Jongen *et al*. (2007, p. 142) point out that "one of the most challenging debates in the financial economics literature is the failure of the forward exchange rate as predictor of future spot exchange rates. This failure is often referred to as the forward premium puzzle." Thus, our use of exchange rate expectation to study the effects on exports is different from that of forward rates.

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[7] This literature belongs to a larger literature on how the exchange rate affects aggregate trade. See reviews of this literature in Auboin and Ruta (2013) and Burstein and Gopinath (2014).

The rest of the paper is organized as follows. Section 2 describes the institutional background of the Chinese exchange rate system and reform, data, and measure of exchange rate expectation. Section 3 presents the main empirical model and results. Sections 4 and 5 conduct various robustness checks and derive heterogeneous effects, respectively. Finally, Section 6 concludes the study.

2. Institutional Background, Data, and Measurement

2.1. Institutional Background

China adopted a fixed exchange rate regime from 1994 to 2005, with the local currency pegged to the U.S. dollar at the rate of 8.27 yuan per U.S. dollar.[8] On July 21, 2005, the PBC revalued the yuan to 8.11 per U.S. dollar. Although it is only a small revaluation (2.1%), this event sent out a strong policy signal. On the one hand, this sudden change of policy shows that the PBC is willing to adjust the RMB exchange rate. On the other hand, it is not just a revaluation to fix the rate at another level but also a modification of the exchange rate system. That is, the PBC also announced that "the yuan will be no longer pegged to the U.S. dollar" and "China will reform the exchange rate regime by moving into a managed floating exchange rate regime based on market supply and demand with reference to a basket of currencies."[9] RMB continued to appreciate and reached 6.83 yuan per U.S. dollar by the end of 2008.[10]

Prior to July 2005, scholars, government officials, and politicians had frequent and intense debates on China's exchange rate policy. The dominant view from academic studies, media, and foreign governments is the misalignment and undervaluation of the RMB, with supporting evidence, such as the rapid growth of Chinese export, large current account surplus, and drastic accumulation of foreign exchange reserves.[11] Partly because of this influential view, in reality, even before July 2005, people held a belief that the PBC would

[8] In 1994, the exchange rate was first fixed at 8.7 yuan per U.S. dollar. The government made a few changes over time and eventually fixed it at 8.28 yuan per U.S. dollar from October 1997 to July 2005.

[9]. Public Announcement by the PBC (www.pbc.gov.cn/english/).

[10] See Das (2019) for China's evolving exchange rate regime after 2005.

[11] Skeptical views about the undervaluation arguments also exist.

eventually change its exchange rate regime (to a more flexible one). When it does, it would be a revaluation (rather than devaluation) of the yuan. This expectation was later confirmed by the policy reform announced on July 21, 2005. As the revaluation in July 2005 was not sufficiently large, people continued to expect that RMB would further appreciate.

2.2. Trade Data

Our trade data come from the General Administration of Customs of the People's Republic of China. The Customs records each transaction of Chinese firms' export and import, including the value, industry (HS8 digit), destination of export, and origin of import. We aggregate transaction values on a monthly basis. As this study regards the impact of exchange rate on exports, we focus on three countries/regions, namely, the U.S., Japan, and the European Union (E.U.), as China's export destinations.[12] We use data from January 2000 to December 2006. The total number of valid observations, defined by a triplet (i.e., destination, firm, and month), is 5,227,171.

2.3. Firm Financial Data

As the Customs data contain firm-level export sales, we rely on the Above-Scale Industrial Firms Panel (ASIFP) survey data, which are maintained by the National Bureau of Statistics of China, to obtain other firm-level financial information. The ASIFP dataset covers all SOEs and non-SOEs with annual sales of more than 5 million RMB in mining, manufacturing, and utility industries. This dataset is the most comprehensive firm-level panel data in China available from 1998 to 2007. We use this dataset to calculate each firm's domestic sales and productivity.

2.4. Exchange Rate Data

We obtain nominal exchange rate data from Bloomberg. In Bloomberg's database, spot and forward

[12] The 19 countries of the E.U. include Germany, France, Italy, Netherlands, Belgium, Luxembourg, Ireland, Spain, Portugal, Austria, Finland, Lithuania, Latvia, Estonia, Slovakia, Slovenia, Greece, Malta, and Cyprus.

exchange rates are expressed as units of RMB per foreign currency. Hence, an increase in the exchange rate represents RMB depreciation.

We calculate real exchange rates using the consumer price index (CPI) from International Financial Statistics and the nominal exchange rates from Bloomberg.[13] Specifically, following the convention, we define the CPI-based real exchange rate in time t as $REx_{ct} = Spot_{ct} \times CPI_{ct}/CPI_{CHNt}$, where $Spot_{ct}$ is RMB's nominal spot rate against country c, CPI_{ct} is (foreign) country c's CPI, and CPI_{CHNt} is China's CPI. An increase in $Spot_{ct}$ implies a real depreciation of the RMB.

2.5. Exchange Rate Expectations

As discussed in Section 1, existing studies in the literature constructed exchange rate expectations based on surveys. Surveys are usually conducted by asking a small group of experts or financial institutions about their views and predictions on exchange rates at a certain time in the future. Evidently, we are not able to conduct such a retrospective survey back to the years 2000–2006. Alternatively, we follow the recent trend in many branches of the economic literature to use news reports as a source of information to construct economic variables and outcomes. In particular, we construct our exchange rate variable based on news archives. As discussed earlier in Subsection 2.1, during 2000–2006, an expectation about the RMB exchange rate is an expectation of RMB appreciation. Therefore, our task is to construct a measure of *RMB-appreciation expectation*.

To this end, we first search and collect relevant news articles from the Factiva database, one of the largest global digital business archives. Then, we construct a measure of RMB-appreciation expectation based on those articles. The Factiva database has a wide coverage of news sources. It provides access to news articles that appear in over 36,000 newspapers, trade presses, magazines, newswires, television and audio transcripts, websites, and social media in 200 countries. The Factiva database includes global and local news reported by big news agencies, such as the Associated Press and Reuters, which have offices in most countries. Although

[13] In the case of EU, we take the average of all countries' CPI.

the Factiva database is based on English articles, major news agencies from non-English speaking countries often provide an English version of their news articles in Factiva. Examples are the Jiji Press of Japan and Xinhua News Agency of China. Ultimately, the widely covered database of Factiva allows us to search for nearly all debates on the RMB exchange rate worldwide.

We have our text search and analysis via machine learning to construct our variable of RMB-appreciation expectation in four steps as described below.

Step 1: Article collection. We first obtained all news articles related to the RMB exchange rate from Factiva. Specifically, we input two key words "China & exchange rate" and searched "All sources" for the time period "January 2000–December 2006." We obtain 83,317 pieces of news.

Step 2: Data cleaning. Double counting exists. For example, several pieces of news come from the same source. Another example is that an article appears twice within a day, with the later one being just an update version of the earlier one. We propose a data deduplication algorithm to eliminate the repeated articles. First, we categorize all articles published on a given day with a title similarity higher than 60% into one group. Second, we calculate the similarity between any two articles, say i and j, from the same group. The similarity index is defined as follows:

$$Similarity(i,j) = \frac{1}{2}\left(\frac{WordLen_{ij}}{WordLen_i} + \frac{WordLen_{ij}}{WordLen_j}\right),$$

where $WordLen_i$ is the number of unique words in article i, $WordLen_j$ is the number of unique words in article j, and $WordLen_{ij}$ is the number of unique words in both articles.[14] If the similarity score exceeds a given threshold (e.g., 0.6), we consider the two articles identical and put them in the same subgroup. Finally, for each subgroup that contains more than one article, we retain the latest article or the one with more words if the article's time stamp is missing or unrecorded. Applying this algorithm, we delete 10,401 articles and

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[14] In machine learning, unique is a function that removes duplicate words in an article. Thus, unique words refer to words without repetition. For example, in the following sentence from the article titled "China keeps stability of Renminbi" published by Xin Hua News Agency on the 28th of November 2001: "at *the* same time *the* daily 0.3 percent fluctuation could be used fully to make *the* market gradually comply with exchange rate fluctuations," the word "the" appears three times. By keeping only one of them, the resulting number of unique words in this sentence is 21 instead of 23.

therefore obtain 72,916 unrepeated news, which form our news-article dataset.

Step 3: Manual annotation. We randomly choose 1,800 articles from our news-article dataset for manual annotation. This number is sufficiently large for manual annotation by machine learning standards. We read all 1,800 articles and labeled every article in the following way. If a news article contains information supporting RMB appreciation (e.g., a U.S. government official criticizes China's exchange rate system and presses China to revalue the yuan), then we label the article with "appreciation." If a news article's main point is that the RMB will remain stable (e.g., a Chinese government official indicates that China will not change its exchange rate policy), then we label the article with "no change." If a news article provides no information about the possible change of RMB although it mentions RMB (e.g., a Chinese exporter receives a certain amount of RMB from its exports based on the current exchange rate of 8.27 yuan per dollar), then we label the article with "irrelevant." As a result, among the 1800 articles that we read, 875 are labeled with "appreciation," 197 with "no change," and 728 with "irrelevant."[15]

Step 4: Machine learning. We gave a simple description of our machine learning process in the paper and added a detailed description in the Appendix. Based on the 1,800 labeled articles, we use machine learning algorithms to build a textual classifier. Specifically, we first tokenize each of the 1,800 articles into a list of words and lemmatize each word. We then exploit the term frequency, that is, the inverse document frequency (TF-IDF) algorithm (Salton and Buckley, 1988), to extract discriminative words or features from the word list. We feed the feature and label of each sample to the support vector machine (SVM) model (Cortes and Vapnik, 1995) to build a classifier. We apply the 10-fold cross-validation algorithm (Stone, 1974) to the 1,800 labeled articles to validate the performance of the textual classifier. The precision, recall, and f1-scores (Tharwat, 2018), which measure the precision of the classifier, are 0.89, thereby suggesting that the SVM model is reliable and stable. Finally, we utilize the classifier to predict a label for each of the 71,116 unlabeled articles. Hence, among all the articles in our dataset, 26,850 news articles are labeled with "appreciation," 3,265 with "no change," and

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[15] Given the special situation during the period of 2000–2006, almost no article reported the opinion of RMB depreciation. Therefore, we do not create a category for "depreciation."

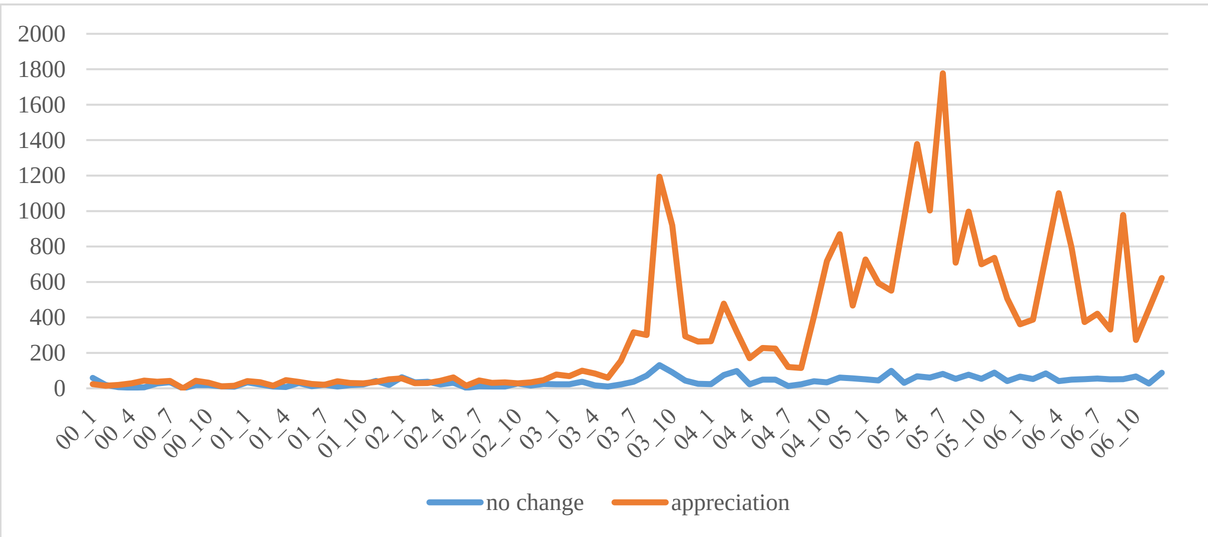
42,801 with "irrelevant." For all the relevant articles, 89% are "appreciation," and 11% are "no change." Figure 1 presents the frequencies of these two types of articles on a monthly basis.

We construct our key variable, called *appreciation expectation*, as follows:

$$Appreciation_t = \frac{N_t^{App}}{N_t^{App}+N_t^{No}}, \tag{1}$$

where t is the time (on a monthly basis) from January 2000 to December 2006, N_t^{App} is the number of "appreciation" news, and N_t^{No} is the number of "no change" news. This variable is the share of RMB-relevant news that supports RMB appreciation. As shown in Table 1, the summary statistics table, the minimum value of this variable is 0.448 (in March 2002), and the maximum is 0.969 (in April 2005). The variation of this variable is quite large, with a standard deviation equal to 0.135.

Figure 1: Number of News about Changes in the RMB Exchange Rate



Source: Authors' calculation.

2.6. Exchange Rate Uncertainty

We have two measures of the exchange rate uncertainty. Both measures are constructed based on exchange rate volatility. The first measure is the standard deviation of the forward rate, denoted as *Forward_sd*, which is the deviation between the actual (spot) and predicted (6-month forward) exchange rates (Greenaway *et al*., 2010). We adopt the 6-month forward rates based on the assumption that the time lag between placing a trade order and receiving payment is 6 months, which is used by Greenaway *et al*. (2010) for the U.K. exporters and

Tang and Zhang (2012) for Chinese exporters. Specifically, we first define $\Delta_{t-j} = Spot_{t-j} - Forward_{t-j-6}$ and $mean_{t-1}^{\Delta} = (\Delta_{t-1} + \Delta_{t-2} + \cdots + \Delta_{t-12})/12$, where *Spot* and *Forward* are the rates at the beginning of the month. Then, we construct the standard deviation of the forward rate as follows:

$$Forward\_sd_t = \sqrt{\frac{(\Delta_{t-1} - mean_{t-1}^{\Delta})^2 + (\Delta_{t-2} - mean_{t-2}^{\Delta})^2 + \cdots + (\Delta_{t-12} - mean_{t-12}^{\Delta})^2}{12}}.$$

Our second measure of exchange rate uncertainty is the standard deviation of the first difference of the logarithmic real spot exchange rate, denoted as *Spot_sd*, which is the most widely used measure in the trade-exchange rate volatility literature (Clark *et al.*, 2004). Specifically, we define $\tau_{t-j} = \ln(RealSpot_{t-j}) - \ln(RealSpot_{t-j-1})$, where $RealSpot$ is the real spot exchange rate, and $mean_{t-1}^{\tau} = (\tau_{t-1} + \tau_{t-2} + \cdots + \tau_{t-12})/12$. Then,

$$Spot\_sd_t = \sqrt{\frac{(\tau_{t-1} - mean_{t-1}^{\tau})^2 + (\tau_{t-2} - mean_{t-2}^{\tau})^2 + \cdots + (\tau_{t-12} - mean_{t-12}^{\tau})^2}{12}}.$$

2.7. Summary Statistics

Tables 1 and 2 present the summary statistics of the key variables and their correlations, respectively.

<Tables 1 & 2 Here>

3. Basic Empirical Model and Results

We build our empirical specifications with firm exports as the dependent variable and RMB-appreciation expectation as the key explanatory variable. Clark *et al*. (2004) used exchange rate volatility as their key independent variable, whereas we include it as one of the control variables in our model. Based on Chinese experience between 2000 and 2011, Fatum *et al*. (2018) examined the effects of exchange rate changes on exports. Correspondingly, we introduce the spot rate as another control variable in our model.[16] Our empirical model is given below:

[16] We do not include the forward rate as a control variable because it is not a good predictor of future exchange rate (Jongen, *et al*., 2017). Based on our data, the correlation between RMB appreciation expectation and forward rate is very low, only 0.1025.

$$\text{Ln}(Export_{fct}) = \beta_0 + \beta_1 Appreciation_{t-6} + \beta_2 Spot\_sd_{ct-6} + \beta_3 Spot_{ct-6} + \gamma_{fy} + \gamma_{cy} + \gamma_m + +\varepsilon_{fct}. \tag{2}$$

In the above model, *f* represents firm, *c* represents export destination (importing country), *y* represents year, m represents the month of a year, and t represents time (on a monthly basis). All the explanatory and control variables take a 6-month time lag, which is the normal time lag for exports after pre-committed contracts have been signed. This time lag is also used by Greenaway *et al*. (2010) for the U.K. exporters and Tang and Zhang (2012) and Fatum *et al*. (2018) for Chinese exporters to study the impacts of exchange rates on exports.

The outcome variable, $\text{Ln}(Export_{fct})$, is the log value of firm *f*'s exports to country *c* in time *t*. As the export values from the Customs data are all given in terms of U.S. dollar, we convert the value of exports to Japan into yen and that of exports to the E.U. into euro.[17] The key explanatory variable, $Appreciation_{t-6}$, is the RMB-appreciation expectation 6 months before time *t*. The two control variables are the exchange rate uncertainty ($Spot\_sd_{ct-6}$) and the spot rate ($Spot_{ct-6}$). Pieces of evidence from the literature suggest that the effect of exchange rate uncertainty on exports (β_2) should be negative (e.g., Clark *et al*. 2004), that is, uncertainty reduces exports. Moreover, that of the spot exchange rate (β_3) should be positive (e.g., Li *et al*., 2015), that is, local currency depreciation encourages exports.

We include three fixed effects to control for some unobservable factors that may influence a firm's export decision. The firm-year fixed effects γ_{fy} capture the firm characteristics that change over the years, such as firm size and productivity. The country-year fixed effects γ_{cy} capture the export destination's factors that change over the years, such as GDP. The month fixed effect γ_m control for the cyclic features associated with the months, such as February (Chinese New Year) and December (Christmas). The error term ε_{fct} is clustered at the firm level.

We are most interested in knowing the sign, magnitude, and statistical significance of parameter β_1. Although no theory exists about the effects of exchange rate expectations on exports, we conjecture that the

[17] We also repeat the analysis using U.S. dollar as the value for exports to all countries. The qualitative results remain the same as those in the main analysis using the destination country's currency.

effects are similar to those of forward and spot rates. Therefore, we expect that currency appreciation reduces exports, that is, β_1 is negative.

We run the ordinary least squares (OLS) regression based on Model (2) using Chinese data from January 2000 to December 2006. Columns (1)−(4) of Table 3 show the regression results. The standard errors are clustered at the firm level. The four columns are different in terms of their various inclusions of the fixed effects, with column (4) controlling for all fixed effects. Evidently, the effect of RMB appreciation expectation on Chinese firms' exports is negative and statistically significant. Specifically, according to column (4), a 1% increase in the expectation of RMB appreciations reduces the value of Chinese firms' exports by 6.4%. According to our data, on average, 359 news are related to RMB exchange rate changes per month, and 276 of them support RMB appreciation. Thus, our estimation result implies that, in each month, when four additional pieces of news support RMB appreciation, the average firm's exports drop by 6.4%, which is approximately US$ 16,974. The estimation results of the two control variables are consistent with most studies in the literature (Clark, 1973; Fung and Lai, 1991; Fatum *et al*., 2018; Tang and Zhang, 2012): depreciation increases exports (positive β_3), whereas uncertainty reduces exports (negative β_2).[18]

<Table 3 Here>

The control variables may work together with the explanatory variable to affect exports. To determine if our main result still holds when we introduce the control variables to the model one at a time, we run three regressions, with all fixed effects included. Columns (5)−(6) of Table 3 present the results. We observe that our conclusion that RMB-appreciation expectation reduces export, obtained from column (4) when both control variables are included, does not change with various combinations of the control variables. Column (8) of Table 3 shows that the exchange rate effects obtained from existing studies in the literature, that is, not including exchange rate expectation ($Appreciation_{t-6}$), are also preserve in our model and data.

Does exchange rate appreciation reduce a firm's exports only? In other words, does it also affect a firm's

[18] Clark, *et al*. (2004) examined data over 30 years for many countries. They found some evidence of the negative effect of exchange rate volatility on exports, but the effect is not robust.

sales in the domestic market? To answer this, we replace the outcome variable in Model (2) by $\mathrm{Ln}(DomesticSale_{ft})$, where $DomesticSale_{ft}$ is firm f's domestic sales in year t. Notably, information on a firm's domestic sales is not directly available from the ASIFP data, which contains a firm's total sales. We obtain a firm's domestic sales by subtracting export sales from total sales. Moreover, the ASIFP data are given on an annual basis. Accordingly, we modify the time dimension of Model (2) from monthly to yearly regression.[19] The estimation results are reported in column (9) of Table 3, which shows that expectation of exchange rate appreciation has a positive and significant effect on firms' domestic sales. This finding, together with that on exports, indicates that in response to a higher expectation of RMB appreciation, Chinese firms switch sales from export to domestic markets. This market-shifting behavior also implies that RMB-appreciation expectation should reduce a firm's export share, which is defined as the ratio of export sales over total sales. This result is confirmed by the regression outcome presented in column (10) of Table 3.

4. Robustness Checks

In this section, we address several concerns by checking the robustness of our benchmark results, which are reported in column (4) of Table 3, with all fixed effects included.

4.1. Export Quantity

In the above analysis, the outcome variable is the value of Chinese firms' exports in terms of the destination country's currency. Value is affected by quantity, price, and exchange rate. However, the exchange rate is also a control variable in Model (2). We address this problem in two ways. First, we drop the spot rate as a control variable in the regression. This case has actually been done with the results reported in column (6) of Table 3. The conclusion that RMB-appreciation expectations reduce exports remains unchanged. Second, we replace the export value with export quantity in Model (2) and rerun the regression. Another benefit of this analysis is

[19] The average value of each explanatory variable is calculated based on 12 months with a 6-month lag. For example, for t = 2003, the average value of RMB-appreciation expectations is calculated using the monthly values from July 2002 to June 2003.

that we can see how export quantities are affected by exchange rate expectations. Column (1) of Table 4 shows the results. The sign and significance of the explanatory variable do not change. In particular, Chinese firms' export quantities decrease in response to a higher expectation of RMB appreciations.

<Table 4 Here>

4.2. Exchange Rate Uncertainty

Recall that in Subsection 2.6, we have discussed exchange rate uncertainty measured using forward rates. We do not include forward rates and the corresponding uncertainty in Model (2) together with the spot rates and the uncertainty measured using spot rates because they are highly correlated, as indicated in Table 2.[20] We now replace $Spot\_sd_{ct-6}$ and $Spot_{ct-6}$ with $Forward\_sd_{ct-6}$ and $Forward_{ct-6}$, respectively, in Model (2) to check the robustness of our results. Column (2) of Table 4 presents the regression results. We found that, similar to the spot rate, the forward rate has a positive effect on exports, whereas uncertainty, measured by forward rate volatility, has a negative effect on exports. More importantly, the negative effect of RMB-appreciation expectations on exports remains significant.

4.3. Sentiment

We construct our RMB-appreciation expectation variable $Appreciation_t$ in (1). The news data can be used in other ways to capture appreciation expectations. Antweiler and Frank (2004) proposed a sentiment measure to analyze the influence of business news on stock price fluctuation. Following their idea, we propose two alternative measures of RMB-appreciation expectations in this subsection as a robustness check of our main finding obtained using $Appreciation_t$. They are called sentiment.

Our first sentiment measure is defined as follows:

$$Sentiment_t^* = \ln\left(\frac{1+N_t^{App}}{1+N_t^{No}}\right),$$

which is the relative number of news reporting appreciation over that reporting no change. Our second measure

[20] For studies using the forward rate, refer to Ethier (1973), Fung and Lai (1991), McKenzie (1999), and Greenaway *et al.* (2010).

is defined as follows:

$$Sentiment_t^{**} = Appreciation_t \times \ln(1 + N_t^{App} + N_t^{No}),$$

which is constructed based on our original RMB-appreciation expectations $Appreciation_t$ but augmented by the total number of news related to RMB exchange rates. Both sentiment measures capture the expectations of RMB appreciations, and we should expect them to have a negative effect on firms' exports, as $Appreciation_t$ does.

We run two regressions of Model (2), replacing $Appreciation_{t-6}$ with $sentiment_{t-6}^{*}$ and $sentiment_{t-6}^{**}$, respectively. Columns (3) and (4) of Table 4 present the results. The coefficients of $sentiment_{t-6}^{*}$ and $sentiment_{t-6}^{**}$ are negative and statistically significant, confirming our main finding.

4.4. Popularity

Strictly speaking, our measure of RMB-appreciation expectations $Appreciation_t$ is in a relative term, that is, it is the share of news about appreciation among all news concerning RMB exchange rates. An apparent weakness of this measure is that it does not capture the popularity of the RMB appreciation issue. Suppose that only a few news regarding RMB exchange rates exist in a month, and most of them support appreciation. In such a case, the value of $Appreciation_t$ is high, but under this kind of situation, people do not really have high expectations of appreciation. Thus, the use of $Appreciation_t$ runs a risk of overestimation of the effect of RMB-appreciation expectations. To address this concern, we conduct two robustness checks below. First, we measure the hotness of the RMB exchange rate issue. The idea is that when more people pay attention to this issue, firms expect that the Chinese government will likely make changes to the policy. Accordingly, we construct the following measure:

$$Popularity_t = \frac{Num_t^{change} + Num_t^{no}}{3000}. \tag{3}$$

Evidently, the numerator is the total number of news articles discussing RMB exchange rates, which captures the popularity of the issue in absolute terms. However, this absolute number does not make perfect sense about popularity if we do not know the total number of news articles in the data. Hence, we construct the measure in terms of the share of RMB-related news among all news. In which case, the denominator should be the total number of news in the same period. However, the total number of news each month is very large. To make the share not too small, we choose 3000 as the denominator, considering two justifications. On the one hand, given the fixed space of all newspapers, the total number of news in each month may not vary too much. Thus, choosing a fixed number as the denominator is not too innocuous. On the other hand, the maximum number of RMB exchange rate news (i.e., the numerator) in our data is 1859, which implies that we must choose the denominator larger than this number. Thus, we randomly choose 3000. Evidently, the qualitative aspect of the result would not be affected by the exact value of the denominator. We add $Popularity_t$ as an additional control variable in Model (2). In theory, we do not have any *a prior* about the effects of $Popularity_t$ on firms' exports as a high value of $Popularity_t$ is not equivalent to high expectation of appreciation. However, in reality, when the news talked about the RMB exchange rate from 2000 to 2006, most of them were about appreciation. Hence, we expect to see a negative effect of $Popularity_t$ on exports, which is confirmed by the regression results reported in column (5) of Table 4. As $Popularity_t$ is a supplement to our main appreciation variable $Appreciation_t$, this new result lends an additional support to our finding about the negative effects of RMB-appreciation expectations on exports.

4.5. Readability of News

Readability is a linguistic feature that measures the effectiveness of written communications. Previous studies showed that greater readability allows readers to get more precise information from a financial report (De Franco *et al*., 2015), whereas lower readability is associated with greater overall uncertainty in analyst earnings forecasts (Lehavy *et al*., 2011). Inspired by these studies, we conjecture that the readability of the news reporting RMB exchange rates also matters in influencing firms' understanding of the issue and, therefore, their export decisions. More readable news can make it easier for readers to grasp the author's view and reduce misunderstanding. Thus, the higher the readability of news, the greater its importance. As a robustness check, we redefine our RMB-appreciation expectation variable using the readability of news as the weight of each news article.

Readability depends on many factors, including the average sentence length, the number of new words, and grammatical complexity. Loughran and Mcdonald (2014) and Jegadeesh and Wu (2013) showed three popular readability measures. In the present study, we employ characters per word, which is one of the most widely used readability metrics.

We modify our appreciation variable $Appreciation_t$, considering the readability of the news. First, we define $PerWord_{ti}$ as the average number of characters per word in news *i* appearing in time *t*. A smaller value of $PerWord_{ti}$ indicates better readability. Second, we calculate the maximum value of $PerWord_{ti}$ in the entire sample of RMB-related news.[21] This maximum is denoted as $MaxPerWord$. Third, we define $weight_{ti} = 1 - \frac{PerWord_{ti}}{MaxPerWord}$. The larger this value, the more readable this news report relative to the least readable one. Finally, we define the weighted appreciation expectation as $WAppreciation_t = \frac{\sum_i weight_{ti}^{App}}{\sum_i weight_{ti}^{App} + \sum_i weight_{ti}^{No}}$. This modified RMB-appreciation expectation variable puts different weights to different news articles according to their readability as opposed to our original appreciation expectation variable that treats every news article equally. We expect that the impact of $WAppreciation_t$ on exports is significantly negative. We run a regression of Model (2) with $Appreciation_{t-6}$ replaced with $WAppreciation_{t-6}$ and report the results in columns (1) of Table 5. We found that the effect of $WAppreciation_{t-6}$ is significant and negative.

<Table 5 Here>

4.6. Cluster of Standard Errors

In Model (2), the dependent variable is defined at the firm-country-time level, whereas the key explanatory variable is at the time or country-time level. Heteroscedasticity may cause a bias in estimation. To eliminate the possible bias caused by heteroscedasticity, we follow Fatum *et al.* (2018) to run all the previous regressions with the standard errors clustered at the firm level. However, Cameron and Miller (2015) pointed out that the

[21] We also calculate the maximum value of $PerWord_{ti}$ in the sample of RMB-related news in period *t*. The qualitative aspects of the results do not change.

rule of thumb is to cluster the standard errors at the level as that of the key explanatory variable. To check whether our results are affected by various clusters of standard errors, we rerun Model (2) four times with the standard errors clustered at the country level, country-firm level, country-firm-month level, and country-firm-year-month level, respectively. Columns (2)−(5) of Table 5 show the regression results. Our main results are robust.

4.7. Yearly vs. Monthly Data

Li *et al.* (2015) and Fatum *et al.* (2018) examined the impacts of RMB appreciation on Chinese firms' exports in the period overlapping with that in our study, that is, 2000–2006. They used annual data without time lags in their analyses. Our monthly data allow us to examine the quick responses to RMB-appreciation expectations by the firms. However, we want to check whether our results are robust to using annual data as in the aforementioned two studies. To do this, we use our monthly data to calculate the average value of each variable for each year to rerun regression based on Model (2) but without time lags in the independent variables. As the three key independent variables, namely, $Appreciation_t$, $Spot\_sd_{ct}$, and $Spot_{ct}$, are at year or country-year level, we do not add firm-year and country-year fixed effects in Model (2). Instead, we include China's GDP (GDP_{CHNt}), each importing country' GDP (GDP_{ct}), and each importing country's fixed effect.[22] The country fixed effect absorbs the distance between China and the importing country and other time-invariant bilateral relations. In addition, we control for the firm fixed effect to absorb time-invariant industry and firm characteristics. Column (6) of Table 5 presents the regression results. Our main results are robust. Moreover, the effects of China's and importing countries' GDP are all positive and statistically significant.

5. Heterogeneous Effects

Our earlier analysis and results are about the average effects of RMB-appreciation expectations on Chinese firms' exports. We will understand this issue better by examining the heterogeneous effects, which is the

[22] GDP data come from the World Bank.

objective of this section.

5.1. Types of Trade: Processing versus Ordinary Trade

The Chinese General Administration of Customs classifies all trade into two types, which are ordinary and processing trade. Among all processing trades, "processing with supplied materials" and "processing with imported materials" are the most important ones, accounting for more than 90%.[23] In what follows, we focus on these two groups of processing trade. There are two key differences between ordinary and processing trade: in the processing trade, (1) most of the inputs and materials are imported at zero tariff, and (2) all of the processed/finished products must be exported. Owing to the first difference, RMB appreciation may benefit the processing trade more on the import side, which implies that processing exports may respond less to exchange rate appreciation than ordinary exports. Owing to the second difference, the sensitivity of processing exports to changes in the exchange rate may be smaller than that of ordinary exports. Thus, both reasons indicate that RMB-appreciation expectation should have smaller effects on processing exports than on ordinary exports.

A firm may engage in processing trade of certain products and exporting to certain markets within certain periods. However, a firm also has ordinary export of certain products to certain markets in certain periods. Given that the dependent variable in Model (2) is at the firm-destination-time level, we define ordinary and processing exports based on the firm-destination-time level accordingly. Specifically, we define a firm's exports to a destination c in time t as (i) ordinary exports if none of the firm's export transactions to that market during the same time period is coded as processing trade, (ii) pure processing exports if all of the firm's export transactions to that market during the same time are coded as processing trade, and (iii) mixed exports if the firm engages in processing and ordinary transactions to that market in the same time period. Accordingly, we introduce two dummy variables. First, $Process_{fct} = 1$ if firm f's exports to country c in time t are pure

[23] Processing trade has 16 groups, including overseas assistance (Code: 12), compensation trade (Code: 13), processing supplied trade (Code: 14), processing imported materials (Code: 15), consignment and consignment of goods (Code: 16), goods leasing (Code: 17), border small trade (Code: 19), engineering contracting (Code: 20), outward processing (Code: 22), barter trade (Code: 30), import and export trade of bonded warehouse (Code: 33), and Free Trade Zone entrepot trade (Code: 34).

processing exports and $Process_{fct} = 0$ if otherwise. Second, $Mix_{fct} = 1$ if *f*'s exports to country *c* in time *t* are mixed exports and $Mix_{fct} = 0$ if otherwise. Evidently, the reference group is ordinary export (when $Process_{fct} = 0$ and $Mix_{fct} = 0$). We modify Model (2) as follows:

$$\text{Ln}(Export_{fct}) = \beta_0 + \beta_1 Appreciation_{t-6} + \beta_2 Spot\_sd_{ct-6} + \beta_3 Spot_{ct-6} + \beta_4 Process_{fct}$$
$$+\beta_5 Appreciation_{t-6} \times Process_{fct} + \beta_6 Mix_{fct} + \beta_7 Appreciation_{t-6} \times Mix_{fct} + \gamma_{fy} + \gamma_{cy} + \gamma_m + \varepsilon_{fct}.$$

Our earlier discussion suggests that the estimates of β_5 and β_7 should be positive. We run the above regression using the whole sample of our data, that is, including all firms and transactions. Column (1) of Table 6 shows the regression results. The study has two observations. First, the estimates of the processing and mixed exports dummies, both of which are positive, indicate that, on average, processing and mixed exports are larger than ordinary exports on the firm-destination-time basis, with mixed exports as the largest. This comparison result is consistent with those of Brandt *et al*. (2021) and Halpern *et al*. (2015).

Second, the estimation results show that RMB-appreciation expectations reduce ordinary exports (-0.003, the estimated coefficient of the *Appreciation* variable), reduce processing exports more (-0.008, the estimated coefficient of the interaction term) than ordinary exports, and reduce mixed exports less (0.005, the estimated coefficient of the interaction term) than ordinary exports.[24] The result of negative β_5 is surprising. On the one hand, this notion is opposite to our conjecture discussed earlier. Second, the result is not in line with the result obtained by Berman *et al*. (2012), who found that processing exports respond to RMB appreciation less than ordinary export. However, Berman *et al*.'s (2012) result is based on actual appreciation, whereas our result is based on the expectation of appreciation. One implication or explanation of our finding is that processing trade decisions are mainly made by the foreign partners who are more aware of or sensitive to the expectations of RMB appreciations than Chinese domestic exporters.

We also run regressions based on Model (2) for various sub-samples of our data. The estimation results

[24] Instead of using a processing dummy, we also try to use a continuous variable, represented by the share of processing exports in total exports, to capture the degree of processing trade. The result (not presented in Table 6 to save space) is consistent: a firm's exports with a larger share of processing exports decrease more in response to RMB-appreciation expectations.

are consistent with those obtained in column (1). We do not report the estimates in the table to save space.

<Table 6 Here>

5.4. Product Similarity and Differentiation

Following Broda and Weinstein (2006), we divide products into similar and differentiated goods. Broda and Weinstein (2006) proposed a method to distinguish goods with different degrees of product differentiation and market competition. Broda and Weinstein (2006) calculated product substitution elasticity at the Standard International Trade Classification (SITC) 4 product level, whereas our product data are at the Harmonization Code System (HS) 6 level. Thus, we match the SITC-4 product code in Broda and Weinstein (2006) with the HS-6 product code in our study.[25] We use $Similarity_{fct}$ to represent the substitution elasticity of the product exported by firm *f* to country *c* in time *t*. A larger elasticity means more similar, or less differentiated, products. We add two terms to Model (2): $Similarity_{fct}$ and the interaction of $Similarity_{fct}$ and $Appreciation$. Column (2) of Table 6 shows the estimation results. The estimate of the interaction term is negative and statistically significant, thereby implying that the larger the elasticity of substitution (i.e., more similar products), the greater the negative impact of exchange rate expectation on the firms' exports. This finding is similar to that of Fatum *et al.* (2018) about the effects of exchange rate appreciation on exports.

5.3. Categories of Goods

Following the United Nations' BEC classification, we classify all export goods into three categories, that is, final goods, intermediate goods, and capital goods.[26] We introduce dummy variables to Model (2) to examine the differential effects of RMB-appreciation expectations on exports of different categories of goods. First, we introduce the intermediate goods dummy at the firm-destination-time level: $MExport_{fct} = 1$ if all of the export transactions of firm *f* to country *c* in time *t* are intermediate goods; otherwise, $MExport_{fct} = 0$.

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[25] A matching table between HS and SITC is available at https://wits.worldbank.org/product.html.

[26] Based on the Standard International Trade Classification, the BEC classification defines the industrial categories with codes of 111, 121, 21, 22, 31, 322, 42, and 53 as intermediate goods, the industrial categories with codes of 61, 62, 63, 112, 122, and 522 as final consumer goods, and the industrial categories with codes of 41 and 521 as capital goods.

Second, we introduce the capital goods dummy at the firm-destination-time level: $KExport_{fct} = 1$ if all of the export transactions of firm f to country c in time t are capital goods; otherwise, $KExport_{fct} = 0$. Last, we introduce the mix good dummy at the firm-destination-time level: $MixExport_{fct} = 1$ if firm f has at least two types of goods exported to country c in time t; otherwise, $MixExport_{fct} = 0$. The reference group is the final goods (when all three dummies take a value of 0).

We modify Model (2) by adding the above three dummies, $MExport_{fct}$, $KExport_{fct}$, and $MixExport_{fct}$, individually, and their interaction terms with the expectation variable *Appreciation*, respectively. Column (3) of Table 6 shows the results. However, to avoid making the table too long, we did not report the estimates of the coefficients of the three individual dummy variables. First, the estimation results show that RMB-appreciation expectations reduce final goods exports (-0.008, the estimated coefficient of the *Appreciation* variable). Second, all three interaction terms are positive and significant, suggesting that the export-reducing effects of RMB-appreciation expectation are the largest for final goods exports. This result is perhaps because the competition for Chinese final goods in the international market is fiercer than that of other goods. Third, the negative effect on intermediate goods exports (0.007, the estimated coefficient of the interaction term) is larger than that on capital goods exports (0.009, the estimated coefficient of the interaction term). This result is consistent with Hayakawa and Kimura's (2009) finding based on Asian countries that intermediate goods trade is very sensitive to exchange rate fluctuations.

5.4. Firm Productivity and Size

Firms with different sizes may respond to exchange rate changes differently because of their different bargaining powers, production flexibility, and others. The literature (e.g., Berman *et al*., 2012; Amiti *et al*., 2014; Fatum *et al*., 2018) generally found that adjustments of exports by large firms in response to exchange rate changes are smaller than those of small firms. Although the firm size and productivity are correlated, our interest is to examine the heterogeneous effects of RMB-appreciation expectations, as opposed to the realized changes of exchange rates, focusing on different productivity levels of the firms.

We use the methodologies of Olley and Pakes (1996) (OP) and Levinsohn and Petrin (2003) (LP) to calculate firms' total factor productivity (TFP). We introduce a dummy variable $Productivity_{ft}$, with $Productivity_{ft} = 1$ if firm *f*'s TFP in time *t* exceeds the mean value of all firms' TFP in the same industry in time *t*, and $Productivity_{ft} = 0$ for otherwise. We add the interaction term of this variable and *Appreciation* to Model (2). Notably, we could also add the individual term $Productivity_{ft}$ to the model, but it will be absorbed by the firm-year fixed effect. We report the regression results of the OP method in column (4) and the LP method in column (5) of Table 6. The interaction term is positive and significant in both cases. The result indicates that low-productivity firms reduce their exports more than high-productivity firms when they face higher expectations of RMB appreciations. One possible explanation is that high-productivity Chinese firms have a stronger bargaining power over their international buyers compared with low-productivity firms. Thus, when facing a higher expectation of RMB appreciations, the former are able to pass more of the rising cost to their foreign importers than the latter.[27]

We have also examined the heterogeneous effects based on firm size. We obtain that larger firms respond to RMB-appreciation expectation less than smaller firms. We did not report the estimation results in the table to save space.

5.5. Firm Ownerships

Unlike other countries, SOEs were still a big part of the Chinese economy from 2000 to 2006. Firms with different ownerships may respond to exchange rate expectations differently. To examine this conjecture, we divide the whole sample into SOEs and non-SOE.[28] We define an ownership dummy as $SOE_f = 1$ if the firm is an SOE, and $SOE_f = 0$ if otherwise. We add an interaction term between SOE_f and $Appreciation_{t-6}$ to

[27] Li *et al.* (2015) found that in percentage, high-productivity firms reduce their exports (value) more than low-productivity firms in response to RMB appreciation because the former are able to price more to market. This result seems different from our finding, but they are not directly comparable because our finding is based on the response to RMB-appreciation expectations, whereas theirs is based on actual RMB appreciations.

[28] We delete the data with missing information about firm ownership and those with changing ownership types during the sample period. As a result, 98680 observations are deleted. In our dataset, the share of firms that change their ownership types is very small.

Model (2). Column (6) of Table 6 reports the regression results. The results show that in response to a higher expectation of RMB appreciations, the SOEs and non-SOEs reduce their exports, but the SOEs reduce more. As the non-SOEs, in general, have higher productivity than the SOEs, the reason for this differential effect may be the same as that for heterogeneous firms in the preceding subsection.

We also run another regression by adding two more interaction terms to Model (2), which are the interaction term between the SOE dummy variable with $Spot\_sd_{ct-6}$ and that with $Spot_{ct-6}$, respectively. We obtain (but do not report in the table to save space) the estimates as 0.042 and -0.036, respectively, both of which are statistically significant at the 1% level. These results indicate that the SOEs' exports, compared with those of the non-SOEs, respond less to exchange rate volatility but more to RMB appreciations.

6. Conclusions

The notion that changes in exchange rates affect international trade is well known. However, no research exists on whether the expectation of exchange changes, as opposed to the realized ones, such as spot rates, influence trade. Our study is the first to answer this question.

We construct a measure of RMB-appreciation expectations based on news articles related to RMB change rate changes in 2000−20006. Using Chinese firm-level export data, we found that a higher expectation of RMB appreciations reduces Chinese firms' exports. This negative effect is statistically significant and economically important. This effect is robust to various changes in the regression model, measures of RMB-appreciation expectations, and the types of exports (i.e., value versus quantity). We also find heterogeneous effects interesting, for example, high-productivity Chinese exports respond less to RMB-appreciation expectations than low-productivity exporters.

Although the exchange rate literature included studies on exchange rate expectations, our work extends this literature in two important directions. First, existing studies relied on surveys to construct their expectations, whereas our measure of RMB-appreciation expectations is constructed based on news achievements. The benefits of our approach are twofold. First, our approach covers opinions not confining to experts and does not subject to the limitation of the availability of historical data. Second, we are not to analyze the exchange rate expectations per se but to examine their real effects on trade.

Further studies are required to have a deeper understanding of the expectation effects. A theoretical model and analysis will be useful. More analyses will be helpful in explaining the heterogeneous effects. The observed effects of RMB-appreciation expectations on Chinese firms' exports and the magnitudes could be the outcomes of the specific economic and regulatory environments in China from 2000 to 2006.

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Table 1: Summary Statistics of the Key Variables (January 2000–December 2006)

Variables	Mean	Median	Standard deviation	Min	Max
Ln_Export	9.379	9.862	2.969	0	20.717
Appreciation	0.828	0.878	0.135	0.448	0.969
Forward_sd	0.173	0.056	0.218	0.002	0.801
Spot_sd	0.015	0.009	0.016	0.001	0.061
Forward	5.997	8.081	4.073	0.063	10.749
Spot	6.075	8.276	4.132	0.062	11.144

Note: N = 4, 512,758.

Table 2: Correlations of Key Variables

	Appreciation	*Forward_sd*	*Spot_sd*	*Forward*	*Spot*
Appreciation	1				
Forward_sd	0.0808	1			
Spot_sd	0.1322	0.8678	1		
Forward	0.1025	0.6166	0.6113	1	
Spot	0.115	0.6158	0.6112	0.9997	1

Table 3: Basic Regression Results

	(1) Ln(Export)	(2) Ln(Export)	(3) Ln(Export)	(4) Ln(Export)	(5) Ln(Export)	(6) Ln(Export)	(7) Ln(Export)	(8) Ln(Export)	(9) Domestic sales	(10) Export share
$Appreciation_{t-6}$	−0.296***	−0.280***	−0.079***	−0.064***	−0.091***	−0.055***	−0.093***		0.042***	−0.004***
	(−35.57)	(−30.39)	(−8.64)	(−7.20)	(−14.90)	(−6.21)	(−15.23)		(8.21)	(−5.53)
$Spot\_sd_{ct-6}$	−17.530***	−17.449***	−2.390***	−2.191***		−2.181***		−2.209***	0.526***	−0.051***
	(−97.89)	(−96.97)	(−27.96)	(−25.90)		(−25.77)		(−26.12)	(12.70)	(−8.39)
$Spot_{ct-6}$	0.612***	0.612***	0.019***	0.020***			0.025***	0.017***	0.013***	−0.002***
	(484.55)	(483.03)	(5.57)	(5.85)			(7.47)	(4.99)	(7.62)	(−7.47)
γ_{fy}	N	N	N	Y	Y	Y	Y	Y	Y	Y
γ_{cy}	N	N	Y	Y	Y	Y	Y	Y	Y	Y
γ_m	N	Y	Y	Y	Y	Y	Y	Y	N	N
γ_f	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
γ_y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	4495626	4495626	4495626	4461499	4959300	4461499	4959300	4461499	1802823	1802823
R^2	0.769	0.770	0.780	0.811	0.810	0.811	0.810	0.811	0.872	0.884
Adj R^2	0.762	0.762	0.773	0.793	0.793	0.793	0.793	0.793	0.868	0.881
F	8.7e+04	8.7e+04	295.811	253.518	221.987	353.604	138.668	357.060	95.507	48.615

Note: Standard errors are clustered at the firm level. The numbers in parentheses are t values. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Table 4: Robust Check I

	(1)	(2)	(3)	(4)	(5)
	Ln(Quantity)	Ln(Export)	Ln(Export)	Ln(Export)	Ln(Export)
$Appreciation_{t-6}$	−0.020**	−0.102***			−0.052***
	(−1.90)	(−14.71)			(−5.65)
$sentiment^{*}_{t-6}$			−0.012***		
			(−8.27)		
$sentiment^{**}_{t-6}$				−0.010***	
				(−8.95)	
$Popularity_{t-6}$					−0.036***
					(−5.12)
$Spot\_sd_{ct-6}$	−0.907***		−2.167***	−2.111***	−2.124***
	(−9.09)		(−25.63)	(−24.91)	(−25.03)
$Spot_{ct-6}$	0.006		0.021***	0.021***	0.021***
	(1.48)		(6.02)	(6.17)	(6.01)
$Forward\_sd_{t-6}$		−0.173***			
		(−12.55)			
$Forward_{ct-6}$		0.016***			
		(4.39)			
γ_{fy}	Y	Y	Y	Y	Y
γ_{cy}	Y	Y	Y	Y	Y
γ_{m}	Y	Y	Y	Y	Y
N	4461499	4737222	4461499	4461499	4461499
R^2	0.669	0.810	0.811	0.811	0.811
$Adj\ R^2$	0.639	0.793	0.793	0.793	0.793
F	29.688	137.926	256.463	257.792	192.884

Note: Standard errors are clustered at the firm level. The parentheses are t values, and ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Table 5: Robustness Check II

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(Export)	Ln(Export)	Ln(Export)	Ln(Export)	Ln(Export)	Ln(Export)
		Cluster c	Cluster c-f	Cluster c-f-m	Cluster c-f-y-m	Cluster f
$WAppreciation_{t-6}$	−0.079***					Yearly data
	(−8.94)					
$Appreciation_{t-6}$		−0.064**	−0.064***	−0.064***	−0.064***	−1.993***
		(−2.42)	(−7.22)	(−6.82)	(−6.33)	(−19.76)
$Spot\_sd_{ct-6}$	−2.185***	−2.191***	−2.191***	−2.191***	−2.191***	−1.911***
	(−25.83)	(−8.29)	(−25.81)	(−29.58)	(−26.69)	(−10.29)
$Spot_{ct-6}$	0.021***	0.020	0.020***	0.020***	0.020***	0.182***
	(6.12)	(0.95)	(5.67)	(5.66)	(5.82)	(32.33)
GDP_{ct}						0.118***
						(12.25)
GDP_{CHNt}						0.374***
						(24.35)
FEs	Y	Y	Y	Y	Y	Y
N	4461499	4461499	4461499	4461499	4461499	4770831
R^2	0.811	0.811	0.811	0.811	0.811	0.780
$Adj\ R^2$	0.793	0.793	0.793	0.793	0.793	0.773
F	262.27	.	250.384	316.068	261.298	2.7e+04

Note: Standard errors are clustered at the year-month level and country-year-month level. FEs include γ_{fy}, γ_{cy}, and γ_m in columns (1)–(5). We include firm, industry, and country FEs in column (6). The parentheses are t values, and ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Table 6: **Heterogeneous Effects**

	(1)	(2)	(3)	(4)	(5)	(6)
$Appreciation_{t-6}$	−0.003***	−0.003***	−0.008***	−0.005***	−0.005***	−0.002***
	(−4.12)	(−4.24)	(−10.20)	(−7.84)	(−7.80)	(−2.94)
$Spot\_sd_{ct-6}$	−0.012***	−0.012***	−0.012***	−0.012***	−0.012***	−0.012***
	(−26.74)	(−25.16)	(−26.41)	(−25.92)	(−25.92)	(−25.96)
$Spot_{ct-6}$	0.031***	0.026***	0.028***	0.027***	0.027***	0.027***
	(6.63)	(5.24)	(6.07)	(5.73)	(5.74)	(5.57)
$Process_{fct}$	0.250***					
	(59.01)					
$Appreciation_{t-6}$	−0.008***					
$\times Process_{fct}$	(−5.85)					
Mix_{fct}	0.535***					
	(149.15)					
$Appreciation_{t-6}$	0.005***					
$\times Mix_{fct}$	(3.40)					
$Similarity_{fct}$		0.003***				
		(11.57)				
$Appreciation_{t-6}$		−0.0003***				
$\times Similarity_{fct}$		(−2.68)				
$Appreciation_{t-6}$			0.007***			
$\times MExport_{fct}$			(5.50)			
$Appreciation_{t-6}$			0.009***			
$\times KExport_{fct}$			(3.28)			
$Appreciation_{t-6}$			0.006***			
$\times MixExport_{fct}$			(4.55)			
$Appreciation_{t-6}$				0.003***	0.003***	
$\times Productivity_{fct}$				(3.41)	(3.34)	
$Appreciation_{t-6}$						−0.007***
$\times SOE_f$						(−6.79)
FEs	Y	Y	Y	Y	Y	Y
N	4406694	4158066	4428298	4455772	4455701	4308251
R^2	0.823	0.809	0.823	0.811	0.811	0.810
$Adj\ R^2$	0.806	0.790	0.806	0.793	0.793	0.793
F	3573.491	171.787	4094.438	193.902	193.741	160.890

Note: Standard errors are clustered at the firm level. FEs include γ_{fy}, γ_{cy}, and γ_m in all columns. The parentheses are t values, and ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Appendix: Text Analysis and Machine Learning

Considering the large sample size of the news articles, manually labeling the news articles is highly labor-intensive and time-consuming, if not prohibitive. We rely on machine learning to do the job. We design a machine learning algorithm to determine the linguistic features from our labeled samples, and learn to quantify the weight of each feature on the classification labels.

We start the first stage by transforming variable-length news articles into fixed-length feature vectors. The length of the vector (denoted as L) is equal to the number of all unique words used in the collection of labeled articles. In addition, we lemmatize each word to its base form, such as converting "rises" to "rise." This process allows us to reduce the scale of the whole word list while maintaining rich semantic information. Next, we exploit the TF-IDF algorithm to evaluate the importance of a word to an article in the labeled corpus. As it implies, TF-IDF is the product of TF and IDF. Specifically, for each word i in article d, $TF_{i,d}$ is defined as: $TF_{i,d} = \frac{c_{i,d}}{|d|}$, where $c_{i,d}$ is the count of word i in article d, and $|d|$ is the count of all words in article d. IDF measures the amount of information of word i, which is inversely proportional to its frequency in dataset D. Thus, $IDF_{i,D}$ is defined as $IDF_{i,D} = log\frac{N}{|\{d \in D: i \in d\}|}$, where N is the total number of articles in the labeled corpus, and $|\{d \in D: i \in d\}|$ is the number of articles where word i appears. We calculate the TF-IDF score (denoted as $x_{i,d}$) for each word in each article, subsequently obtaining the distributed feature vector $x_i = \{x_{i,1}, x_{i,2}, \dots, x_{i,L}\}$ for each article.

Next, we feed the structured data into the classification model, that is, SVMs. We adopt SVM for the following reasons. First, SVM is effective when the number of feature dimensions is greater than the number of samples. Second, facing limited labeled samples, SVM can efficiently avoid underfitting and improve the robustness of the model. Finally, SVM is competitive with neural networks in terms of prediction performance but requires fewer parameters.

SVM was originally devised to solve binary classification problems, aiming to create a line or a hyperplane to separate feature vectors into two classes. With a one-vs-rest strategy, SVM can further handle the multi-class problem by training multiple binary classification models. Taking the class of "appreciation," for example, we denote the labeled dataset as $T = \{(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)\}$, where $x_i \in X = \mathcal{R}^L, y_i \in Y = \{+1, -1\}$. x_i is the feature vector of the ith article, and y_i is its label, in which $+1$ represents "appreciation" and -1 represents "non-appreciation." As shown in Figure A1, the goal of the algorithm is to identify an optimal hyperplane $f(x)$ that maximizes the margin between "appreciation" articles and "non-appreciation" articles: $f(x) = w \cdot \varphi(x) + b$, where $\varphi(\cdot)$ is a kernel function that maps the feature space into high-dimensional space, making two classes of articles linearly separable, and w and b are learnable weights and bias, respectively. Based on the learned classification model, we then predict labels for the rest of the unlabeled articles. If the distance between an article and the hyperplane surpasses 0, then it is automatically labeled as "appreciation" and "non-appreciation" if otherwise.

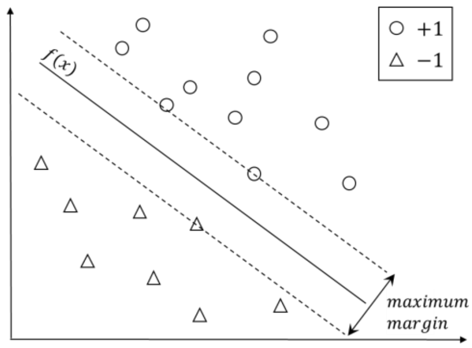

Figure A1. Examples of Maximum Margin Separating Hyperplane

To evaluate the performance of the model, we employ 10-fold cross-validation on the labeled articles. In particular, we divide the labeled dataset into 10 equivalent folds, in which one fold is denoted as the test dataset, and the remaining nine folds are denoted as the training dataset. We then fit the model with the training dataset and report the prediction results on the test dataset. After 10 runs, each article will be assigned a predicted label. Along with the true man-annotated labels, we measure the quality of the model by precision, recall, and F1 score.

For a given label, such as "appreciation," the prediction results have four possible outcomes: True Positive (TP), which represents articles with true "appreciation" labels and is classified into the "appreciation" category; True Negative (TF), which represents articles with "non-appreciation" labels and is classified into other categories; False Positive (FP), which represents articles with "non-appreciation" labels but predicted as "appreciation" labels; and False Negative (FN), which represents articles with "appreciation" labels but predicted as "non-appreciation" labels. Then, precision indicates the ratio of correctly predicted labels to the total positive predictions:

$$precision = \frac{num(TP)}{num(TP)+num(FP)}.$$

Recall is the ratio of correctly predicted labels to the actual positive articles:

$$recall = \frac{num(TP)}{num(TP)+num(FN)}.$$

F1 score is the weighted average of precision and recall:

$$F1\ score = \frac{2*(precision*recall)}{(precision+recall)}.$$

Table A1 reports the precision, recall, and F1 score of three classes and the weighted average results on the labeled dataset. The overall performance achieves an average F1 score of 0.89, indicating that our model can produce high-quality predicted labels.

Table A1: Performance of the Classification Model on the Labeled Dataset

	Precision	Recall	F1 score	Number
No change	0.75	0.71	0.73	176
Appreciation	0.9	0.92	0.91	896
Irrelevant	0.9	0.89	0.89	728
Weighted average	0.89	0.89	0.89	1800