Faking Trade for Capital Control Evasion: Evidence from Dual Exchange Rate Arbitrage in China[†]

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Abstract

By using a unique institutional setting of dual exchange rates of the Chinese currency, this paper provides novel evidence for an old question on how firms manipulate trade data to evade capital controls. We propose a model in which firms over-report international trade to evade capital controls for foreign exchange arbitrage but face heterogeneous probabilities of being caught. The model predicts that the aggregate bilateral trade data gap between trading partners is positively (negatively) correlated with the exchange rate spread when the spread is positive (negative). At the disaggregated level, such correlations are predicted to be more pronounced for products for which Customs officials are less likely to detect fraudulent transactions. We test the aggregate-level predictions using the threshold regressions and the disaggregated-level prediction using Benford's law in the trade data between mainland China and Hong Kong. The empirical results provide evidence for dual exchange rate arbitrage activities camouflaged under the trade account. In addition, we show that the traded products that violate Benford's law may be the vehicle arbitragers use in their fake trade for foreign exchange arbitrage scheme.

Keywords: Capital controls, dual exchange rates, missing trade, Benford's law
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1 Introduction

Capital controls have regained popularity since 2008, following the Federal Reserve's extraordinary monetary easing over the subprime crisis. Countercyclical capital control policies are generally recommended even for the economies with flexible exchange rates to maintain their monetary autonomy and domestic financial market stability (International Monetary Fund, 2012; Rey, 2013; Farhi and Werning, 2014; Korinek, 2018; Davis and Presno, 2017; Wang and Wu, 2018).[1] With the new round of quantitative easing in 2020 to combat the COVID-19 pandemic, many countries may again resort to capital controls in the future to defend their financial markets from dramatic global capital flows.

However, capital controls are not a "free lunch" (Forbes, 2005).[2] As discussed in Mendoza (2016), those policies face many practical implementation challenges, and their effectiveness can be easily undermined by various evasion activities, particularly in countries with weak institutions (Edison and Reinhart, 2001; Edwards, 1999; Forbes et al., 2015; Lin and Ye, 2018; Lin et al., 2020). Manipulating trade data is perhaps the most notorious activity and is pervasive in many countries with capital controls. However, it is difficult to detect those activities by their very nature, although anecdotal evidence has been widely discussed in the media and academic studies.[3] A systematic examination of capital control evasion through faking trade data is crucial to understand the nature of such

[1] These policy suggestions echo an early voice in the 1990s that suggested capital control policies should be adopted in countries that were not ready for liberalizing their capital accounts, such as when their currencies were still pegged to the U.S. dollar or their domestic financial market remained underdeveloped (Rodrik, 1998; Prasad et al., 2003; Kose et al., 2006).

[2] Previous studies document many costs for capital controls such as their adverse effects on the financial conditions and stock valuations of domestic firms and allocation distortions of resources toward politically connected firms (Forbes, 2007; Alfaro et al., 2017; Johnson and Mitton, 2003). Some studies also question if countercyclical capital flow management policies are actively implemented in practice. Fernández et al. (2015) find that capital controls are acyclical over business cycles in 78 countries, and Acosta-Henao et al. (2020) document that capital controls do not change frequently in emerging markets.

[3] Forbes (2005) surveys the anecdotal evidence in Russia and Chile, and Aizenman (2008) and Wei and Zhang (2007) argue that such activities are common in China and other emerging markets. Various financial media outlets have reported trade data manipulations in China. For instance, in January 2016, a large number of media outlets including the *Wall Street Journal*, *Reuters*, and *Bloomberg* reported the fake trade between mainland China and Hong Kong based on the surging trade data discrepancies between the two economies.

activities, assess their costs, and find solutions to mitigate their adverse effects.

By taking advantage of a unique institutional setting of dual exchange rates for the Chinese Renminbi (RMB), this article presents theory and empirical evidence that firms manipulate trade data to evade capital controls. In addition to its onshore market in the mainland, China also set up an offshore RMB/USD foreign exchange market in Hong Kong in late 2010 to promote the RMB internationalization. The RMB offshore market is relatively market-driven as Hong Kong is an international financial center with high capital mobility, while the RMB onshore market is highly regulated by the People's Bank of China. Since 2011, large and persistent spreads have frequently existed between onshore and offshore RMB-USD exchange rates due to China's strict capital controls, which incentivized arbitrage activities through fake trade.[4] The empirical research on foreign exchange arbitrage in countries with capital controls is largely held back by the unavailability of reliable market exchange rates. Thus, the dual exchange rates of the RMB offer a unique opportunity to test whether firms manipulate the trade data to evade capital controls for foreign exchange arbitrage.

We first develop a model in which firms over-report trade data to evade capital controls for dual exchange rate arbitrage but face heterogeneous probabilities of being caught. The model shows that the aggregate bilateral trade data gap between mainland China and Hong Kong is positively (negatively) correlated with the spread between the offshore market exchange rate and the onshore official exchange rate when the spread is positive (negative). At the disaggregated level, our model predicts that the above relations are more pronounced for products for which Customs officials are less likely to detect fraudulent transactions.

We test the implications of the model by using both the aggregate time series data of trade and exchange rates and the disaggregated firm-product level customs trade data. First, following the literature on "missing trade," we measure the trade gap by using

[4]Moreover, geographical proximity and low trade costs between mainland China and Hong Kong also facilitate capital control evasions through fake trade between these two places.

the (100*log) difference between mainland China's reported imports from (or exports to) Hong Kong and Hong Kong's reported exports to (or imports from) mainland China (Feenstra et al., 1999; Fisman and Wei, 2004).[5]

Next, we adopt threshold regressions for the aggregate time series data (Hansen, 2000; Yu and Phillips, 2018) and find that the RMB-USD exchange rate spreads are important driving forces for the monthly fluctuations of the trade gap between mainland China and Hong Kong. More specifically, the over-reporting in imports and exports is negatively correlated with the exchange rate spread before 2014 when the spread was mostly negative, while the correlation becomes positive between 2014 and 2016, when the spread was mostly positive. Our results are both statistically and economically significant. On average, the import and export gaps increase by 34% and 36% of a standard deviation for a one standard deviation increase in the exchange rate spread. The spread explains a large fraction of trade data discrepancies, especially when the spread is large. For instance, according to our estimation, a spread of 0.07 RMB/USD (1% of the exchange rate) in December 2015 induced fake trade of about 7.2 billion USD, which accounts for 27% of the total trade data gap between mainland China and Hong Kong in that month and 15% of the total trade between the two economies.

At the disaggregated level, we adopt the Benford's law test (BLT) to detect possible trade data manipulations (Barabesi et al., 2018; Cerioli et al., 2019; Demir and Javorcik, 2020). According to Benford's law, the leading digits in accounting and economic data follow a certain frequency distribution, while forged data usually do not (Newcomb, 1881; Benford, 1938). Thus, the BLT has been widely used to detect fraud in accounting numbers and economic data (Nigrini, 2012; Berger and Hill, 2015; Michalski and Stoltz, 2013). Recently Cerioli et al. (2019) and Demir and Javorcik (2020) show that the BLT is also

[5] Ideally, mainland China's reported imports from Hong Kong should equal the exports reported by Hong Kong and vice versa, after taking into account trade costs and measurement errors. However, large trade data discrepancies generally exist in the bilateral trade data reported by importing and exporting countries for various reasons such as different statistical rules, tariff/tax evasion, and capital control evasion (Ferrantino et al., 2012; Javorcik and Narciso, 2008).

useful in detecting fraud in large-scale trade data.

It is likely that firms have a stronger incentive to manipulate data for the products that Customs officials are less likely to catch. Based on the 2015 firm-HS 8-digit level disaggregated trade data between mainland and Hong Kong, which is very close to transaction-level data, we conduct the BLT for each of the 21 HS sections to identify products prone to manipulation.[6] According to the classification of Rauch (1999), most of the goods that do not conform to Benford's law (classified as the BLT-rejection (BLTR) group) are found to be intermediate inputs or differentiated goods such as optical and photographic instruments, jewelery and precious metal or stones, electrical equipment, and works of art. By contrast, the goods that pass the BLT (classified the Non-BLTR group) include primary goods such as animal and vegetable products, and products with low value to weight such as textiles, wood, and transportation vehicles. This finding is not surprising as differentiated goods usually have no reference prices and thus it is difficult for Chinese Customs to detect whether the reported trade values of those goods are fraudulent. It is also consistent with Javorcik and Narciso (2008) who find that differentiated products are more likely to be used for tariff evasion than homogeneous goods.

More interestingly, we find that the exchange rate spreads play an important role in driving the monthly fluctuations in the trade gap of the products that do not conform to Benford's law, in a manner similar to our main finding on the exchange rate spreads and the aggregate bilateral trade gap. By contrast, we find no significant relationship between the spreads and the monthly trade gap of other products that fit Benford's law well. These findings are consistent with the model prediction that the relationship between fake trade and exchange rate spreads is more pronounced for products that are less likely to be detected as fraudulent. Thus, our findings suggest that the "fraudulent" products detected by the BLT may be the vehicle used by arbitrageurs to evade capital controls for foreign

[6]We use the Chinese Customs data in 2015 because the exchange rate spread was large and the fake trade was believed prevalent in this year as indicated by media reports and our analysis using aggregate time series data.

exchange arbitrage.[7]

Our empirical results are robust to various extensions and sensitivity analysis. For instance, our findings hold up well after controlling for possible autocorrelation in the error terms, lagged dependent and independent variables, economic policy uncertainty, changes in foreign political relations, and different dates for the structural break. The main results still hold when we use an alternative two-step estimation method by first testing the unknown structural changes following Andrews (1993) and then estimating the model with structural change in the coefficient of the exchange rate spread. In addition, we also conduct two placebo tests by randomly assigning products into pseudo BLTR and Non-BLTR groups to ensure that our BLT results are not driven by random factors or statistical errors. Cross-country evidence also supports that Hong Kong is a major destination of the fake trade for dual exchange rate arbitrage.

This paper contributes to the literature by providing systematic empirical evidence on faking trade data for capital control evasion (Edison and Reinhart, 2001; Edwards, 1999). Previous studies have examined the adverse effects of capital control policies on firms' financial conditions and stock valuations as well as on economic performance (Forbes, 2007; Alfaro et al., 2017; Song et al., 2014). To our best knowledge, this study is the first to provide evidence of fake trade for the purpose of capital control evasion. Moreover, we also identify the products that are prone to data manipulation by using the BLT method. Our findings support the traditional argument that capital flows camouflaged under the trade account could reduce the effectiveness of capital control policies.

This study also makes important contributions to the literature of "missing trade." Previous studies mainly focus on the motivation of tariff and tax evasion by exploring the cross-section relationship between the under-reporting of imports and tariff/tax rates at the product level. For example, Fisman and Wei (2004) find that tax and tariff evasion

[7]In addition, our results also suggest that capital control evasion for exchange rate arbitrage plays an important role in the fake trade between mainland China and Hong Kong. Otherwise, the fake trade identified from the BLT may not be related to exchange rate spreads if they are mainly driven by tax and tariff evasion.

plays an important role in the large gap of China's reported imports from Hong Kong and Hong Kong's reported exports for the same product. Ferrantino et al. (2012) find that the value added tax and tariffs are important factors for the trade discrepancies between China and the U.S. Javorcik and Narciso (2008) find similar results in the trade data between Germany and its ten Eastern European trading partners. By contrast, this paper highlights the role of capital control evasion in trade data discrepancies by exploring the time-series relationship between trade data discrepancies and the exchange rate spread. The trade data gap between mainland China and Hong Kong fluctuated substantially in our sample period (between January 2011 and December 2016) and such large fluctuations can not be reconciled by tariff or tax evasion as tariffs and taxes change infrequently.

The remainder of the paper is arranged as follows. Section 2 introduces the institutional background, the data, and the construction of the key variables. Section 3 develops testable predictions from a simple model of dual exchange rate arbitrage. Section 4 presents the econometric strategy and regression results using the time-series aggregate trade data between mainland China and Hong Kong, and Section 5 applies the BLT to the disaggregated trade data. Section 6 concludes.

2 Institutional Background

This section briefly describes the capital control policy in mainland China, the onshore and offshore dual exchange rate markets for the RMB, and trade data discrepancies between mainland China and Hong Kong.

2.1 Capital controls

Portfolio flows to and from mainland China are subject to pervasive controls, although since 1996, the country has liberalized its current account transactions, and since 2001, when China gained access to WTO, it has gradually removed most restrictions on the inward direct investment. In recent years, the Chinese government has taken steps to liberalize international portfolio investment flows by establishing programs such as "qualified foreign institutional investors" (QFIIs) and "qualified domestic institutional investors" (QDIIs). However, capital flows in China remain relatively small and are still subject to restrictive regulations such as quotas and qualification approval. The country's capital controls policy also changes with the external economic environment China faces. For example, China stopped approving new quotas for overseas investment by residents and suspended the approval of QDIIs in 2014 when it faced large capital outflows and depreciation pressures of the RMB. It is evident in Table 1 that due to capital controls, China's cross-border portfolio investment flows remain suppressed. For both inward and outward investment, portfolio flows were even lower than direct investment flows in most years between 2005 and 2019, while portfolio flows in countries without capital controls are usually much higher than FDI flows. The share of portfolio investment flows in GDP remains at only about 1% or less in China, indicating its severe capital controls.

According to the Chinn-Ito index, which measures a country's degree of capital account openness, China ranked 146 out of 174 economies in 2016, much lower than other emerging markets such as Mexico, India, and Russia.[8] The restrictive capital controls in China induce cross-border price discrepancies such as in interest rates and exchange rates. For instance, Ma and McCauley (2008) find that capital controls in China cause sustained and significant gaps between onshore and offshore RMB interest rates and persistent U.S. dollar/RMB interest rate differentials. As we will show in the next section, China's capital controls also introduce persistently nonzero spread of the onshore and offshore exchange rates of the RMB.

[8]The Chinn-Ito index is a de jure measure of financial openness based on the binary dummy variables that codify the tabulation of restrictions on cross-border financial transactions reported in the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER). Please see the detailed construction method in Chinn and Ito (2006).

2.2 The dual exchange rates of the RMB

There are two exchange rates between the RMB and the U.S. dollar, one in mainland China's onshore market and another in offshore markets such as Hong Kong. China used to fully peg its currency to the U.S. dollar, but after 2005, the RMB has been allowed to fluctuate against the U.S. dollar within a small floating band.[9] To maintain the official onshore RMB-USD exchange rate in mainland China (denoted by CNY), the Chinese government imposes various controls on the country's capital flows. Meanwhile, in order to promote the RMB internalization, China set up an offshore RMB market in Hong Kong in 2010.[10] The offshore RMB-USD exchange rate (denoted by CNH) is not subject to the same capital controls as in mainland China and thus is mainly determined by the global market demand and supply of the RMB.

Due to China's capital controls, persistently nonzero spreads between the onshore and offshore exchange rates were constantly observed. Define the offshore-onshore RMB-USD exchange rate spreads as the log difference between CNH and CNY ($EXS_t = 100*(s_t^{CNH} - s_t^{CNY})$), where s_t^{CNH} and s_t^{CNY} denote log values of the RMB per dollar in offshore and onshore markets, respectively. We multiple the log difference by 100 so the unit is log percentage point. By definition, a positive spread indicates that the RMB is more expensive or overvalued in the onshore market than the offshore market. The spread can be as large as 2% in the daily data and over 1% even in the monthly average data.[11] Figure 1 presents the spreads calculated from the monthly average onshore and offshore exchange rates from January 2011 to December 2016.[12] As we can see, the spread can be roughly

[9]In 2010, China started to follow a "crawl-like arrangement," as classified by the IMF, for its currency relative to the USD. In 2015, the People's Bank of China announced it would anchor the RMB on a basket of currencies rather than the USD. However, the USD remains the dominant currency in the basket.

[10]Similar offshore markets were also set up in Taiwan, Singapore, and London in subsequent years. But Hong Kong remains the dominant RMB offshore market.

[11]The spreads between the CNH and the central parity rate set by the PBC were usually even higher than the spreads between the CNH and the CNY.

[12]The results are very similar if the monthly exchange rate spread is computed as the average of daily exchange rate spreads. Our sample starts from January 2011 because the RMB offshore market in Hong Kong was initially small but started to grow rapidly in 2011.

divided into two subsamples. Before early 2014, the spread was largely negative, indicating the RMB was mostly undervalued in mainland China.[13] Between early 2014 and 2016, the spread was largely positive, suggesting that the RMB was mostly overvalued in the onshore market relative to the offshore market. The large and persistent exchange rate spreads offer opportunities of cross-border arbitrage through fake trade between Hong Kong and mainland China.[14]

On top of the dual-exchange rate system, two additional factors make mainland China and Hong Kong an exemplary laboratory to study the fake trade driven by capital control evasion. First, the two economies are geographically connected and trade intensively with each other, as Hong Kong is an important entrepôt for mainland China. Second, in 2003, they have signed the Closer Economic Partnership Arrangement (CEPA), which removed all tariffs for most goods originally made in these two places. These factors reduce the costs and risks of capital control evasion through the fake trade between Hong Kong and mainland China compared with China's other trading partners.

2.3 Trade data gaps

The intensive trade between mainland China and Hong Kong facilitates exchange rate arbitrages through over- or under-reporting imports and exports. Hong Kong is consistently ranked as the third-largest trading partner of mainland China, after the European Union and the U.S. In particular, the trade between Hong Kong and mainland China increased about 50% during our sample period, putting the Hong Kong-mainland trade volume on par with U.S.-China trade in 2016. Meanwhile, the large trade data discrepancies between Hong Kong and mainland China have raised significant attention from

[13] This is true except for a few months around the end of 2011, when the RMB was under the pressure of depreciation due to the intensification of the Eurozone sovereign debt crisis.

[14] Similar arbitrage activities may also exist in other economies with capital controls, but it is difficult to study because such activities usually go through a black market whose exchange rate is difficult to measure. See Pitt (1981), Pitt (1984), and Adams and Greenwood (1985) for theoretical studies on foreign exchange arbitrage.

policymakers and the media over concerns that firms may evade capital controls through fake trade.

To measure the possible fake trade for capital control evasion, we follow the literature of "missing trade" and define fake trade as the log difference between reported exports or imports for mainland China and the corresponding counterparts reported in Hong Kong with adjustment for iceberg trade cost as follows:

$$Y_t^{EXP} = 100 * \{\ln[EXP_t^{CN} * (1 + CIF)] - \ln(IMP_t^{HK})\}, \quad (1)$$

$$Y_t^{IMP} = 100 * \{\ln(IMP_t^{CN}) - \ln[EXP_t^{HK} * (1 + CIF)]\}, \quad (2)$$

where EXP_t^{CN} and IMP_t^{CN} are mainland China's reported exports to and imports from Hong Kong, respectively.[15] IMP_t^{HK} and EXP_t^{HK} are Hong Kong reported direct imports from and exports to mainland China. Following the literature (e.g., Cheung et al. (2016)), we include a fixed cost, insurance, and fright (CIF) of 10% to capture the trade cost between importers and exporters. The choice of CIF does not affect our empirical results.[16] Y_t^{EXP} is positive/negative if firms over-report/under-report exports from mainland China to Hong Kong and it is similar for Y_t^{IMP}. The over-reporting of exports facilitates capital flow from Hong Kong to mainland China, while the over-reporting of imports moves the capital out of mainland China to Hong Kong.

As shown in Figure 2, substantial trade gaps exist between mainland China and Hong Kong. On average, mainland China over-reported both exports to and imports from Hong Kong with a mean of 33 percentage points for Y_t^{EXP} and 28 percentage points for Y_t^{IMP}. The trade gaps also fluctuate significantly from month to month: the standard deviation is 16 percentage points for Y_t^{EXP} and 35 percentage points for of Y_t^{IMP}. During our sample period, Hong Kong's trade with mainland China was about the same size as the trade

[15]We multiply the log difference by 100 so the unit is log percentage point.

[16]CIF is set to 10% by following the literature, although the actual trade costs between Hong Kong and mainland China may be lower. CIF may also be time varying in some countries and see Cheung et al. (2020) for a study on Germany.

between the U.S. and mainland China. However, the trade data discrepancies between mainland China and the U.S. are much smaller with a mean of -13 percentage points for Y_t^{EXP} and 18 percentage points for Y_t^{IMP}, and are also less volatile as indicated by smaller standard deviations of export and import gaps (10 and 15 percentage points respectively).

As we discussed above, previous studies on trade discrepancies mainly focus on the tax and tariff evasion by examining the cross-sectional relationship between the under-reporting of imports and the tariff or tax rates at the product level (Fisman and Wei, 2004; Ferrantino et al., 2012; Javorcik and Narciso, 2008). However, the large monthly fluctuations of trade gaps between mainland China and Hong Kong cannot be explained by the tariff or tax evasion as the tax and tariff policies change at a much less frequency. Instead, we find that the monthly trade discrepancies are highly correlated with the RMB exchange rate spreads between onshore and offshore markets in a manner consistent with a simple theory of dual exchange rate arbitrage.

3 A Simple Model of Dual Exchange Rate Arbitrage

In this section we develop a simple model of dual exchange rate arbitrage in which heterogeneous firms conduct fake trade to evade capital controls. We show that the over-reporting of aggregate imports and exports between mainland China and Hong Kong has a positive (negative) linear relationship with the exchange rate spread when the spread is positive (negative). The elasticity of over-reporting with respect to the spread decreases with the severity of punishment for fake trade and the average probability of being caught. From this model, we derive three insightful testable predictions for our empirical analysis.

3.1 Model and testable predictions

Figure 3 illustrates the arbitrage mechanism for a positive exchange rate spread, which we will model formally later. Consider a case in which one USD equals 6.9 RMB in Hong Kong ($S_t^{CNH} = 6.9$) and 6.8 RMB in mainland China ($S_t^{CNY} = 6.8$). Given that capital flows go in the opposite direction of goods flows, to arbitrage on the dual exchange rates, an exporting firm (Firm A) in mainland China will buy the USD at the onshore rate (6.8 RMB per dollar) from a bank (e.g., the Bank of China) and transfer the USD to Hong Kong by over-reporting its imports (settled in the USD) to Hong Kong. Next, Firm A's affiliated or partner company in Hong Kong (Firm B) sells the dollar to the market at a higher rate (6.9 RMB per dollar). In the end, Firm A transfers the RMB back to mainland China by over-reporting its exports (settled in the RMB) to Firm B in Hong Kong.[17]

To capture the above activities, we develop a model of dual exchange rate arbitrage in which firms have heterogeneous beliefs about their chance of being caught. Suppose mainland China and Hong Kong exchange for N symmetric goods, and let z denote one particular good. Consumers have the same CES preference with the elasticity of substitution $\sigma > 1$, and thus the sale of each good is $r(z) = Ap(z)^{1-\sigma} = Ap^{1-\sigma}$ when there is no trade data manipulation. For each good, a continuum of firms with a mass of 1 import and export this product in both economies. For simplicity we assume no trade cost between the two economies.

When the exchange rate spread is positive, the arbitrage strategy is to buy the USD in the onshore market and sell it in the offshore market through fake trade. For a transaction in which mainland China imports from Hong Kong, we denote the true value reported by Hong Kong as $r_{hk}^{ex}(z)$ in the U.S. dollar, while the mainland reports its import value as $r_{cn}^{im}(z)$, which inflates the true value by a factor of $1 + \delta^{im}$ with $\delta^{im} = \frac{r_{cn}^{im}(z) - r_{hk}^{ex}(z)}{r_{hk}^{ex}(z)} > 0$. Thus, the USD outflows from mainland China to Hong Kong through import over-

[17]In reality, the arbitrage activity may involve multiple companies and mix with genuine international trade to conceal the activity from Customs and other authorities.

reporting. Suppose the firm sells the USD for the RMB in Hong Kong and transfers the corresponding RMB back to mainland China through export over-reporting. Similarly, for a transaction in which mainland China exports to Hong Kong, we denote the true value reported by Hong Kong as $x_{hk}^{im}(z)$ in RMB and the export value reported by mainland China as $x_{cn}^{ex}(z)$, which inflates the true value by a factor of $1+\delta^{ex}$ with $\delta^{ex} = \frac{x_{cn}^{ex}(z)-x_{hk}^{im}(z)}{x_{hk}^{im}(z)} > 0$.[18] In the absence of trade costs between the two economies, a firm's total over-reporting in imports should equal its total over-reporting in exports after being adjusted by the RMB exchange rate in the offshore market for the arbitrage:

$$\delta^{im} r_{hk}^{ex}(z) S^{CNH} = \delta^{ex} x_{hk}^{im}(z). \tag{3}$$

Clearly, the over-reporting in exports is tightly connected with the over-reporting in imports. Under symmetric assumption, we can further simplify this equation to get $\delta^{im} = \delta^{ex}$. Therefore, in the following discussions, we will focus on the optimal decision of import over-reporting as the over-reporting in exports is identical to the over-reporting in imports in our model. The total RMB-denominated revenue generated from the above dual exchange rate arbitrage is given by

$$\delta^{im} r_{hk}^{ex}(z)(S^{CNH}/S^{CNY} - 1) = \delta^{im} r_{hk}^{ex}(z) EXS, \tag{4}$$

where EXS is the exchange rate spread and we first consider the scenario of $EXS > 0$.[19]

Suppose that each firm faces a random probability ($\lambda \in [0, 1]$) of being caught for the fake trade of good z, and once caught by Customs the firm has to pay a fine of $\frac{\eta}{2}(\delta^{im})^2$ for each unit of the true trade value, where $\eta > 0$ denotes the severity of punishment for the fake trade. The quadratic form reflects that the government usually increases the level of punishment with the amount of fake trade. For a given positive exchange rate spread, the

[18] Note $x(z)$ is denominated in RMB and $r(z)$ is denominated in USD.

[19] Here we slightly abuse the notation of EXS; in the empirical analysis, the exchange rate spread is defined as the 100*log difference between the onshore and offshore exchange rates of RMB.

risk-neutral firm chooses δ^{im} to maximize its expected profit from the foreign exchange arbitrage:

$$\max_{\delta^{im}} \pi = (1-\lambda)\delta^{im} r_{hk}^{ex}(z) EXS - \lambda \frac{\eta}{2} (\delta^{im})^2 r_{hk}^{ex}(z). \tag{5}$$

The inner solution to the above optimal problem is $\delta^{im*} = \frac{(1-\lambda)EXS}{\lambda\eta}$.[20] Clearly, the optimal over-reporting in imports increases with the exchange rate spread and decreases with the probability of being caught (λ) and the severity of punishment(η).

For each good z, a continuum of firms with a mass of 1 import and export the good in both economies. In reality, firms may have different abilities to conceal the fake trade from Customs' inspections. Thus, firms face different probability (λ) of being caught, and we assume that λ for each firm is a random draw from a $Beta(\alpha, \beta)$ distribution with $\alpha \geq 2$ and $\beta \geq 1$. We choose $Beta$ distribution as it is flexible, intuitive, and generates closed form solutions for our aggregation. For example, the expected probability of being caught is $\bar{\lambda} = E(\lambda) = \frac{1}{1+\beta/\alpha}$, and thus it increases with α but decreases with β. In the extreme, $\bar{\lambda} \to 1$ as $\alpha \to \infty$ and $\bar{\lambda} \to 0$ as $\beta \to \infty$.

The total imports of mainland China from Hong Kong with fake trade is given by:

$$R_{cn}^{im} = \sum_{z=1}^{N} \int_0^1 (1 + \delta^{im*}) r_{hk}^{ex}(z) dF(\lambda). \tag{6}$$

As goods are symmetric, the true value of $r_{hk}^{ex}(z)$ is the same for all goods. Thus we have,

$$R_{cn}^{im} = N r_{hk}^{ex} \int_0^1 (1 + \delta^{im*}) dF(\lambda) = R_{hk}^{ex} \left(1 + \int_0^1 \delta^{im*} dF(\lambda) \right). \tag{7}$$

[20] It is easy to verify that the optimal profit $\pi(z) = \frac{(1-\lambda)^2 EXS^2}{2\lambda\eta} r_{hk}^{ex}(z) \geq 0$, and the equality holds when $\lambda = 1$. Note that the arbitrage profits also increase with the exchange rate spread and decrease with the probability of being caught (λ) and the severity of punishment (η).

The over-reporting in aggregated imports is given by [21]

$$Y^{IMP} \equiv \frac{R_{cn}^{im} - R_{hk}^{ex}}{R_{hk}^{ex}} = \int_0^1 \delta^{im*} dF(\lambda) = \frac{\beta}{(\alpha-1)\eta} EXS \approx \frac{1-\bar{\lambda}}{\bar{\lambda}\eta} EXS. \quad (8)$$

The last approximate equality holds when α is sufficiently large. In this case, the over-reporting in aggregated imports is the same as the firm's over-reporting when the probability of being caught is the mean of the $Beta(\alpha, \beta)$ distribution.

Equation (8) shows that the over-reporting in aggregated imports has a positive linear relationship with the exchange rate spread when it is positive. Moreover, given the positive exchange rate spread, the over-reporting in aggregated imports decreases with the severity of punishment η and the average odd ratio of being caught ($\frac{\bar{\lambda}}{1-\bar{\lambda}}$).

Under the symmetric assumption, the over-reporting in exports for each firm is the same as the over-reporting in imports (i.e., $\delta^{im} = \delta^{ex}$). Moreover, firms that over-report trade face the same $Beta(\alpha, \beta)$ distribution for all goods. Thus, the over-reporting in aggregated exports $Y^{EXP} \equiv \frac{X_{cn}^{ex} - X_{hk}^{im}}{X_{hk}^{im}}$ is the same as the over-reporting in aggregated imports in equation (8).[22] Thus, the discussion in the previous paragraph also applies to the over-reporting in aggregated exports. Therefore, we obtain the first key prediction from our model:

Prediction 1. *The over-reporting in imports and exports is positively correlated with the exchange rate spread when the spread is positive.*

Following the same process, we can derive the optimal trade gaps for the negative exchange rate spread ($EXS < 0$). In this case, firms transfer the RMB from mainland China to Hong Kong by over-reporting imports settled in RMB and transfer the USD

[21] Please see the appendix for the proof. Here we also slightly abuse the notation of Y^{IMP}; in the empirical analysis, we define the over-reporting factor as 100*log difference between R_{cn}^{im} and R_{hk}^{ex}.

[22] For simplicity, the symmetric assumption on goods implies the bilateral trade balance between mainland and Hong Kong without data manipulation, i.e., $R_{hk}^{ex} S^{CNH} = X_{hk}^{im}$. However, the qualitative relationship between the exchange rate spread and over-reporting in imports and exports still holds if we extend the model to include trade imbalance.

back to the mainland by over-reporting exports settled in USD. It is easy to show that

$$Y^{IMP} = \frac{\beta}{(\alpha-1)\eta}(-EXS) \approx \frac{1-\bar{\lambda}}{\bar{\lambda}\eta}(-EXS). \tag{9}$$

Thus, the over-reporting in imports (similarly in exports) is negatively correlated with EXS when the spread is negative. Therefore, we obtain the second key prediction from our model:

Prediction 2. *The over-reporting in imports and exports is negatively correlated with the exchange rate spread when the spread is negative.*

Equations (8) and (9) suggest that fake trade may be more common for certain products as firms are more likely to choose products that Customs officials have a harder time detecting fake trade. For example, it is relatively easier for Customs to detect fraud in transactions of homogenous goods than differentiated goods, as homogenous goods usually have reference prices while differentiated goods do not.

To show this point, we relax the assumption that all products have the same $Beta$ distribution for the probability of being detected. Suppose we have two groups of products with N_1 and $N - N_1$ products in each group, and their probability of being caught follows the distributions of $Beta(\alpha_i, \beta_i)$ for $i = 1, 2$, respectively. Without loss of generality, we also assume the first group of products has a lower average probability of being detected than the second group, i.e., $\bar{\lambda}_1 < \bar{\lambda}_2$, which holds when $\alpha_1/\beta_1 < \alpha_2/\beta_2$. Clearly, given the same exchange rate spread and severity of punishment, the over-reporting in trade will be higher for the first group than the second one, i.e., $Y_1^{imp} > Y_2^{imp}$ and $Y_1^{exp} > Y_2^{exp}$.[23] As a result, we may be able to find evidence for Predictions 1 and 2 for the goods that have low risk of being detected, but not for the goods with high risk of being detected. This gives our third prediction:

[23] In the extreme case of $\alpha \to \infty$, the expected probability of being caught $\bar{\lambda} \to 1$. The over-reporting in trade will be zero in this case, no matter how large the exchange rate spread. In contrast, as $\beta \to \infty$, $\bar{\lambda} \to 0$, the over-reporting in trade will be infinitely high as long as the spread is nonzero.

Prediction 3. *The relationship between fake trade and the exchange rate spread is more prominent for products that have low risk of being detected.*

In the empirical analysis, we will adopt threshold regressions to test the non-monotonic relationship between the exchange rate spreads and trade gap as indicated in the first two predictions. Testing the third prediction is more challenging as it is difficult to know which products have low probabilities of being detected. One may suspect that differentiated goods are more likely to be used in faking trade; however, not all of them would be suitable for fake trade. For example, some differentiated goods may be very heavy and have low value to weight, and therefore it is costly to ship them between Hong Kong and the mainland. Thus, it is hard to know which good will be used to evade capital controls. To overcome this problem, we follow recent studies by applying the BLT to detect trade data manipulations (Barabesi et al., 2018; Cerioli et al., 2019; Demir and Javorcik, 2020). As firms are more likely to choose the products with a lower probability of being detected when they manipulate the trade data, we expect that there will be a more pronounced relationship between fake trade and exchange rate spreads for products that fail the BLT than for products that pass the BLT.

3.2 Remarks

One caveat of the model is that each firm's over-reporting in imports and exports is the same (i.e., $\delta^{im} = \delta^{ex}$), due to the symmetric assumption of the traded products. This greatly simplifies our model by allowing us to focus on one side of over-reporting and to show the key determinants of the aggregate over-reporting in trade. However, this result is not as restrictive as it looks. We can relax it by allowing asymmetric demand for products and bilateral trade imbalance between mainland China and Hong Kong. In this way the over-reporting in aggregate imports and exports will be different by a factor of the share of the trade imbalance in Hong Kong's exports to mainland China, and our Predictions 1-3 hold qualitatively. However, the elasticities of over-reporting in aggregate imports and exports with respect to exchange rate spreads will be different.

Throughout the model we assume that the exchange rate spreads are exogenous for individual firms who manipulate trade data for capital evasion, as individual firms are less likely to affect the exchange rate of the RMB. Moreover, the size of the dual exchange rate arbitrage seems not significant enough to remove the exchange rate spreads, given that exchange rate spreads are quite persistent as shown in Figure 1. Last but not least, if the spreads quickly vanish due to the dual exchange rate arbitrage, it would be less likely to empirically detect the relationship between the trade gap and the exchange rate spreads as indicated in Predictions 1-3.

4 Empirical Evidence from the Aggregate Trade Data

In this section, we adopt threshold regressions to test the first two predictions of the model, which suggest a non-monotonic relationship between the RMB-USD exchange rate spread and trade discrepancies between mainland China and Hong Kong. Threshold models have been developed to deal with potential shifts in economic relationships and become increasingly popular in a wide variety of economic applications that use time series, cross-sectional, and panel data.[24]

In a threshold model, the sample is split into two or more regimes based on endogenously determined value(s) of a chosen threshold variable. The coefficients of the variables of interest can have different values in these regimes. In Predictions 1 and 2, the correlations between the exchange rate spread and the trade data discrepancies have opposite signs depending on whether the spread is positive or negative. The threshold

[24] For the development of the econometric methodology in threshold regressions, please see Hansen (2000) and Yu and Phillips (2018), among others. Threshold models have been widely used in time series settings, for instance, to capture asymmetric effects of shocks over business cycles and to model arbitrage, purchasing power parity, exchange rates, and stock returns (Hansen, 2011). They are also particularly common in cross-sectional or panel data applications, such as for cross-country analysis of economic growth (Durlauf and Johnson, 1995) and for the study of safe haven currency in finance (Hossfeld and MacDonald, 2015).

model with regime-specific coefficients is perfect to test the above predictions in the data.

At first glance, the exchange rate spread seems to be a natural choice for the threshold variable. However, we choose time rather than the exchange rate spread as our threshold variable for the following reasons. First, the simple theory of dual exchange rate arbitrage assumes costless arbitrage and thus the threshold of the spread for arbitrage is zero. However, in reality, the arbitrage cost through fake trade is not zero and varies with the customs inspection and banking regulations; therefore, the threshold of the exchange rate spread is time varying and difficult to estimate precisely. Second, it is clear from Figure 1 that the exchange rate spreads in our sample can be roughly divided into two subsamples: negative before early 2014 and positive after that. The threshold model with time as the threshold variable can capture this pattern well and estimate the break point from the data. Third, we believe that time is a better threshold variable than the exchange rate spread because it takes time to arbitrage through fake trade. Unlike arbitrage in financial markets, arbitrage through fake trade may take weeks or even months. As a result, active fake trade activities only happen when there are persistent positive or negative exchange rate spreads. If we use the exchange rate spread as our threshold variable, the short-lived nonzero exchange rate spread in the data may make it difficult to detect our predictions about fake trade. Finally, we use the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) for model selection on the threshold variable, and both AIC and BIC indicate that the models with time as the threshold variable are preferable. Therefore, we use time as the threshold variable in our empirical analysis.

In addition to the threshold regressions, we also incorporate a more straightforward method of "two-step" regressions. In the first step, we test for an unknown structural change point with the sup Wald/LM/LR tests proposed by Andrews (1993). Specifically, we consider the case of partial structural change in which the coefficient of the exchange rate spread is assumed to have a structural change. Next, we estimate the coefficients from a regression model with the change point estimated by the sup tests. In this way, we can exam whether the parameter instability detected in the threshold regressions is robust to different estimation methods. In the next subsection we describe our empirical model.

4.1 Econometric specification

We construct our benchmark specification as follows, which holds for both threshold regressions and the regressions with structural change:

$$Y_t = \alpha + \beta_1 EXS_t * I(t <= T) + \beta_2 EXS_t * I(t > T) + X_t\theta + \epsilon_t, \tag{10}$$

where Y_t is the trade gap between mainland China and Hong Kong (Y_t^{EXP} and Y_t^{IMP}) as defined in Section 2.3. EXS_t is the offshore-onshore RMB-USD exchange rate spread, and its coefficient is allowed to be different in the two regimes. Because the units for trade gap and exchange rate spreads are both percentage points, thus the coefficients β_1 and β_2 are the elasticities of fake trade with respective to exchange rate spreads. T is the date of the structural change estimated by either the threshold model or the structural change test, and $I(\cdot)$ is an index function. As we discussed before, the exchange rate spread is largely negative before early 2014, and then becomes positive; thus we expect that $\beta_1 < 0$ and $\beta_2 > 0$.

X_t contains other control variables capturing different forces that may drive capital control evasion. Following the literature, we include deviations from the covered interest rate parity (CIP) condition between the RMB and the USD (CID_t) to quantify the effect of carry trade on the capital flight as discussed in Cheung et al. (2016). By definition, a positive CID_t stands for an excessive return on RMB-denominated assets, which may induce capital inflows through fake trade.[25]

[25]Following the literature, the covered interest differential (CID_t) is calculated from the nominal interest rate differential minus the non-deliverable forward premium, i.e., $CID_t = 100 * \{(r_t - r_t*)/(1 + r_t*) - (F_t - S_t)/S_t)\}$, where r_t is the monthly Chinese interbank rate from the CEIC database, r_t* is the monthly USD LIBOR rate from the FRED database, F_t is the one-month RMB non-deliverable forward rate (RMB/USD)

Capital control evasion through fake trade may also be caused by expectations that the RMB will appreciate/depreciate against the USD and the exchange rate spread may partially reflect such expectations.[26] We only consider the dual exchange rate arbitrage as the motivation for capital control evasion in our model. In reality, the exchange rate spread may also cause speculative capital flows through the fake trade, which may or may not work in the same direction as our model predictions. For instance, when the onshore RMB is expected to appreciate (the negative exchange rate spread), a mainland company can transfer the USD from Hong Kong to China by over-reporting its exports (settled in USD) to Hong Kong. This activity also implies a negative correlation between export over-reporting and the exchange rate spread, which is in the same direction as the exchange rate arbitrage. However, when the onshore RMB is expected to depreciate (the positive exchange rate spread), a mainland company can over-report USD-denominated imports to transfer the USD to Hong Kong and/or under-report USD-denominated exports to keep the USD in Hong Kong. The under-reporting of exports in this case works against the positive correlation between export over-reporting and the exchange rate spread in Prediction 1.

To control for the effect of the above speculative capital flows, we include the inflation differential and the risk premium to capture exchange rate expectations. Holding everything else constant, a high-inflation currency usually depreciates in the future against its low-inflation counterparts. Therefore, we expect that higher inflation in mainland China relative to the U.S. increases import over-reporting (positive coefficient) and decreases export over-reporting (negative coefficient), indicating net capital outflows from mainland China to Hong Kong. The risk premium of the RMB (RP_t) is estimated using the

from the CEIC database and S_t is the spot exchange rate (RMB/USD) from Bloomberg. We multiply the variable by 100 so the unit for CID_t is percentage point.

[26]For instance, the market expected the RMB to depreciate in the summer of 2011 when the eurozone financial crisis intensified. The offshore exchange rate in Hong Kong priced in such expectation immediately while the onshore market did not, resulting in a large positive exchange rate spread. In general, Cheung and Rime (2014) find that the offshore exchange rate has a significant predictive power for the onshore central parity rate set by the People's Bank of China.

method of Hamilton and Wu (2014), and by definition, a negative risk premium indicates that the RMB is expected to depreciate.[27] As a result, the coefficient estimate for the risk premium is expected to be negative for import over-reporting but positive for export over-reporting. It suggests that the negative risk premium (when the RMB is expected to depreciate) encourage net capital outflows from mainland China to Hong Kong.

Finally, the growth rate of China's total imports and exports are included to control for the export and import demand, and a linear time trend is included to control for possible trends in the over-reporting in imports and exports. The monthly trade data reported by Hong Kong are obtained from Comtrade, and the trade data of mainland China is from CEIC. Table 2 provides summary statistics, and the appendix provides more details about the data source. We also conduct the Dickey-Fuller test and the Philips-Perron test for unit roots in our key dependent and independent variables, and both of them reject the unit root hypothesis, indicating that those variables are stationary.

4.2 Baseline results

The benchmark results for both the threshold model (TR) and the model with structural change (SCR) in Table 3 strongly confirm our predictions. The left and right panels report the results for the import gap (Y_t^{IMP}) and the export gap (Y_t^{EXP}), respectively. In both cases, the trade data gap between mainland China and Hong Kong is negatively correlated with the exchange rate spread in the first subsample ($\hat{\beta}_1 < 0$ as predicted by Prediction 2), while the correlation is positive in the second subsample ($\hat{\beta}_2 > 0$ as predicted by Prediction 1). The coefficient estimates are statistically significant at either the 1% or 5% level. Note that the estimated break dates are highly consistent across the two

[27] We construct the measure for the risk premium following the method proposed by Hamilton and Wu (2014), which studies the risk premium of crude oil futures contracts. We apply their method to the RMB-USD foreign exchange forward contracts and the data are obtained from Bloomberg. If the sellers of RMB-USD forward contracts want to hedge their exchange rate risk (e.g., multinational companies operating in China), the buyers of these forward contracts should be compensated for assuming the foreign exchange risks.

methodologies with 2013m9 and 2013m10 for the import gap and 2014m2 and 2014m3 for the export gap. For comparison, columns (3) and (6) also report the results of a simple OLS model without structural changes. In contrast to our benchmark results, the coefficient estimates of the exchange rate spread from the OLS are not statistically significant, indicating the importance of capturing the non-monotonic relationship between the exchange rate spread and the over-reporting of imports and exports.

The fake trade activities that we detect are also economically significant, especially over some periods with large exchange rate spreads such as the second half of 2015.[28] Figure 4 shows the fitted trade gaps from our model along with the raw data and in general, the fitted data trace the raw trade data well. Following China's foreign exchange reform on August 11, 2015, the onshore and offshore exchange rate spread widened sharply. The average exchange rate spread during the period between August 2015 and January 2016 rose to 0.63 percentage points, from an average of 0.08 percentage points in the first seven months of 2015. Based on our estimation, the fake trade due to foreign exchange arbitrage between mainland China and Hong Kong amounted to over 24 billion U.S. dollars during this period, which accounts for over 12% of the total trade between the two economies.

We also observe an asymmetric effect of the exchange rate spread on the import and export gaps. In both regimes before and after the break, the import gap is more sensitive to the exchange rate spread than the export gap, consistent with the fact that capital controls in China are more restrictive for capital outflows and thus the demand for capital outflow through the over-reporting of imports is relatively high, particularly when the exchange rate spread is large. For example, given the mean of the exchange rate spread after the break date, the import gap due to exchange rate arbitrage is estimated as 5.5 percentage points, while it is only 3.9 percentage points for the export gap.

[28]The adjusted R-squared increases from 0.075 and 0.09 to 0.13 and 0.17 when the exchange rate spread is included in the model for the import gaps and the export gaps, respectively. It suggests that on average, the exchange rate spread explains around 5-8% of the trade gaps in our sample.

4.3 Extensions and sensitivity analysis

Our results are robust to various extensions and sensitivity analysis as shown in Tables 4 and 5. First, we find that it is important to control for the exchange rate expectations in our regressions. The coefficient estimates of the inflation differential and the risk premium in Table 3 are consistent with the prediction of speculative capital flows discussed in Section 4.1. It suggests that these variables may appropriately capture the market expectations about the RMB-USD exchange rate. If we remove these two variables from the regressions, the coefficient estimates of the exchange rate spread become less significant for the export gap as shown in the column (5) of Table 4. In particular, the coefficient estimate becomes statically insignificant in the second regime where the RMB is expected to depreciate (positive exchange rate spread). This finding is consistent with our previous prediction that firms may under-report exports to leave their USD incomes in Hong Kong when they expect the RMB is about to depreciate. The under-reporting of exports works against the over-reporting in foreign exchange arbitrage activities, inducing a smaller and statistically insignificant coefficient estimate in column (5) when we do not control for such an expectation effect. In contrast, the coefficient estimate of β_2 for the import gap in column (1) becomes larger and statistically more significant if we remove the risk premium and inflation differential from the regression. When the RMB is expected to depreciate in the second regime, the over-reporting of imports is used for both capital flight and foreign exchange arbitrage. If we do not control for exchange rate expectations, the results in column (1) will mistakenly attribute the effect of capital flight to foreign exchange arbitrage.

Second, our findings hold up well when we add lagged dependent variables and key independent variables (EXS) to control for possible auto-correlations in the error term. In columns (2) and (6) of Table 4, the lagged dependent variable is added to the regressions, and the lagged exchange rate spread is added in columns (3) and (7). In all cases, our main findings hold qualitatively well. In addition, our results are robust to including the economic policy uncertainty (EPU) index and changes in foreign relations, which the literature find to affect trade and financial activities.[29] The EPU index is from Baker et al. (2016) and the data for foreign political relations are from Du et al. (2017). The coefficient estimates of these two variables are statistically insignificant in columns (4) and (8) of Table 4, and our main findings are qualitatively unchanged.

In addition, we adjust the structural break date manually to make sure that our results are robust to a wide range of break dates in Table 5. We manually fix the break dates of both import and export gaps in the last quarter of 2013 and estimate our benchmark regressions in each subsample. Table 5 shows that our results hold up qualitatively in all cases.

Last but not least, we also find evidence of exchange rate arbitrage from China' data of net RMB receipts and net foreign exchange payments under the trade account. From the description of arbitrage activities in Section 3, there is a net RMB outflow when the exchange rate spread is negative, due to the over-reporting of RMB-denominated imports of mainland China from Hong Kong, but a net RMB inflow when the exchange rate spread is positive. As a result, we expect a positive correlation between the exchange rate spread and the net receipt of RMB by mainland China from Hong Kong. Similarly, there is a net USD inflow from Hong Kong to mainland China due to the over-reporting of USD-denominated exports from Hong Kong to the mainland when the exchange rate spread is negative, while a net USD outflow is expected when the exchange rate spread is positive. Therefore, we expect a positive correlation between the exchange rate spread and mainland China's net USD payment to Hong Kong under the trade account. Unfortunately, we are not able to find the RMB and USD transaction data between mainland China and Hong Kong. Therefore, we use China's net RMB receipts from the rest of the world and its overall net foreign exchange payments under the trade account as proxies to test the

[29]For instance, Handley and Limao (2017) document that reduced trade policy uncertainty accounts for over one-third of China's export growth to the U.S. following China's 2001 WTO accession. Du et al. (2017) find that political shocks influence short-term exports to China.

above predictions.[30] The coefficient estimate of the exchange rate spread in Table 6 is significantly positive for both the RMB net receipts and the foreign exchange net payments, supporting our predictions.

5 Empirical Evidence from the Disaggregated Trade Data

In this section, we adopt Benford's law to test the third theoretical prediction. The BLT is a simple and effective statistical method to detect data irregularity; recently, it has been widely used in detecting fraud in accounting and economic data (Nigrini, 2012; Berger and Hill, 2015; Michalski and Stoltz, 2013). In particular, recent studies apply the BLT to disaggregated customs data to detect tariff evasion (Barabesi et al., 2018; Cerioli et al., 2019; Demir and Javorcik, 2020). Thus, we employ this method to Chinese customs data in 2015 to identify the products prone to manipulations, and explore whether the goods that do not conform to Benford's law are used as the vehicle for fake trade and exchange rate arbitrage.

5.1 Benford's law test

Newcomb (1881) and Benford (1938) independently observed and described the empirical distribution of the first digit of numbers in various data sets, which has been called Benford's law ever since. The law predicts that the leading digits follow a particular logarithmic distribution instead of being uniformly distributed as might be expected. The exact law for the first digit is:

$$P(\text{First digit is } d) = log_{10}(1 + 1/d), \textit{ for } d = 1, 2, .., 9.$$[31]

[30] Since Hong Kong is the most important RMB offshore market (about 70%), China's net RMB receipts are likely to be a good proxy for the net RMB receipts between mainland China and Hong Kong.

[31] Benford's law can be generalized to describe the frequencies of occurrences of the next digits, but we will focus on the first digit as most of the literature does.

Hill (1995) provide a formal statistical derivation of Benford's law and show that the law naturally arises when data are generated by an exponential growth process or when independent processes are pooled together.[32] Pearson's Chi-square statistics can be used to test whether the data conform to Benford's law. More specifically, the goodness-of-fit-statistics of the BLT is given by

$$D^2 = N \sum_{d=1}^{9} (f_d - \hat{f}_d)^2 / f_d \overset{H_0}{\sim} \chi^2(8)$$

where $\hat{f}_d$ denotes the observed fraction of leading digit d in our data and f_d denotes the fraction predicted by Benford's law. The Pearson's Chi-square statistic, D^2, converges to the χ^2 distribution with eight degrees of freedom as the number of observations N goes to infinity under the null hypothesis that the observed data conform to Benford's law. A large value of this statistic above the critical values indicates significant deviations from Benford's law.

Deviations from Benford's law have been widely used to detect irregularities in data reporting since the manipulated data are unlikely to conform to the above distribution; people usually cannot replicate the underlying data-generating process and they may be biased toward simpler and more intuitive distributions, such as the Uniform distribution, as shown by experimental studies (Hill, 1988; Camerer, 2003).[33] Benford's law was initially used as a forensic auditing and accounting tool to detect anomalies in financial data.[34] Recently many economists have started to adopt the BLT to verify the authentic-

[32] Hill (1995) show that Benford's law naturally arises if the data are a mixed of several random samples chosen from random distributions that are selected in an unbiased way. Michalski and Stoltz (2013) offer an excellent review and discussion on three natural data-generating processes leading to Benford's law, which support that economic data without manipulations should follow the law.

[33] Hill (1988) conducted an experiment by asking 742 undergraduate students to invent a six-digit random number. His subjects have no incentive to bias upward or downward. He found that the leading digit of invented numbers did not conform to Benford's law based on Chi-square tests and Kolmogorov-Smirnoff tests.

[34] For example, Nigrini (1996) and Nigrini and Mittermaier (1997) apply BLT to individual taxpayers' data and companies' auditing data, respectively. Because of its usefulness, the BLT now has been included in many popular accounting and auditing software packages (e.g., ACL and CaseWare 2020). Durtschi et al. (2004) provide practical guidance on how to use the BLT to detect data manipulation in accounting.

ity and reliability of economic data. For example, Michalski and Stoltz (2013) find that countries more vulnerable to capital flow reversals are more likely to misreport their economic data strategically, which is evident from the deviations of their balance of payment data from Benford's law. Rauch et al. (2011) use the BLT to investigate the quality of macroeconomic data relevant to the government deficit criteria reported to Eurostat by the EU member states, and find that data reported by Greece shows the greatest deviation from Benford's law among all euro states, confirming the European Commission's independent allegations of data manipulation by Greece.[35]

Researchers have recently applied the BLT to disaggregated international trade data as a simple and effective tool to detect tariff evasion and other illegal activities (Barabesi et al., 2018; Cerioli et al., 2019; Demir and Javorcik, 2020). Arguably, the distribution of leading digits of import and export values without manipulation may well conform to Benford's law. The standard trade models including Eaton and Kortum (2002) and Melitz (2003) assume that firms within the same industry/country draw productivity from certain distributions, and different industries/countries have different distributions of productivity (Caliendo and Parro, 2015). Thus, in the view of Hill (1995), import and export values without manipulation are likely to conform to Benford's law as they are random samples taken from various different distributions.[36] In addition, the sample size of disaggregated trade data usually is large and thus the premise of Benford's law—the central limit theory—is likely to hold. More convincingly, Demir and Javorcik (2020) show that the simulated data from standard international trade models without tax evasion comply with Benford's law. They further find that the BLT is useful in detecting tax evasion in Turkey's import data following an unexpected policy change in importing finance.

Thus, we employ the BLT to the disaggregated trade data between mainland China

[35]For more examples, see Judge and Schechter (2009), Holz (2014), and Huang et al. (2020) for their applications of the BLT in cross-country survey data and Chinese macroeconomic and firm-level data, respectively.

[36]Cerioli et al. (2019) provide a similar argument that international transactions made with different counterparties may be characterized by different economic processes, and thus trade data may be approximated well by Benford's law.

and Hong Kong in 2015 to detect the fake trade. We use the Chinese Customs data in 2015 because the exchange rate spread was large and the fake trade is believed to have been prevalent in that year as discussed earlier. The data contain values and quantities of each firm's imports and exports at the HS 8-digit product level, as well as information about trade partners, units, customs regimes, ports, and transportation modes. It also covers other information about the trading firms in China, such as firm name, location, phone number, contact person, and ownership. Note that our data are close to the transaction level and more disaggregated than the product-level data used in previous studies on tax evasion, such as Feenstra et al. (1999) and Fisman and Wei (2004).

The harmonized system of international trade groups products into 21 sections; we apply the BLT to the trade data in each of these sections.[37] Significant deviations from Benford's law for the trade data in a given section signal potential data manipulation in that section. We conduct the BLT for the trade data at the section level rather than at the HS 8-digit product level for two reasons. First, Cerioli et al. (2019) suggest that the trade data for a single product at the HS 8-digit level is unlikely to conform to Benford's law even without data manipulation and it is better to use the trade data with multiple products. Each HS section covers multiple firms and multiple products across different industries, and thus is more likely to adhere to Benford's law when the data are not manipulated. Second, more than half of the HS 8-digit-level trade data between mainland China and Hong Kong have less than 13 observations and thus are not suitable for the BLT due to the limited number of observations.[38]

Figure 5 presents an example of the BLT results for textiles (HS 2: 50-63) and jewelery products (HS 2: 71), respectively. The histograms show the observed probabilities of each digit and the dots present the expected probabilities following Benford's law. The

[37] Each HS section consists of a number of chapters at HS 2-digit level ranging from 1 to 99 as listed in Table 7.

[38] Moreover, the monthly trade data between mainland China and Hong Kong is only available at the HS section level or more aggregated levels. Therefore, HS section is the most disaggregated level that we can compare our BLT results to our aggregate evidence of foreign exchange arbitrage.

top panel shows that the distribution of the first digit of 116,591 transactions of textile products between Hong Kong and mainland China conforms to Benford's law very well. By contrast, the distribution of the first digit of 3,469 transactions of jewelery products significantly deviate from Benford's law as shown in the bottom panel. The corresponding Pearson's Chi-square statistics (and the associated p-values) are 4.42 (0.82) and 18.52 (0.02) for the textiles and jewelery respectively, indicating potential data manipulations for the jewelery but not for the textiles.

Table 7 presents the BLT results for each HS section with the Chi-square statistics and associated p-values, and several interesting patterns emerge. First, 9 out of 21 HS sections fail to pass the BLT as their p-values are less than 0.1, indicating the possibility of data manipulation. Most of them are intermediate inputs or differentiated products that do not have reference prices (Rauch, 1999), such as optical and photographic instruments (HS 2: 90–92), jewelery and precious metal or stones (HS 2: 71), electrical equipment (HS 2: 84–85), and works of art (HS 2: 97–99). Thus, we group those sections as the BLT-rejected group (BLTR). Second, we find that all primary goods including vegetable and animal products, minerals, and prepared foodstuffs (HS 2: 1–27) pass the BLT as the p-values for those sections are above 0.1. This is consistent with the fact that those products are perishable and homogenous and thus less likely to be the vehicle for fake trade. These two findings are intuitive as it is easier to manipulate the reported values of differentiated goods than homogeneous goods, consistent with the findings by Javorcik and Narciso (2008). Moreover, other goods with low value to weight such as textiles (HS 2: 50–63) and transportation vehicles (HS 2: 86–89) also pass the BLT, indicating less likelihood of manipulation on the transactions of those goods.[39]

[39]The sample size sometimes matters for Pearson's Chi-square test for Benford's law. Large samples would lead to over-rejection of the null hypothesis, while a small sample would lead to biased inference. In our case, a small sample might not be an issue as all HS-2 sections have more than 100 observations except for the section of arms and ammunition, which has a small trade value. We also do not observe a significant relationship between the p-values and the (log) number of observations across sections. In fact, the average number of observations in the BLTR group is far less than the non-BLTR group of other goods as shown in Table 7, indicating that the over-rejection issue might not be a serious concern in our setting. As a robustness check, we also adopt the likelihood ratio test and the results are virtually the same.

Based on those observations, we divide 21 HS sections into three groups: the sections that are rejected by the BLT (BLTR), the sections that pass the BLT and mainly contain primary goods (Non-BLTR: Primary goods), and the sections that pass the BLT and mainly contain other goods (Non-BLTR: Others), as listed in Table 7. Next, we check whether the monthly import and export gaps of the BLTR group are also systematically related to the exchange rate spread as in our baseline results of Table 3, while other groups that pass the BLT are not. For each group, we aggregate monthly imports and exports, compute the corresponding import and export gaps, and conduct the baseline regression (10). Table 8 presents the results for the BLTR and non-BLTR groups (primary and other products separately). In the first two columns, the results for the BLTR group are very similar to our baseline results in Table 3. The coefficient estimates of the exchange rate spread are significantly negative for both import and export gaps before the break date, whereas the estimates become significantly positive afterwards. The estimated break months are also the same as our baseline results from the aggregate trade data. By contrast, the coefficient estimates of the exchange rate spread are mostly insignificant for both import and export gaps of Non-BLTR goods (for both primary goods and other goods), as shown in columns (3)–(6).[40] Thus, our findings suggest that the BLTR group of goods is likely to be the vehicle of the fake trade for exchange rate arbitrage. The difference between the two groups of goods also supports Prediction 3 that the relationship between fake trade and exchange rate spreads is more significant for the trade of products that are easy to manipulate.

5.2 Placebo tests

To ensure that our results for the BLTR and Non-BLTR groups are informative rather than driven by random factors or statistical errors, we conduct two placebo tests. The first randomly splits the 21 sections of HS goods into pseudo BLTR and Non-BLTR groups and then estimates the model with the same threshold dates in the baseline results to obtain

[40] The results are similar if we pool the primary goods and other Non-BLTR goods into one group.

the key estimates of the exchange rate spreads.[41] After repeating this simulation 1000 times, we compute the mean and the standard deviation of the estimates of the exchange rate spread. In the second placebo test, we exclude the primary products first and then randomly split the remaining sections of HS goods into pseudo BLTR and Non-BLTR groups. The second test allows us to directly compare with the results of the BLTR group and the Non-BLTR group of other goods in Table 8.

Table 9 presents the results of the two placebo tests. The coefficient estimate of the exchange rate spreads for import and export gaps in the pseudo BLTR and Non-BLTR groups is negative before the break date and becomes positive afterwards. This pattern is largely consistent with the baseline results in Table 3, except that the effects are insignificant for imports gaps in the two groups. This result is largely expected and reasonable as this placebo exercise randomly allocates fraud transactions into two groups and thus it should still partially capture the time series relationship between the exchange rate spread and the trade gaps. However and more importantly, given the same independent variable, the estimates of the exchange rate spread are very similar between the pseudo BLTR and Non-BLTR groups (compare column (1) with (3) and column (2) with (4)). This pattern is sharply different from our findings in Table 8, in which the estimates from the BLTR group are similar to the baseline results while the estimates from the non-BLTR group are not. This suggests that our classification of goods into two groups based on Benford's law test is informative in detecting possible manipulation in the trade data. Finally, the results from the two placebo tests are similar, indicating that our results are not sensitive to the way the primary goods are handled.

[41] To avoid zero trade flows in some months, we ensure that each group has at least 5 out of 21 sections of HS goods.

5.3 Cross-country evidence

In a cross-country robustness check, we test our benchmark results for the trade discrepancies between China and the U.S. Hong Kong is likely to be the major place to evade China's capital controls through fake trade due to the city's strong trade and financial ties with mainland China. The geographical proximity also makes the arbitrage costs much lower in Hong Kong than other places. As a result, we may not be able to find similar empirical patterns in the data regarding China's other trading partners such as the U.S.

Our results for the U.S. in Table 10 provide support to the above prediction. Columns (1) and (2) report the estimation results from the threshold regressions for all goods traded between mainland China and the U.S. Although the signs of $\hat{\beta}_1$ and $\hat{\beta}_2$ are the same as for our Hong Kong results, only one out of four estimates is statistically significant. We also repeat the exercises using the BLT and the results are reported in columns (3) to (8). For the group of products that fail to pass the BLT, there is some evidence of fake trade for imports. $\hat{\beta}_1$ is statistically negative and $\hat{\beta}_2$ is statistically positive for the import gap in the BLTR group (column (3)). However, the coefficient estimates for the export gap in column (4) do not exhibit the pattern of foreign exchange arbitrage as we discussed before, and they are not statistically significant either. These findings suggest that the fake trade between the U.S. and China might be used for capital flight (e.g., through import over-reporting). But we find no evidence of foreign exchange arbitrage like what we found in the trade data between Hong Kong and mainland China. For the goods that pass the BLT, there is no evidence for fake trade. Only two out of eight coefficients estimates in columns (5) to (8) are statistically significant and have the right signs.

6 Conclusion

Our paper shreds light on the nature of capital control evasion through the manipulation of international trade data. Capital controls may not be as effective as they are supposed to be due to various capital control evasion activities such as fake trade. However, due to its nature, fake trade for capital control evasion is difficult to detect in the data, making it hard to estimate its size, evaluate its costs and find solutions to reduce it. By taking advantage of the special institutional setups between mainland China and Hong Kong, we document empirical evidence that is consistent with foreign exchange arbitrage through over-reporting the trade between the two economies. Although fake trade is identified through two distinct methods, our results are surprisingly consistent with each other.

Our paper highlights the dilemma faced by policymakers, especially those in emerging markets. Despite various shortcomings and costs, the capital control policy has its own merits and is likely to stay in place, especially in emerging markets, in the foreseeable future. Policymakers should keep in mind the unintended consequences when they design such policies.[42] In particular, it is crucial to understand the nature of capital control evasion activities and design mechanism to diminish their adverse effects.

[42]For instance, Wei and Zhang (2007) show that capital control measures will substantially increase the real trade costs and discourage international trade.

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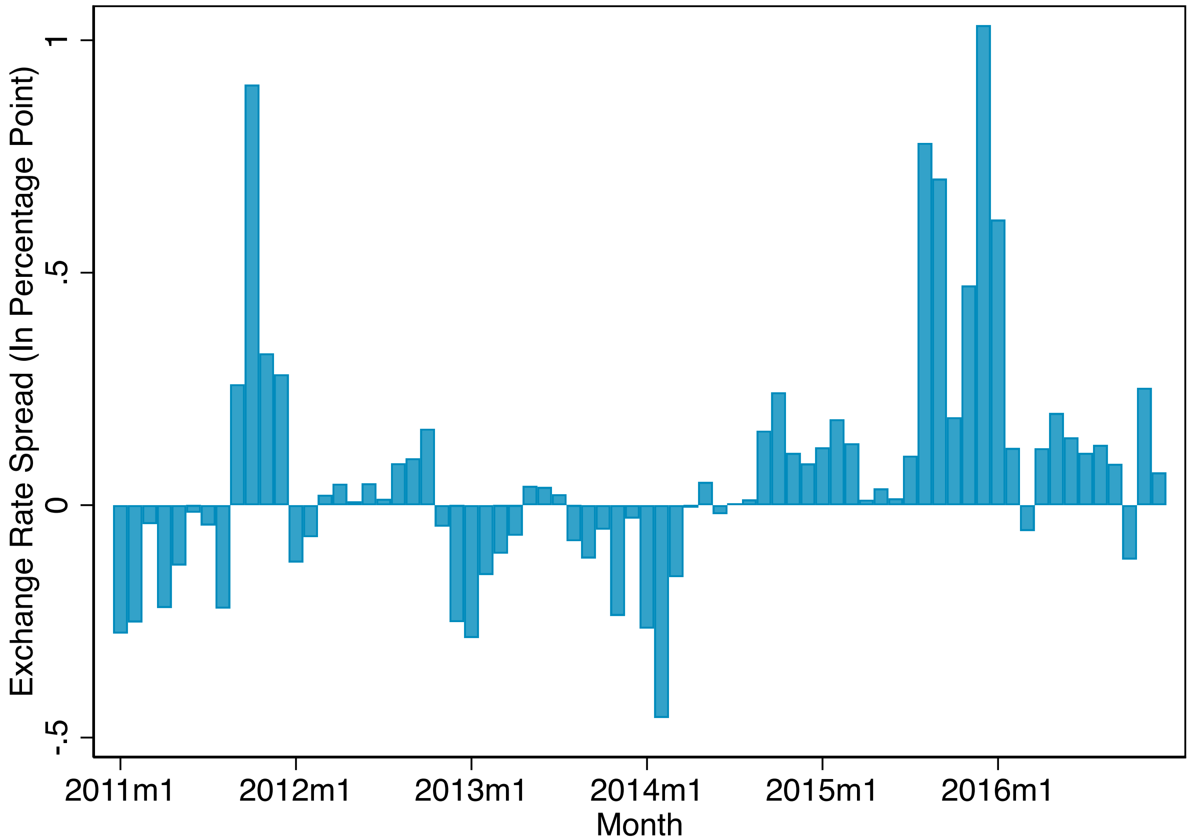
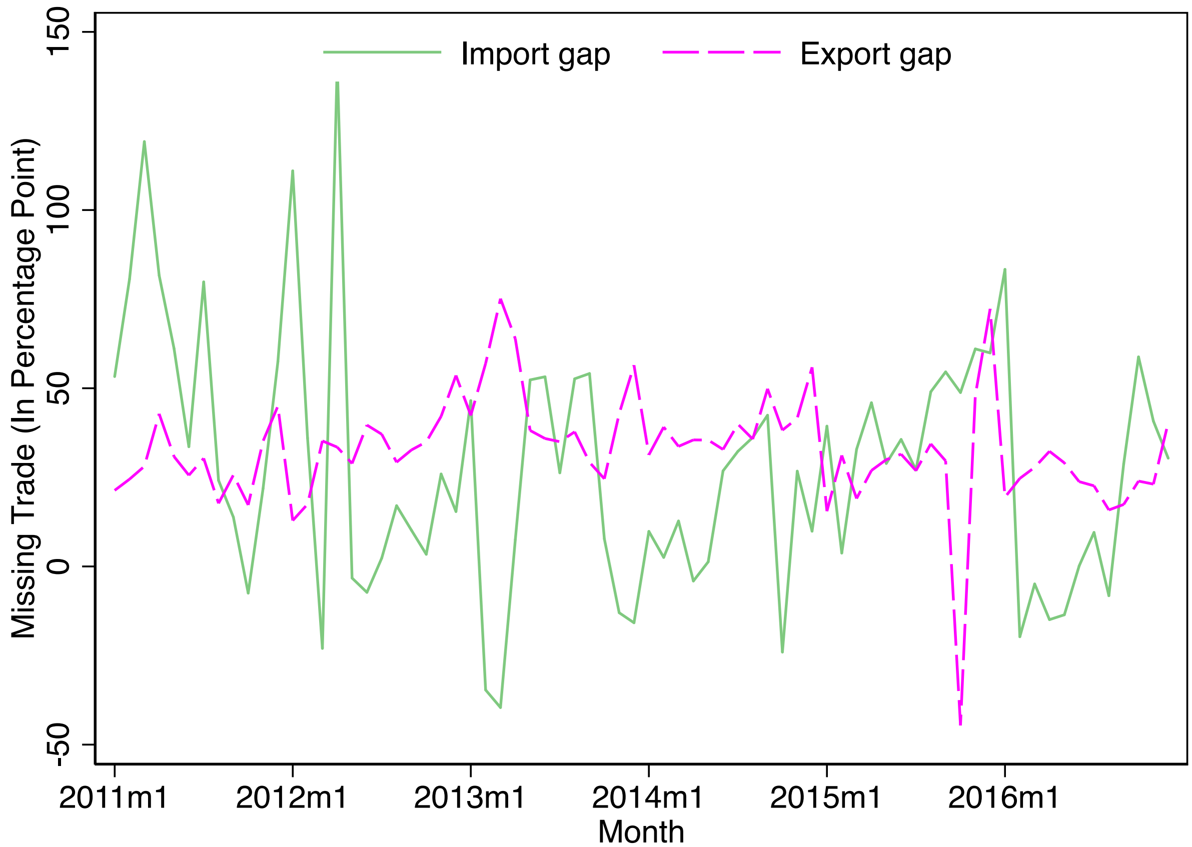


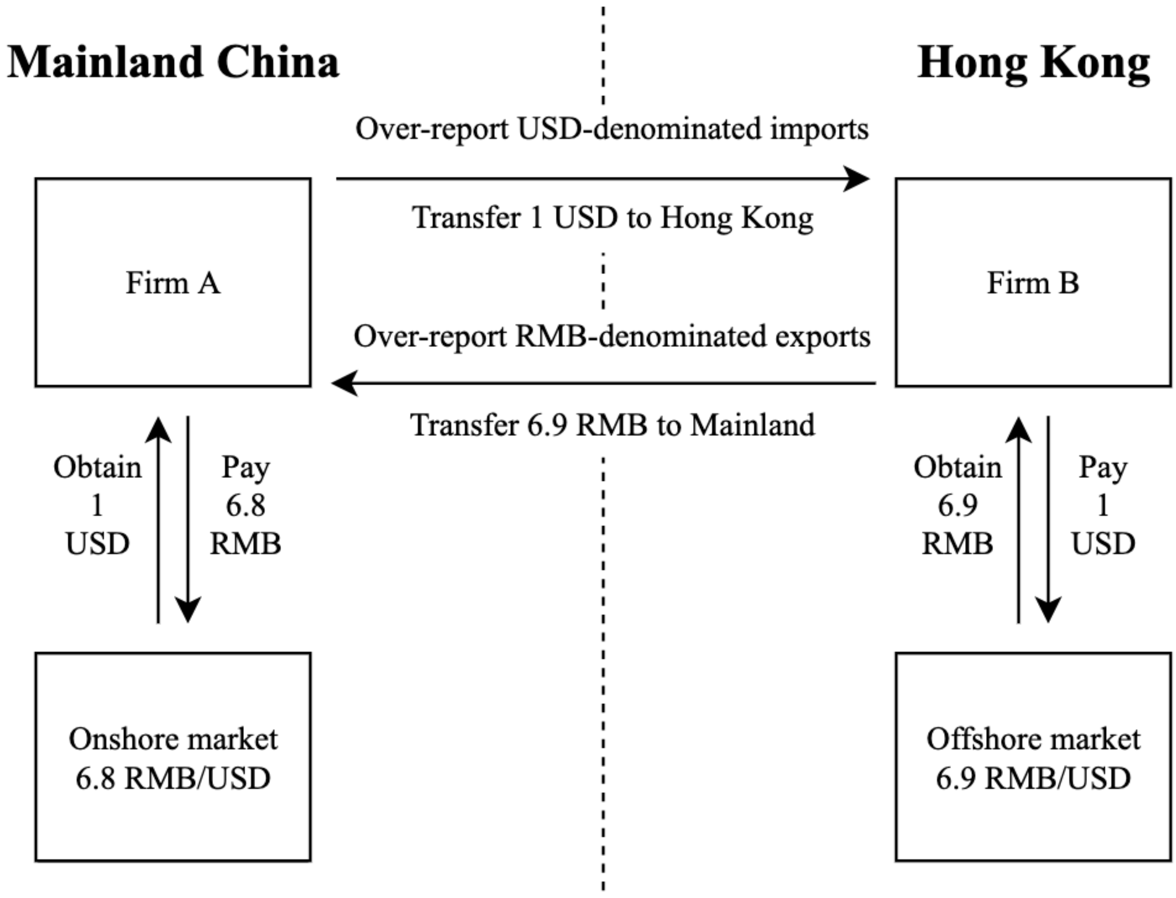
Note: This figure shows the exchange rate spreads of the RMB in onshore and offshore markets. A positive spread implies that the RMB is more expensive (relative to the USD) in the onshore market than in the offshore market.

Figure 1: The spreads of the RMB between onshore and offshore markets



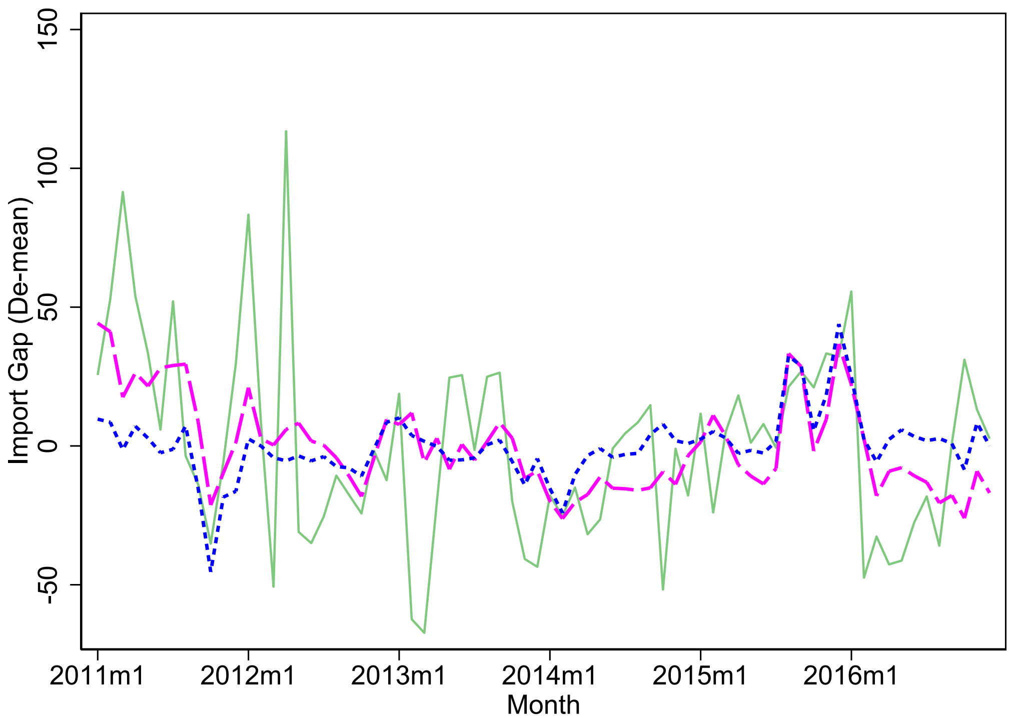
Note: This figure shows the missing trade between mainland China and Hong Kong. The import and export gaps are defined as the (100*) log difference between imports to Hong Kong (or exports from Hong Kong) reported by mainland China, and the corresponding ones reported by Hong Kong, adjusted by trade costs.

Figure 2: Missing trade between mainland China and Hong Kong

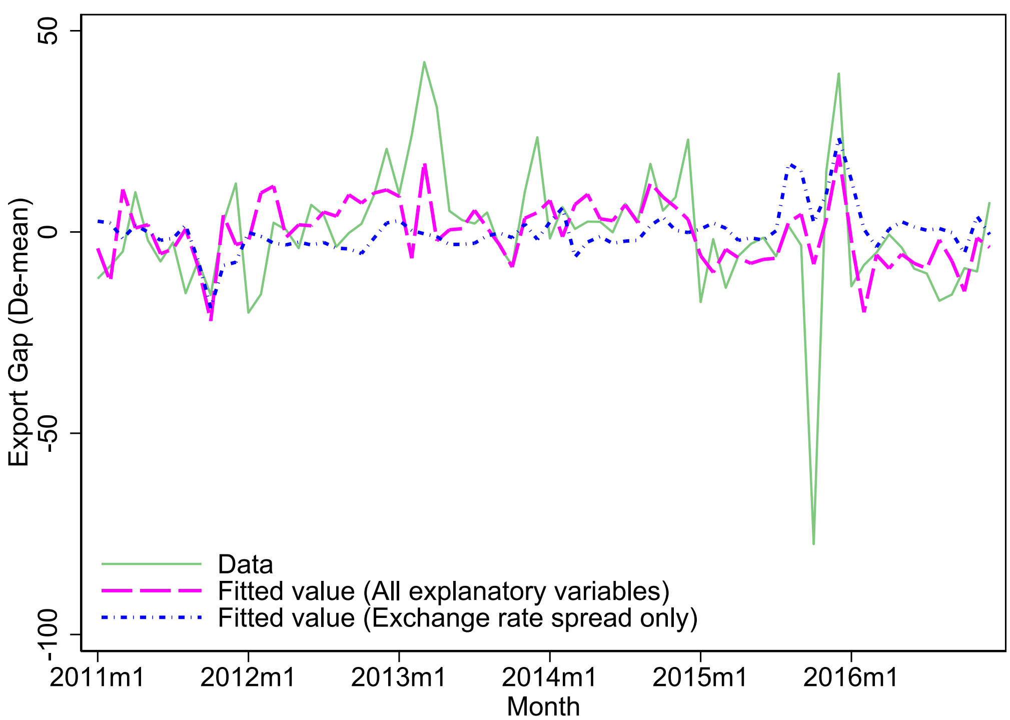


Note: This figure shows an example of the dual exchange rate arbitrage under a positive exchange rate spread. An arbitrager can make risk-free profits by buying the USD in mainland China and selling the USD in Hong Kong. The detailed steps of arbitrage can be illustrated as follows: First, convert the RMB into USD from a bank in mainland China. Second, firm A over-reports USD-denominated imports to transfer the USD to Hong Kong. Third, convert the USD into RMB in Hong Kong. Last, firm A over-reports RMB-denominated exports to transfer the RMB back to mainland China.

Figure 3: The dual exchange rate arbitrage: An example



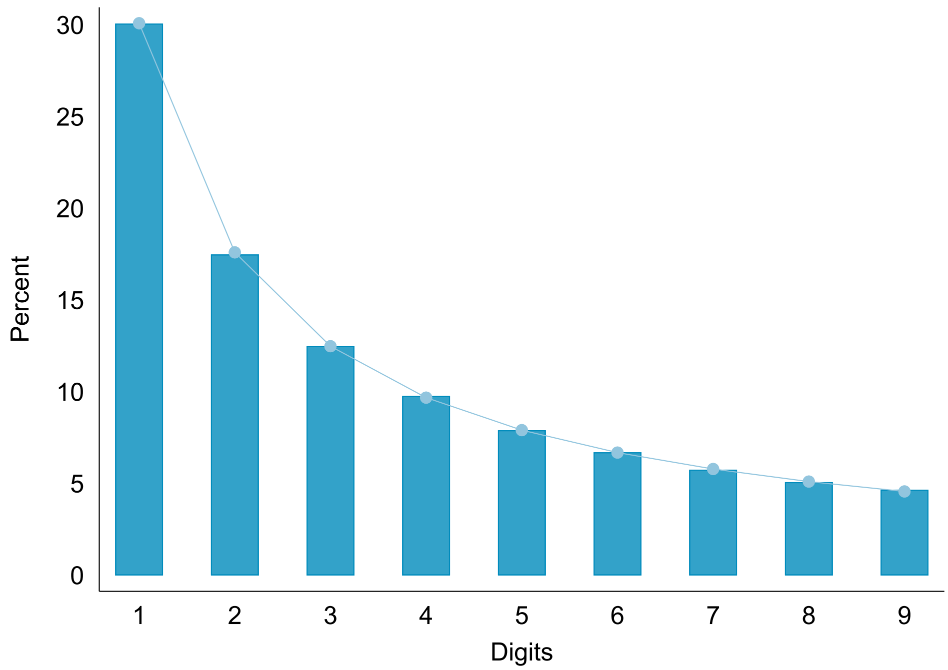
(a) Import gap



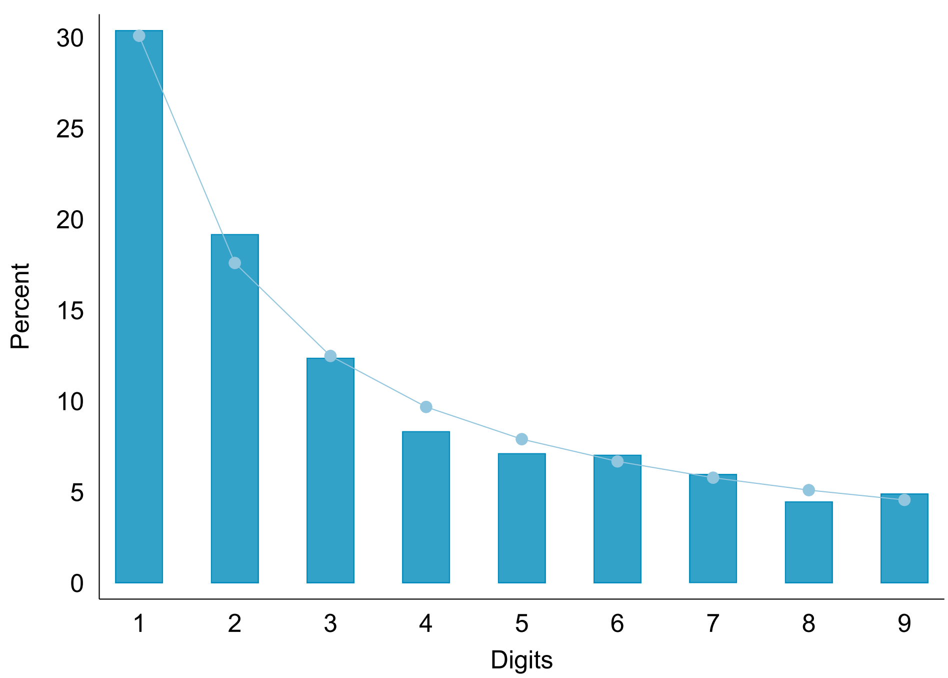
(b) Export gap

Note: This figure shows the raw data and fitted values (all de-meaned) for the trade data gaps between mainland China and Hong Kong. The scale for y-axis is percentage point.

Figure 4: The trade gaps: Data and fitted values



(a) Textiles



(b) Jewelry

Note: This figure shows the results for Benford's law test for textiles and jewelry in the top and bottom panels, respectively. The histograms show the observed probabilities of each digit and the dots present the expected probabilities following Benford's law.

Figure 5: Benford's law test

Table 1: China's capital flows

	In billions of U.S. dollars				In percentage of GDP			
	Inward investment		Outward investment		Inward investment		Outward investment	
Year	Direct	Portfolio	Direct	Portfolio	Direct	Portfolio	Direct	Portfolio
2005	104.11	21.45	13.73	26.16	4.55	0.94	0.60	1.14
2006	124.08	42.86	23.93	111.28	4.51	1.56	0.87	4.04
2007	156.25	20.96	17.15	4.52	4.40	0.59	0.48	0.13
2008	171.53	9.65	56.74	-25.20	3.73	0.21	1.23	-0.55
2009	131.06	29.61	43.89	2.53	2.57	0.58	0.86	0.05
2010	243.70	31.68	57.95	7.64	4.00	0.52	0.95	0.13
2011	280.07	13.39	48.42	-6.25	3.71	0.18	0.64	-0.08
2012	241.21	54.17	64.96	6.39	2.83	0.63	0.76	0.07
2013	290.93	58.24	72.97	5.35	3.04	0.61	0.76	0.06
2014	268.10	93.24	123.13	10.81	2.56	0.89	1.18	0.10
2015	242.49	6.74	174.39	73.21	2.19	0.06	1.58	0.66
2016	174.75	50.50	216.42	102.77	1.56	0.45	1.93	0.91
2017	166.08	124.30	138.29	94.80	1.35	1.01	1.12	0.77
2018	235.37	160.38	143.03	53.51	1.69	1.15	1.03	0.39
2019	155.82	147.37	97.70	89.42	1.09	1.03	0.68	0.62
Mean	199.04	57.64	86.18	37.13	2.92	0.69	0.98	0.56

Note: The capital flows data are from the Balance of Payment table on the website of the State Administration of Foreign Exchange. The GDP data are from the China Statistical Yearbook.

Table 2: Summary statistics

Variables	N	Mean	STD	Min	Max
Y^{IMP} (100*log)	72	27.722	35.139	-39.588	141.127
Y^{EXP} (100*log)	72	32.922	15.560	-44.615	75.144
EXS (100*log)	72	0.067	0.261	-0.458	1.032
CID (%)	72	3.204	1.100	1.409	5.731
Risk premium (100*log)	72	-0.279	0.853	-2.721	1.110
Inflation diff (%)	72	1.074	0.804	-0.462	3.268
Trade growth rate (%)	72	0.013	0.140	-0.343	0.515
Changes in foreign relationship	72	-0.019	0.107	-0.418	0.323
Log(EPU)	72	8.345	26.029	-52.933	50.199
FX net payments by mainland (100*log)	72	-22.426	22.669	-85.877	52.290
RMB net receipts by mainland (100*log)	23	-37.625	41.549	-172.012	25.696

Table 3: Benchmark results

	Dependent variable					
	Import gap			Export gap		
	TR	SCR	OLS	TR	SCR	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
$EXS_t(\beta_1)$	-46.627***	-45.964**		-18.264***	-17.209**	
	(17.300)	(17.493)	7.596	(6.870)	(7.743)	4.563
$EXS_t(\beta_2)$	45.671**	45.018**	(26.382)	24.884***	24.446**	(10.447)
	(17.944)	(20.750)		(9.597)	(10.105)	
CID_t	1.193	1.121	-1.618	1.568	1.451	1.095
	(4.420)	(5.284)	(5.507)	(1.838)	(1.939)	(2.020)
Risk premium	-7.006	-7.214	-8.080	1.917	1.908	2.275
	(8.470)	(8.618)	(8.588)	(3.192)	(3.075)	(2.835)
Inflation diff.	9.166**	9.090*	12.651**	-7.873***	-7.782***	-6.257***
	(4.431)	(4.924)	(5.277)	(1.643)	(1.772)	(1.487)
Trade growth	-14.581	-14.428	-17.966	33.472**	31.727**	27.966**
	(38.672)	(34.053)	(32.950)	(13.802)	(13.028)	(13.847)
Trend	-0.590*	-0.597*	-0.498	-0.196*	-0.197	-0.088
	(0.313)	(0.330)	(0.339)	(0.116)	(0.124)	(0.108)
Constant	30.622	31.115	34.982	41.267***	41.571***	39.327***
	(22.390)	(24.154)	(25.285)	(7.448)	(9.092)	(9.752)
Observations	72	72	72	72	72	72
R-squared	0.229	0.227	0.142	0.259	0.252	0.162
Break month	2013m9	2013m10		2014m2	2014m3	

Note: This table shows the benchmark results of threshold regressions (TR), the regressions with structural change (SCR) based on sup Wald/LM/LR tests, and simple OLS regressions for the import and export gaps, respectively. CID_t is the covered interest rate parity (CIP) deviations between the RMB and the USD. The RMB risk premium is constructed by following the approach of Hamilton and Wu (2014). Inflation diff. is the CPI inflation differentials between China and the U.S. The trade growth rate of China and a time trend t are also included in the regressions. The break months are identified from the data by either threshold regressions or sup tests. The threshold regression adopts robust standard errors in estimation, while structural change regression and OLS regression use the Newey-West robust standard error to control for heteroskedasticity and autocorrelation in error terms. Superscripts *, ** and *** represent statistical significance at the ten, five and one percent levels, respectively.

Table 4: Robustness checks

	Import gap				Export gap			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$EXS_t(\beta_1)$	-46.611***	-39.896**	-63.355***	-42.498**	-15.412**	-16.502**	-15.283**	-17.238**
	(15.077)	(19.692)	(20.473)	(17.194)	(6.711)	(7.010)	(6.960)	(7.109)
$EXS_t(\beta_2)$	59.750***	41.949**	37.397*	37.367*	16.254	23.566**	39.659***	23.158**
	(13.876)	(18.825)	(20.499)	(20.162)	(10.891)	(9.915)	(14.026)	(11.580)
CID_t	1.164	1.320	0.433	0.334	1.093	1.344	1.634	1.407
	(4.483)	(4.318)	(4.077)	(4.617)	(1.623)	(1.875)	(1.770)	(1.891)
Risk premium		-5.796	-2.446	-9.562		1.707	-3.090	1.345
		(8.678)	(8.791)	(8.772)		(3.234)	(4.552)	(3.226)
Inflation diff.		7.770*	10.078**	8.875**		-7.259***	-7.383***	-7.799***
		(4.285)	(4.456)	(4.487)		(1.866)	(1.608)	(1.543)
Lagged dep. var.		0.111				0.107		
		(0.166)				(0.153)		
$EXS_{t-1}(\beta_1)$			40.044				-10.494	
			(31.565)				(9.655)	
$EXS_{t-1}(\beta_2)$			21.386				-38.635	
			(23.361)				(23.621)	
Changes in foreign				18.599				-0.296
relations				(23.155)				(13.437)
Lnepu				-0.138				-0.050
				(0.125)				(0.062)
Trade growth	-15.871	-11.798	-9.523	-9.192	32.010**	34.099**	22.522*	34.809***
	(42.080)	(38.299)	(41.944)	(40.848)	(15.620)	(13.554)	(12.555)	(13.399)
Trend	-0.564**	-0.507	-0.510*	-0.677**	-0.114	-0.184	-0.246**	-0.219*
	(0.254)	(0.365)	(0.308)	(0.318)	(0.097)	(0.117)	(0.114)	(0.113)
Constant	40.643*	26.118	29.542	38.161	31.581***	37.433***	42.852***	42.936***
	(23.385)	(24.953)	(21.887)	(24.297)	(7.961)	(8.573)	(7.505)	(8.098)
Observations	72	72	72	72	72	72	72	72
R-squared	0.191	0.238	0.255	0.239	0.130	0.269	0.362	0.265
Break month	2013m9	2013m9	2013m9	2013m9	2014m2	2014m2	2014m5	2014m2

Note: Please see the detailed explanation for key variables in Table 3. In addition, changes in foreign relation measures China's overall foreign relation with the rest of the world. Lnepu is the economic policy uncertainty. Robust errors are in parentheses. Superscripts *, ** and *** represent statistical significance at the ten, five and one percent levels, respectively.

Table 5: Robustness checks: Predetermined break dates

	Import gap			Export gap		
Pre-specified break	2013m10	2013m11	2013m12	2013m10	2013m11	2013m12
	(1)	(2)	(3)	(4)	(5)	(6)
$EXS_t(\beta_1)$	-45.964**	-38.950*	-38.382*	-15.505*	-16.507*	-16.846*
	(17.493)	(20.389)	(20.745)	(8.467)	(8.515)	(8.608)
$EXS_t(\beta_2)$	45.018**	41.557*	40.999*	18.585*	19.937*	20.117*
	(20.750)	(20.985)	(20.970)	(10.955)	(10.845)	(10.766)
CID_t	1.121	0.354	0.253	2.121	1.988	1.966
	(5.284)	(5.494)	(5.515)	(1.989)	(1.940)	(1.930)
Risk premium	-7.214	-7.497	-7.577	2.599	2.539	2.509
	(8.618)	(8.595)	(8.596)	(3.033)	(3.067)	(3.062)
Inflation difference	9.090*	9.224*	9.291*	-7.591***	-7.808***	-7.822***
	(4.924)	(5.117)	(5.122)	(1.776)	(1.812)	(1.811)
Trade growth	-14.428	-16.405	-16.558	29.292**	28.673**	28.621**
	(34.053)	(34.188)	(34.188)	(13.716)	(13.456)	(13.442)
Trend	-0.597*	-0.613*	-0.615*	-0.125	-0.140	-0.143
	(0.330)	(0.339)	(0.340)	(0.120)	(0.121)	(0.121)
Constant	31.115	33.944	34.274	37.878***	38.857***	38.997***
	(24.154)	(25.164)	(25.256)	(9.031)	(8.884)	(8.845)
Observations	72	72	72	72	72	72
R-squared	0.227	0.209	0.207	0.223	0.232	0.234

Note: This table shows the robustness checks for the benchmark threshold regressions by manually choosing predetermined break dates. The Newey-West robust standard error in parentheses is adopted to control for heteroskedasticity and autocorrelation in error terms. Superscripts *, ** and *** represent statistical significance at the ten, five and one percent levels, respectively.

Table 6: Results for China's RMB receipts and FX payments

	Dependent variable					
	RMB net receipts			FX net payments		
	(1)	(2)	(3)	(4)	(5)	(6)
EXS_t	105.652**	124.235***	102.036**	62.893***	56.334***	56.424***
	(45.792)	(38.864)	(39.840)	(13.780)	(15.879)	(16.077)
CID_t	13.672	18.669*	16.355	-0.926	0.511	0.422
	(11.831)	(10.202)	(10.335)	(2.477)	(2.247)	(2.438)
Risk premium		-4.918	-7.505		-6.833	-6.719
		(22.372)	(21.596)		(4.549)	(4.702)
Inflation diff.		-29.824**	-26.558*		-2.203	-2.198
		(13.271)	(12.942)		(2.600)	(2.611)
Trade growth			-64.224			-2.387
			(42.129)			(10.010)
Trend	1.966	0.216	0.026	0.086	-0.099	-0.099
	(2.612)	(2.467)	(2.219)	(0.138)	(0.186)	(0.187)
Constant	-109.631	-75.054*	-61.926	-26.782**	-23.734*	-23.413*
	(74.682)	(39.249)	(35.760)	(12.261)	(12.514)	(13.252)
Observations	23	23	23	72	72	72
R-squared	0.332	0.575	0.622	0.600	0.620	0.621

Note: The quarterly net RMB receipt data is obtained from CEIC with the sample period from 2011Q1 to 2016Q4. The monthly foreign exchange net payments under the trade account is obtained from the State Administration of Foreign Exchange (SAFE) of China. The sample period is from 2011m1 to 2016m12. The Newey-West robust standard error in parentheses is adopted to control for heteroskedasticity and autocorrelation in error terms. Superscripts *, ** and *** represent statistical significance at the ten, five and one percent levels, respectively.

Table 7: HS groups based on Benford's law test

HS Group	HS 2 Section	χ^2	P-value	N	Section Description
	90-92	19.35	0.01	22396	Optical, Photographic, Cinematographic, Measuring, Checking, Precision, Medical or Surgical Instruments and Apparatus; Clocks and Watches; Musical Instruments; Parts and Accessories Thereof
	41-43	19.34	0.01	14788	Raw Hides and Skins, Leather, Furskins and Articles Thereof; Saddlery and Harness; Travel Goods, Handbags and Similar Containers; Articles of Animal Gut (Other Than Silk-Worm Gut)
BLTR	71	18.52	0.02	3469	Natural or Cultured Pearls, Precious or Semi-Precious Stones, Precious Metals, Metals Clad with Precious Metal and Articles Thereof; Imitation Jewellery; Coin
	68-70	18.15	0.02	18038	Articles of Stone, Plaster, Cement, Asbestos, Mica or Similar Materials; Ceramic Products; Glass and Glassware
	28-38	16.46	0.04	14980	Products of the Chemical or Allied Industries
	64-67	15.08	0.06	15363	Footwear, Headgear, Umbrellas, Sun Umbrellas, Walking-Sticks, Seat-Sticks, Whips, Riding-Crops and Parts Thereof; Prepared Feathers and Articles Made Therewith; Artificial Flowers; Articles of Human Hair
	39-40	14.92	0.06	47365	Plastics and Articles Thereof; Rubber and Articles Thereof
	84-85	13.82	0.09	116534	Machinery and Mechanical Appliances; Electrical Equipment; Parts Thereof; Sound Recorders and Reproducers, Television Image and Sound Recorders and Reproducers, and Parts and Accessories of Such Articles
	97-99	13.60	0.09	743	Works of Art, Collectors' Pieces and Antiques; Article of Special Trade and Goods Unclassified
Non-BLTR:	15	11.44	0.18	130	Animal or Vegetable Fats and Oils and Their Cleavage Products; Prepared Edible Fats;Animal or Vegetable Waxes
	1-5	10.03	0.26	1328	Live Animals; Animal Products
Primary goods	6-14	9.30	0.32	3610	Vegetable Products
	25-27	8.87	0.35	1534	Mineral Products
	16-24	6.28	0.62	3670	Prepared Foodstuffs; Beverages, Spirits and Vinegar; Tobacco and Manufactured Tobacco Substitutes
Non-BLTR:	72-83	12.09	0.15	50886	Base Metals and Articles of Base Metal
	94-96	11.95	0.15	36579	Miscellaneous Manufactured Articles
	47-49	8.16	0.42	26645	Pulp of Wood or of Other Fibrous Cellulosic Material; Recovered (Waste and Scrap) Paper or Paperboard; Paper and Paperboard and Articles Thereof
Others	86-89	7.76	0.46	4731	Vehicles, Aircraft, Vessels and Associated Transport Equipment
	93	6.33	0.61	27	Arms and Ammunition; Parts and Accessories Thereof
	50-63	4.42	0.82	116591	Textiles and Textile Articles
	44-46	3.75	0.88	2838	Wood and Articles of Wood; Wood Charcoal; Cork and Articles of Cork; Manufactures of Straw, of Esparto or of Other Plaiting Materials; Basketware and Wickerwork

Table 8: Results for the BLTR and Non-BLTR groups

	BLTR group		Non-BLTR group			
			Primary goods		Other goods	
	Import gap	Export gap	Import gap	Export gap	Import gap	Export gap
	(1)	(2)	(3)	(4)	(5)	(6)
$EXS_t(\beta_1)$	-58.149***	-14.668**	-41.581	-0.819	-8.484	-22.717***
	(17.503)	(6.937)	(31.243)	(7.618)	(13.797)	(6.050)
$EXS_t(\beta_2)$	52.417**	28.444***	3.896	10.603	2.909	-6.609
	(20.758)	(9.464)	(14.106)	(11.285)	(13.112)	(12.892)
CID_t	-0.018	0.005	-0.033	0.020	0.013	0.013
	(0.055)	(0.019)	(0.066)	(0.025)	(0.030)	(0.014)
Risk premium	-4.947	4.536	2.839	-4.047	-7.673	-6.797**
	(9.903)	(3.394)	(8.103)	(4.002)	(6.346)	(3.013)
Inflation diff.	0.187***	-0.081***	0.013	-0.062***	-0.240***	0.005
	(0.052)	(0.016)	(0.071)	(0.020)	(0.031)	(0.018)
Trade growth	-0.158	0.295**	0.092	0.213**	0.162	0.131*
	(0.439)	(0.134)	(0.335)	(0.089)	(0.242)	(0.078)
Trend	-0.004	-0.002	-0.001	0.000	0.002	0.002
	(0.004)	(0.001)	(0.004)	(0.001)	(0.002)	(0.001)
Constant	0.082	0.467***	0.163	0.375***	1.601***	0.129*
	(0.279)	(0.082)	(0.337)	(0.100)	(0.147)	(0.074)
Observations	72	72	72	72	72	72
R-squared	0.279	0.319	0.0375	0.202	0.546	0.335
Break month	2013m9	2014m2	2013m7	2013m12	2014m1	2014m2

Note: Robust errors are in parentheses. Superscripts *, ** and *** represent statistical significance at the ten, five and one percent levels, respectively.

Table 9: Two placebo tests

A. Random splitting all HS sections				
	BLTR group		Non-BLTR group	
	Import gap	Export gap	Import gap	Export gap
	(1)	(2)	(3)	(4)
$EXS_t(\beta_1)$	-32.7	-16.737***	-33.025	-16.657***
	(25.483)	(4.658)	(24.58)	(4.239)
$EXS_t(\beta_2)$	32.164	21.898*	31.395	21.948*
	(41.553)	(11.711)	(41.558)	(11.598)

B. Random splitting excluding primary goods				
	BLTR group		Non-BLTR group	
	Import gap	Export gap	Import gap	Export gap
	(1)	(2)	(3)	(4)
$EXS_t(\beta_1)$	-30.774	-18.078***	-30.391	-18.148***
	(26.383)	(4.83)	(24.313)	(4.582)
$EXS_t(\beta_2)$	31.620	22.587*	34.878	22.324*
	(41.119)	(12.201)	(38.507)	(12.392)

Note: The table shows the results from the threshold regressions for the placebo tests. Other control variables are included but not reported. Robust errors are in parentheses. Superscripts *, ** and *** represent statistical significance at the ten, five and one percent levels, respectively.

Table 10: Results for China-U.S. trade

	All goods		BLTR group		Non-BLTR group			
					Primary goods		Other goods	
	Import gap	Export gap	Import gap	Export gap	Import gap	Export gap	Import gap	Export gap
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$EXS_t(\beta_1)$	-31.385***	-1.571	-13.576**	0.817	-121.800***	18.726*	-6.817	-7.232
	(7.231)	(3.807)	(6.789)	(3.251)	(16.287)	(10.864)	(7.202)	(5.891)
$EXS_t(\beta_2)$	13.809	5.924	24.101***	3.586	-19.946	7.481	13.876*	9.025
	(9.521)	(3.935)	(6.326)	(3.124)	(30.992)	(4.908)	(7.130)	(6.108)
CID_t	2.511	1.505	0.015	0.012	0.059	0.001	0.030*	0.021
	(1.810)	(1.622)	(0.016)	(0.013)	(0.053)	(0.022)	(0.018)	(0.024)
Risk premium	-3.544	-1.365	4.944*	-0.966	-21.101*	1.501	0.334	-2.623
	(4.119)	(2.681)	(2.913)	(2.224)	(12.426)	(3.611)	(3.833)	(3.864)
Inflation diff.	-3.409	-1.756	-0.061***	-0.016	0.013	-0.028	-0.040**	-0.018
	(2.539)	(1.236)	(0.017)	(0.010)	(0.073)	(0.019)	(0.020)	(0.020)
Trade growth	51.325***	42.075***	0.348***	0.310***	1.000***	0.711***	0.398***	0.676***
	(10.714)	(7.865)	(0.098)	(0.065)	(0.253)	(0.133)	(0.138)	(0.109)
Trend	-0.119	0.046	0.001	0.000	-0.006	0.001	0.002	0.001
	(0.129)	(0.064)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)
Constant	14.531*	-19.003***	0.386***	-0.204***	-0.001	0.144	-0.181*	-0.183*
	(8.617)	(6.875)	(0.071)	(0.054)	(0.239)	(0.095)	(0.096)	(0.106)
Observations	72	72	72	72	72	72	72	72
R-squared	0.293	0.396	0.365	0.339	0.229	0.467	0.275	0.430
Break month	2014m2	2014m1	2014m2	2014m1	2013m7	2014m3	2014m2	2014m1

Note: The table shows the results from the threshold regressions for fake trade between mainland China and the U.S. Robust errors are in parentheses. Superscripts *, ** and *** represent statistical significance at the ten, five and one percent levels, respectively.

Appendix

A.1 Proof

In this section, we show the proof for equation (8). Given that $\lambda \sim Beta(\alpha, \beta)$ and plugging in the optimal solution of δ^{im*}, we get

$$\begin{aligned}
\int_0^1 \delta^{im*} dF(\lambda) &= \int_0^1 \frac{(1-\lambda)EXS}{\eta\lambda} dF(\lambda) \\
&= \frac{EXS}{\eta}\left[\int_0^1 \frac{1}{\lambda} dF(\lambda) - 1\right] \\
&= \frac{EXS}{\eta}(\frac{\alpha+\beta-1}{\alpha-1} - 1) \\
&= \frac{EXS}{\eta}(\frac{\beta}{\alpha-1}),
\end{aligned}$$

where

$$\begin{aligned}
\int_0^1 \frac{1}{\lambda} dF(\lambda) &= \int_0^1 \frac{1}{\lambda} \frac{\lambda^{\alpha-1}(1-\lambda)^{\beta-1}}{B(\alpha,\beta)} d\lambda \\
&= \int_0^1 \frac{\lambda^{\alpha-2}(1-\lambda)^{\beta-1}}{B(\alpha-1,\beta)} d\lambda \frac{B(\alpha-1,\beta)}{B(\alpha,\beta)} \\
&= \frac{B(\alpha-1,\beta)}{B(\alpha,\beta)} = \frac{\frac{\Gamma(\alpha-1)\Gamma(\beta)}{\Gamma(\alpha-1+\beta)}}{\frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}} \\
&= \frac{\Gamma(\alpha-1)}{\Gamma(\alpha)} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha+\beta-1)} \\
&= \frac{\alpha+\beta-1}{\alpha-1}.
\end{aligned}$$

A.2 Data

This section presents the data sources we refer to in this study. We start by focusing on the data used in the benchmark regressions. To calculate the trade discrepancies between Hong Kong and mainland China, we need the direct trade data reported by both sides.

We obtain the trade data reported by mainland China (aggregate-level and section-level) from the CEIC database and the counterpart data reported by Hong Kong from the Comtrade database, at monthly frequency. The trade discrepancies for imports and exports (Y_t^{IMP} and Y_t^{EXP}) are calculated following their definitions in equations (1) and (2).

The daily exchange rate data for both onshore CNY and offshore CNH RMB markets are obtained from the Bloomberg database. Both variables are converted to their monthly means to calculate monthly EXS_t. Our results are similar if we first calculate the daily exchange rate spread and then use its monthly mean in our analysis. Following the literature, the covered interest differential (CID_t) is calculated from the nominal interest rate differential minus the non-deliverable forward premium (i.e. $CID_t = (r_t - r_t*)/(1 + r_t*) - (F_t - S_t)/S_t)$. Where r_t is the monthly Chinese interbank rate from the CEIC database, r_t* is the monthly USD LIBOR rate from the FRED database, F_t is the one-month RMB non-deliverable forward rate (RMB/USD) from the CEIC database, and S_t is the spot exchange rate (RMB/USD) from Bloomberg.

We construct the risk premium (RP_t) following Hamilton and Wu (2014). To apply their methodology, we collect the RMB forward rates for three durations (i.e., 1-month, 2-month, and 3-month) from the Bloomberg database, all at daily frequency.

The trade growth rate of mainland China is obtained from the CEIC database, and the CPI inflation rates for both China and the U.S. are from the FRED database. Finally, we obtain the data of RMB net receipts by mainland China from the CEIC database, and the data of China's foreign exchange net payments from the State Administration of Foreign Exchange of China.