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

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Jan 9, 2021

Abstract

Using a unique institutional setting of dual exchange rates of Chinese currency, this paper provides novel evidence that firms manipulate trade data to evade capital controls. We develop a model showing that the trade data over-reporting is positively (negatively) correlated with the exchange rate spread when the spread is positive (negative), and such correlations are more pronounced for products with low risks of being caught. Empirical results from threshold regressions using time series data and Benford's law using firm-product trade data between mainland China and Hong Kong support the theoretical predictions of dual exchange-rate arbitrage camouflaged under the trade account.

Keywords: Capital controls, dual exchange rates, missing trade, Benford's law
JEL codes: F31, F38, F14, G14, G15, G28

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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 (or fake trade) 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 fake trade 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. For instance, 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.[4] 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.[5] Between 2011 and 2016, the RMB offshore market was 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. Over this period, large and persistent spreads frequently existed between onshore and offshore RMB-USD exchange rates, which incentivized arbitrage activities through fake trade.[6] 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 RMB's dual exchange rates 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 discrepancy between mainland China and Hong Kong is positively (negatively) correlated with the spread between offshore and onshore RMB/USD exchange rates 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 above model predictions by using both the aggregate time series data of

[4]China's capital controls include both a "wall" case in the terminology of Klein (2012) and countercyclical policy adjustments as documented in Wang and Wu (2018). See Section 2.1 for more details.

[5]Besides the offshore RMB market, geographical proximity and low trade costs between mainland China and Hong Kong also facilitate capital control evasions through fake trade between these two places.

[6]The spread became much smaller after 2016 because the People's Bank of China intensified its interventions to narrow the exchange rate spread between the onshore and offshore RMB markets after the RMB was included in the SDR basket by IMF in late 2016. See Section 2.2 for more discussions.

trade and exchange rates and the disaggregated firm-product level customs trade data between mainland China and Hong Kong. Following the literature on "missing trade," the trade data gap or discrepancy is measured by 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).[7] We apply threshold regressions (Hansen, 2000; Yu and Phillips, 2018) to the aggregate monthly trade data gap between mainland China and Hong Kong and find that the RMB-USD exchange rate spread is an important driving force for the fluctuations of the trade data gap. 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 data 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,

[7]We use the data of direct trade between mainland China and Hong Kong. See Section 2.3 for more details. 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). See Feenstra et al. (1999) and Marquez and Workman (2001) for studies on global trade data discrepancies.

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 useful in detecting fraud in large-scale trade data.

As firms have stronger incentives to manipulate trade data for the products that customs officials are less likely to catch, the products that fail the BLT are expected to show stronger evidence of fake trade for foreign exchange arbitrage than those pass the test as predicted by our model, if foreign exchange arbitrage is an important reason for the fake trade. Based on the 2015 firm-HS 8-digit level disaggregated trade data between mainland China 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 trade data manipulation.[8] We find that the exchange rate spread plays an important role in driving monthly fluctuations of trade data gaps for the group of products that do not conform to Benford's law. The correlation between the exchange rate spread and trade data gaps for this group of products displays the same pattern as predicted by our theoretical model. Thus, it suggests that the "fraudulent" products detected by the BLT may be used as vehicles by arbitrageurs to evade capital controls for foreign exchange arbitrage.[9] By contrast, we find no significant relationship between the exchange rate spread and trade data gaps for the group of products that fit Benford's law well. The documented difference between these two groups of products is consistent with our model prediction that the relationship between the exchange rate spread and trade data gaps is more pronounced for the products that are less likely to be detected as fraudulent.

Most of the goods that do not conform to Benford's law are found to be intermediate inputs or differentiated goods such as optical and photographic instruments, jewelery

[8]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.

[9]The fake trade identified from the BLT may not be related to the exchange rate spread if it is mainly driven by tax and tariff evasion.

and precious metal or stones, electrical equipment, and works of art.[10] By contrast, the goods that pass the BLT 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.

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, different dates for the structural break and an alternative estimation method for the structural break (Andrews, 1993). In addition, we also conduct two placebo tests 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.[11] Moreover, we also identify the products that are prone to data manipulation by using the BLT method. Our findings support the argument that capital controls may induce capital flows camou-

[10] However, not all differentiated goods classified in Rauch (1999) are suitable for fake trade as we will discuss in Prediction 3 of our model.

[11] In a recent paper, Liu et al. (2020) examine capital control evasion through China's reimports for currency carry trade. The purpose of capital control evasion in their paper is different from ours and they do not investigate trade data manipulation, which is the focus of this paper.

flaged under the trade account, which reduces the effectiveness of the policy and brings other economic losses.

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 plays an important role in the large gap of mainland 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 data 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 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 the 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. 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.

China imposes long-standing controls that cover a broad range of assets ("walls" in the terminology of Klein (2012)) to manage the value of RMB against the U.S. dollar. In addition, China's capital controls policy also changes with the external economic environment the country faces. 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, 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. Wang and Wu (2018) find that China adjusts its capital controls policy counter-cyclically in response to U.S. monetary policy shocks.

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.[12] 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.

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.[13] 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 internationalization, China set up an offshore RMB market in Hong Kong in 2010.[14] 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

[12] Although the Chinn-Ito index includes both capital and current account restrictions, China's recent ranking is mainly determined by its capital account restrictions as the country liberalized current account transactions after 1996. Please see the detailed construction method in Chinn and Ito (2006). The results are similar in the capital control indexes that include only capital account restrictions such as the Quinn index and the index of Fernández et al. (2016).

[13] 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.

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

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 USD 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.[15] Figure 1 presents the spreads calculated from the monthly average onshore and offshore exchange rates from January 2011 to December 2016.[16] As we can see, the spread can be roughly divided into two subsamples. Before early 2014, the spread was largely negative, indicating the RMB was mostly undervalued in mainland China.[17] 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.[18]

The exchange rate spread shrunk substantially after 2016 because the People's Bank of China (PBC) intensified its intervention on Hong Kong's market and reduced the supply of the RMB, when the RMB faced the pressure of depreciation on offshore market. Such policy changes are partially due to the inclusion of the RMB in the SDR in December 2016 as the onshore-offshore exchange rate spread was a key concern the IMF expressed in its SDR basket report (e.g., see Gagnon (2016) and Ba (2019)). It is likely that the capital

[15]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.

[16]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.

[17]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.

[18]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.

control evasion through fake trade continues to exist after 2016. However, it just becomes difficult to empirically detect such activities when the offshore market exchange rate is less market-driven under PBC's intervention.

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

We only consider direct trade between mainland China and Hong Kong in our data. For the data from mainland China, the reported imports and exports only include those that specify Hong Kong as destination (obtained from CEIC database). Hong Kong reports both total trade data and re-export trade data with mainland China (obtained from Comtrade database) and direct trade is defined as the difference between these two variables. Note that not all goods are produced and consumed in Hong Kong, even though they are labelled as direct trade. For example, firms in Hong Kong can import goods from mainland China by indicating Hong Kong as destination, and then export the same goods to other countries after providing some value-added service in Hong Kong. This practice is very common for companies that specialize in R&D and other high value-added service, but outsource their production to mainland China.[19]

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:

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

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

where EXP_t^{CN} and IMP_t^{CN} are mainland China's reported exports to and imports from Hong Kong, respectively.[20] 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 iceberg trade cost between importers and exporters. However, the value of CIF does not affect our empirical results.[21] 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.

[19] According to the General Rule of origin under CEPA, the origin criterion of Hong Kong is that the regional value content of a product is greater than or equal to 30% when calculated by using the Build-up method; or greater than or equal to 40% when calculated by using the Build-down method.

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

[21] CIF is set to 10% by following the literature and it may also be time varying in some countries (e.g., see Cheung et al. (2020) for a study on Germany). The actual trade costs between Hong Kong and mainland China may be lower than 10% and our results are unlikely to be qualitatively affected by the time variations of the trade cost as the trade cost and the exchange rate spread are unlikely to be highly correlated.

As shown in Figure 2, substantial trade data 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 data 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 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 data 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 model of dual exchange rate arbitrage.

3 A Simple Model of Dual Exchange Rate Arbitrage

In this section we develop a model of dual exchange rate arbitrage in which firms face heterogeneous risks of being caught when conducting fake trade to evade capital controls. From this model, we derive three testable predictions for our empirical analysis.

3.1 Model setup

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 USD) 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 USD). 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.[22]

To capture the above activities, we develop a static model of dual exchange rate arbitrage in which firms face heterogeneous risks of being caught when they conduct fake trade for capital control evasion.[23] We assume that there is a continuum of firms with a mass of M and each firm produces a differentiated product variety in both Hong Kong and mainland China. Consumer preferences over the set of product varieties Ω in two economies are represented by a standard CES utility function with the elasticity of substitution $\sigma > 1$:

$$U = \left(\int_{z \in \Omega} q(z)^{\frac{\sigma-1}{\sigma}} dz \right)^{\frac{\sigma}{\sigma-1}}, \tag{3}$$

where $q(z)$ is the demand of product variety z. We use z as the index for both product varieties and firms as each product variety is produced by a single representative firm. The sale of each variety is $r(z) = Ap(z)^{1-\sigma}$ if there is no trade data manipulation, where $p(z)$ denotes the price. A is the demand shifter and defined as $\frac{E}{P^{1-\sigma}}$, where E is the total expenditure, and P is the standard CES price index. For simplicity we assume no trade

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

[23]Capital controls are not state-contingent in our model. However, we can consider our model as a static condition in which capital controls are imposed either as long-run restrictions or counter-cyclical policies.

cost between two economies in the model.[24] We further assume that two economies are symmetric, i.e., their total expenditures E and price indices are the same.

Firms have the same productivity in our model so that they charge the same prices and receive the same revenues $r(z) = r$ if there is no trade data manipulation.[25] However, when firms conduct fake trade for capital control evasion, they face heterogeneous probability $\lambda \in [0, 1]$ of being caught, where λ follows a parametric distribution $F(\lambda)$ on the interval $[0, 1]$. Since firms and products are interchangeable in our model, it is the same to assume that products face heterogenous probability of being caught for fake trade. Next, we consider firm's optimal arbitrage strategy when the dual exchange rate spreads are non-zero.

3.2 Optimal arbitrage

We assume that the exchange rate spread is exogenous for individual firms, who manipulate trade data for capital evasion, as individual firms are unlikely to affect the RMB exchange rate.[26] We first consider the case when the exchange rate spread is positive. In this case, 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 firm z over-reports its imports from Hong Kong, we denote the true value reported by Hong Kong as $r_{hk}^{ex}(z)$ in the U.S. dollar, while in the mainland firm z reports its imported 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,

[24]This assumption makes it easy to compare reported imports (or exports) by Chinese firms and the corresponding ones by Hong Kong firms in the model. In the empirical analysis, as shown in Equations (1) and (2) we adjust the trade data gap by taking account into the trade cost between mainland China and Hong Kong.

[25]Our model is based on the standard Krugman trade model where firms are homogeneous (Krugman, 1979). However, it is easy to extend to have firms with heterogeneous productivity (Melitz, 2003). In Krugman model, the price of each firm is the product of constant markup and marginal cost, and thus the revenue for each firm is the same. We did not show explicitly the production of firms in order to focus on firms' arbitrage behavior.

[26]Due to China's strict capital controls, the size of foreign exchange arbitrage seems not large enough to eliminate the exchange rate spread, given that the spread is quite large and persistent over our sample period as shown in Figure 1.

the USD outflows from mainland China to Hong Kong through import over-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 firm z 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 firm z in mainland China as $x_{cn}^{ex}(z)$, which inflates the true value by a factor of $1 + \delta^{ex}$ with $\delta^{ex} = \frac{x_{cn}^{ex}(z) - x_{hk}^{im}(z)}{x_{hk}^{im}(z)} > 0$.[27] 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 arbitrage:[28]

$$\delta^{im} r_{hk}^{ex}(z) S^{CNH} = \delta^{ex} x_{hk}^{im}(z). \tag{4}$$

Clearly, the over-reporting in exports is tightly connected with the over-reporting in imports. Under the assumption of symmetric sales, we can further simplify this equation and obtain $\delta^{im} = \delta^{ex}$. Therefore, in the following discussions, we can 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. Our results hold qualitatively when we relax the assumption of symmetric sales.[29]

The RMB-denominated revenue generated from the above dual exchange rate arbitrage is given by

$$\delta^{im} r_{hk}^{ex}(z)(S^{CNH}/S^{CNY} - 1) = \delta^{im} r_{hk}^{ex}(z) EXS, \tag{5}$$

where EXS is the exchange rate spread and it is positive in the current scenario, i.e., $EXS > 0$.[30] Following Yang (2008) and Demir and Javorcik (2020), we also assume that faking trade is subject to a cost that is proportional to the true trade value and quadratic

[27] Note that $x(z)$ is denominated in RMB, while $r(z)$ is denominated in USD.

[28] Here we assume that arbitragers transfer all their funding back to the origin place.

[29] Please see the online appendix for details.

[30] Note here we slightly abuse the notation of EXS compared with the empirical analysis, in which the exchange rate spread is defined as the 100*log difference between the onshore and offshore exchange rates of RMB.

in the extent of over-reporting. The latter assumption captures the fact that it is more difficult to hide evidence of trade data over-reporting of larger scales. Thus, the cost of faking trade for firm z is given by $\frac{\kappa}{2}\delta^2 r(z)$, where $\kappa > 0$ measures the cost sensitivity to over-reporting.

With probability λ, firms in China are subject to a more careful inspection at the border, which reveals the true value of trade. In this case, firm z pays a penalty for the over-reporting amount, denoted by $\eta\delta r(z)$, where $\eta > 0$ denotes the severity of punishment for fake trade. For a given positive exchange rate spread, the risk-neutral firm z chooses δ^{im} to maximize its expected profits from the dual exchange arbitrage:

$$\max_{\delta^{im}} \pi = (1-\lambda)\delta^{im} r_{hk}^{ex}(z) EXS - \lambda\eta\delta^{im} r_{hk}^{ex}(z) - \frac{\kappa}{2}(\delta^{im})^2 r_{hk}^{ex}(z), \tag{6}$$

which yields the optimal over-reporting in imports:

$$\delta^{im*} = \begin{cases} \frac{(1-\lambda)EXS-\lambda\eta}{\kappa} & \text{if } \lambda \leq \frac{EXS}{EXS+\eta} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

Thus, given a positive exchange rate spread, only firms with the probability of being caught below a threshold ($\mu \equiv \frac{EXS}{EXS+\eta}$) will engage in fake trade. For firms who engage in fake trade, their optimal over-reporting δ^{im*} increases with the positive spread (EXS), but decreases with the risk of being caught (λ), punishment level (η), and cost sensitivity of faking trade (κ). As the threshold μ increases with the spread but decreases in the punishment level, a higher spread will not only increase the over-reporting for incumbent arbitragers, but also induce more firms to engage fake trade as their profits of arbitrage turn to positive.

We assume that λ follows a parametric distribution $F(\lambda)$ on the interval $[0, 1]$. The total imports of mainland China from Hong Kong with fake trade is given by:

$$R_{cn}^{im} = M \int_0^1 (1 + \delta^{im*}) r_{hk}^{ex}(z) dF(\lambda). \tag{8}$$

As the true value of $r_{hk}^{ex}(z)$ is the same for all varieties, i.e., $r_{hk}^{ex}(z) = r_{hk}^{ex}$, we have

$$R_{cn}^{im} = M r_{hk}^{ex} \int_0^1 (1 + \delta^{im*}) dF(\lambda) = R_{hk}^{ex} \left(1 + \int_0^1 \delta^{im*} dF(\lambda)\right), \tag{9}$$

where the true exports from Hong Kong to mainland China $R_{hk}^{ex} \equiv M r_{hk}^{ex}$. Thus, the over-reporting in aggregated imports is given by [31]

$$\begin{aligned} Y^{IMP} &\equiv \frac{R_{cn}^{im} - R_{hk}^{ex}}{R_{hk}^{ex}} = \int_0^1 \delta^{im*} dF(\lambda) \\ &= \int_0^{\mu} \frac{(1-\lambda)EXS - \lambda\eta}{\kappa} dF(\lambda) = \frac{(EXS + \eta)}{\kappa} \int_0^{\mu} F(\lambda) d\lambda \end{aligned} \tag{10}$$

As the threshold μ increases with the spread but decreases in the punishment level, it is easy to verify that $\frac{\partial Y^{IMP}}{\partial \kappa} < 0$, $\frac{\partial Y^{IMP}}{\partial \eta} < 0$, and $\frac{\partial Y^{IMP}}{\partial EXS} > 0$ from the second line of equation (10). Thus, the over-reporting in aggregated imports also increases with the positive spread, but decreases with the punishment level and cost sensitivity of faking trade. We will show shortly that the distribution $F(\lambda)$ capturing the risk of being caught also matters for fake trade.

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 exports also face the same distribution of risk of being caught. 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 (10).[32] Thus, the discussion in the previous paragraph also applies

[31] Please see the online 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}.

[32] For simplicity, the symmetric assumption on two economies implies the balanced bilateral trade between mainland China 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 imbalances.

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 over-reporting 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 back to the mainland by over-reporting exports settled in USD. For the proof we can simply use $-EXS$ to replace EXS in equation (7) and (10). 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.*

The intuition behind Predictions 1 and 2 is simply from the fact that the optimal level of trade over-reporting depends on the absolute value of foreign exchange spreads in the model: larger spreads between onshore and offshore exchange rates encourage more fake trade.

We assume in the above model that the risk of being caught in fake trade (λ) follows the same distribution ($F(\lambda)$) for all goods. An interesting prediction emerges if we relax this assumption. Suppose there are two groups of products (or two industries) in the same model setting as above except that their probability of being caught follows different distributions, $F_i(\lambda)$ for $i = 1, 2$. Without loss of generality, we also assume the first industry has a lower probability of being detected than the second one. For example, in reality it is relatively easier for Customs to detect fraud in transactions of homogenous goods, such as textile, than differentiated goods, such as jewelery, as homogenous goods usually have reference prices, while differentiated goods do not. More technically speaking, we assume that $F_2(\lambda)$ second-order stochastically dominates $F_1(\lambda)$. This implies that $E_2(\lambda) \geq E_1(\lambda)$, i.e., the expected chance of being caught is higher for firms in the second industry than the first one.[33] Clearly, given the same exchange rate spread, severity of punishment, and cost sensitivity of fake trade, the equation (10) implies that the over-reporting in imports and exports will be higher for the first industry than the second one, i.e., $Y_1^{imp} > Y_2^{imp}$ and $Y_1^{exp} > Y_2^{exp}$. As a result, we may be able to find evidence for Predictions 1 and 2 for the products that have low risk of being caught, but not for the products with high risk of being detected. This gives our third prediction:

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

In the empirical analysis, we will adopt threshold regressions to test the non-monotonic relationship between the exchange rate spread and trade data gaps as indicated in the first two predictions. Testing the third prediction is more challenging as the distribution $F(\lambda)$ is unobservable. In other words, it is difficult to know which products (or industries) have low probabilities of being detected. One may suspect that differentiated goods, if they are used in fake trade, are less likely to be caught than homogenous goods. However, not all differentiated goods are suitable for fake trade. For instance, for the differentiated goods that have a very low unit value, their trade volumes or prices have to be substantially inflated in fake trade to achieve a certain amount of arbitrage profits, which increases the chance of being caught by Customs officials.

To overcome this problem, we employ a data-driven method to identify products (or industries) that have lower probability of being detected in fake trade, by applying the BLT to detect possible trade data manipulations. The BLT has been widely used to detect fraud in accounting numbers and economic data (Nigrini, 2012; Berger and Hill, 2015;

[33] In the online appendix, we give a particular example of $F(\lambda) = Beta(\alpha, \beta)$ where $\alpha > 0$ and $\beta = 1$, which yields a close form solution and easy interpretation of the results. The expected probability of being caught for Beta distribution is $E(\lambda) = \frac{\alpha}{\alpha+1}$, which increases with α. As a result, we show that the over-reporting in aggregated imports decreases when the average risk of being caught increases (captured by an increase in α).

Michalski and Stoltz, 2013; Barabesi et al., 2018), and recently it has been adopted to detecting fraud in large-scale trade data (Cerioli et al., 2019; Demir and Javorcik, 2020). It is reasonable to believe that firms have stronger incentives to manipulate trade data for goods that have low risk of being caught.[34] As a result, the reported trade values of those products are less likely to conform to Benford's Law. Thus, We expect that the relationship between the exchange rate spread and trade data gaps is more prominent for the group of products that do not pass the BLT than the group whose data are consistent with Benford's law.

The above data-driven approach has two distinct advantages. First, it does not require prior information on which products have low probability of being detected. Instead, we use disaggregated Chinese customs data at the firm-product level to detect the products whose data are more likely to be manipulated in transactions.[35] Second, although the violation of Benford's law only indicates possible fraud in trade data without revealing the underlying driving forces for fraudulent trade, the comparison of the relationships between exchange rate spreads and trade data gaps of the two groups of products whether they violate Benford's law can help to verify whether the fraudulent trade is linked to dual exchange rate arbitrage.

4 Empirical Evidence from the Aggregate Trade Data

In this section, we adopt threshold regressions to test the first two theoretical predictions, which suggest a particular non-monotonic relationship between the RMB-USD exchange rate spread and trade data discrepancies between mainland China and Hong Kong. Threshold models have been developed to deal with potential shifts in economic

[34]We show this in our model of foreign exchange arbitrage and the same logic may also apply to the trade data manipulations for other reasons such as tax and tariff evasions.

[35]Although our model suggests that fake trade will be more prevalent if the government punishment level and the cost of fake trade (governed by parameters η and κ) are lower, those two parameters are unlikely to be product-specific. Thus, the violation of Benford's law for different groups of products is likely to reflect the products' likelihood of being caught by Customs officials.

relationships and become increasingly popular in a wide variety of economic applications.[36]

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 trade data discrepancies have opposite signs depending on the sign of the spread. The threshold 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, when the spread deviates only slightly from zero, our model predicts that only a few firms engage in fake trade for arbitrage. Therefore, the relationship between the spread and trade data gaps may be quite weak for small spreads, making it difficult to estimate the threshold value(s) precisely in the data. Second, it is clear from Figure 1 that the exchange rate spread 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 the exchange rate spread is persistently positive or negative. If we use the exchange rate spread as our threshold variable, the noises from short-lived nonzero exchange rate spreads in the data

[36] 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).

may make it difficult to detect our theoretical 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.

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.

4.1 Econometric specification

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

$$Y_t = \alpha + \beta_1 EXS_t * I(t <= T) + \beta_2 EXS_t * I(t > T) + X_t\theta + \epsilon_t, \tag{11}$$

where Y_t is the trade data 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 the trade data gap and the exchange rate spread are percentage points, thus the coefficients β_1 and β_2 are the elasticities of the trade data gap with respective to the exchange rate spread. 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 afterwards. Therefore, we expect that $\beta_1 < 0$ and $\beta_2 > 0$.

X_t contains other control variables capturing different forces that may drive the trade data gap. 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.[37]

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.[38] 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 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 (negative exchange rate spread), a mainland company can transfer the USD from Hong Kong to mainland 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 (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

[37] 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) 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.

[38] 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.

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 method of Hamilton and Wu (2014), and by definition, a negative risk premium indicates that the RMB is expected to depreciate.[39] 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. Table 2 provides summary statistics, and the online 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.

[39]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.

4.2 Baseline results

The benchmark results for both the threshold model (TR) and the model with structural change (SCR) in columns (1)-(2) and (4)-(5) of Table 3 strongly confirm Predictions 1 and 2 from our theoretical model. 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 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 change. 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.[40] Figure 4 shows the fitted trade data 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. dol-

[40]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 data gaps in our sample.

lars 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.

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 finds to affect trade and financial activities.[41] The EPU index is from Baker et al. (2016) and the data for foreign political relations is 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 with the pre-specified breaks. 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 import-

[41]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.

s 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 above predictions.[42] The coefficient estimate of the exchange rate spread in Table 6 is significantly positive for both the RMB net receipts and 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 irregularities in accounting and economic data. In particular, recent studies show that the method is useful in detecting trade data manipulation (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 data manipulations. Since firms usually manipulate trade data for the products that are less likely to be detected by the customs, our Prediction 3 suggests that the products that fail the BLT show stronger relations between the exchange rate spread

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

and trade data gaps as described in our Predictions 1 and 2 than the products that pass the BLT, if foreign exchange arbitrage is an important reason behind the detected trade data manipulation.

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. In particular, the exact distribution for the first digit is:

$$P(\text{First digit is } d) = log_{10}(1 + 1/d),\ \textit{for}\ d = 1, 2, .., 9.$$[43]

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.[44] 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

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

[44]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.

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).[45] Benford's law was initially used as a forensic auditing and accounting tool to detect anomalies in financial data.[46] Recently many economists have started to adopt the BLT to verify the authenticity 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.[47]

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

[45] 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.

[46] 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.

[47] 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.

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.[48] 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 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 and we apply the BLT to the trade data in each of these sections.[49] Significant deviations from

[48] 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.

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

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 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.[50]

Figure 5 gives an illustrative example for the BLT. The histograms in the figure present the observed probabilities of each digit and the dots present the expected probabilities following Benford's law for textiles (HS 2: 50-63, top panel) and jewelery products (HS 2: 71, bottom panel), respectively. It is evident 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 deviates from Benford's law. The corresponding Pearson's Chi-square statistics (and the associated p-values) for BLT are 4.42 (0.82) and 18.52 (0.02) for textiles and jewelery, respectively, indicating potential data manipulations for jewelery but not for 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.[51] 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

[50]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.

[51]As a robustness check, we also adopt the likelihood ratio test and the results are qualitatively the same.

(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 ratios such as textiles (HS 2: 50–63) and transportation vehicles (HS 2: 86–89) also pass the BLT, indicating small likelihood of trade data manipulation for those goods.[52] Similarly, Liu et al. (2020) find that products with hight value-to-weight ratios are more likely to be used in the reimports between mainland China and Hong Kong for currency carry trade.

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 the groups that pass the BLT are not, as our model suggests in Prediction 3. For each group, we aggregate monthly

[52]The sample size sometimes matters for Pearson's Chi-square test for Benford's law. Large samples could lead to over-rejection of the null hypothesis, while small samples would lead to biased inference. In our case, the small sample bias should 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 volume. We do not observe a significant correlation between the p-values and the (log) number of observations across the 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 may not be a serious concern in our results. We further alleviate the concern about the the effect of large sample size on our results in a robustness check. We randomly select 3000 observations for the 15 HS sections that have more than 3000 observations, and compute their p-values of the Pearson's Chi-square test. We bootstrap this experiment for 1000 times and rank the 15 HS sections according to the incidence of p-value below 10% and find that the ranking of these 15 HS sections is very close to that in Table 7, indicating the same grouping of BLT and Non-BLTR categories.

imports and exports, compute the corresponding import and export gaps, and conduct the baseline regression in Equation (11).

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).[53] Thus, our findings suggest that the BLTR group of goods is likely to be the vehicle of the fake trade for exchange rate arbitrage. Overall, the difference between the two groups of goods supports Prediction 3 that the relationship between the exchange rate spread and trade data gaps is more significant for the products that have low risk of being caught.

5.2 Placebo tests

To further 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 test 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 the key coefficient estimates of the exchange rate spread.[54] After repeating this simulation 1000 times, we compute the mean and standard deviation of the coefficient estimates. 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-

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

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

BLTR groups. The second test allows us to directly compare placebo test results of the BLTR group and the Non-BLTR group of other goods with the corresponding benchmark results in Table 8.

Table 9 presents the results of the two placebo tests. The coefficient estimates of the exchange rate spread for import and export gaps in the pseudo BLTR and Non-BLTR groups are 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 import gaps in the two groups. This finding is not surprising as the placebo exercise randomly allocates fraud transactions into two groups and thus both groups display some evidence for the time series relationship between the exchange rate spread and trade data gaps. More importantly, given the same independent variables, the coefficient 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 benchmark findings in Table 8, in which the coefficient estimates for the BLTR group are similar to the baseline results, while the coefficient estimates for the non-BLTR group are not. This suggests that our classification of goods into two groups based on the BLT is informative in detecting possible trade data manipulation that is associated with foreign exchange arbitrage. Finally, our results from the two placebo tests are similar, indicating that our results are not sensitive to the way of handling primary goods in the data.

5.3 Cross-country evidence

In a cross-country robustness check, we test our benchmark results for the trade data 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 those in our Hong Kong results, only one out of four estimates is statistically significant. Using the U.S. data, we also repeat the threshold regressions for the BLTR and Non-BLTR groups identified in our Hong Kong data and report the results 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 indicate no evidence of foreign exchange arbitrage like what we found in the trade data between Hong Kong and mainland China, although fake trade between the U.S. and China might be used for capital flight (e.g., through import over-reporting). 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 sheds 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, and also show that the traded products which violate Benford's law may be the vehicle arbitragers use in their fake trade for foreign exchange arbitrage scheme.

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.[55] Policymakers should keep in mind the unintended consequences when they design such policies. For instance, Wei and Zhang (2007) show that capital control measures will substantially increase the real trade costs and discourage international trade. In particular, it is crucial to understand the nature of capital control evasion activities and design mechanism to diminish their adverse effects. Our study provides empirical foundations for studies on the design of macroprudential policies under leakages and evasion such as Bengui and Bianchi (2018).

[55] See Rebucci and Ma (2020) for a survey on recent theoretical and empirical studies on capital controls.

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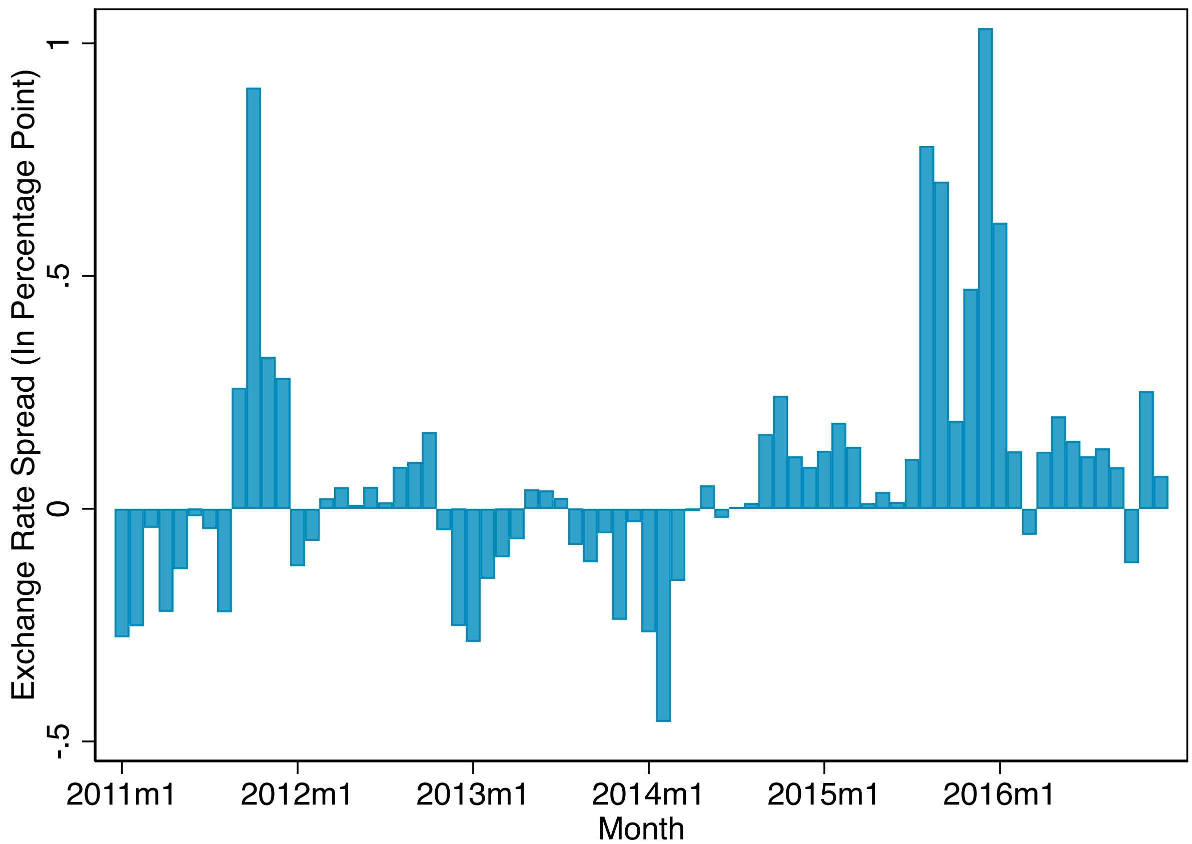
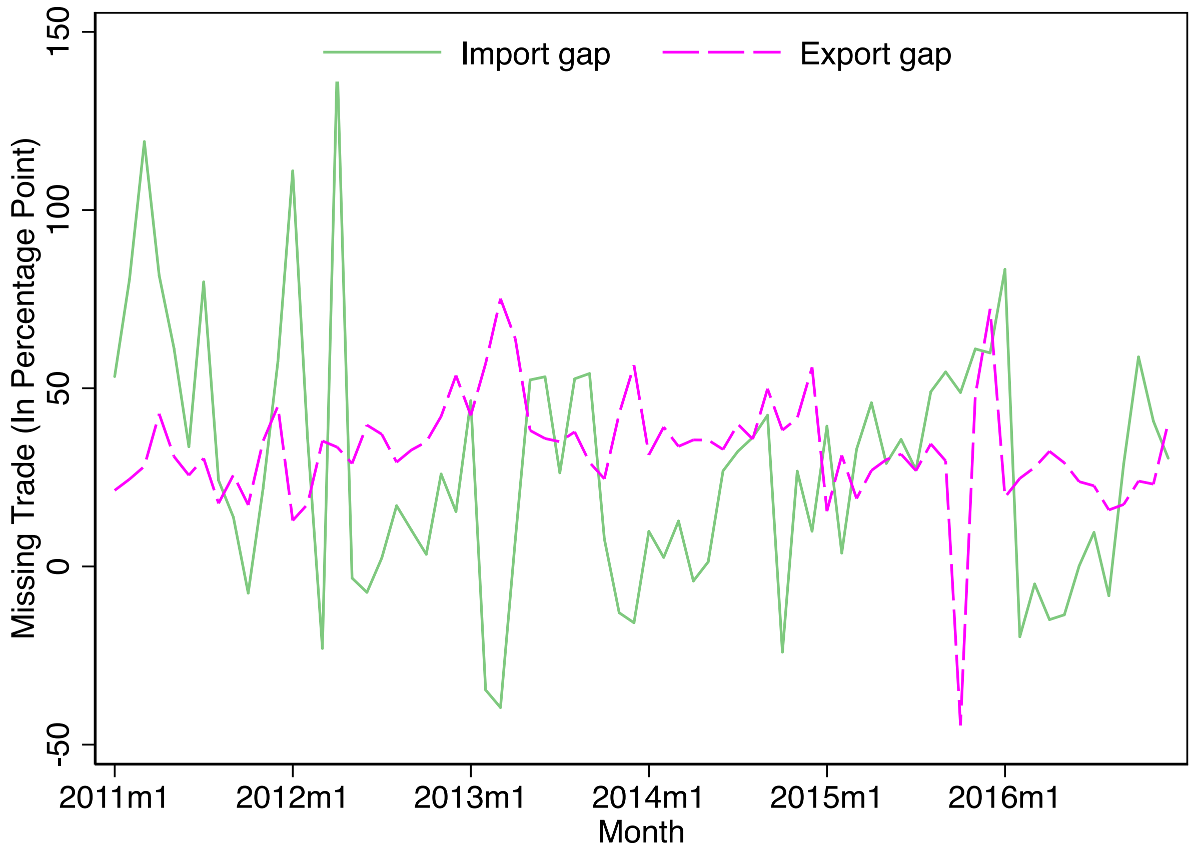


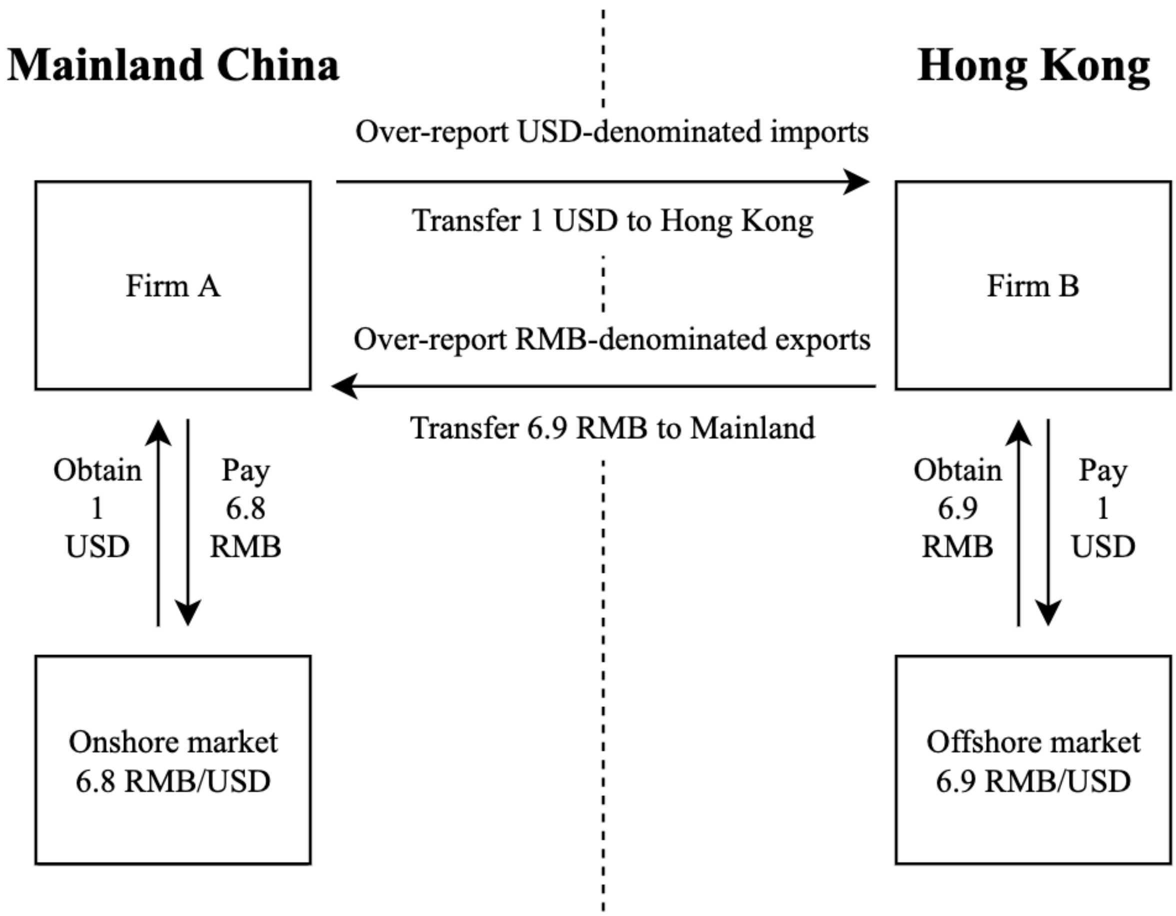
Note: This figure shows the offshore-onshore exchange rate spreads of the RMB-USD. A positive spread indicates that the RMB is more expensive (relative to the USD) in the onshore market than the offshore market.

Figure 1: Offshore-onshore RMB-USD exchange rate spread



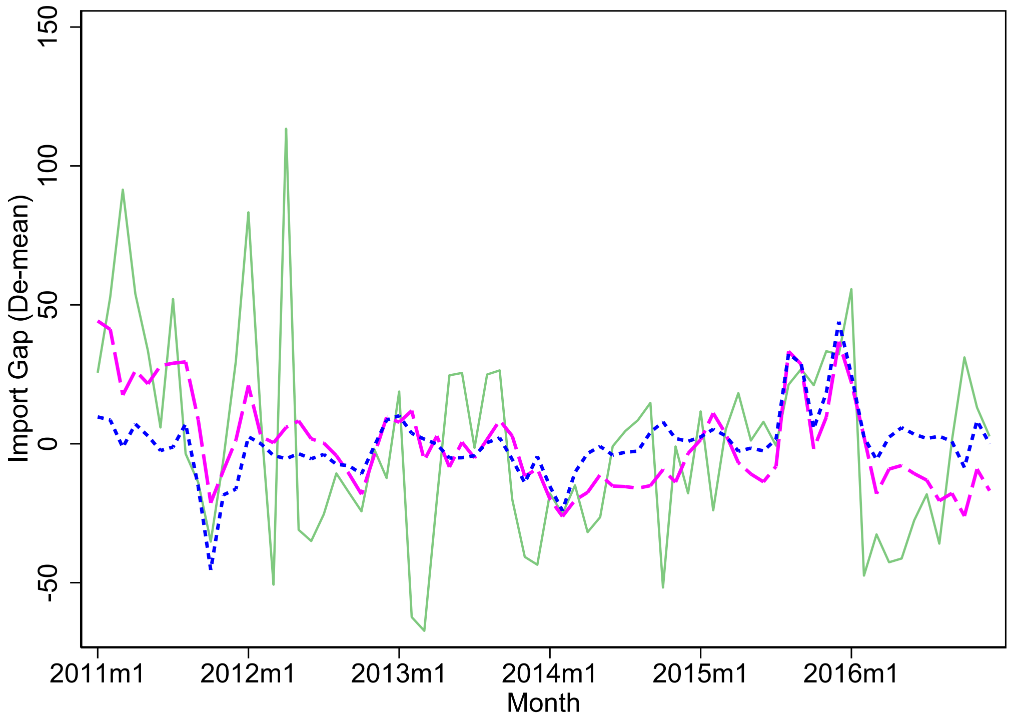
Note: This figure shows the missing trade between mainland China and Hong Kong. The import and export gaps are defined as the (100*) log difference between imports from Hong Kong (or exports to Hong Kong) reported by mainland China and the corresponding ones reported by Hong Kong, adjusted by trade costs.

Figure 2: Trade data gaps between mainland China and Hong Kong

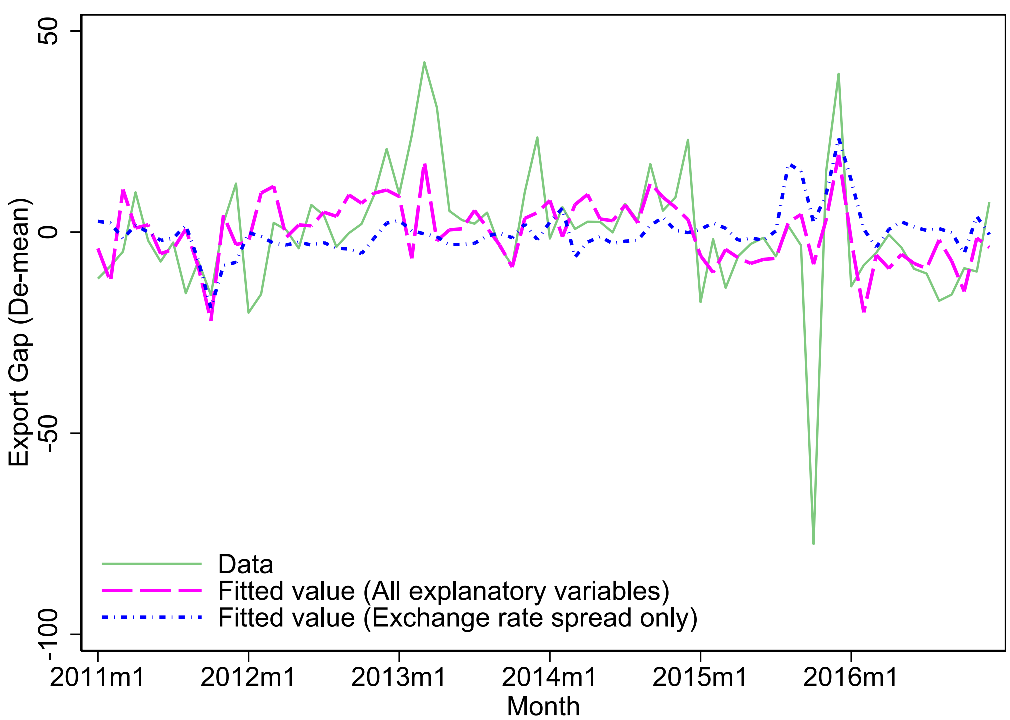


Note: This figure shows an example of the dual exchange rate arbitrage under a positive exchange rate spread. An arbitrager can make profits by buying the USD in mainland China and selling the USD in Hong Kong. The detailed steps of arbitrage can be illustrated as follows: First, convert the RMB into 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: An example of dual exchange rate arbitrage



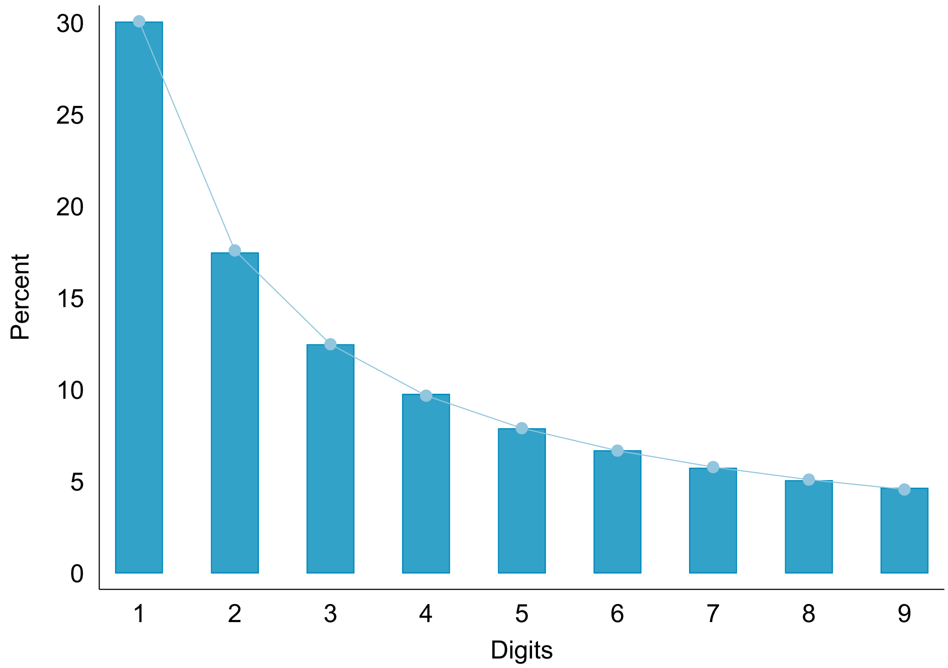
(a) Import gap



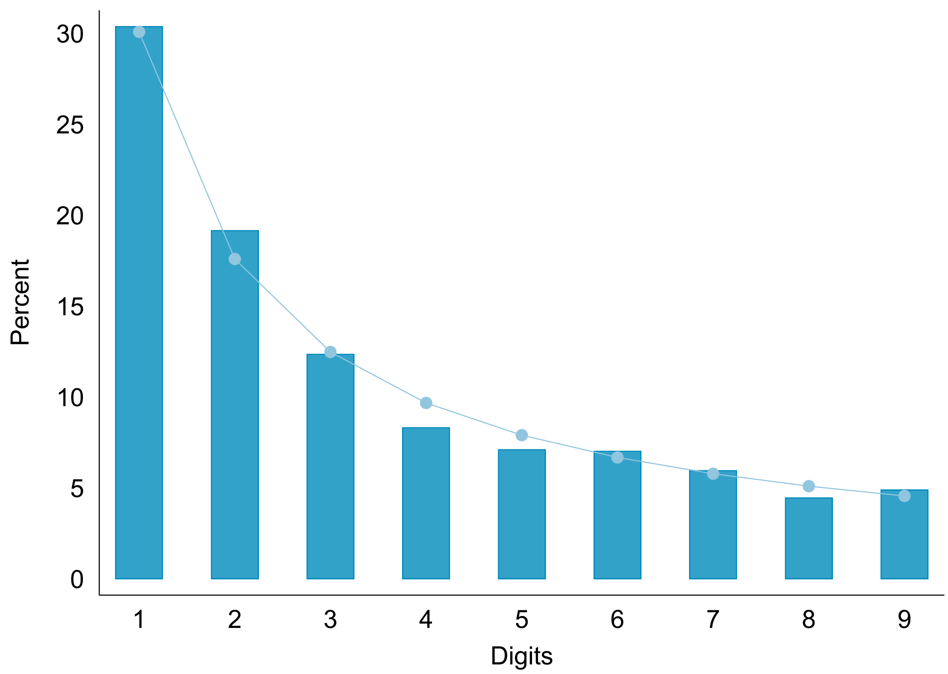
(b) Export gap

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: Trade data gaps: Raw data and fitted values



(a) Textiles



(b) Jewelry

Note: The histograms show the observed probabilities of each digit and the dots present the expected probabilities following Benford's law for textiles (top panel) and jewelry (bottom panel).

Figure 5: Examples of Benford's law

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 the threshold regressions (TR), regressions with a structural change point (SCR) based on the sup Wald/LM/LR tests, and simple OLS regressions for trade data 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 month is identified from the data by either the threshold regressions or sup tests. The threshold regressions adopt robust standard errors in estimation, while the structural change regressions and OLS regressions 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 relations				18.599				-0.296
				(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: This table shows the robustness checks for the benchmark threshold regressions. See Table 3 for the explanation of key variables in the regression. Changes in foreign relation is obtained from Du et al. (2017) which measures China's overall foreign relation with the rest of the world. LnEUP is the logarithm of the economic policy uncertainty (EPU) index obtained from Baker et al. (2016). Robust errors are in parentheses and 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. See Table 3 for the explanation of key variables in the regression. 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: This table presents the results for China's RMB receipts and foreign exchange payments under the trade account. See Table 3 for the explanation of key variables in the regression. 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	6-14	9.30	0.32	3610	Vegetable Products
goods	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: This table shows the results of the threshold regressions for the BLTR and Non-BLTR groups. See Table 3 for the explanation of key variables in the regression. Robust errors are in parentheses. Superscripts *, ** and *** represent statistical significance at the ten, five and one percent levels, respectively.

Table 9: Results for 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 of the threshold regressions for the trade data gaps between mainland China and the U.S. See Table 3 for the explanation of key variables in the regression. Robust errors are in parentheses. Superscripts *, ** and *** represent statistical significance at the ten, five and one percent levels, respectively.

Online Appendix (not for publication)

A.1 Different over-reporting in imports and exports

In the benchmark model we assume that firms are symmetric and thus the true sales of each firm are the same. This implies that the over-reporting in imports is identical to that of exports for each firm, and thus we can just focus on the over-reporting in imports. Below we show that firm's optimal decision remains the same if the true sales of each product variety vary and the over-reporting in imports is different from that of exports. In other words, a firm can choose different true values of imports and exports for over-reporting, i.e., $r^{ex}_{hk}(z)S^{CNH} \neq x^{im}_{hk}(z')$. However, the equation (4) remains to hold for firms who conduct dual exchange rate arbitrage, as the total amounts of fund through over-reporting in imports and exports need to be equal for arbitrage. Thus, firm's arbitrage profit can be written as

$$\begin{aligned}\max_{\delta^{im},\delta^{ex}} \pi = (1-\lambda)\delta^{im} r^{ex}_{hk}(z) EXS - \lambda\eta_1[\delta^{im} r^{ex}_{hk}(z) + \delta^{ex} x^{im}_{hk}(z')/S^{CNH}] \\ - \frac{\kappa_1}{2}(\delta^{im})^2 r^{ex}_{hk}(z) - \frac{\kappa_1}{2}(\delta^{ex})^2 x^{im}_{hk}(z')/S^{CNH}\end{aligned} \tag{A.1.1}$$

The equation (4) implies that $\delta^{ex} x^{im}_{hk}(z')/S^{CNH} = \delta^{im} r^{ex}_{hk}(z)$, and thus we can simplify the profit function as follows:

$$\begin{aligned}\max_{\delta^{im}} \pi = (1-\lambda)\delta^{im} r^{ex}_{hk}(z) EXS - 2\lambda\eta_1 \delta^{im} r^{ex}_{hk}(z) \\ - \frac{\kappa_1}{2}(\delta^{im})^2 r^{ex}_{hk}(z)\left(1 + \frac{r^{ex}_{hk}(z)}{x^{im}_{hk}(z')/S^{CNH}}\right)\end{aligned} \tag{A.1.2}$$

Thus, if we define $\eta = 2\eta_1$ and $\kappa = \kappa_1 * \left(1 + \frac{r^{ex}_{hk}(z)}{x^{im}_{hk}(z')/S^{CNH}}\right)$, firm's optimal decision of over-reporting in imports is equivalent to the original one in the equation (6).

A.2 Proof of Equation (10)

In this section, we show the proof for equation (10). Given that $\lambda \sim F(\lambda)$ and plugging in the optimal solution of δ^{im*}, we get

$$
\begin{aligned}
Y^{IMP} &= \int_0^1 \delta^{im*} dF(\lambda) = \int_0^{\mu} \frac{(1-\lambda)EXS - \lambda\eta}{\kappa} dF(\lambda) \\
&= \frac{1}{\kappa}\int_0^{\mu} (1-\lambda)EXS - \lambda\eta dF(\lambda) = \frac{(EXS+\eta)}{\kappa}\int_0^{\mu}(\mu-\lambda)dF(\lambda) \\
&= \frac{(EXS+\eta)}{\kappa}\left(\int_0^{\mu}\mu dF(\lambda) - \int_0^{\mu}\lambda dF(\lambda)\right) = \frac{(EXS+\eta)}{\kappa}\left(\mu F(\mu) - \int_0^{\mu}\lambda dF(\lambda)\right) \\
&= \frac{(EXS+\eta)}{\kappa}\int_0^{\mu} F(\lambda)d\lambda
\end{aligned}
\tag{A.2.3}
$$

Next we give a particular example of $F(\lambda)$. We choose $Beta$ distribution as it is flexible, intuitive, and can generate closed form solutions for the 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. For simplicity we fix $\beta = 1$, so we can focus on the parameter α. The CDF for $Beta(\alpha, 1) = \lambda^{\alpha}$. Thus, we have

$$
\begin{aligned}
Y^{IMP} &= \frac{(EXS+\eta)}{\kappa}\int_0^{\mu}\lambda^{\alpha}d\lambda \\
&= \frac{(EXS+\eta)\mu^{1+\alpha}}{\kappa(1+\alpha)} \\
&= \frac{EXS+\eta}{\kappa(1+\alpha)}\left(\frac{EXS}{EXS+\eta}\right)^{1+\alpha}
\end{aligned}
\tag{A.2.4}
$$

It is easy to verify that $\frac{\partial Y^{IMP}}{\partial \kappa} < 0$, $\frac{\partial Y^{IMP}}{\partial \eta} < 0$, and $\frac{\partial Y^{IMP}}{\partial EXS} > 0$. In addition, we can also show that $\frac{\partial Y^{IMP}}{\partial \alpha} < 0$, indicating that the over-reporting in imports decreases with the average risk of being caught.

A.3 Data

In this section, we present additional information for the data we use in this paper (i.e., sources and variable construction). We start by focusing on the data used in the baseline regressions. To calculate the trade data discrepancies between mainland China and Hong Kong, we need the direct trade data reported by both sides. We obtain the direct trade data reported by mainland China (aggregate-level and section-level) from the CEIC database, at monthly frequency. The counterpart data reported by Hong Kong is calculated from the total trade data and re-export trade data, both retrieved from the Comtrade database. Specifically, direct export data is equal to total export data minus re-export data. Next, the trade data 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 RMB (CNY) and offshore RMB (CNH) 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 the Bloomberg database.

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. To test the relationship between the exchange rate spread and currency settlements of PBC, 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.