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

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Abstract

Using a unique institutional setting of dual exchange rates in China, this paper provides novel evidence that firms manipulate international trade data to evade capital controls for foreign exchange arbitrage. We develop a model showing that trade data overreporting is positively (negatively) correlated with the exchange rate spread when the spread is positive (negative) if firms fake trade data to engage in foreign exchange arbitrage, and such correlations are more pronounced for products with a low risk of being detected. Empirical results from threshold regressions using the aggregate time series data and Benford's law using the disaggregated firm-product trade data between mainland China and Hong Kong support the theoretical predictions of dual exchange rate arbitrage camouflaged under international trade. Our results highlight the challenges to implementing capital controls and may help improve the effectiveness of such policies.

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

Capital controls have regained popularity among emerging markets since 2008, following the Federal Reserve's extraordinary monetary easing in response to the subprime crisis (e.g., (Rey, 2013)).[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 large and volatile global capital flows.

However, the effectiveness of capital controls can be significantly undermined by various evasion activities, particularly in developing countries with weak institutions, as discussed in Mendoza (2016) and Wei (2018).[2] Manipulating international trade data (or fake trade) to evade capital controls is perhaps the most notorious activity and is pervasive in developing countries with capital controls. The World Customs Organization documents a significant amount of illicit financial flows via trade mis-invoicing originating from developing countries in its 2018 study report (Choi et al., 2018). According to a report by the *Financial Times*, China's foreign exchange regulator uncovered USD 10 billion in fake trade stemming from capital control evasion between April 2013 and September 2014.[3] Although anecdotal evidence has been widely discussed in the media and academic studies, the very nature of fake trade makes it difficult to detect.[4]

A systematic examination of capital control evasion through fake trade is crucial to understanding the nature of such activities, assess their costs, and find solutions to mit-

[1]Counter-cyclical capital control policies are generally recommended even for economies with flexible exchange rates to maintain their monetary autonomy and domestic financial market stability (International Monetary Fund, 2012; Farhi and Werning, 2014; Davis and Presno, 2017; Korinek, 2018; Wang and Wu, 2021). These policy suggestions echo an early position in the 1990s that 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 markets remained underdeveloped (Rodrik, 1998; Prasad et al., 2003; Kose et al., 2006).

[2]Other influential studies on this topic include Edwards (1999), Edison and Reinhart (2001), Forbes et al. (2015), Lin and Ye (2018), and Lin et al. (2020), among others.

[3]Please see the news report at ft.com for details.

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

igate their adverse effects. By taking advantage of a unique institutional setting of dual exchange rates for the Chinese renminbi (RMB), our paper presents theoretical and empirical evidence that firms manipulate international trade data to evade capital controls for a particular purpose: foreign exchange arbitrage.[5]

When the official exchange rate deviates from the market exchange rate, arbitrage opportunities emerge if agents can evade capital controls.[6] The empirical research on foreign exchange arbitrage is largely held back by the unavailability of reliable market exchange rates in countries with capital controls and managed exchange rates. Fortunately, the RMB's dual exchange rates offer a unique opportunity to study this issue. In addition to its onshore market in the mainland, China set up an offshore RMB/USD foreign exchange market in Hong Kong in late 2010 to promote RMB internationalization. Between 2011 and 2016, the RMB offshore market was mainly market-driven, while the onshore market was highly regulated by the People's Bank of China (PBC). Over this period, large and persistent exchange rate spreads frequently existed between these two markets, which incentivized arbitrage activities through fake trade.[7]

We first develop a model in which firms overreport trade data to evade capital controls for foreign exchange arbitrage, but face heterogeneous probabilities of being caught by the authorities. To arbitrage over two foreign exchange markets, firms overreport imports to transfer funding abroad and overreport exports to transfer money back. The overreporting of trade data creates trade data discrepancies between importing and exporting countries.[8] The trade data overreporting is costly and firms also face the risk of being

[5]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 (2021). See Section 2.1 for more details.

[6]See Pitt (1981), Pitt (1984), and Adams and Greenwood (1985) for theoretical studies on foreign exchange arbitrage.

[7]The exchange rate spread became much smaller after 2016 because the PBC intensified interventions in Hong Kong to narrow the spread after the RMB was included in the IMF's special drawing rights (SDR) basket in late 2016. See Section 2.2 for more discussion. In additional to 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.

[8]Unfortunately, the trade data discrepancies are not used to detect fake trade as customs in importing and exporting countries do not share sufficient information of the international transactions.

caught and penalized by the authorities. Thus, firms choose the optimal level of fake trade to maximize their expected profits from foreign exchange arbitrage. By aggregating individual firms' optimal overreporting, our model shows that the aggregate overreporting in trade data is positively (negatively) correlated with the exchange rate spread when the spread is positive (negative). At the disaggregated level, the model also predicts that the above correlations are more pronounced for the products whose fraudulent transactions are less likely to be detected by customs officials.

We test the above model predictions by using both the aggregate time series trade data and the disaggregated firm-product level customs trade data between mainland China and Hong Kong. At the aggregate level, we apply threshold regressions (Hansen, 2000; Yu and Phillips, 2018) to the trade data discrepancies between mainland China and Hong Kong. Following the literature on "missing trade," the trade data discrepancy or gap 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).[9] The monthly aggregate trade data gap is on average as large as 30% of the total trade between mainland China and Hong Kong and it fluctuates substantially over time.

The threshold regressions show that the relationship between the exchange rate spread and trade data gap is consistent with our model predictions. The overreporting 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. The spread explains a large fraction of trade data discrepancies, especially when the spread is large. According to our estimation, a spread of 1% of the

[9]Our data only include 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 data for various reasons such as different statistical rules, tariff/tax evasion, and capital control evasion. See Feenstra et al. (1999) and Marquez and Workman (2001) for early studies on global trade data discrepancies.

exchange rate (0.07 RMB/USD) in December 2015 induced fake trade of about USD 7.2 billion, 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 products that are prone to trade data manipulations. The BLT has been widely used to detect fraud in accounting and economic data (Nigrini, 2012; Michalski and Stoltz, 2013; Berger and Hill, 2015). According to Benford's law, the leading digits in accounting and economic data follow a certain frequency distribution, while forged data usually do not (Newcomb, 1881; Benford, 1938). In particular, Barabesi et al. (2018), Cerioli et al. (2019), and Demir and Javorcik (2020) show that the BLT is also useful in detecting fraud in large-scale trade data. Using the disaggregated trade data (at the firm-HS 8-digit level) between mainland China and Hong Kong, we find that most of the goods that do not conform to Benford's law are intermediate inputs or differentiated goods such as electrical equipment, jewelry and precious metal or stones, and works of art. 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 customs to detect whether the reported values are fraudulent.[10]

Furthermore, consistent with our model predictions, we find that the monthly overreporting in those fraudulent products that failed the BLT displays similar correlation patterns with the exchange rate spread in threshold regressions, suggesting that the fraudulent products detected by the BLT may be used as vehicles in fake trade to evade capital controls for foreign exchange arbitrage.[11] By contrast, we find no significant relationship between the spread and trade data gap for the products that fit Benford's law well.

[10] 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. However, not all differentiated goods are suitable for fake trade as some of them have high weights or low unit values.

[11] 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.

Our empirical findings are robust to various extensions and sensitivity analysis such as controlling for possible autocorrelation in the error terms, lagged dependent and independent variables, economic policy uncertainty, changes in foreign political relations, China's anti-corruption campaign, different dates for the structural break, and an alternative estimation method for the structural break (Andrews, 1993). We also show in two placebo tests that the BLT results are not driven by random factors or statistical errors.

This paper contributes to the literature on capital control evasion (Edwards, 1999; Edison and Reinhart, 2001) by developing a novel theoretical framework and providing systematic empirical evidence on how firms fake trade data to evade capital controls for foreign exchange arbitrage. Our paper complements previous empirical studies on capital control evasion for different purposes and through different channels, for example, Liu et al. (2020) for carry trade through re-imports and Wong (2021) for capital flight through international travel spending.[12] Moreover, we also identify the products that are prone to data manipulation by using the BLT method, while previous studies mainly focus on aggregate-level evidence.

Our study also makes important contributions to the literature on "missing trade" (Feenstra et al., 1999; Fisman and Wei, 2004). Previous studies mainly focus on the motivation of *tariff and tax evasion* by exploring the *cross-sectional* relationship between the underreporting of imports and tariff/tax rates at the product level.[13] By contrast, this paper highlights the role of *capital control evasion* by exploring the *time-series* relationship between trade data discrepancies and the exchange rate spread.

The remainder of the paper is arranged as follows. Section 2 introduces the institutional background and data. Section 3 develops testable predictions from a simple model of dual exchange rate arbitrage. Section 4 presents the econometric strategy and regres-

[12] We depart from Wong (2021) by focusing on trade in goods instead of services such as travel spending. While China's trade in service has increased sharply in the last decade as documented in Wong (2021), its size remains small relative to trade in goods, which makes trade in service less suitable for foreign exchange arbitrage than trade in goods.

[13] For example, see Fisman and Wei (2004), Javorcik and Narciso (2008), Ferrantino et al. (2012), Liu (2013) and Demir and Javorcik (2020), among others.

sion results using the aggregate time series 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

China maintains tight controls on portfolio flows, although the country liberalized its current account in the 1990s and has gradually relaxed some restrictions on capital flows in recent years. In addition, the exchange rate between RMB and USD in mainland China (onshore market) is heavily regulated by the PBC to maintain a stable rate between the two currencies. As a result, private agents find creative ways to circumvent China's capital controls especially when the RMB is under pressures of appreciation or depreciation.[14]

In 2010, China set up an offshore RMB-USD market in Hong Kong to promote RMB internationalization. The exchange rate discrepancies between the onshore and offshore markets provide an excellent indicator for the pressure of capital control evasion for foreign exchange arbitrage. The remainder of this section briefly describes China's institutional background to facilitate our understanding of dual exchange rate arbitrage between mainland China and Hong Kong through fake trade.

2.1 Capital controls

China imposes long-standing capital 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. According to the Chinn-Ito financial openness index, China ranked 146 out of 174 economies in 2016, much lower than other emerging markets such as Mexico, India, and

[14]For instance, Agarwal et al. (2019) document that China recorded large negative net errors and omissions (E&O) in its international investment position in 2014 and 2015 when the RMB was under substantial depreciation pressures due to the economic slowdown in China, while the net E&O was significantly positive between 2000 and 2008 when the RMB was under appreciation pressures. Such patterns indicate that E&O may represent unaccounted capital flows through capital control evasion, rather than measurement errors.

Russia.[15] 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.

Although the Chinese government has taken steps to liberalize international portfolio investment flows in recent years by establishing programs such as "qualified foreign institutional investors" (QFIIs) and "qualified domestic institutional investors" (QDIIs), the approved quotas in these programs remain very small relative to China's economic size. Such liberalization policies also vary with the external economic environment the country faces. For instance, China stopped approving new quotas for overseas investment by its residents and suspended the approval of QDIIs in 2014 when it faced large capital outflows and depreciation pressures of the RMB. Wang and Wu (2021) find that China adjusts its capital controls policy counter-cyclically in response to U.S. monetary policy shocks.

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.[16] To maintain the official onshore RMB-USD exchange rate in mainland China (denoted by CNY), the Chinese government imposes various controls on capital flows. Meanwhile, in order to promote

[15] 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).

[16] 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.

RMB internationalization, China set up an offshore RMB market in Hong Kong in 2010.[17] The offshore RMB-USD exchange rate (denoted by CNH) is not subject to the same interventions as in mainland China and was mainly determined by the global market demand and supply of the RMB before 2016.

Due to the difference in exchange rate determination between onshore and offshore markets, large and persistent exchange rate spreads were constantly observed between these two markets. Define the offshore-onshore RMB-USD exchange rate spread 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 relative to the offshore market. The spread can be as large as 2% in the daily data and over 1% even in the monthly average data. Figure 1 presents the spread calculated from the monthly average onshore and offshore exchange rates from January 2011 to December 2016.[18] 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.[19] 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.

The exchange rate spread shrunk substantially after 2016 because the PBC intensified its intervention on Hong Kong's offshore market. Before the IMF added the RMB to its SDR basket in December 2016, RMB's onshore-offshore exchange rate spread is a key

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

[18] 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.

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

concern expressed in IMF's SDR basket report (e.g., see Gagnon (2016) and Ba (2019)). To address this concern, the PBC started in 2016 to intervene the offshore market in Hong Kong to reduce the spread. It is likely that the capital 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, they removed all tariffs for most goods originally made in these two places in 2003, after signing the Closer Economic Partnership Arrangement (CEPA). These factors substantially reduce the costs and risks of capital control evasion through fake trade.

2.3 Trade data gaps

Hong Kong is a very important trading partner of mainland China and maintains large trade data gaps with the mainland. Hong Kong consistently ranked as the third-largest trading partner of mainland China, following 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 the U.S.-China trade in 2016. In our data, we only consider direct trade between mainland China and Hong Kong. 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.[20]

Following the literature of "missing trade", we define trade data gaps 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:

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

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

where EXP_t^{CN} and IMP_t^{CN} are mainland China's reported exports to and imports from Hong Kong, respectively. 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 CIF (cost, insurance, and fright) of 10% to capture the iceberg trade cost between importers and exporters.[21] Y_t^{EXP} is positive/negative if firms overreport/underreport exports from mainland China to Hong Kong and it is similar for Y_t^{IMP}. The overreporting of exports facilitates capital flows from Hong Kong to mainland China, while the overreporting of imports moves capital in the opposite direction.

As shown in Figure 2, substantial trade data gaps exist between mainland China and Hong Kong. On average, mainland China overreported both exports to and imports from Hong Kong with a mean of 33 percentage points for Y_t^{EXP} and 28 percentage points for

[20]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 from the build-up method; or greater than or equal to 40% when calculated from the build-down method.

[21]It will become clear shortly that the value of CIF does not affect our empirical results. CIF may be time varying in some countries (e.g., see Cheung et al. (2020) for a study on Germany). Our results may not be qualitatively affected by the time variation of trade costs as the costs and the exchange rate spread are unlikely to be highly correlated.

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 (10 and 15 percentage points for export and import gaps, respectively).

Previous studies on trade data discrepancies mainly focus on the tax and tariff evasion by examining the cross-sectional relationship between imports underreporting and tariff or tax rates at the product level (Fisman and Wei, 2004; Ferrantino et al., 2012; Javorcik and Narciso, 2008). However, the tax and tariff evasion cannot explain the large monthly fluctuations of trade data gaps between mainland China and Hong Kong as tax and tariff policies change infrequently. Instead, we find that the monthly trade data discrepancies are highly correlated with the RMB exchange rate spread between onshore and offshore markets in a manner that is 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 through fake trade, from which 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 exchange rate spread, 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 overreporting 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 overreporting its exports (settled in the RMB) to Firm B in Hong Kong.[22]

To study the above dual exchange rate arbitrage, we develop a static model 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 a demand shifter and is defined as $\frac{E}{P^{1-\sigma}}$, where E is total expenditure, and P is the standard CES price index. For simplicity we assume no international trade cost 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

[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.

[24]Our theoretical results do not change qualitatively if we assume a trade cost that is proportional to the total trade volume.

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.

3.2 Optimal arbitrage

We assume that the exchange rate spread is exogenous when individual firms choose their optimal arbitrage strategy.[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 overreports its imports from Hong Kong, we denote the true value reported by Hong Kong as $r^{ex}_{hk}(z)$ in the U.S. dollar, while in the mainland firm z reports its imported value as $r^{im}_{cn}(z)$, which inflates the true value by a factor of $1 + \delta^{im}$ with $\delta^{im} = \frac{r^{im}_{cn}(z) - r^{ex}_{hk}(z)}{r^{ex}_{hk}(z)} > 0$.[27] Thus, the USD outflows from mainland China to Hong Kong through import overreporting. Suppose the firm sells the USD for the RMB in Hong Kong and transfers the corresponding RMB back to mainland China through export overreporting. Similarly, for a transaction in which mainland China firm z exports to Hong Kong, we denote the true value reported by Hong Kong as $x^{im}_{hk}(z)$ in RMB and the export value reported by firm z in mainland China as $x^{ex}_{cn}(z)$, which inflates the true value by a factor

[25]It is easy to extend our model to have firms with heterogeneous productivity like Melitz (2003), although firms are homogeneous in our benchmark model like in a standard Krugman trade model (Krugman, 1979). 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.

[27]The trade data gap disappears if the firm in Hong Kong also inflates its trade data. However, inflating the trade data in Hong Kong will increase additional and unnecessary risks of being caught. So we assume that the trade data in Hong Kong is genuine.

of $1+\delta^{ex}$ with $\delta^{ex}=\frac{x_{cn}^{ex}(z)-x_{hk}^{im}(z)}{x_{hk}^{im}(z)}>0$.[28] In the absence of trade costs, a firm's total overreporting in imports should equal its total overreporting in exports after being adjusted by the RMB exchange rate in the offshore market for arbitrage:[29]

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

Clearly, the overreporting in exports is tightly connected with the overreporting in imports in the model. Under the assumption of symmetric sales, we can further simplify this equation and obtain $\delta^{im}=\delta^{ex}$. Therefore, in the following discussions, we only need to focus on the optimal decision of import overreporting δ^{im}. Our results hold qualitatively if we relax the assumption of symmetric sales.[30]

The RMB-denominated revenue from the above dual exchange rate arbitrage is:

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

where EXS is the exchange rate spread and it is positive in the current scenario, i.e., $EXS>0$.[31] 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 in the extent of overreporting. The latter assumption captures the fact that it is more difficult to hide trade data overreporting for larger volumes. 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 overreporting.

With a probability λ, traded goods will be inspected at the border and the true value of trade will be revealed. In this case, firm z pays a penalty for the over-reported amount, $\eta\delta r(z)$, where $\eta>0$ denotes the severity of penalty for fake trade. For a given positive

[28]Note that $x(z)$ is denominated in RMB, while $r(z)$ is denominated in USD.
[29]Here we assume that arbitragers transfer all their funding back to the origin place.
[30]Please see the online appendix A.1 for details.
[31]Note here we slightly abuse the notation of EXS compared with the empirical analysis, in which the exchange rate spread is defined as 100 multiplying the log difference between the onshore and offshore exchange rates of RMB.

exchange rate spread, the risk-neutral firm z chooses δ^{im} to maximize its expected profits from the dual exchange rate 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 overreporting 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 whose probability of being caught is below a cutoff point ($\mu \equiv \frac{EXS}{EXS+\eta}$) will engage in fake trade. For these firms, the optimal overreporting 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 cutoff μ increases with the spread but decreases in the punishment level, a higher spread will not only increase the overreporting for incumbent arbitragers, but also induce more firms to participate in fake trade.

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 overreporting in aggregated imports is given by [32]

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

As the cutoff 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 overreporting in aggregated imports also increases with the positive spread, but decreases with the punishment level and cost sensitivity of faking trade. Under the assumption $\delta^{im} = \delta^{ex}$, the above results for the overreporting in aggregated imports also apply to the overreporting in aggregated exports. Therefore, we obtain the first key prediction from our model:

Prediction 1. *The overreporting 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 overreporting for the negative exchange rate spread ($EXS < 0$). In this case, firms transfer the RMB from mainland China to Hong Kong by overreporting imports settled in RMB and transfer the USD back to the mainland by overreporting exports settled in USD. For the proof we can simply use $-EXS$ to replace EXS in equations (7) and (10). Thus, the overreporting 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 overreporting 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 overreporting depends on the absolute value of foreign exchange spreads in the

[32]Please see the online appendix for the proof. Here we slightly abuse the notation of Y^{IMP}; in the empirical analysis, we define the overreporting factor Y^{IMP} as 100 multiplying the log difference between R^{im}_{cn} and R^{ex}_{hk}.

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 extension is to relax this assumption. Suppose there are two groups of products (or two industries) and their probabilities of being caught follow different distributions, $F_i(\lambda)$ for $i = 1, 2$. Without loss of generality, we assume that the first industry has a lower probability of being detected than the second one. For example, it is relatively easier for the customs to detect fraud in transactions of homogeneous goods, such as textile, than differentiated goods, such as jewelry, because homogeneous 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, equation (10) implies that the overreporting 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 with a low risk of being caught, but not for the products with a high risk. This gives our third prediction:

Prediction 3. *The patterns between trade overreporting and the exchange rate spread predicted in Predictions 1 and 2 are more prominent for industries (or products) that have lower risk of being detected by the customs in fake trade.*

[33]In the online appendix A.2, 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 overreporting in aggregated imports decreases when the average risk of being caught increases (captured by an increase in α).

3.3 Empirical strategy

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 homogeneous 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. This increases the chance of being caught by customs officials.

To test Prediction 3, we employ a data-driven method, the BLT, to identify products (or industries) that have low probability of being detected in fake trade. It is reasonable to believe that firms have stronger incentives to manipulate trade data for goods that have lower risk of being caught. As a result, the reported trade values of those products are less likely to conform to 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.[34] 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 can help to verify whether the fraudulent trade is linked to dual exchange rate arbitrage.

[34] 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.

4 Empirical Evidence from the Aggregate Trade Data

In this section, we adopt threshold regressions to test the first two theoretical predictions. Threshold models have been developed to deal with potential nonlinearities in economic relationships and become increasingly popular in a wide variety of economic applications.[35] 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.

Our results are robust to an alternative method of "two-step" regressions (structural change regressions). In the first step, we test for an unknown structural change point with the sup Wald/LM/LR tests proposed by Andrews (1993). Next, we estimate the coefficients from a regression model with the change point estimated by the sup tests.

4.1 Econometric specification

In a threshold or structural change model, the sample is split into two or more regimes based on endogenously determined value(s) of a chosen variable (labeled as the threshold variable, e.g., time). The variables of interest can have different coefficients in these regimes. The benchmark specification of our empirical analysis is as follows:

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

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,

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

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 $\beta_2 > 0$.

We choose time rather than the exchange rate spread as our threshold variable for the following reasons. First, 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 may make it difficult to detect our theoretical predictions.[36] 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 model with time as the threshold variable can capture this pattern and estimate the break point well from the data. Finally, both the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) for model selection indicate that models with time as the threshold variable are preferable.

X_t in equation (11) contains other control variables. Following the literature, we include deviations from covered interest rate parity (CIP) 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]

[36] In addition, 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.

[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)

In addition to foreign exchange arbitrage, the appreciation/depreciation pressures of the RMB can also induce fake trade to evade capital controls and the exchange rate spread may partially reflect such pressures.[38] In this case, the exchange rate spread may cause capital flight or hot money inflows (labeled as speculative flows) through fake trade as well as the flows for foreign exchange arbitrage. These different types of fake trade 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 overreporting its exports (settled in USD) to Hong Kong. This activity implies a negative correlation between export overreporting 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 overreport USD-denominated imports to transfer the USD to Hong Kong and/or under-report USD-denominated exports to keep the USD in Hong Kong. The under-reporting of exports in this case works against the positive correlation between export overreporting and the exchange rate spread in Prediction 1.

To control for the above effect of 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 overreporting (positive coefficient) and decreases export overreporting (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

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 RMB was expected 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.

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 overreporting but positive for export overreporting. It suggests that the negative risk premium (when the RMB is expected to depreciate) encourages 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 overreporting in imports and exports. Table 1 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.

4.2 Baseline results

The benchmark results in Table 2 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 in Prediction 1). The coefficient estimates are statistically significant at either the 1% or 5% level in both threshold regressions (TR) and structural change regressions (SCR). Note that the estimated break dates are highly consistent across the TR and SCR models 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

[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.

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, highlighting the importance of modelling the non-monotonic relationship between the exchange rate spread and the trade gaps.

The fake trade activities that we detect are also economically significant, especially over some periods of large exchange rate spreads, for instance, 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 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 between mainland China and Hong Kong due to foreign exchange arbitrage amounted to over 24 billion U.S. dollars during this period, which accounts for over 12% of the total trade between the two economies.

4.3 Extensions and sensitivity analysis

Our results are robust to various extensions and sensitivity analysis as shown in Tables 3 and 4. 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 the benchmark results of Table 2 are consistent with the prediction of speculative capital flows discussed in Section 4.1. If we remove these two variables from the regressions, the coefficient estimates in the second regime (β_2) in columns (1) and (5) of Table 3 are consistent with the prediction that pressures of RMB depreciation will induce import overreporting and export under-reporting for speculative capital flight. Note that the

[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 variation of trade data gaps in our sample.

exchange rate spread in the second regime is positive, indicating depreciation pressures for the RMB. In this case, firms overreport imports for both capital flight and foreign exchange arbitrage. If our regressions do not control for exchange rate expectations as in column (1), the effect of speculative capital flight on import gap will be mistakenly attributed to foreign exchange arbitrage, resulting in larger and statistically more significant coefficient estimate for β_2. Meanwhile, firms will also 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 export overreporting 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.

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 3, 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, changes in foreign relations and the anti-corruption campaign in China, 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 anti-corruption variable is measured by Baidu's anti-corruption index. The coefficient estimates of these variables are statistically insignificant in columns (4) and (8) of Table 3, 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 4. We manually fix the break dates of both import and export gaps in different months of the last quarter of 2013 and estimate our benchmark regressions with these pre-specified breaks. Table 4 shows that our results

[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.

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 overreporting of RMB-denominated imports of mainland China from Hong Kong, but a net RMB inflow when the exchange rate spread is positive. As a result, we expect a positive correlation between the exchange rate spread and the net receipt of RMB by mainland China from Hong Kong. Similarly, there is a net USD inflow from Hong Kong to mainland China due to the overreporting 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 5 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. Recent studies show that the BLT 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 Chi-

[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.

nese 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 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

Benford's 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

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

[43] 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. 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] 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.

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

Deviations from Benford's law have been widely used to detect irregularities in data reporting since people usually do not know Benford's law and are biased toward simpler and more intuitive distributions, such as the uniform distribution, when they manipulate data, as shown by experimental studies (Hill, 1988; Camerer, 2003).[45] 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). Standard international trade models suggest that the distribution of leading digits of import and export values without manipulation should conform to Benford's law. For instance, 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.[46] 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

[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] 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.

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 fake trade. We use the Chinese Customs data in 2015 because the exchange rate spreads were large and the fake trade is believed to have been prevalent in that year. 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.[47] Significant deviations from Benford's law for the trade data in a given section signal potential data manipulation in that section. We conduct the BLT for the trade data at the section level rather than 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.[48]

[47]The HS Nomenclature structures 21 sections based on economic activity or component material. Each HS section consists of a number of chapters at the HS 2-digit level ranging from 1 to 99 as listed in Table 6.

[48]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.

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 jewelry 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 jewelry 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 jewelry, respectively, indicating potential data manipulations for jewelry but not for textiles.

Table 6 presents the BLT results for each HS section with the Chi-square statistics and associated p-values, and several interesting patterns emerge.[49] First, 9 out of 21 HS sections fail to pass the BLT as their p-values are less than 0.1, indicating the possibility of data manipulation. Most of them are intermediate inputs or differentiated products that do not have reference prices (Rauch, 1999), such as optical and photographic instruments (HS 2: 90–92), jewelry 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.[50] Similarly, Liu et al. (2020) find that

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

[50] The sample size sometimes matters for Pearson's Chi-square test for Benford's law. Large samples

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 6. 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 2, while the groups that pass the BLT are not, as our model suggests in Prediction 3. For each group, we aggregate monthly imports and exports, compute the corresponding import and export gaps, and conduct the baseline regression in Equation (11).

Table 7 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 2. 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).[51] 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

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 6, 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 3,000 observations for the 15 HS sections that have more than 3,000 observations, and compute their p-values of the Pearson's Chi-square test. We bootstrap this experiment for 1,000 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 6, indicating the same grouping of BLT and Non-BLTR categories.

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

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.[52] After repeating this simulation 1,000 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-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 7.

Table 8 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 2, 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

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

groups (compare column (1) with (3) and column (2) with (4)). This pattern is sharply different from our benchmark findings in Table 7, 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 Challenges for detecting foreign exchange arbitrage

Trade mis-reporting for illicit capital flows is quite common in countries with capital controls according to a report submitted to the 2016 G20 Summit by the World Custom Organization (Choi et al., 2018). As shown in this paper, one important motivation for such trade mis-reporting is foreign exchange arbitrage, along with other reasons examined in previous studies, such as tax evasion and capital flight. However, by its very nature, trade mis-reporting for foreign exchange arbitrage is difficult to detect in the data. Empirical studies face many challenges such as lacking market exchange rate data. In addition, arbitrage activities may be sensitive to many factors including trade costs, trade volume, arbitrage risks, etc. As a result, we may not be able to find similar evidence of foreign exchange arbitrage for China's other trading partners for whom arbitrage costs are higher than Hong Kong.

Table 9 displays the results for the trade gap between mainland China and the U.S. Columns (1) and (2) report the estimation results from the threshold regressions using the aggregate trade data and the remaining columns show the BLT results. Although the signs of $\hat{\beta}_1$ and $\hat{\beta}_2$ in columns (1) and (2) are the same as those in our Hong Kong results, only one out of four estimates is statistically significant. We do not find significant evidence for foreign exchange arbitrage in the BLT either. 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. 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.

Several factors may contribute to the failure of detecting fake trade for foreign exchange arbitrage in the China-U.S. data. For example, the offshore exchange rate in Hong Kong may not appropriately capture the market RMB-USD exchange rate in the U.S. In addition, the arbitrage costs and risks between China and the U.S. may be too high such that foreign exchange arbitrage activities are mainly located in Hong Kong. For instance, the long distance between the U.S. and China makes the U.S. much less desirable than Hong Kong for foreign exchange arbitrage through fake trade.

6 Conclusion

Our paper sheds light on the nature of capital control evasion through the manipulation of international trade data. The effectiveness of capital controls may be eroded by various capital control evasion activities such as fake trade. 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 trade overreporting between the two economies. We also show that the products that violate Benford's law may be used as vehicle in the fake trade for foreign exchange arbitrage.

Our paper highlights the dilemma faced by policymakers when they design capital control policies. 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.[53] 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).

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

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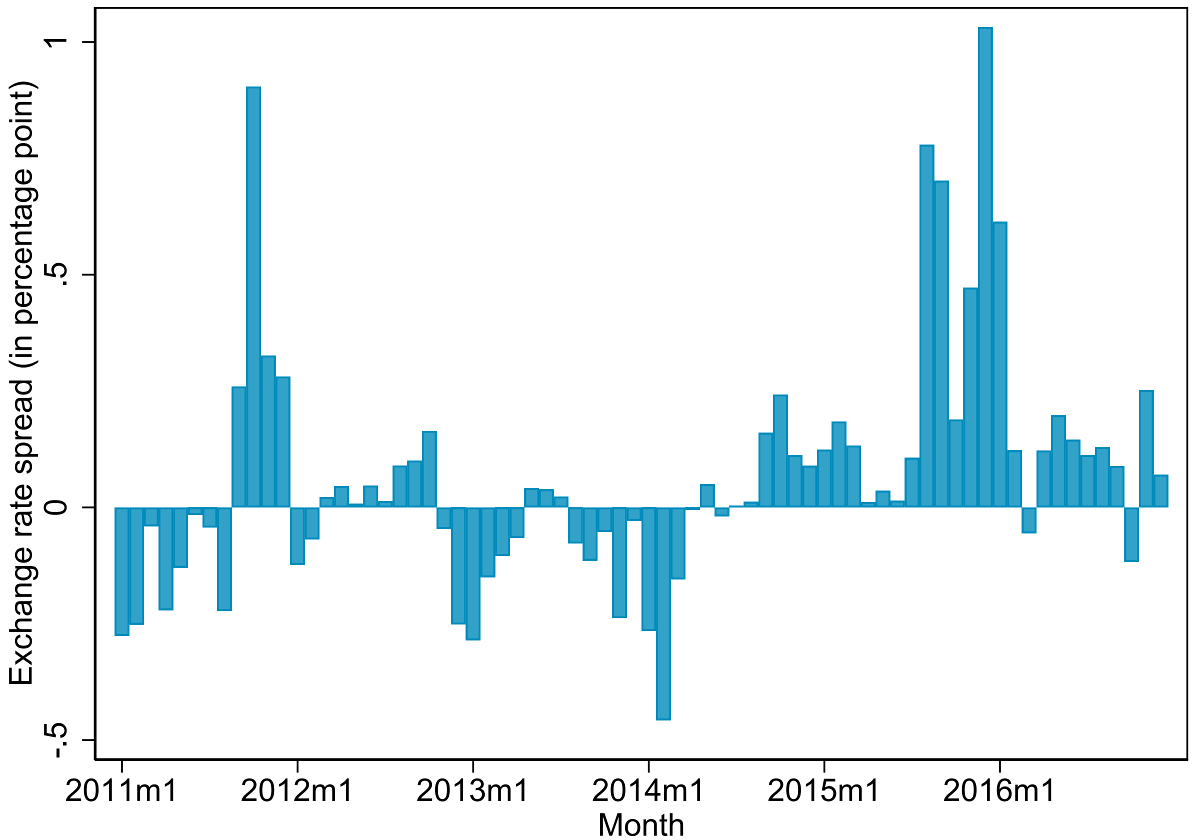
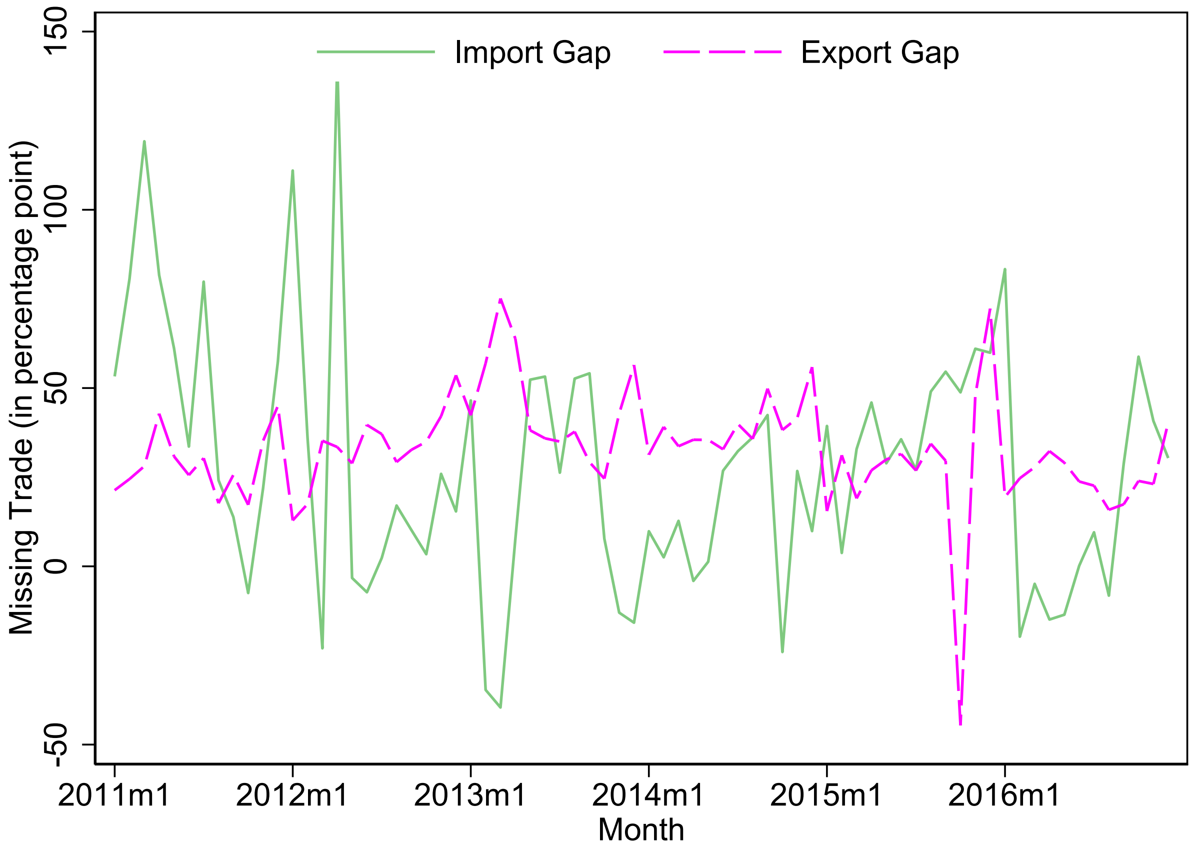


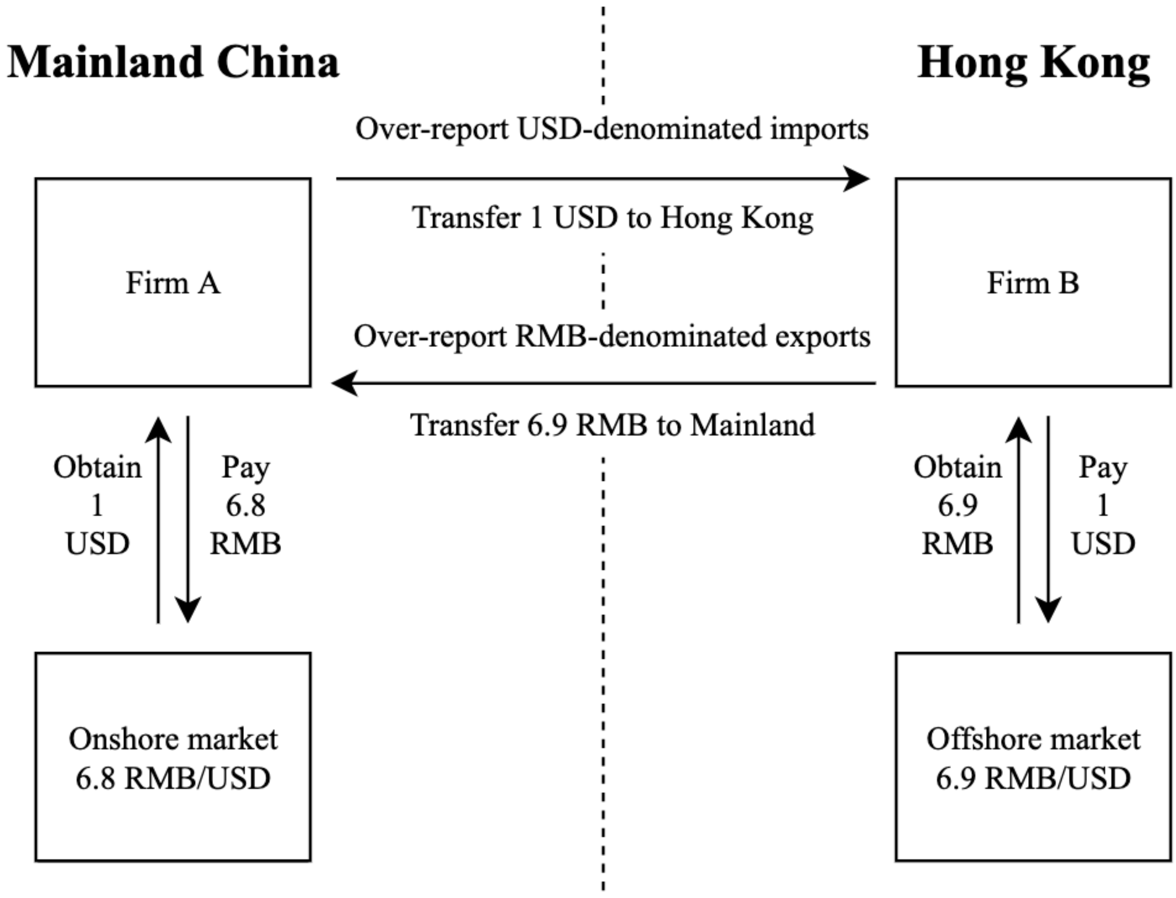
Note: This figure shows the offshore-onshore exchange rate spreads of the RMB-USD. A positive spread indicates that the RMB is more expensive (relative to the USD) in the onshore market than the offshore market.

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



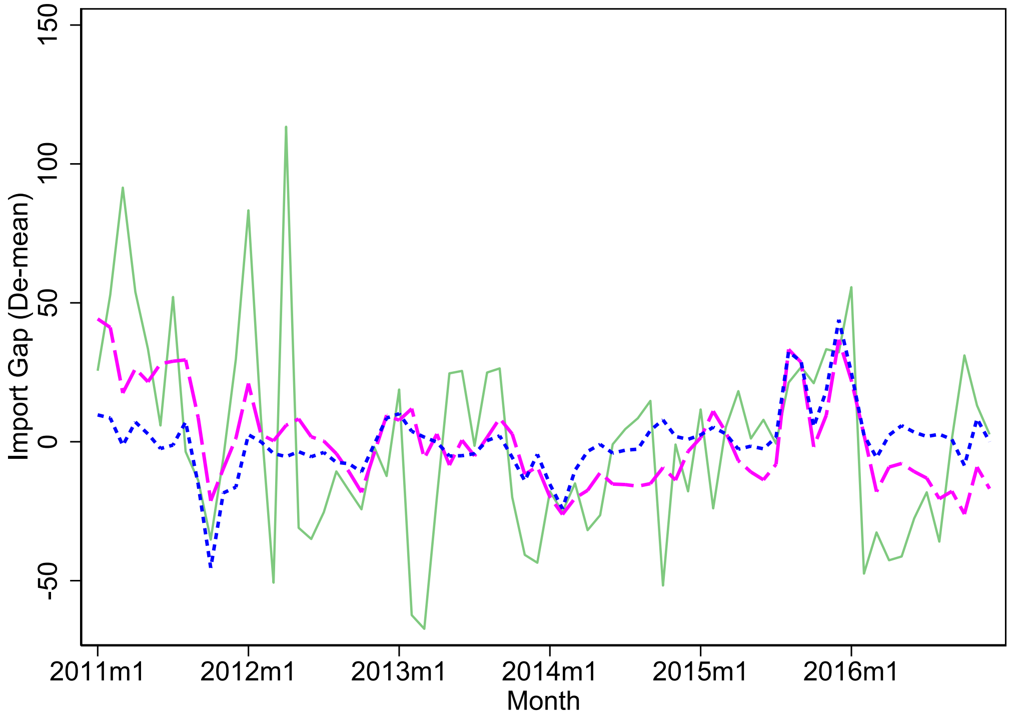
Note: This figure shows the missing trade between mainland China and Hong Kong. The import and export gaps are defined as the (100*) log difference between imports from Hong Kong (or exports to Hong Kong) reported by mainland China and the corresponding ones reported by Hong Kong, adjusted by trade costs.

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

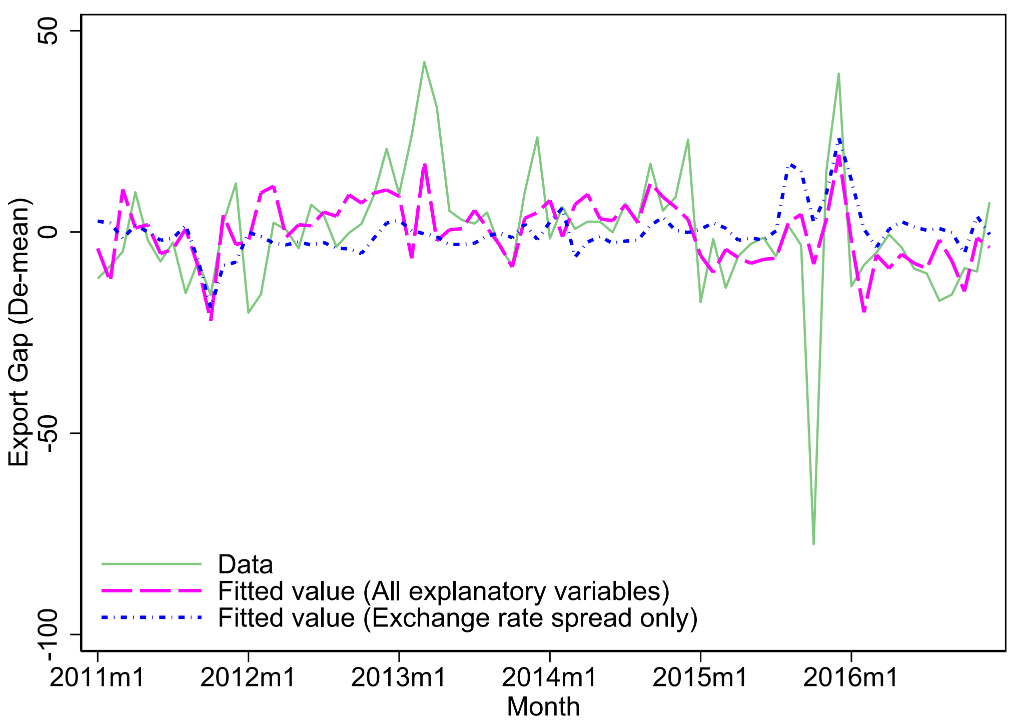


Note: This figure shows an example of the dual exchange rate arbitrage under a positive exchange rate spread. An arbitrager can make profits by buying the USD in mainland China and selling the USD in Hong Kong. The detailed steps of arbitrage can be illustrated as follows: First, convert the RMB into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



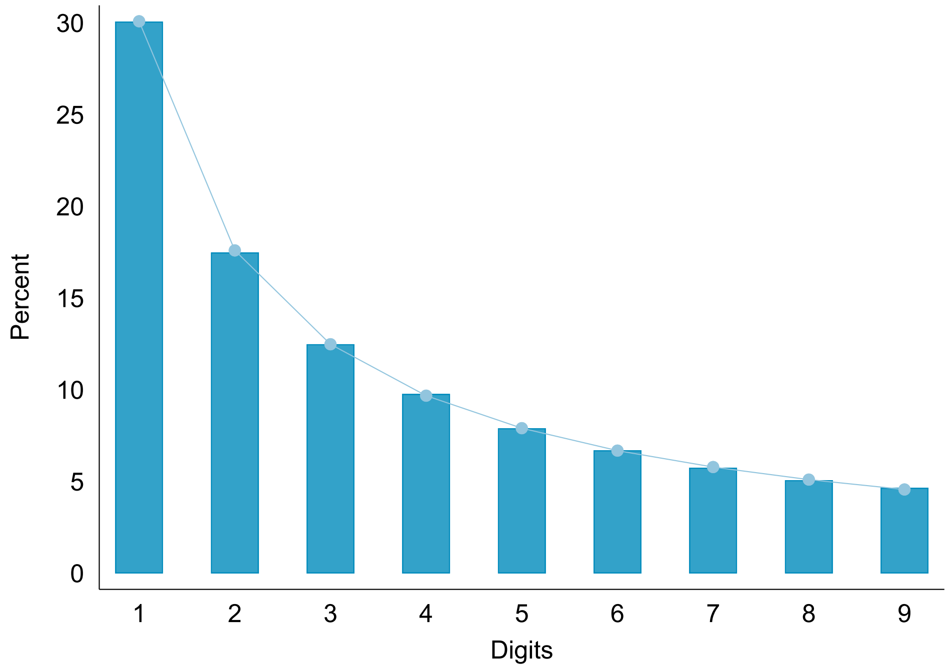
(a) Import gap



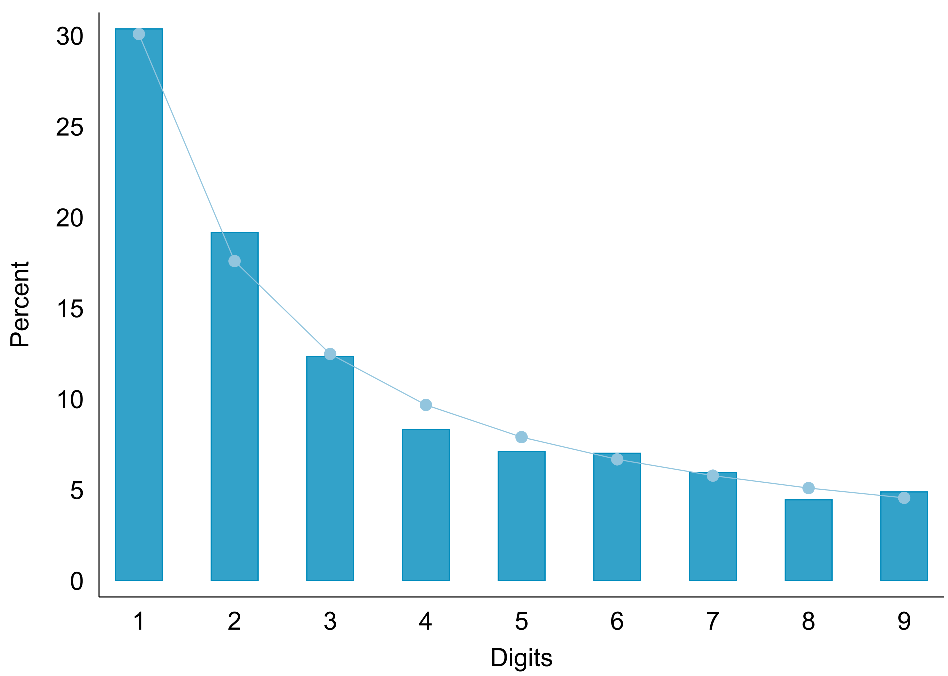
(b) Export gap

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: 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
Changes in anti-corruption	71	1.929	26.831	-74.368	117.604
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 2: 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 3: Robustness checks

	Import gap				Export gap			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$EXS_t(\beta_1)$	-46.611***	-39.896**	-63.355***	-46.319**	-15.412**	-16.502**	-15.283**	-18.339**
	(15.077)	(19.692)	(20.473)	(18.621)	(6.711)	(7.010)	(6.960)	(7.722)
$EXS_t(\beta_2)$	59.750***	41.949**	37.397*	36.065*	16.254	23.566**	39.659***	22.678*
	(13.876)	(18.825)	(20.499)	(20.159)	(10.891)	(9.915)	(14.026)	(11.981)
CID_t	1.164	1.320	0.433	0.225	1.093	1.344	1.634	1.407
	(4.483)	(4.318)	(4.077)	(4.680)	(1.623)	(1.875)	(1.770)	(1.891)
Risk Premium		-5.796	-2.446	-10.137		1.707	-3.090	1.345
		(8.678)	(8.791)	(8.966)		(3.234)	(4.552)	(3.226)
Inflation diff.		7.770*	10.078**	9.691**		-7.259***	-7.383***	-7.799***
		(4.285)	(4.456)	(4.801)		(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				27.136				2.496
				(23.309)				(14.512)
Lnepu				-0.121				-0.045
				(0.128)				(0.062)
Changes in anti-corruption				0.019				0.004
				(0.127)				(0.044)
Trade growth	-15.871	-11.798	-9.523	-10.068	32.010**	34.099**	22.522*	34.809***
	(42.080)	(38.299)	(41.944)	(40.974)	(15.620)	(13.554)	(12.555)	(13.399)
Trend	-0.564**	-0.507	-0.510*	-0.699**	-0.114	-0.184	-0.246**	-0.219*
	(0.254)	(0.365)	(0.308)	(0.331)	(0.097)	(0.117)	(0.114)	(0.113)
Constant	40.643*	26.118	29.542	38.692	31.581***	37.433***	42.852***	43.165***
	(23.385)	(24.953)	(21.887)	(24.082)	(7.961)	(8.573)	(7.505)	(8.016)
Observations	72	72	72	71	72	72	72	71
R-squared	0.191	0.238	0.255	0.234	0.130	0.269	0.362	0.257
Break month	2013m9	2013m9	2013m9	2013m9	2014m2	2014m2	2014m5	2014m2

Note: This table shows the robustness checks for the benchmark threshold regressions. See Table 2 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 4: 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 2 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 5: 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 2 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 6: HS groups based on Benford's law test

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

Table 7: 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 2 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 8: 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 9: 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 2 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., $r_{hk}^{ex}(z)S^{CNH} \neq x_{hk}^{im}(z')$. 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

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

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

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

Thus, if we define $\eta = 2\eta_1$ and $\kappa = \kappa_1 * \left(1 + \frac{r_{hk}^{ex}(z)}{x_{hk}^{im}(z')/S^{CNH}}\right)$, 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.