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

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Abstract

Capital controls prohibit the standard financial market transactions for foreign exchange arbitrage. However, this paper provides novel evidence that firms manipulate international trade data to arbitrage across foreign exchange markets in mainland China and Hong Kong. We develop a model showing that international 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. The above theoretical predictions are supported by the 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. Our findings highlight the challenges to implementing capital controls and may help improve the effectiveness of such policies.

Keywords: Capital control evasion, dual exchange rates, 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 (Rey, 2013).[1] With the new round of quantitative easing by the Fed in 2020 to combat the COVID-19 pandemic and the recent policy reversal in 2022, many countries may again resort to capital controls 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 (Mendoza, 2016; Wei, 2018).[2] Inflating international trade data (often labeled as fake trade in media reports) 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, assessing their costs, and finding solutions

[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.

to mitigate 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.

When official exchange rates diverge from market ones, arbitrage opportunities emerge if agents can evade capital controls.[5] However, 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 offshore-onshore exchange rate spreads frequently existed between these two markets, which incentivized arbitrage activities through fake trade.

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. The trade data overreporting is costly and firms also face the risk of being 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 offshore-onshore RMB exchange rate spread when the spread is positive (negative). At the disaggregated

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

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, 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).[6] 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 trade data gap and the exchange rate spread 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 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 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

[6] Our data only include direct trade between mainland China and Hong Kong. See Section 2.3 for more details.

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 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, 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.[7]

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. By contrast, we find no significant relationship between the spread and trade data gap for the products that fit Benford's law well.

Our empirical findings are robust to various extensions and sensitivity analyses 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 sys-

[7]It is 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.

tematic empirical evidence on how firms fake trade data to evade capital controls for foreign exchange arbitrage. It also complements previous studies on capital control evasion for different purposes and through different channels, for example, Liu et al. (2023) for carry trade through re-imports, Lin et al. (2020) for carry trade through trade of cost-efficient products, Wong (2021) for capital flight through international travel spending, and Biswas et al. (2022) for two-way capital flows through FDI and trade mis-reporting.[8] 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.

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 regression 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

This section briefly describes the institutional background of China's capital controls and the dual exchange rate system, which creates the incentive of dual exchange rate arbitrage between mainland China and Hong Kong through fake trade.

2.1 Capital controls

China maintains tight controls on cross-border portfolio flows, although the country liberalized its current account in the 1990s (Klein, 2012; Chang et al., 2015). According to

[8] 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 the trade in goods. Lin et al. (2020) analyze the response of Chinese micro-level trade data to carry returns, without considering fake trade. Biswas et al. (2022) use a VAR and an ARDL model to study the dynamics of FDI mismatch and trade data discrepancies between China and the U.S., which is different from the present paper.

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 Russia (Chinn and Ito, 2006).[9] The restrictive capital controls in China induce cross-border price discrepancies such as in interest rates and exchange rates and incentivize various evasion activities. 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. Moreover, Agarwal et al. (2019) find 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, while the net E&O was significantly positive between 2000 and 2008 when the RMB was under appreciation pressures, indicating that E&O may represent unaccounted capital flows through capital control evasion, rather than measurement errors.

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). However, the approved quotas in these programs remain very small relative to China's economic size. Moreover, the government usually tightened its capital controls policy when facing large capital outflows and depreciation pressures of the RMB (Wang and Wu, 2021).

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.[10] To maintain the offi-

[9]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).

[10]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.

cial 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 RMB internationalization, China set up an offshore RMB market in Hong Kong in 2010. 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. 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. 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.[11] 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.[12] 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 interventions on Hong Kong's offshore market, to address the concern of the IMF on the spread when it considered including the RMB in its SDR basket in December 2016

[11]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.

[12]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.

(e.g., see Gagnon (2016) and Ba (2019)). It is likely that capital control evasion through fake trade continues to exist after 2016, but it may become difficult to detect such activities when the offshore exchange rate became less market-driven under PBC's interventions.

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 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 the destination (obtained from the CEIC database). Hong Kong reports both total trade data and re-export trade data with mainland China (obtained from the Comtrade database) and direct trade is defined as the difference between these two variables.[13]

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

[13] Note that not all goods are produced and consumed in Hong Kong, even though they are labeled as direct trade. For example, firms in Hong Kong can import goods from mainland China by indicating Hong Kong as the destination, and then export the same goods to other countries after providing some value-added service in Hong Kong.

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.[14] 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.

Previous studies on trade data discrepancies mainly focus on tax and tariff evasions 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), which cannot explain the large monthly fluctuations of trade data gaps between mainland China and Hong Kong as tax and tariff rates change infrequently. In the rest of the paper, we show that the monthly trade data discrepancies are highly correlated with the RMB exchange rate spreads.

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.

[14]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 spreads are unlikely to be highly correlated.

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.[15]

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.[16] 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

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

[16]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.

trade cost in the model.[17] We further assume that the two economies are symmetric, i.e., their total expenditures E and price indices are the same.

Firms have the same productivity in our model so that they charge the same prices and receive the same revenues $r(z) = r$ if there is no trade data manipulation (Krugman, 1979).[18] 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 heterogeneous probabilities of being caught for fake trade. This assumption follows Demir and Javorcik (2020) and is consistent with the anecdotal evidence and news reports that small and new firms are more likely to engage in faking trade, and the trade data of differentiated products without reference prices, such as expensive jewelry, biological technology, and medical equipment, are easier to be manipulated than homogeneous goods (Rauch, 1999; Fisman and Wei, 2004).

3.2 Optimal arbitrage

We assume that the exchange rate spread is exogenous when individual firms choose their optimal arbitrage strategy.[19] 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 $r_{hk}^{ex}(z)$ in the U.S. dollar, while in the mainland firm z reports its imported value as $r_{cn}^{im}(z)$, which inflates the true value by a factor of $1 + \delta^{im}$ with

[17] Our theoretical results do not change qualitatively if we assume the conventional iceberg trade cost.

[18] It is easy to extend our model to heterogeneous firms like Melitz (2003). We did not show explicitly the production of firms in order to focus on firms' arbitrage behavior.

[19] 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.

$\delta^{im} = \frac{r_{cn}^{im}(z) - r_{hk}^{ex}(z)}{r_{hk}^{ex}(z)} > 0$.[20] 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 $x_{hk}^{im}(z)$ in RMB and the export value reported by firm z in mainland China as $x_{cn}^{ex}(z)$, which inflates the true value by a factor of $1 + \delta^{ex}$ with $\delta^{ex} = \frac{x_{cn}^{ex}(z) - x_{hk}^{im}(z)}{x_{hk}^{im}(z)} > 0$. 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:[21]

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

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 $\delta^{im} = \delta^{ex}$. Thus, in the remaining 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, as shown in the online appendix A.1. As a result, the USD-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., $EXS > 0$.[22] 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

[20] 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.

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

[22] We define $EXS = S^{CNH}/S^{CNY} - 1$ so it approximately equals the log difference between the offshore and onshore exchange rates of RMB, consistent with our definition of the dual exchange rate spread in the empirical analysis except the scale factor of 100.

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 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.

Moreover, it is easy to compute the overreporting in aggregated imports:[23]

$$Y^{IMP} \equiv \frac{R_{cn}^{im} - R_{hk}^{ex}}{R_{hk}^{ex}} = \int_0^1 \delta^{im*} dF(\lambda) = \frac{(EXS+\eta)}{\kappa} \int_0^{\mu} F(\lambda) d\lambda, \tag{8}$$

[23]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_{cn}^{im} and R_{hk}^{ex}.

where R_{cn}^{im} denotes mainland reported imports from Hong Kong, and R_{hk}^{ex} denotes Hong Kong reported exports to mainland. 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 $\frac{\partial Y^{IMP}}{\partial EXS} > 0$. 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 (8). 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 exchange spreads in the model: larger spreads 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 textiles, 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.[24] Clearly, given the same exchange rate spread, severity of punishment, and cost sensitivity of fake trade, equation (8) 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.*

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 differentiated goods that

[24]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).

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 probabilities 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. Thus, the reported trade values of those products are less likely to conform to Benford's Law. This approach has two distinct advantages. First, it does not require prior information on which products have a low risk 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.[25] 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.

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 (Hansen, 2000, 2011; Yu and Phillips, 2018). 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.

[25] 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.

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:

$$Y_t = \alpha + \beta_1 EXS_t * I(t <= T) + \beta_2 EXS_t * I(t > T) + X_t\theta + \epsilon_t, \tag{9}$$

where Y_t is the trade data gap between mainland China and Hong Kong (Y_t^{EXP} and Y_t^{IMP}) as defined in Section 2.3. EXS_t is the offshore-onshore RMB-USD exchange rate spread, and its coefficient is allowed to be different in the two regimes. Because the units for the trade data gap and the exchange rate spread are percentage points, thus the coefficients β_1 and β_2 are the elasticities of the trade data gap with respect 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 spreads were largely negative before early 2014 and then became positive afterward. Therefore, we expect that $\beta_1 < 0$ and $\beta_2 > 0$.[26]

We choose time rather than the exchange rate spread as our threshold variable for the following reasons. First, there are several technical issues for using the exchange rate spread as the threshold variable. Unlike arbitrage in financial markets, arbitrage through fake trade may take weeks or even months. As a result, active fake trade activities

[26] Since time is a discrete variable, the threshold date is chosen by grid searching the month that minimizes the sum of squared residuals.

may 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 can make it difficult to detect our theoretical predictions. In addition, the cutoff value for the exchange rate spread may not be zero. For instance, if we assume there is a lower bound (greater than zero) for the probability of getting caught for all firms/products (λ), the size of exchange rate spreads (EXS) has to be large enough for firms to generate a positive optimal overreporting (δ^{im*}) in equation (7) (see the detailed discussion in the online appendix A.2). The uncertainty about the actual value of the threshold of the spread further complicates our empirical estimation. In contrast, 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, which is supported by the data using a set of single break tests. The model with time as the threshold variable can capture this pattern and estimate the breakpoint 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 (9) 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.

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.[27] In this case, the spread may cause capital flight or

[27] 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.

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 of Hamilton and Wu (2014), and by definition, a negative risk premium indicates that the RMB is expected to depreciate. 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 trade. Table 1 provides summary statistics, and the online appendix A.3 provides more details about the variable construction and 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 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.

For magnitude, columns (1) and (4) indicate that one positive (log) percentage point of exchange rate spread in the second subsample period is associated with 46 and 25 (log) percentage points of over-reporting in imports and exports respectively.[28] Although the observed monthly spreads are mostly less than one percentage point, the estimated fake trade activities due to exchange rate arbitrage are economically significant, especially over some periods of large exchange rate spreads, for instance, the second half of

[28] By contrast, one negative (log) percentage point of exchange rate spread in the first subsample period is associated with 47 and 18 (log) percentage points of over-reporting in imports and exports respectively.

2015.[29] 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.[30] This is consistent with Wong (2021) who also finds substantial capital flights through China's service trade with the rest of the world in 2015.[31]

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

[29] 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.

[30] In the second subsample with positive spreads, the estimated amount of fake imports and exports are computed as $(e^{\hat{\beta}_2^{IMP} EXS_t/100} - 1)EXP_t^{HK}(1 + CIF)$ and $(e^{\hat{\beta}_2^{EXP} EXS_t/100} - 1)IMP_t^{HK}/(1 + CIF)$. In the first subsample with negative spreads, the estimated amount of fake imports and exports can be computed similarly.

[31] The estimated size of capital flows through trade in this paper is smaller than the one studied in Wong (2021) through travel (about 110 billion in 2015) as Wong (2021) considers China's service trade with the rest of the world while we only consider mainland China's goods trade with Hong Kong, which is much smaller than China's total service trade. In addition, Wong (2021) considers capital control evasion due to various reasons including those driven by declining economic growth and exchange rate depreciation expectations, while we focus only on foreign exchange arbitrage. Methodologically, Wong (2021) compares the gravity-model predicted travel imports to the actual travel imports to estimate China's illicit capital flows through travel, while we compute capital flows through trade based on the estimated regression model.

overreporting and export under-reporting for speculative capital flight. Note that the 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 (Handley and Limao, 2017; Du et al., 2017). 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 hold up qualitatively in all cases.

Lastly, we also find evidence of exchange rate arbitrage from China's 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 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.[32] 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

Benford's law has been widely used in detecting fraud in accounting, finance, and economic data. Thus, in this section, we test the third theoretical prediction, by employing this method on the Chinese customs trade 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

[32] 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.

fail the BLT should 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.

5.1 Benford's law test

Benford's law predicts that the leading digits follow a particular logarithmic distribution instead of the commonly expected uniform distribution. In particular, the exact distribution for the first digit is: $P(\text{First digit is } d) = log_{10}(1+1/d)$, *for* $d = 1, 2, .., 9$. Moreover, Pearson's Chi-square statistics can be used to test whether the data conform to Benford's law, which is given by: $D^2 = N \sum_{d=1}^{9} (f_d - \hat{f}_d)^2 / f_d \overset{H_0}{\sim} \chi^2(8)$, where $\hat{f}_d$ denotes the observed fraction of leading digit d in our data and f_d denotes the fraction predicted by Benford's law. 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 in accounting and finance. 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.[33] In addition, the sample size of disaggregated trade data usually is

[33] Cerioli et al. (2019) provide a similar argument that international transactions made with different

large, and thus the premise of Benford's law—the central limit theory—is likely to hold. More convincingly, Demir and Javorcik (2020) show that the simulated data from standard international trade models without tax evasion comply with Benford's law. They further find that the BLT is useful in detecting tax evasion in Turkey's import data following an unexpected policy change in importing finance. Please see the brief review of the history of BLT in the online appendix A.4.

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 the country origin of 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.[34] 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.

counterparties may be characterized by different economic processes, and thus trade data may be approximated well by Benford's law.

[34]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.

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.[35]

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.[36] 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

[35] Moreover, the monthly trade data between mainland China and Hong Kong is only available at the HS section level or more aggregated levels.

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

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 the small likelihood of trade data manipulation for those goods.[37] Similarly, Liu et al. (2023) find that products with high 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 (9).

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 afterward. The estimated break months are also the same as our baseline results from the aggregate trade data. By contrast, the

[37] The sample size sometimes matters for Pearson's Chi-square test for Benford's law. Large samples could lead to over-rejection of the null hypothesis, while small samples would lead to a 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 effect of a 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 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.

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).[38] Thus, our findings suggest that the BLTR group of goods is likely to be the vehicle of the fake trade for exchange rate arbitrage. Overall, the difference between the two groups of goods supports Prediction 3 that the relationship between the exchange rate spread and trade data gaps is more significant for the products that have a 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.[39] 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, thus we can directly compare placebo test results 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 become positive afterward. 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

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

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

evidence for the time series relationship between the exchange rate spread and trade data gaps. More importantly, given the same independent variables, the coefficient estimates of the exchange rate spread are very similar between the pseudo BLTR and Non-BLTR groups (compare column (1) with (3) and column (2) with (4)). This pattern is sharply different from our benchmark findings in Table 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 based on the BLT is informative in detecting possible trade data manipulation 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.

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 over-reporting between the two economies. We also show that the products that violate Benford's law may be used as vehicles in the fake trade for foreign exchange arbitrage.

Our study also contributes 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.[40] By contrast, this paper highlights the role of *capital control evasion* by exploring the *time-series* relationship between trade data

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

discrepancies and the exchange rate spread.[41]

Our paper highlights the dilemma faced by policymakers in countries such as China when they design optimal capital control policies.[42] Although China took steps in capital account liberalization, the pace is slow. Liu et al. (2021) find that gradual capital account liberalization is optimal in countries like China with financial repression, under which state-owned enterprises can obtain funding at favorable terms, despite their lower average productivity than private firms. Our study shows that some unintended consequences such as foreign exchange arbitrage through fake trade emerge when China partially liberalizes its capital account. Although our finding suggests that the method such as Benford's law may help to diminish the adverse effects by assisting the customs to detect fake trade, controlling fake trade remains a daunting job for a large importing/exporting country like China. Wei and Zhang (2007) show that measures to control fake trade can substantially increase the real trade costs and discourage international trade. Therefore, China may want to solve the issue of financial repression through reform and move beyond its current optimal transition policy as soon as possible. Note that China may continue to maintain counter-cyclical capital controls to preserve macroeconomic and financial stability even after it fully liberalizes its capital account, as suggested in the recent literature of macroprudential policies. It is interesting in the future to examine if the extent of capital control evasion through fake trade changes over business cycles with the tightness of capital controls. Such studies provide empirical foundations for the design of macroprudential policies under leakages and evasion such as Bengui and Bianchi (2018).

[41] In the online appendix A.5, we discuss the challenges for detecting foreign exchange arbitrage by taking the trade gap between mainland China and the U.S. for example.

[42] 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.

References

Acosta-Henao, Miguel, Laura Alfaro, and Andrés Fernández, "Sticky capital controls," *NBER Working Paper No. 26997*, 2020.

Adams, Charles and Jeremy Greenwood, "Dual exchange rate systems and capital controls: An investigation," *Journal of International Economics*, 1985, *18* (1-2), 43–63.

Agarwal, Isha, Grace Weishi Gu, and Eswar S. Prasad, "China's impact on global financial markets," *NBER Working Paper No. 26311*, 2019.

Aizenman, Joshua, "On the hidden links between financial and trade opening," *Journal of International Money and Finance*, 2008, *27* (3), 372–386.

Alfaro, Laura, Anusha Chari, and Fabio Kanczuk, "The real effects of capital controls: Firm-level evidence from a policy experiment," *Journal of International Economics*, 2017, *108*, 191–210.

Andrews, Donald WK, "Tests for parameter instability and structural change with unknown change point," *Econometrica*, 1993, *61* (4), 821–856.

Ba, Qing, *The Pivotal Force in RMB Internationalization: The Construction of the Offshore RMB Market Mechanism*, City University of Hong Kong Press, 2019.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis, "Measuring economic policy uncertainty," *The Quarterly Journal of Economics*, 07 2016, *131* (4), 1593–1636.

Barabesi, Lucio, Andrea Cerasa, Andrea Cerioli, and Domenico Perrotta, "Goodness-of-fit testing for the Newcomb-Benford law with application to the detection of customs fraud," *Journal of Business & Economic Statistics*, 2018, *36* (2), 346–358.

Benford, Frank, "The law of anomalous numbers," *Proceedings of the American Philosophical Society*, 1938, pp. 551–572.

Bengui, Julien and Javier Bianchi, "Macroprudential policy with leakages," *NBER Working Paper No. 25048*, 2018.

Berger, Arno and Theodore P Hill, *An Introduction to Benford's Law*, Princeton University Press, 2015.

Biswas, Amit K, Jürgen von Hagen, and Sandip Sarkar, "FDI Mismatch, trade Misreporting, and hidden capital Movements: The USA-China case," *Journal of International Money and Finance*, 2022, *120*, 102534.

Caliendo, Lorenzo and Fernando Parro, "Estimates of the trade and welfare effects of NAFTA," *The Review of Economic Studies*, 2015, *82* (1), 1–44.

Cerioli, Andrea, Lucio Barabesi, Andrea Cerasa, Mario Menegatti, and Domenico Perrotta, "Newcomb–Benford law and the detection of frauds in international trade," *Proceedings of the National Academy of Sciences*, 2019, *116* (1), 106–115.

Chang, Chun, Zheng Liu, and Mark M Spiegel, "Capital controls and optimal Chinese monetary policy," *Journal of Monetary Economics*, 2015, *74*, 1–15.

Cheung, Yin-Wong and Dagfinn Rime, "The offshore renminbi exchange rate: Microstructure and links to the onshore market," *Journal of International Money and Finance*, 2014, *49*, 170–189.

_, Sven Steinkamp, and Frank Westermann, "China's capital flight: Pre- and post-crisis experiences," *Journal of International Money and Finance*, 2016, *66*, 88–112.

_, _, and _, "Capital flight to Germany: Two alternative measures," *Journal of International Money and Finance*, 2020, *102*, 102095.

Chinn, Menzie D and Hiro Ito, "What matters for financial development? Capital controls, institutions, and interactions," *Journal of Development Economics*, 2006, *81* (1), 163–192.

Choi, Yeon Soo, Ian Cremer, Melissa Dejong, Chang-Ryung Han, Philip K. Kong, Etim Ibot, Mark Johnson, Frank Kalzinje, Rachel McGauran, Clement Migai, Massimiliano Mora, Jeffrey Owens, Simon J. Pak, Pashupati Pandey, and Matthew Salomon, "Illicit financial flows via trade mis-invoicing," *World Customs Organization Study Report*, 2018.

Davis, Scott J. and Ignacio Presno, "Capital controls and monetary policy autonomy in a small open economy," *Journal of Monetary Economics*, 2017, *85*, 114–130.

Demir, Banu and Beata Javorcik, "Trade policy changes, tax evasion and Benford's law," *Journal of Development Economics*, 2020, *144*, 102456.

Du, Yingxin, Jiandong Ju, Carlos D Ramirez, and Xi Yao, "Bilateral trade and shocks in political relations: Evidence from China and some of its major trading partners, 1990–2013," *Journal of International Economics*, 2017, *108*, 211–225.

Eaton, Jonathan and Samuel Kortum, "Technology, geography, and trade," *Econometrica*, 2002, *70* (5), 1741–1779.

Edison, Hali J and Carmen M. Reinhart, "Stopping hot money," *Journal of Development Economics*, 2001, *66*, 533–553.

Edwards, Sebastian, "How effective are capital controls?," *Journal of Economic Perspectives*, 1999, *13* (4), 65–84.

Farhi, Emmanuel and Ivan Werning, "Dilemma not trilemma? Capital controls and exchange rates with volatile capital flows," *IMF Economic Review*, 2014, *62* (4), 569–605.

Feenstra, Robert C, Wen Hai, Wing T Woo, and Shunli Yao, "Discrepancies in international data: An application to China-Hong Kong entrepôt trade," *American Economic Review*, 1999, *89* (2), 338–343.

Fernández, Andrés, Alessandro Rebucci, and Martín Uribe, "Are capital controls countercyclical?," *Journal of Monetary Economics*, 2015, *76*, 1–14.

__ **, Michael W Klein, Alessandro Rebucci, Martin Schindler, and Martin Uribe**, "Capital control measures: A new dataset," *IMF Economic Review*, 2016, *64* (3), 548–574.

Ferrantino, Michael J, Xuepeng Liu, and Zhi Wang, "Evasion behaviors of exporters and importers: Evidence from the US–China trade data discrepancy," *Journal of International Economics*, 2012, *86* (1), 141–157.

Fisman, Raymond and Shang-Jin Wei, "Tax rates and tax evasion: Evidence from "missing imports" in China," *Journal of Political Economy*, 2004, *112* (2), 471–496.

Forbes, Kristin J., "The microeconomic evidence on capital controls: No free lunch," *NBER Working Paper No. 11372*, 2005.

__ , "One cost of the Chilean capital controls: Increased financial constraints for smaller traded firms," *Journal of International Economics*, 2007, *71*, 294–323.

Forbes, Kristin, Marcel Fratzscher, and Roland Straub, "Capital-flow management measures: What are they good for?," *Journal of International Economics*, 2015, *96* (Supplement 1), S76–S97.

Gagnon, Joseph E., "Renminbi series part 3: A new development in offshore renminbi," *Peterson Institute for Internatoinal Economics Policy Report*, 2016.

Hamilton, James D and Jing Cynthia Wu, "Risk premia in crude oil futures prices," *Journal of International Money and Finance*, 2014, *42*, 9–37.

Handley, Kyle and Nuno Limao, "Policy uncertainty, trade, and welfare: Theory and evidence for China and the United States," *American Economic Review*, 2017, *107* (9), 2731–83.

Hansen, Bruce E, "Sample splitting and threshold estimation," *Econometrica*, 2000, *68* (3), 575–603.

__ , "Threshold autoregression in economics," *Statistics and its Interface*, 2011, *4* (2), 123–127.

Hill, Theodore P, "A statistical derivation of the significant-digit law," *Statistical Science*, 1995, *10* (4), 354–363.

International Monetary Fund, "The liberalization and management of capital flows: An institutional view," *IMF Policy Papers*, 2012.

Javorcik, Beata S and Gaia Narciso, "Differentiated products and evasion of import tariffs," *Journal of International Economics*, 2008, *76* (2), 208–222.

Johnson, Simon and Todd Mitton, "Cronyism and capital controls: Evidence from Malaysia," *Journal of Financial Economics*, 2003, *67* (2), 351–382.

Klein, Michael, "Capital controls: Gates versus walls," *Brookings Papers on Economic Activity*, 2012, *2012* (2), 317–367.

Korinek, Anton, "Regulating capital flows to emerging markets: An externality view," *Journal of International Economics*, 2018, *111*, 61–80.

Kose, Ayhan, Eswar Prasad, Kenneth Rogoff, and Shang-Jin Wei, "Financial globalization: A reappraisal," *NBER Working Paper No. 12484*, 2006.

Krugman, Paul R, "Increasing returns, monopolistic competition, and international trade," *Journal of International Economics*, 1979, *9* (4), 469–479.

Lin, Shu and Haichun Ye, "Foreign direct investment, trade credit, and transmission of global liquidity shocks: Evidence from Chinese manufacturing firms," *Review of Financial Studies*, 2018, *31* (1), 206–238.

_, Jinchuan Xiao, and Haichun Ye, "Disguised carry trade and the transmission of global liquidity shocks: Evidence from China's goods trade data," *Journal of International Money and Finance*, 2020, *104*, 1–17.

Liu, Xuepeng, "Tax avoidance through re-imports: The case of redundant trade," *Journal of Development Economics*, 2013, *104*, 152–164.

_, Heiwai Tang, Zhi Wang, and Shang-Jin Wei, "Currency carry trade by trucks: The curious case of China's massive imports from itself," *Review of Finance*, 2023, *27* (2), 469–493.

Liu, Zheng, Mark M Spiegel, and Jingyi Zhang, "Optimal capital account liberalization in China," *Journal of Monetary Economics*, 2021, *117*, 1041–1061.

Ma, Guonan and Robert N McCauley, "Efficacy of China's capital controls: Evidence from price and flow data," *Pacific Economic Review*, 2008, *13* (1), 104–123.

Melitz, Marc J, "The impact of trade on intra-industry reallocations and aggregate industry productivity," *Econometrica*, 2003, *71* (6), 1695–1725.

Mendoza, Enrique G., "Macroprudential policy: Promise and challenges," *NBER Working Paper No. 22868*, 2016.

Michalski, Tomasz and Gilles Stoltz, "Do countries falsify economic data strategically? Some evidence that they might.," *The Review of Economics and Statistics*, 2013, *95(2)*, 591–616.

Newcomb, Simon, "Note on the frequency of use of the different digits in natural numbers," *American Journal of Mathematics*, 1881, *4* (1), 39–40.

Nigrini, Mark J, *Benford's Law: Applications for Forensic Accounting, Auditing, and Fraud Detection*, Vol. 586, John Wiley & Sons, 2012.

Pitt, Mark M, "Smuggling and price disparity," *Journal of International Economics*, 1981, *11* (4), 447–458.

— , "Smuggling and the black market for foreign exchange," *Journal of International Economics*, 1984, *16* (3-4), 243–257.

Prasad, Eswar, Kenneth Rogoff, Shang-Jin Wei, and Ayhan Kose, "Effects of financial globalization on developing countries: Some empirical evidence," *IMF Occasional Paper No. 220*, 2003.

Rauch, James E, "Networks versus markets in international trade," *Journal of International Economics*, 1999, *48* (1), 7–35.

Rebucci, Alessandro and Chang Ma, "Capital controls: A survey of the new literature," *Oxford Research Encyclopedia of Economics and Finance*, 2020.

Rey, Hélène, "Dilemma not trilemma: The global financial cycle and monetary policy independence," *Jackson Hole Symposium on Economic Policy*, 2013, pp. 284–333.

Rodrik, Dani, "Who needs capital-account convertibility?," in Stanley Fischer, Richard N. Cooper, Rudiger Dornbusch, Peter M. Gabber, Carlos Massad, Jacques J. Polak, Dani Rodrik, and Savak S. Tarapore, eds., *Should the IMF Pursue Capital Account Convertibility?*, Princeton University, 1998, pp. 55–65.

Wang, Jian and Jason Wu, "Is capital flow management effective? Evidence based on US monetary policy shocks," *Journal of International Money and Finance*, 2021, *118*, 102451.

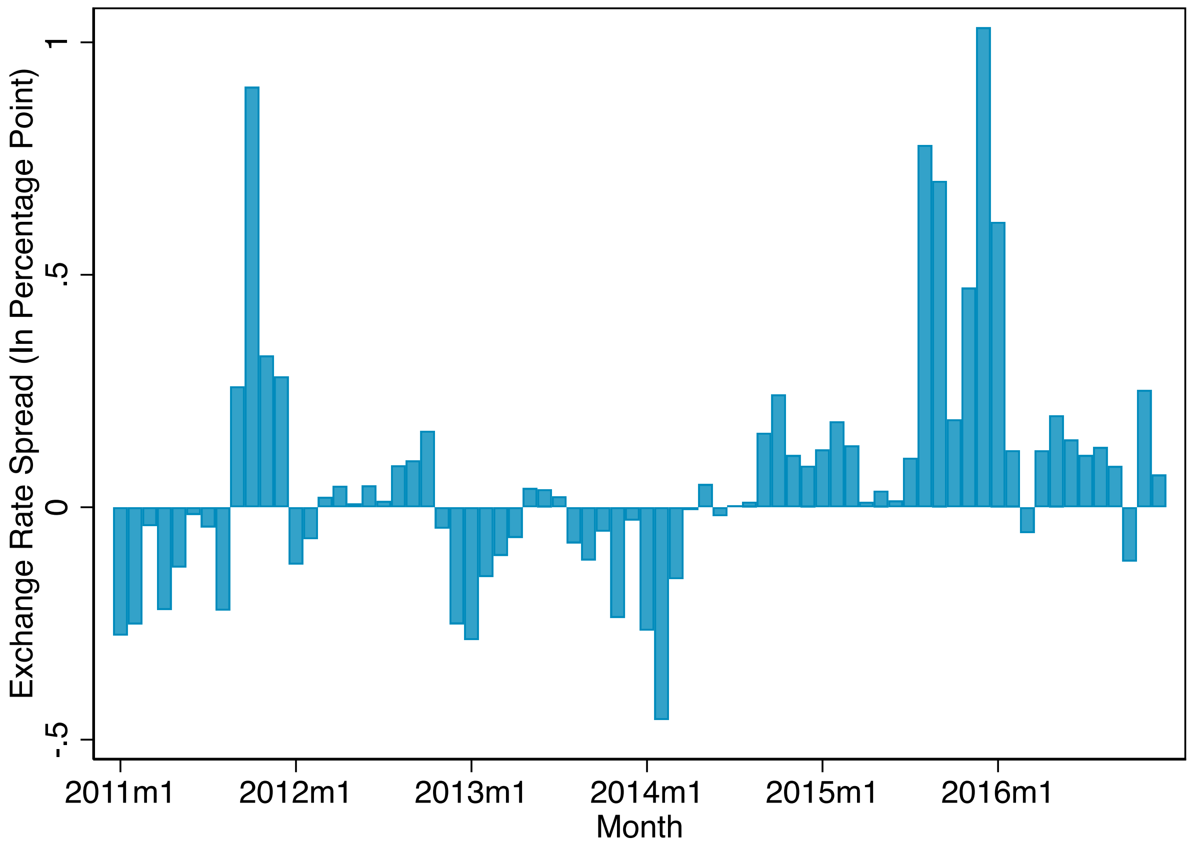
Wei, Shang-Jin, "Managing financial globalization: Insights from the recent literature," *NBER Working Paper No. 12586*, 2018.

— **and Zhiwei Zhang**, "Collateral damage: Exchange controls and international trade," *Journal of International Money and Finance*, 2007, *26* (5), 841–863.

Wong, Anna, "Capital flight: The travel channel," *Journal of International Money and Finance*, 2021, *117*, 102437.

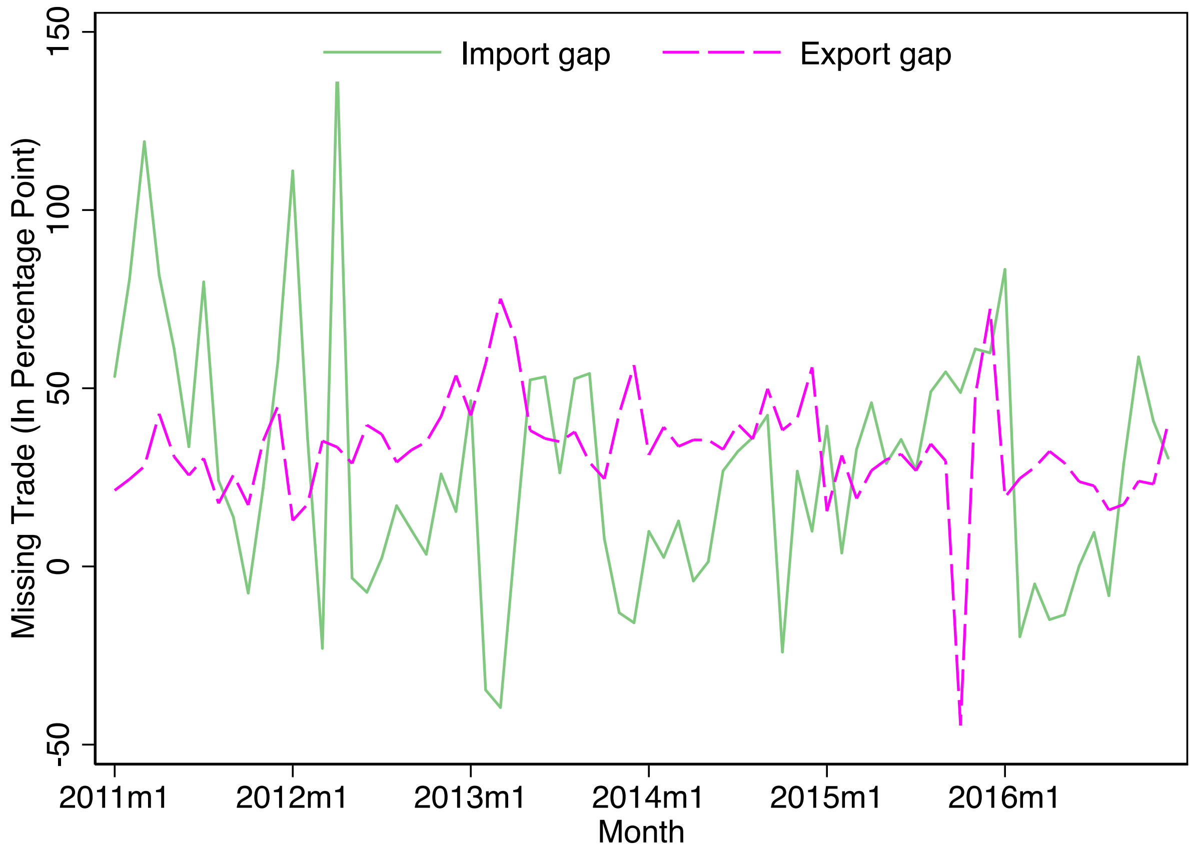
Yang, Dean, "Can enforcement backfire? Crime displacement in the context of customs reform in the Philippines," *The Review of Economics and Statistics*, 2008, *90* (1), 1–14.

Yu, Ping and Peter CB Phillips, "Threshold regression with endogeneity," *Journal of Econometrics*, 2018, *203* (1), 50–68.



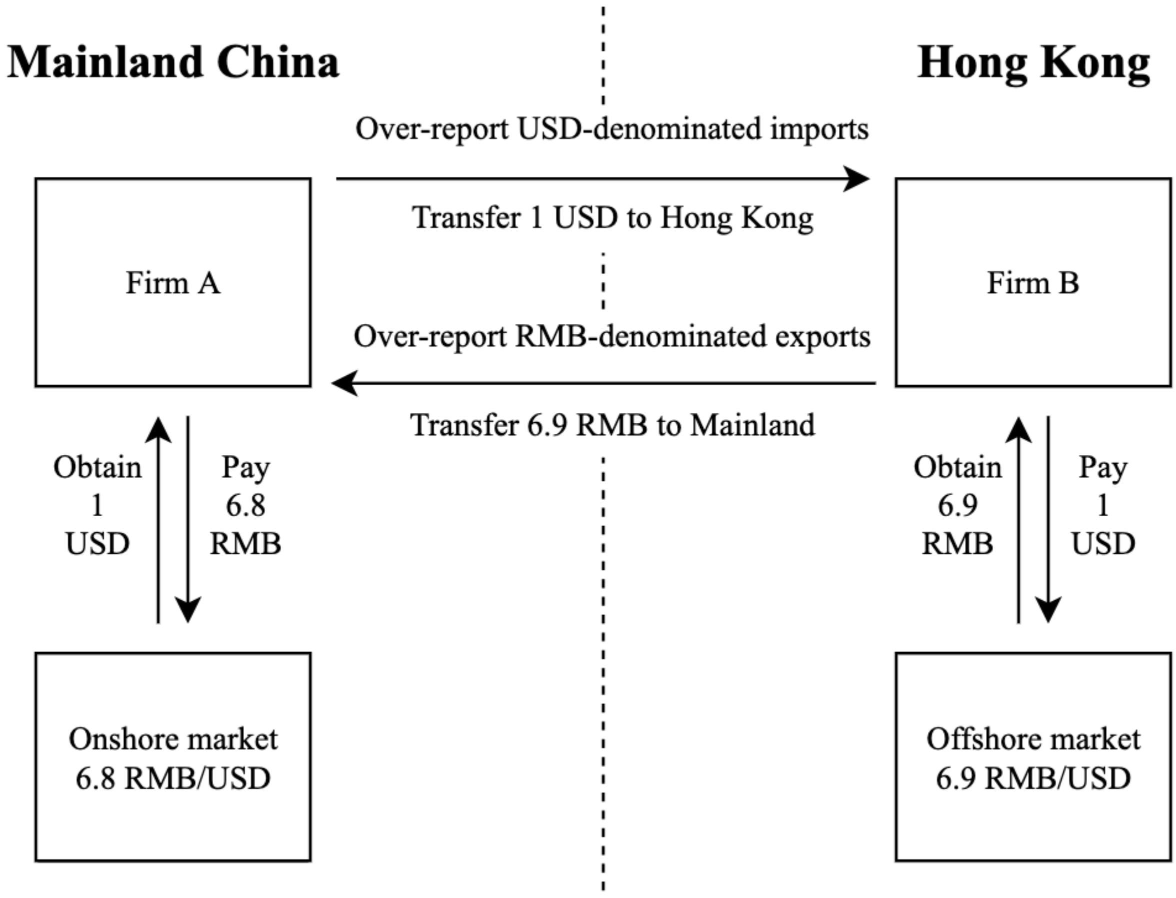
Note: This figure shows the offshore-onshore exchange rate spreads of the RMB-USD. A positive spread indicates that the RMB is more expensive (relative to the USD) in the onshore market than the offshore market.

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



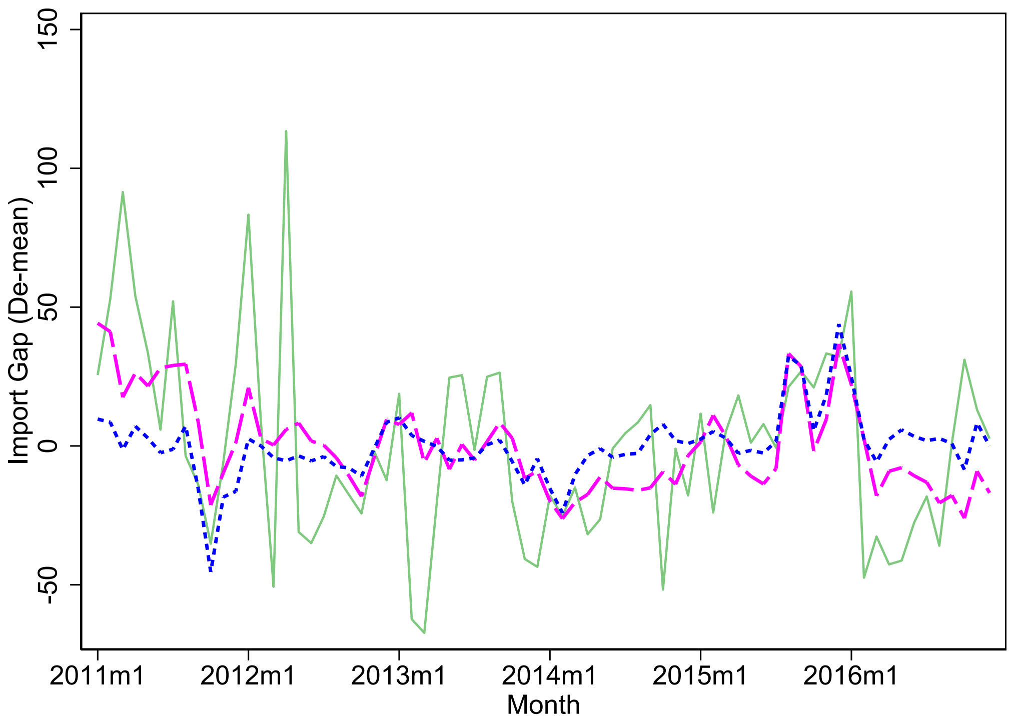
Note: This figure shows the missing trade between mainland China and Hong Kong. The import and export gaps are defined as the (100*) log difference between imports from Hong Kong (or exports to Hong Kong) reported by mainland China and the corresponding ones reported by Hong Kong, adjusted by trade costs.

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

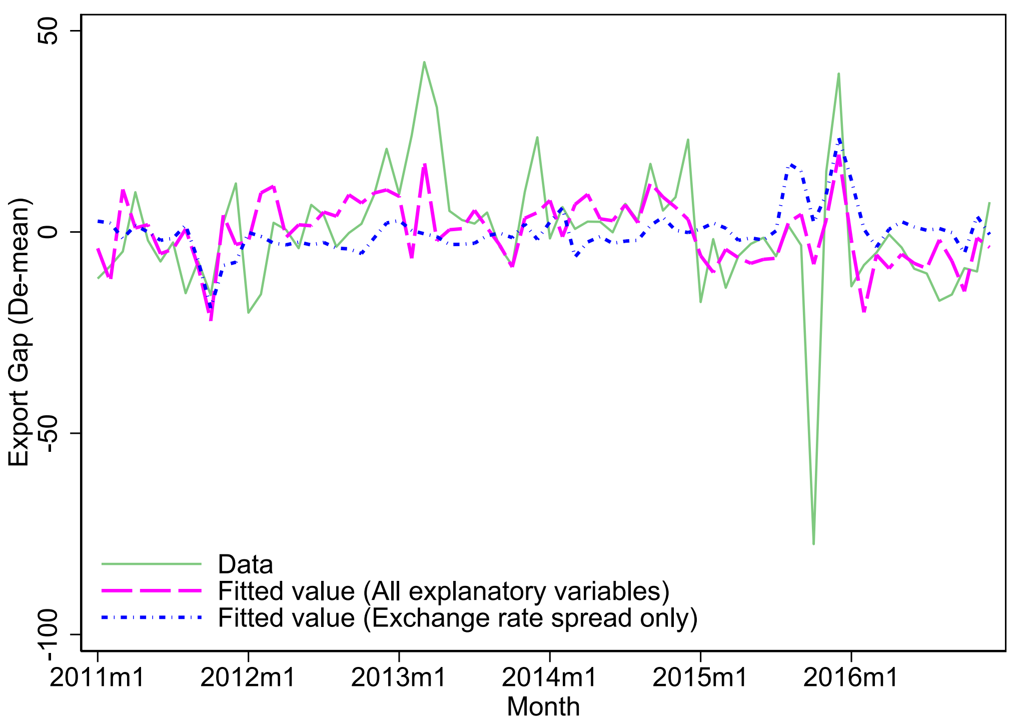


Note: This figure shows an example of the dual exchange rate arbitrage under a positive exchange rate spread. An arbitrager can make profits by buying the USD in mainland China and selling the USD in Hong Kong. The detailed steps of arbitrage can be illustrated as follows: First, convert the RMB into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



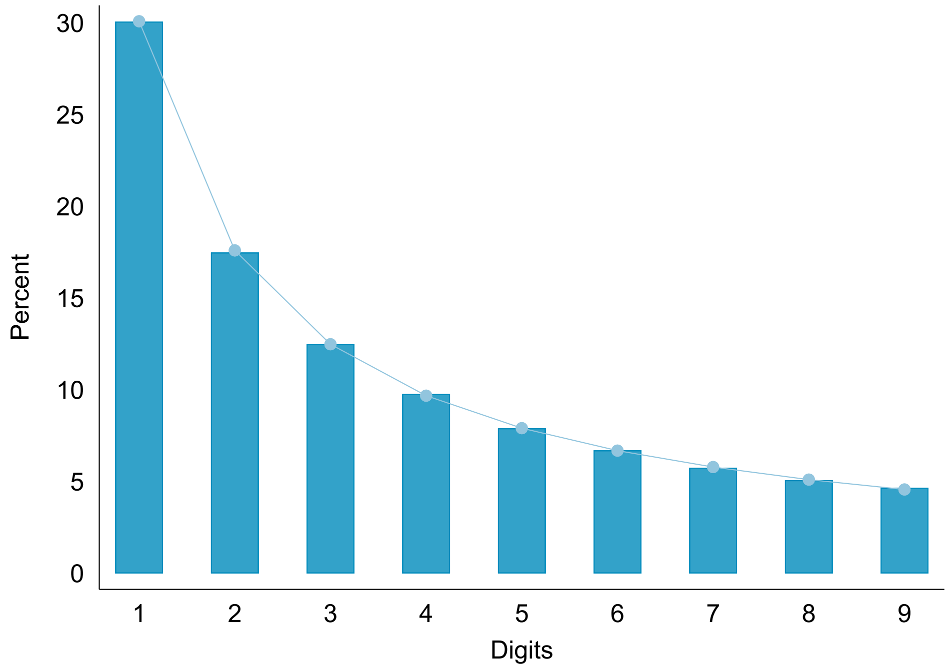
(a) Import gap



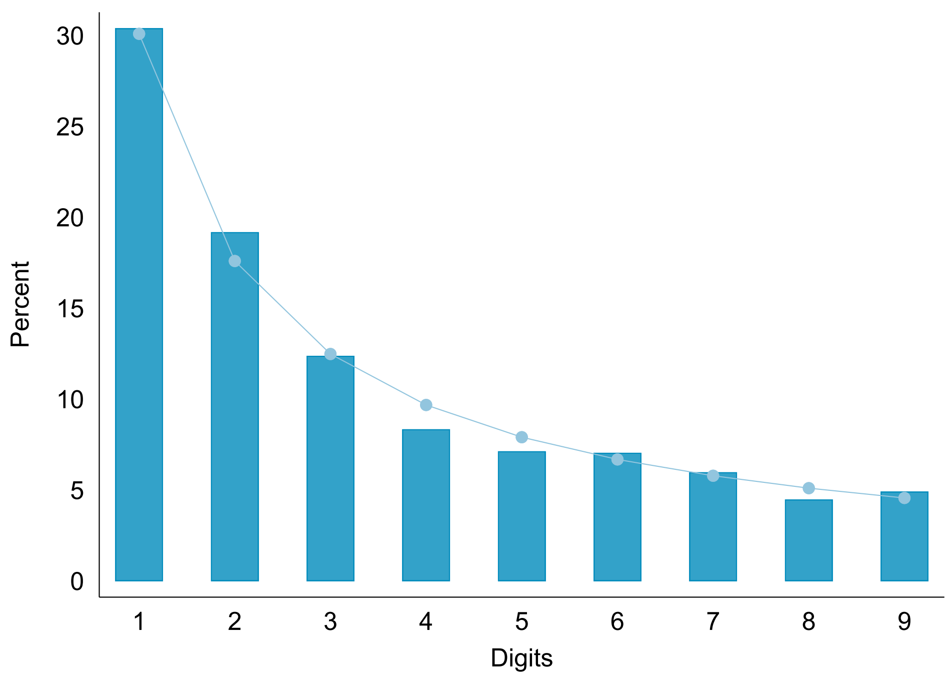
(b) Export gap

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.

Appendix to "Faking Trade for Capital Control Evasion: Evidence from Dual Exchange Rate Arbitrage in China"

For Online Publication

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A.1 Different over-reporting in imports and exports

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

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

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

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

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

A.2 Proof of Equation (8)

In this section, we show the proof for equation (8).

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 are given by:

$$
R^{im}_{cn} = M \int_0^1 (1 + \delta^{im*}) r^{ex}_{hk}(z) dF(\lambda). \tag{A.2.3}
$$

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

$$
R^{im}_{cn} = M r^{ex}_{hk} \int_0^1 (1 + \delta^{im*}) dF(\lambda) = R^{ex}_{hk}\left(1 + \int_0^1 \delta^{im*} dF(\lambda)\right), \tag{A.2.4}
$$

where the true exports from Hong Kong to mainland China $R^{ex}_{hk} \equiv M r^{ex}_{hk}$.

Given that $\lambda \sim F(\lambda)$ and plugging in the optimal solution of δ^{im*}, we get

$$
\begin{aligned}
Y^{IMP} &= \int_0^1 \delta^{im*} dF(\lambda) = \int_0^{\mu} \frac{(1-\lambda)EXS - \lambda\eta}{\kappa} dF(\lambda) \\
&= \frac{1}{\kappa}\int_0^{\mu} (1-\lambda)EXS - \lambda\eta dF(\lambda) = \frac{(EXS+\eta)}{\kappa}\int_0^{\mu}(\mu-\lambda)dF(\lambda) \\
&= \frac{(EXS+\eta)}{\kappa}\left(\int_0^{\mu}\mu dF(\lambda) - \int_0^{\mu}\lambda dF(\lambda)\right) = \frac{(EXS+\eta)}{\kappa}\left(\mu F(\mu) - \int_0^{\mu}\lambda dF(\lambda)\right) \\
&= \frac{(EXS+\eta)}{\kappa}\int_0^{\mu} F(\lambda)d\lambda
\end{aligned}
\tag{A.2.5}
$$

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

$$
\begin{aligned}
Y^{IMP} &= \frac{(EXS+\eta)}{\kappa}\int_0^{\mu}\lambda^{\alpha}d\lambda \\
&= \frac{(EXS+\eta)\mu^{1+\alpha}}{\kappa(1+\alpha)} \\
&= \frac{EXS+\eta}{\kappa(1+\alpha)}\left(\frac{EXS}{EXS+\eta}\right)^{1+\alpha}
\end{aligned}
\tag{A.2.6}
$$

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.

Remarks on $F(\lambda)$: Previously for simplicity we assume the support for λ is the interval $[0, 1]$. This assumption and the equation (7) imply that there always exist some firms with low risks of being caught ($\lambda < \mu$) which will over-report their imports for foreign exchange arbitrage, given a positive exchange rate spread ($EXS > 0$). However, if the lower bound of λ is strictly positive due to the customs' screen and inspection, for example, $\lambda \geq a > 0$, then the spread EXS has to be larger than $a\eta/(1-a)$ to incentivize some firms to engage in fake trade, otherwise no firm will over-report its imports. In this case, the threshold of exchange rate spread is strictly positive.

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. $CID_t = 100 * (r_t - r_t*)/(1 + r_t*) - (F_t - S_t)/S_t)$. Where r_t is the monthly Chinese interbank rate from the CEIC database, r_t* is the monthly USD LIBOR rate from the FRED database, F_t is the one-month RMB non-deliverable forward rate (RMB/USD) from the CEIC database, and S_t is the spot exchange rate (RMB/USD) from the Bloomberg database. We multiply the variable by 100 so the unit is percentage point.

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. 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.

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.

A.4 Benford's Law

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. 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. Michalski and Stoltz (2013) further 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.

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 such as Hill (1988) and Camerer (2003). 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.

Benford's law was initially used as a forensic auditing and accounting tool to detect anomalies in financial data. For example, Nigrini (1996) and Nigrini and Mittermaier (1997) apply BLT to individual taxpayers' data and companies' auditing data, respectively. Because of its usefulness, the BLT now has been included in many popular accounting and auditing software packages (e.g., ACL and CaseWare 2020). Durtschi et al. (2004) provide practical guidance on how to use the BLT to detect data manipulation in accounting.

Recently many economists have started to adopt the BLT to verify the authenticity and reliability of economic data. For example, Michalski and Stoltz (2013) find that countries more vulnerable to capital flow reversals are more likely to misreport their economic data strategically, which is evident from the deviations of their balance of payment data from Benford's law. Rauch et al. (2011) use the BLT to investigate the quality of macroeconomic data relevant to the government deficit criteria reported to Eurostat by the EU member states, and find that data reported by Greece shows the greatest deviation from Benford's law among all euro states, confirming the European Commission's independent allegations of data manipulation by Greece.[1]

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

A.5 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 A.1 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.

Appendix References

Camerer, Colin, *Behavioral Game Theory*, Princeton University Press, 2003.

Durtschi, Cindy, William Hillison, and Carl Pacini, "The effective use of Benford's law to assist in detecting fraud in accounting data," *Journal of Forensic Accounting*, 2004, *5* (1), 17–34.

Hill, Theodore P, "Random-number guessing and the first digit phenomenon," *Psychological Reports*, 1988, *62* (3), 967–971.

Holz, Carsten A, "The quality of China's GDP statistics," *China Economic Review*, 2014, *30*, 309–338.

Huang, Yasheng, Zhiyong Niu, and Clair Yang, "Testing firm-level data quality in China against Benford's Law," *Economics Letters*, 2020, *192*, 109182.

Judge, George and Laura Schechter, "Detecting problems in survey data using Benford's law," *Journal of Human Resources*, 2009, *44(1)*, 1–24.

Nigrini, Mark J, "A taxpayer compliance application of Benford's law," *Journal of the American Taxation Association*, 1996, *18* (1), 72.

_ **and Linda J Mittermaier**, "The use of Benford's law as an aid in analytical procedures," *Auditing*, 1997, *16* (2), 52.

Rauch, Bernhard, Max Göttsche, Stefan Engel, and Gernot Brähler, "Fact and fiction in EU-governmental economic data," *German Economic Review*, 2011, *12* (3), 243–255.

Table A.1: 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.