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Impacts of exchange rate fluctuations on imports and domestic economy in Rwanda

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1 Executive Summary

- In this project, we explore how exchange rate fluctuations affect firms' import and domestic activities.
- Our analysis takes advantage of the transaction-level Customs data and the newly available Electronic Billing Machines (EBM) data, which covers the universe of the firm-to-firm and firm-to-consumer transactions by VAT registered firms in Rwanda.
- Using the Customs data, we find that exchange rate fluctuations significantly affect import prices, with an elasticity of 0.1 to 0.4 depending on the price measure used. Currency depreciation also reduces the quantity of imports. In terms of heterogeneity, small firms and firms importing intermediate goods appear to be affected more (i.e. experience higher pass-through). On the extensive margins, we document suggestive evidence that firms may reduce the number of products they import and the number of countries they source from in response to currency depreciation, and some degree of substitution may happen across the origin countries.
- Using the EBM data, we find evidence of import substitution, i.e., importers increase domestic purchases in response to an increase in exchange rate. We also find limited pass-through of exchange rate shocks to domestic buyers of importers. There are no impacts of exchange rate fluctuations on domestic sales prices. This is partly because of the import substitution as indicated above. We find that large firms, and firms in commerce industries, are less affected by the exchange rate shocks. Lastly, we do not find significant impacts on the markups.
- One important policy takeaway of this study is that we find limited pass-through to domestic prices. This happens both on the margin of import prices, as well as domestic sales prices charged by importers. In other words, a weaker Rwandan Franc is not necessarily leading to higher domestic prices that Rwandan consumers face.

2 Introduction

In recent years, the Rwandan Franc (RWF) has depreciated significantly against a wide basket of currencies (NBR 2018): in the most recent fiscal year 2017/18, the RWF experienced a depreciation of 3.6% against the US Dollar, 5.5% against the Euro, and 4.4% against the GB Pound Sterling. With respect to regional currencies, the RWF depreciated against the Kenyan Shilling, Tanzanian Shilling and Burundian Franc by 6.3%, 1.7%, and 1.5%, respectively. The RWF shows a similar pattern of depreciation in the previous fiscal years (NBR 2016, 2017). The current account deficit, largely driven by the trade deficit, is accounted as the main driver of this nominal depreciation (World Bank Group, 2019).

Given this recent extended period of depreciation of the RWF, an important question from the policy perspective of the National Bank of Rwanda (NBR) is the extent to which this has affected import activity as well domestic activity of firms in Rwanda. We would expect such a nominal depreciation to lead to an increase in import prices in RWF terms, which would affect firms' importing behavior. This may propagate to the domestic economy through importers' domestic sales and purchasing decisions.

This report provides an empirical investigation of this question by studying the impacts of exchange rate fluctuations on import volume and prices, as well as importers' domestic activity and prices. To do so, we mainly utilize two data sets in Rwanda: (1) the Customs data that records the universe of import transactions by Rwandan firms, and (2) the EBM (Electronic Billing Machines) data, which records the item-level firm-to-firm and firm-to-consumer transactions by VAT-registered firms in Rwanda. The latter is a particularly unique data set that can potentially provide new insights on exchange-rate pass-through. In Rwanda, VAT-registered businesses are mandated to submit itemized receipts of all of their sales through Electronic Billing Machines (EBMs). The itemized price information contained in the EBM receipts can be a potentially useful data source to guide monetary and exchange rate policies. For our purpose, the micro-data sheds lights on the heterogeneity of firm-level responses to nominal exchange rates shocks, which the previous studies relying on macro-level data cannot have not been able to address.

Our results are summarized as follows: we document an exchange-rate pass-through to import prices of 10% to 40 % depending on the price measure used and depending on whether we use exchange rates based on the country of import origin or invoice currency. Further exploring the richness of the micro-level data, we document various heterogeneity patterns across time periods, sectors and firms. In particular, we find that small firms and firms importing intermediate goods appear to be affected more (i.e. experience higher pass-through) by exchange rate shocks. The results on high-frequency versus low-frequency importers are mixed, depending on how we define the frequency measure. We have also examined whether the impact of exchange rate fluctuations are different across different periods and did not find much evidence on that. Finally, on the extensive margins, we document suggestive evidence that firms reduce the number of products they import and the number of countries they source from in response to currency depreciation, and some degree of substitution may happen across the origin countries.

We then study importers' domestic purchases and sales, as well as their domestic prices, using the aforementioned EBM data. There are mainly two takeaways from this exercise. First, we find that importers respond by imperfectly substituting to domestic purchases as a response to the exchange rate fluctuations: importers that are more strongly hit by exchange rate shocks reduce import expenditures more, and in compensation, increase domestic purchases more. However, this substitution is imperfect - for one percentage point reduction of import expenditure, the domestic purchase increases by about 0.3 percentage points. Second, the pass-through of exchange rate fluctuations to importers' buyers are limited. There are no impacts of exchange rate fluctuations on sales prices. This is partly because of the import substitution as indicated above. We do not find impacts on the markups. Third, we find that large firms, and firms in commerce industries, are less affected by the exchange-rates fluctuations. Together, the results suggest that importers act as a "shock absorber" in mediating the pass-through of exchange rate fluctuations to the domestic economy and downstream consumers.

The remaining part of this report is organized as follows. Section 3 provides summary statistics of the Customs data and the EBM data. Section 4 reports the impacts of exchange rates fluctuations on importers' import revenue, quantity and prices. Section 5 analyzes the impacts of exchange rate fluctuations on domestic sales and purchases, as well as domestic prices. Section 6 concludes.

2.1 Policy Implications

The first and foremost policy relevance of this project is to provide a comprehensive understanding of the implication of the devaluation of Rwandan Franc on import and domestic prices. Some argue that the depreciation of Rwandan Franc has lead to the increase of domestic prices, while others argue that there are no substantial impacts on consumer prices because firms can effectively substitute to domestic intermediate goods suppliers. Which of these arguments are close to reality is ultimately an empirical question. Our results show that the later is the case.

Beyond the implication of the devaluation, this project provides evidence of strong substitution by Rwandan firms between domestic and foreign inputs. This finding suggests that there is a large scope for import substitution policies (e.g. Made-in-Rwanda Initiative).

Lastly, our analysis provides a first case of effectively using EBM data set for policy analysis. Throughout this process, we have done substantial cleaning of EBM data set, which is useful for other future policy analysis.

In this section, we describe the two main data sets used in the analysis, namely the Customs Database and the Electronic Billing Machines (EBM) Data.

3 Data Description

3.1 Customs Data

The customs data contains the universe of import and export transactions in Rwanda from 2008 to 2018. For the purpose of this project, we focus on imports. For each import transaction over this period, the data reports the importing firm (TIN), date of transaction, the type of product (including its HS classifications), country of origin, the value of the transaction (CIF amount), the net weight of the transaction, the product quantity and units, the number of packages, the invoice currency of the transaction, the exchange rate recorded at the time of the transaction, among many other variables. The information for origin country and invoice currency are missing for the early years of 2008 to 2011.[1] Therefore, for most of our regression analysis, we focus on the period of 2012 to 2018. Our final analysis data set contains 2,551,085 import transactions of 53,214 firms from 207 countries, spanning 4,929 HS 6-digit product sectors.[2]

Figure 1 plots the overall growth of imports (measured in CIF amount) from 2008 to 2018, aggregated at the monthly level.

Figure 2 and 3 plot the top importing origin country and top invoice currency by import value share, aggregated across all years from 2012 to 2018. Figure 4 plots the top import sector during the same period, either by the share of total import value or the share of total number of import transactions.

The Customs data also contains an internal sector classification of every imported transaction: capital and raw materials, finished goods, intermediate goods and sensitive goods.[3] They constitute 36%, 40%, 10% and 14% of the total import revenue during the period of 2012 to 2018 respectively.

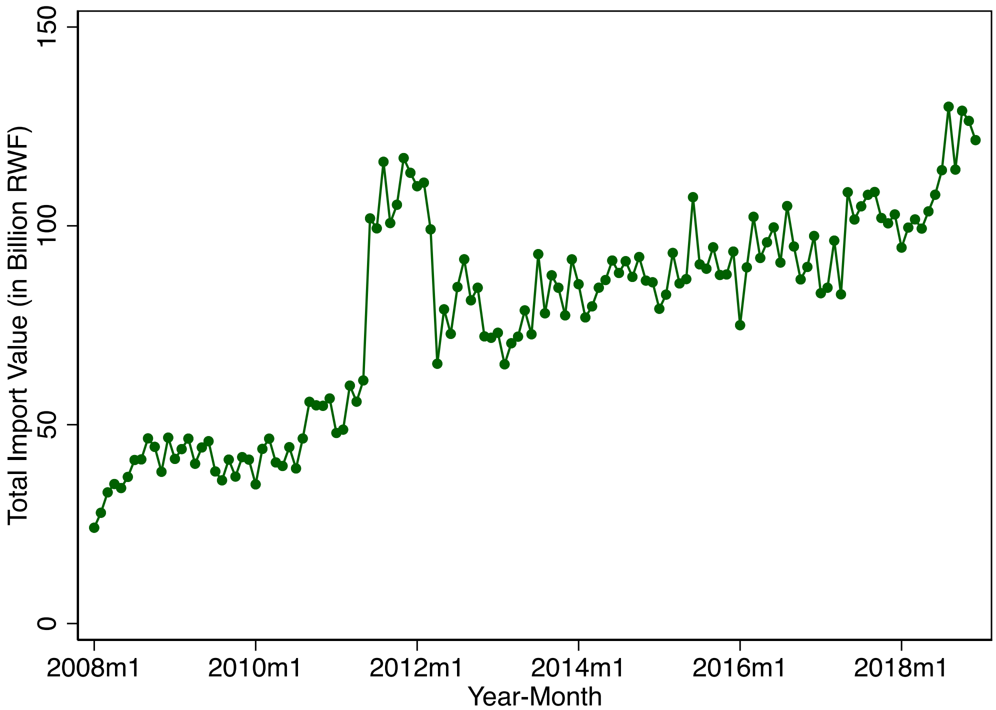
Figures 5, 6 and 7 examine the time trends of import growth by sector, country and currency to shed light on the drivers of import growth. We can see that imports of mineral products and machinery/electrical products contribute most significantly to the overall import growth after 2012. Among all major importing countries, imports from China grow the fastest from 2011 to 2018. Finally, most of the imports are denominated by US dollars.

[1] For the early years of the Customs data (2008-2011), the observations for the two variables origin_country_code and invoice_currency mostly appear as "NA" (100% in 2008, 2009 and 2019; close to 80% in 2011). The fraction of "NA" significantly decreased after 2011. (Note that for origin country, "NA" may stand for "Not applicable (missing)" or "Namibia". We cannot separate the two cases in the data.) Therefore, we focus on the later period of 2012 to 2018 for our main import analysis. We use the early periods to construct various baseline characteristics for the heterogeneity analysis.

[2] From the raw data, we performed a series of data cleaning steps: first, we cleaned the product codes and kept only import transactions; second, we merged in the exchange rate information by invoice currency and origin country currency (as a result, the early years were excluded from the analysis – see the above footnote). Finally, we winsorized the outliers (i.e. top bottom 1%) for import value, quantity and price variables.

[3] Note that these classifications do not perfectly align with the HS classification: in particular, the same HS 6-digit or 8-digit product can be classified into different categories. In particular, the four internal categories are all based on the "purpose of use" of the imported goods in a given importer's production process (e.g. raw materials or intermediate goods) rather than the nature of the goods themselves. Sensitive goods is a list of products classified by the East Africa Customs Union for each member country-year that are subject to specific import and tariff treatments. For Rwanda, the list spans all major HS 2-digit sectors.

Figure 1: Monthly Import Growth (2008-2018)



To further leverage the micro data at transaction level, we zoom into patterns of imports by country-sector and examine how that may evolve over time. For this, we focus on the top 3 importing countries, namely China, Uganda and India. Figures 8, 9 and 10 present the total import value in the top 6 sectors for each country-year. We make several remarks: the major importing products for a given country remain quite stable over time while the specific amounts and rankings may fluctuate. For China, the top importing country, we see steep growth of imports of machinery and electrical products between 2011 and 2018. Imports of textiles have also grown, so do the imports of vehicles.

Finally, in Figures 11 and 12, we plot the time-series movements of total imports from a given origin country or a given currency along with the movement in nominal exchange rate, either at the monthly level or yearly level. Again we focus on the top 3 importing countries and invoice currencies. Overall, we see that the years from 2011 to 2018 experience a steady growth in imports and gradual depreciation of the RWF. However, we do not see salient patterns of positive or negative co-movement between the import value and the exchange rate. This is consistent with the findings in Section 4 as the impact of exchange rate on import value is theoretically ambiguous due to the countervailing effects on price and quantity (see Table 3). The overall time series patterns also mask heterogeneity across firms and sectors, which we delve into in Section 4.2.

Figure 2: Top Importing Country (2012-2018)

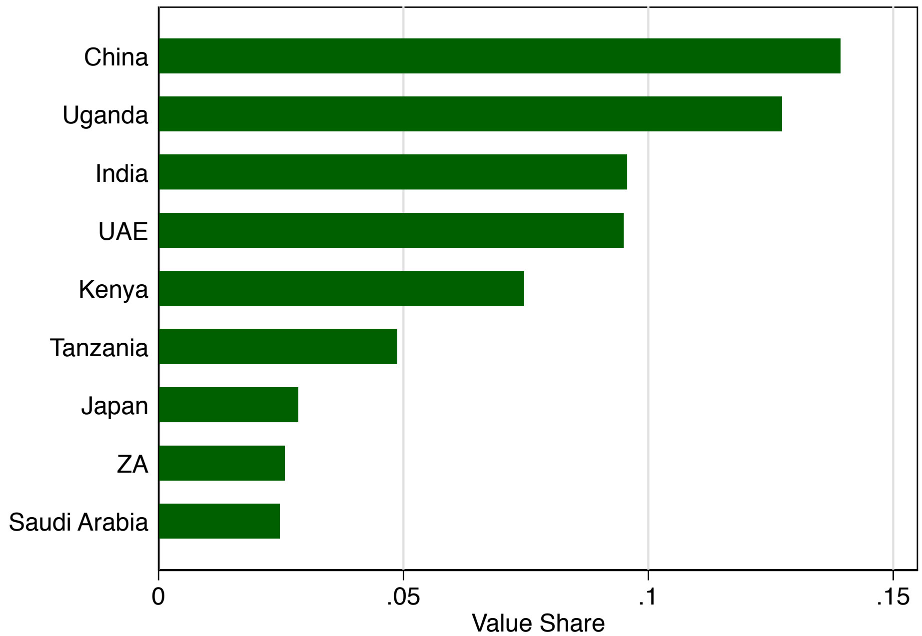


Figure 3: Top Currencies (2012-2018)

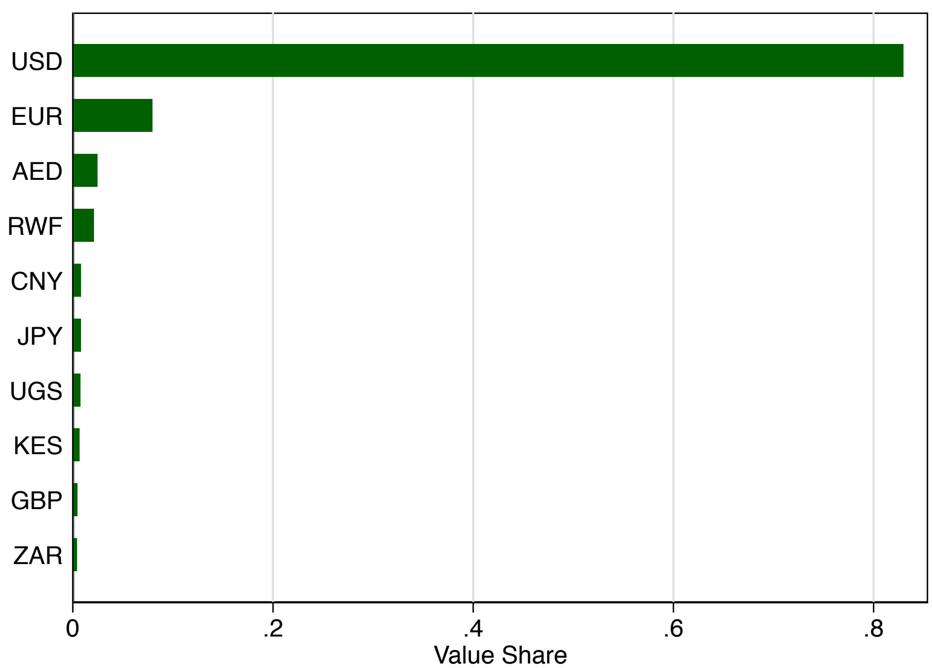
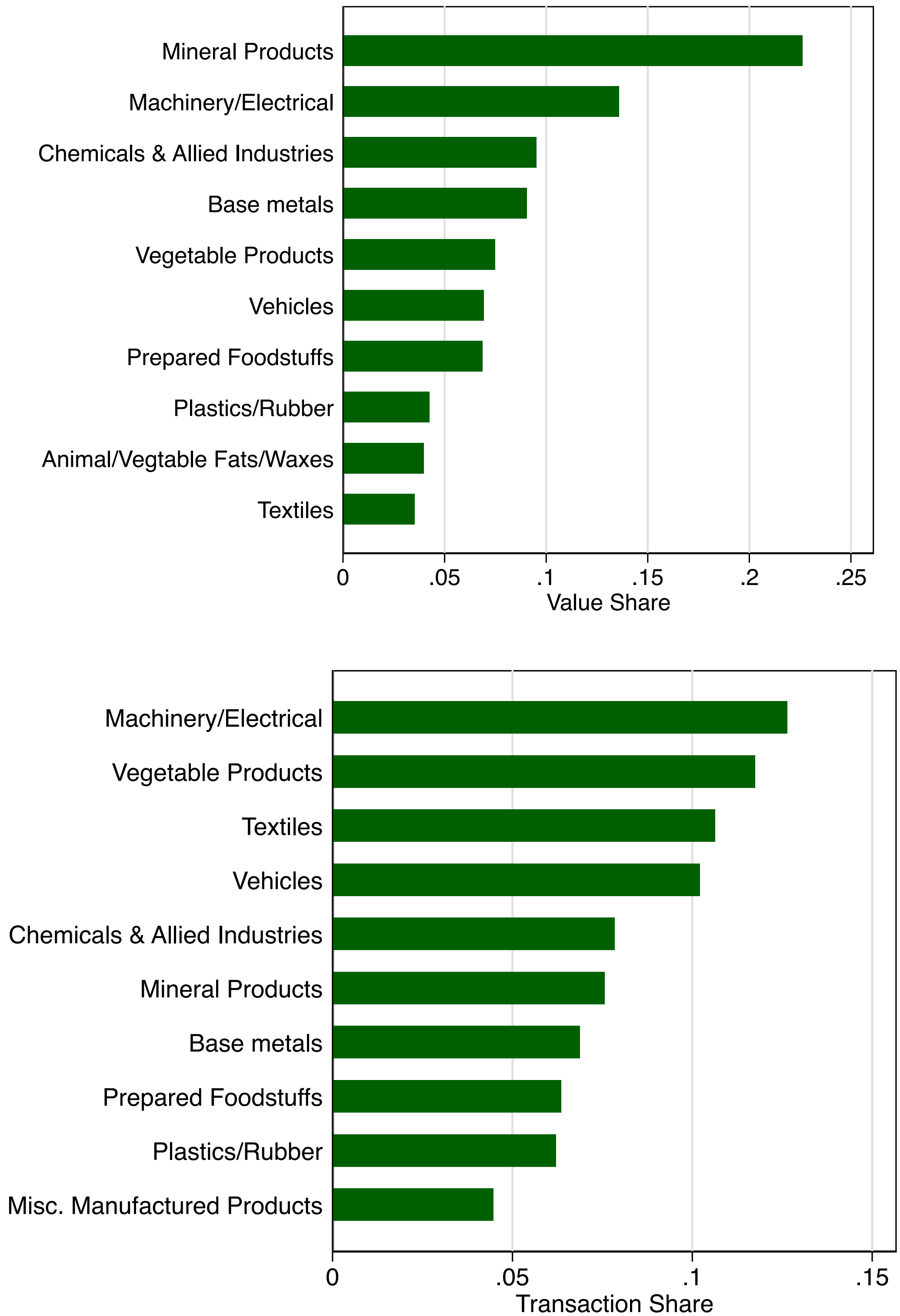


Figure 4: Top Importing Sectors (2012-2018)



Note: Prepared foodstuffs include beverages and tobacco.

Figure 5: Monthly Import Growth by Sector (2008-2018)

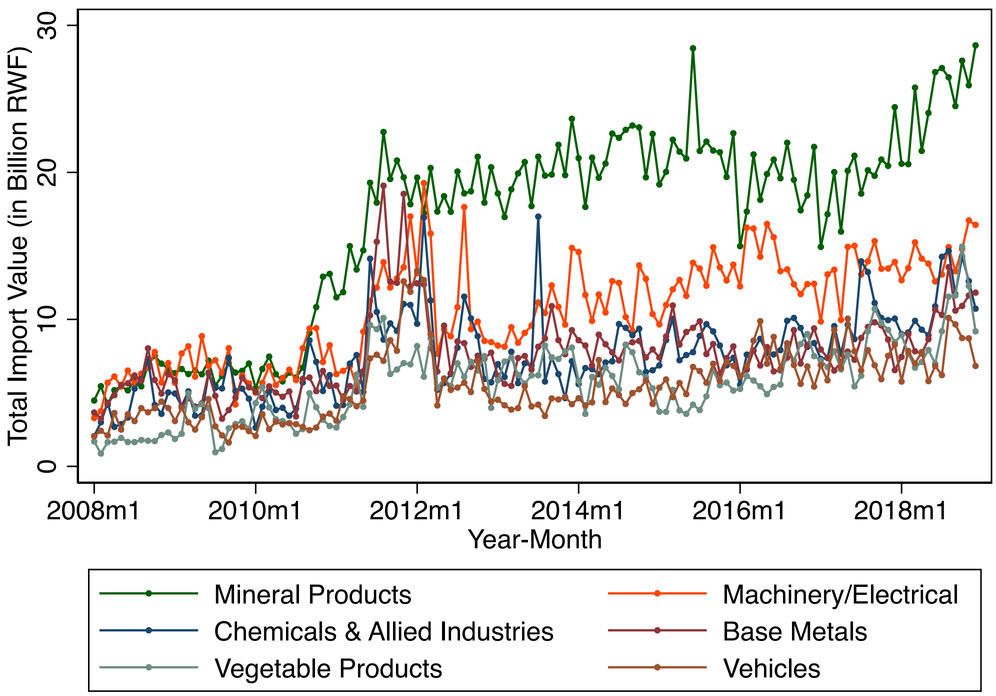


Figure 6: Monthly Import Growth by Country (2008-2018)

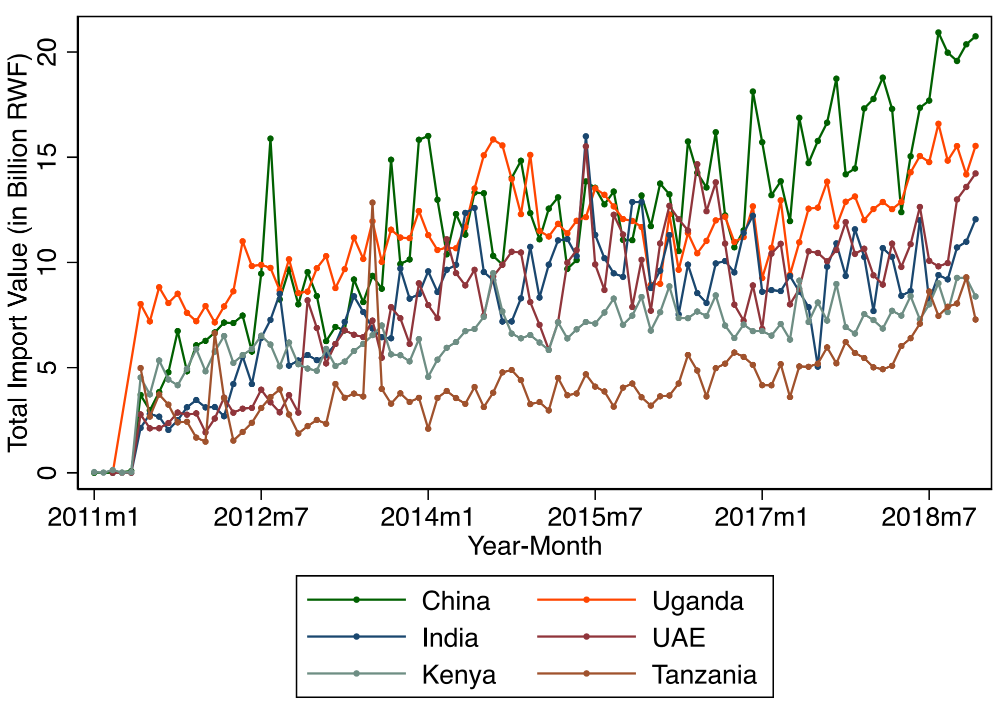


Figure 7: Monthly Import Growth by Currency (2008-2018)

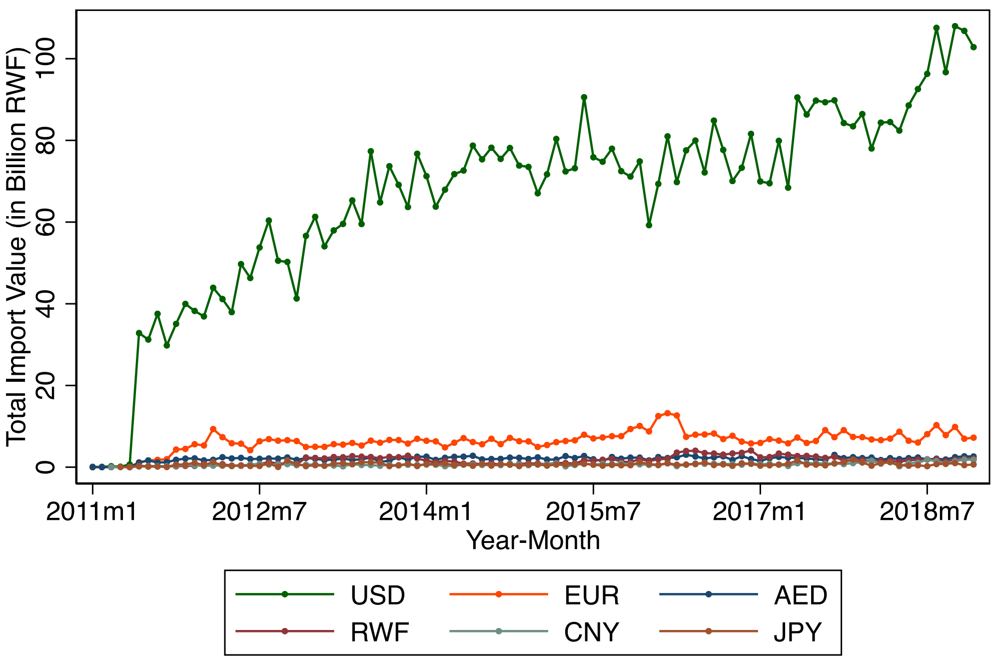
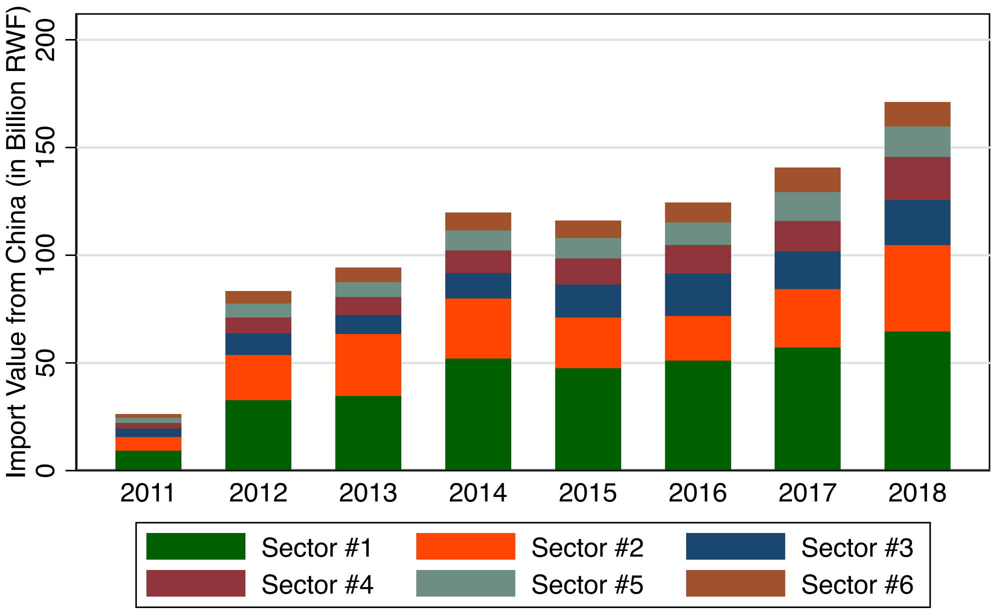
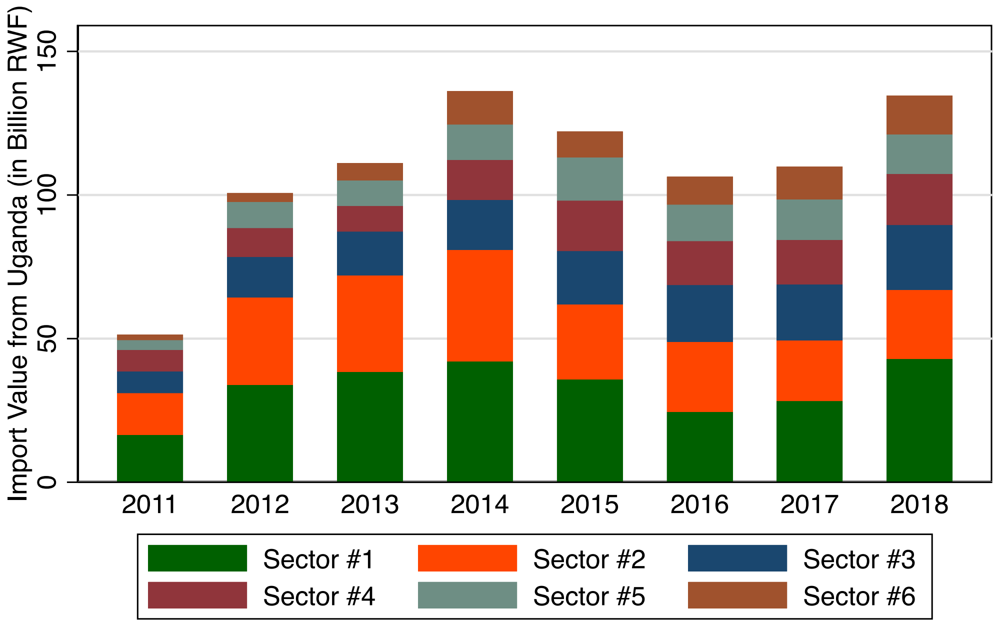


Figure 8: Import Composition by Sector, China (2011-2018)



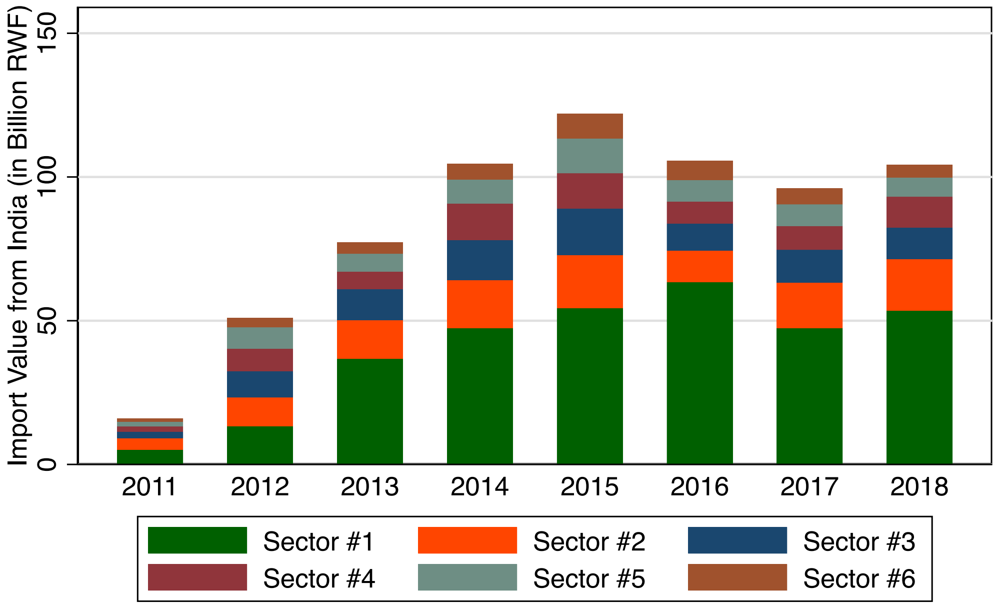
Note: Top sectors in 2011-2 (in order): (1) machinery/electrical, (2) base metals, (3) textile, (4) plastics/rubber, (5) chemicals and allied industries, and (6) stone, cement, ceramics and glass. Top sectors in 2013: (1) machinery/electrical, (2) base metals, (3) textile, (4) plastics/rubber, (5) stone, cement, ceramics and glass, and (6) miscellaneous manufactured. Top sectors in 2014-5: (1) machinery/electrical, (2) base metals, (3) textile, (4) plastics/rubber, (5) stone, cement, ceramics and glass, and (6) chemicals and allied industries. Top sectors in 2016: (1) machinery/electrical, (2) base metals, (3) textile, (4) plastics/rubber, (5) stone, cement, ceramics and glass, and (6) vehicles. Top sectors in 2017: (1) machinery/electrical, (2) base metals, (3) textile, (4) plastics/rubber, 5) vehicles, and (6) stone, cement, ceramics and glass. Top sectors in 2018: (1) machinery/electrical, (2) base metals, (3) textile, (4) plastics/rubber, 5) vehicles, and (6) miscellaneous manufactured.

Figure 9: Import Composition by Sector, Uganda (2011-2018)



Note: Top sectors in 2011 (in order): (1) animal/vegetable fats/waxes, (2) mineral products, (3) base metals, (4) chemicals and allied industries, (5) prepared foodstuffs, and (6) wood pulp/paper. Top sectors in 2012 (in order): (1) animal/vegetable fats/waxes, (2) mineral products, (3) chemicals and allied industries, (4) prepared foodstuffs, (5) base metals, and (6) wood pulp/paper. Top sectors in 2013 (in order): (1) mineral products, (2) animal/vegetable fats/waxes, (3) chemicals and allied industries, (4) vegetable products, (5) base metals, and (6) prepared foodstuffs. Top sectors in 2014 (in order): (1) mineral products, (2) animal/vegetable fats/waxes, (3) chemicals and allied industries, (4) base metals, (5) prepared foodstuffs, and (6) vegetable products. Top sectors in 2015 (in order): (1) mineral products, (2) animal/vegetable fats/waxes, (3) chemicals and allied industries, (4) vegetable products, (5) base metals, (6) animals and animal products. Top sectors in 2016 (in order): (1) vegetable products, (2) mineral products, (3) chemicals and allied industries, (4) animal/vegetable fats/waxes, (5) base metals, (6) animals and animal products. Top sectors in 2017 (in order): (1) vegetable products, (2) chemicals and allied industries, (3) base metals, (4) mineral products, (5) animal/vegetable fats/waxes, (6) animals and animal products. Top sectors in 2018 (in order): (1) vegetable products, (2) base metals, (3) chemicals and allied industries, (4) mineral products, (5) animal/vegetable fats/waxes, (6) animals and animal products.

Figure 10: Import Composition by Sector, India (2011-2018)



Note: Top sectors in 2011 (in order): (1) base metals, (2) vehicles, (3) machinery/electrical, (4) plastics/rubber, (5) chemicals and allied industries, (6) wood pulp/paper. Top sectors in 2012 (in order): (1) base metals, (2) prepared foodstuffs, (3) machinery/electrical, (4) vehicles, (5) chemicals and allied industries, (6) plastics/rubber. Top sectors in 2013 (in order): (1) mineral products, (2) base metals, (3) machinery/electrical, (4) chemicals and allied industries, (5) vehicles, (6) prepared foodstuffs. Top sectors in 2014-5 (in order): (1) mineral products, (2) prepared foodstuffs, (3) base metals, (4) machinery/electrical, (5) chemicals and allied industries, (6) vehicles. Top sectors in 2016 and 2018 (in order): (1) mineral products, (2) chemicals and allied industries, (3) machinery/electrical, (4) vehicles, (5) base metals, (6) prepared foodstuffs. Top sectors in 2017 (in order): (1) mineral products, (2) chemicals and allied industries, (3) machinery/electrical, (4) base metals, (5) vehicles, (6) prepared foodstuffs.

Figure 11: Time-series Patterns of Import Growth and Exchange Rate (2011-2018)
Top importing countries: China, Uganda and India

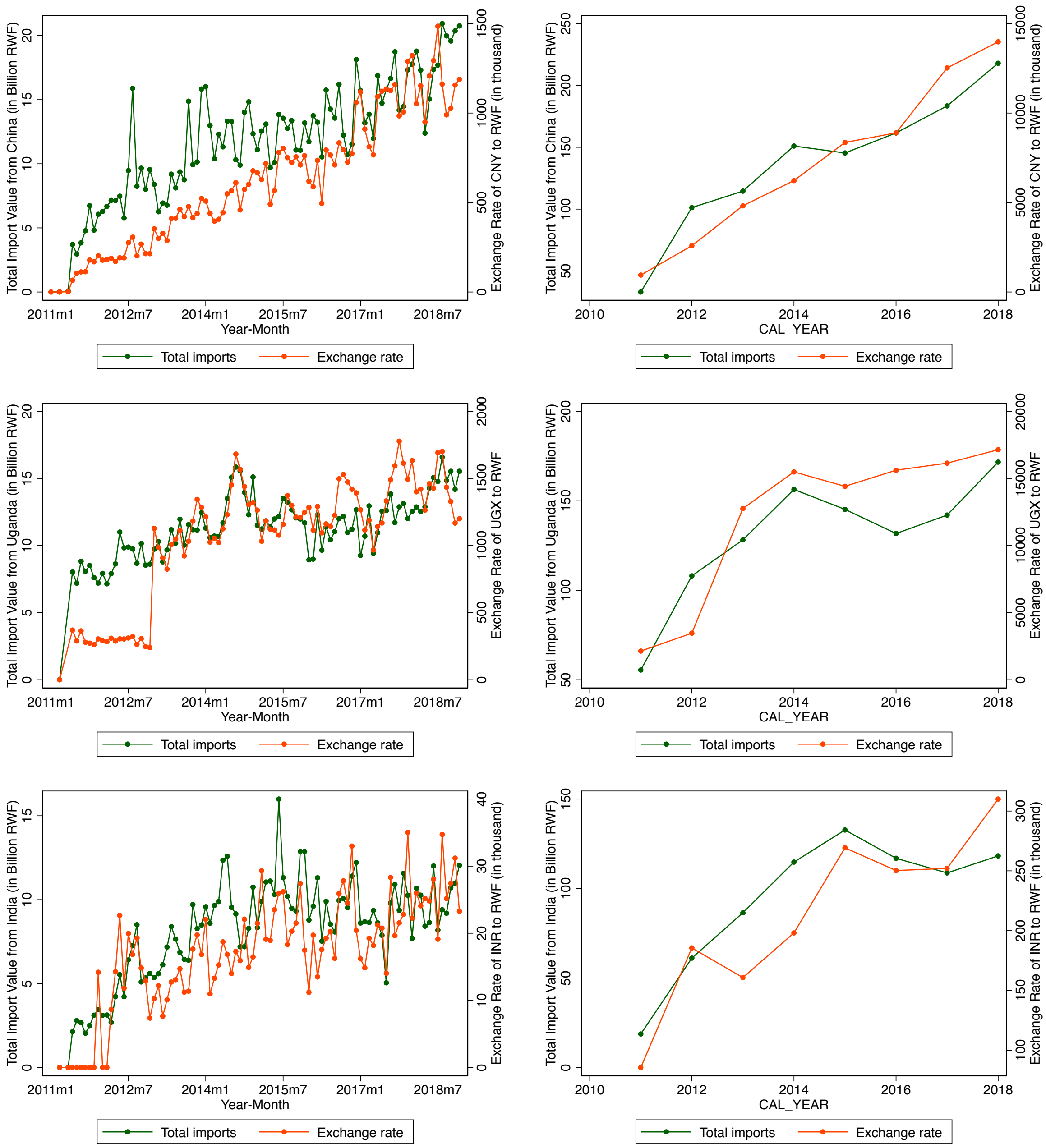
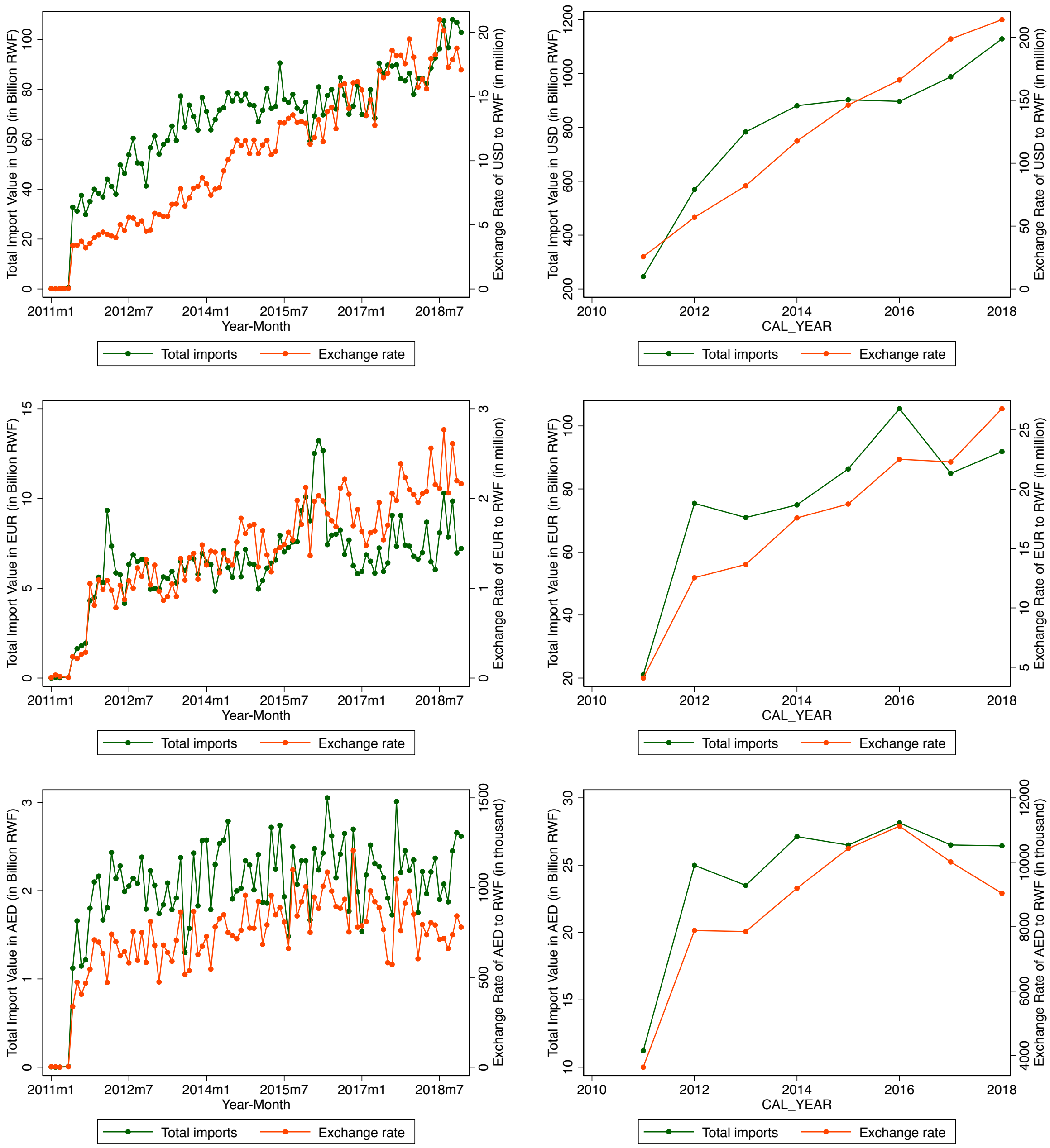


Figure 12: Time-series Patterns of Import Growth and Exchange Rate (2011-2018)
Top currencies: USD, EUR and AED



3.1.1 Measures of Prices

There are three measures of prices in the customs data:[4] (1)package price (P^{pck}) - value divided by the number of packages; (2) net weight price (P^{nwt}) - value divided by net weight (measured in kg)[5]; (3) quantity price (P^{qty}) - value divided by quantity in a given designated unit (e.g. kg).

Table 1 examines the correlations between these different price measures. Each observation is at the transaction level. Column 1-3 report raw correlations, without any fixed effect. Column 4-6 add fixed effects, corresponding to our main specification for the pass-through analysis. We can see that while these prices are significantly positively correlated, the coefficient is lower than 1, especially between package price and the other two price measures (e.g. a 1% increase in package price only translates to roughly 0.5% increase in quantity price). The R-square values, which demonstrate the amount of variance of the dependent variable explained by the independent variable, are also informative. Looking at Column 1 to 3, the R-square ranges from 0.17 to 0.39, indicating that there are still a lot of variations in the log of one price measure not explained by the other price measures. Some of these variations could be driven by firm-specific factors or aggregate time shocks (shifting different price measures to different degrees). In Column 4-6, we further control for firm, HS-country and time fixed effects to absorb some of these variations. Not surprisingly, the overall R-square goes up as we include more fixed effect controls. However, when we look at the within R-square (that is, after demeaning the data by taking out the fixed effects), the value is still modest, suggesting that a lot of unexplained variations remain. Therefore, for the regression analysis, we shall explore all three price (and quantity) measures and compare the estimation results across the different measures.

3.1.2 Measures of Exchange Rates

The customs data also provides information for the nominal exchange rate for each reported invoice currency for a transaction. Using this data, we can construct a country (currency) -time (year or month) level average exchange rate. To validate this internally reported measure, we hand-collected exchange rate information from several external sources—primarily from the IMF and complemented with another official source.[6] Reassuringly, the exchange rates constructed from the Customs data are highly correlated with the external information we collected. For the regression analysis we shall proceed with the former.

[4]There is also a variable called "item price" in the updated extract of the data. However, after some careful exploration of the data, we can conclude that this variable captures the total value of the transaction, rather than the price.

[5]Note: there is also a gross weight price, which is highly correlated (0.99) with net weight price.

[6]The IMF data is from https://www.imf.org/external/np/fin/ert/GUI/Pages/CountryDataBase.aspx. For missing country-year, we complement the data from https://www.exchangerates.org.uk/

Table 1: Price Correlations (Customs Data: 2012-2018)

	No FE			Firm, HS-Country, Time FEs		
	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln P^{qty}$	$\ln P^{qty}$	$\ln P^{pck}$	$\ln P^{qty}$	$\ln P^{qty}$	$\ln P^{pck}$
$\ln P^{nwt}$	1.035***		0.594***	0.822***		0.531***
	(0.001)		(0.001)	(0.001)		(0.001)
$\ln P^{pck}$		0.509***			0.416***	
		(0.001)			(0.001)	
Observations	2414849	2414868	2550427	1994847	1994865	2010013
Rsquare	0.387	0.197	0.172	0.846	0.819	0.845
WithinRsquare				0.250	0.118	0.153

We have winsorized outliers (top and bottom 1%) for all three different price measures. The numbers of observations change slightly from column to column due to missing values. A missing price could be due to missing CIF amount or missing quantity measure.

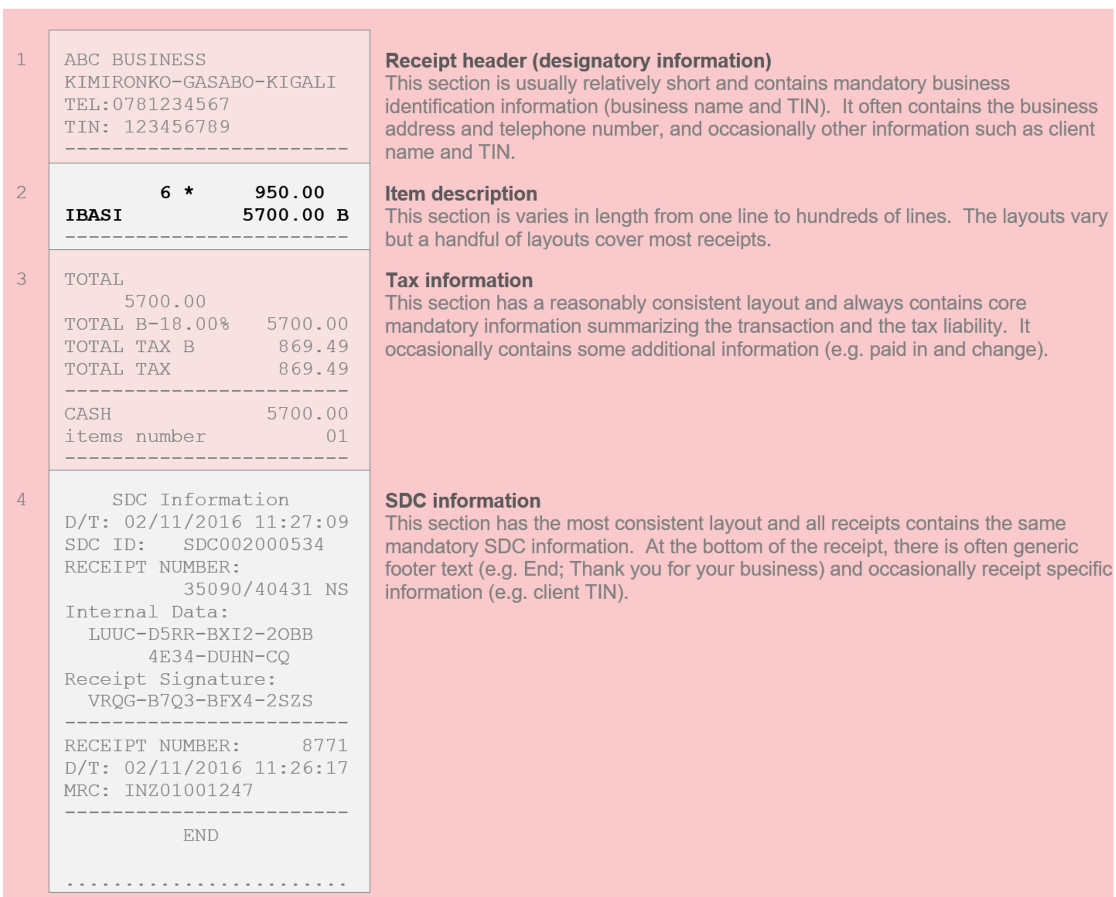
3.2 EBM (Electronic Billing Machines) Data

In 2013, Rwanda mandated the use of Electronic Billing Machines (EBM) for all VAT-registered businesses. For every transaction a business makes, it must provide the customer with an EBM receipt. The EBM's Sales Data Controller regularly transmits the receipt data to the Rwanda Revenue Authority (RRA), and all the receipt information is available at the RRA server. In this section, we explain how we construct a harmonized database from this EBM receipts data, and provide some descriptive statistics of the constructed itemized receipt data.

3.2.1 Constructing Itemized-Receipt Database from EBM Data

A typical EBM receipt electronically submitted to RRA looks like Figure 13. It shows that the EBM receipt data in principle includes information of item name, price and quantity of each item. The challenge is that the information contained in Figure 13 is all recorded as a single unstructured text data. Hence, we need to parse the relevant information from the receipt text data of over 100 GB.

Figure 13: Basic Structure of EBM Receipt



Source: Laterite (2018).

The initial cut has been done by Laterite (2018), as a project supported by the International Growth Center. We improve Laterite (2018) by adopting four different classes of receipt structures (Appendix Table B.1 show examples of these receipt structures). By this improvement, we succeed in extracting 99.9% of the items without any missing information of the item name, quantity and the price (an improvement from 75.6% with the Laterite (2018) code).

Appendix Tables B.1 and B.2 show the examples of the item names extracted from the EBM data. Table B.1 lists up the top 50 items in terms of the number of unique sellers selling the corresponding item. The item names that are used by most number of sellers is "DEPT01", "DEPT02", "DEPT03", followed by some broadly classified products, such as "FANTA", "UMUNYU", "AMAZI". Table B.2 in turn lists up random 40 items that are sold only by one or two sellers. These items tend to be more narrowly specified, e.g., "ELLE & VIRE YAG GO ABRICOT 125GR", "AMAVUTA Y IMASHINI", "ALVITYL 150ML SIROP". The next section describes how we take these data to a harmonized product classification system.

3.2.2 Item Classification

Our next step of converting the data with a statistically analyzable format is to classify each item label into a harmonized product codes. To do so, we rely on a text classification method developed in computational linguistics.

An initial attempt of this classification has been done by Laterite (2018). They randomly choose 10,000 items in EBM receipts, and manually assign the "correct" correspondence between these items and the HS codes. Using 80% of this data as a training set, they report that their algorithm correctly predicts 75% of the validation data (remaining 20% of the samples) at the four-digit HS code level.

The most important improvement from Laterite (2018) is that we use customs data for product classification, instead of the manually created correspondence. In the customs data, each firm reports the HS codes AND the item names for each transaction. The data covers 3,998,106 transactions with over 1,200 four-digit HS codes from 2008 to 2017. On the other hand, the training data set in Laterite (2018) only covers about 200 four-digit HS codes. In other words, about 1000 HS codes can never be matched with the training data set that Laterite (2018) has compiled.

Methodologically, we adopt the text classification method proposed in Joulin et al. (2016), `fastText` algorithm, to assign HS code to each item name. Appendix A details the classification algorithm and its predictive performance. Using the subset of customs data unused to train the model, our algorithms predicts 73.6% of the items correctly at the four-digit HS code level.

3.2.3 Basic Statistics from the EBM Data

Figure 14 shows the number of unique sellers and buyers that appear in the EBM data set. Given that there are possibly mis-typed tax-identification number (TIN), we restrict the sellers and buyers whose Tax Identification Number (TIN) appears in the taxpayers' business registry.

The number of receipts in the data set has increased over time since the introduction phase of 2014. We have access to data up to February 2018. There are currently substantial missing of data from some months in 2015 and 2016, due to the data extraction failure from the RRA server.

Figure 14: Transition of the Number of EBM Receipt

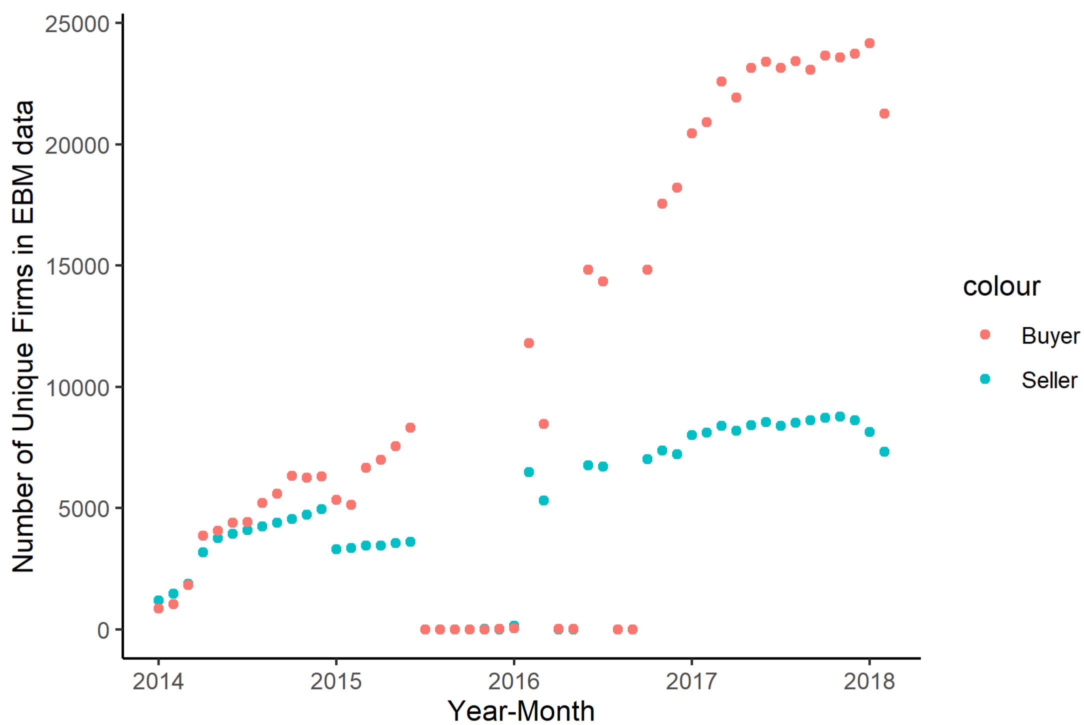


Table 2 shows the basic summary statistics from the EBM data in 2017. Panel (A) shows the characteristics as a seller among 11,873 firms who make at least one sales transaction in 2017. Similarly, Panel (B) shows the characteristics as a buyer among 36,416 firms who make at least one purchase transaction in 2017.

Using our assigned product classification, we find that firms' sales and purchase transactions range over a wide range of products. The median firm sells 7 categories of products and purchases 4 categories of products at the four-digit sectors.

Table 2: Summary Statistics of EBM Data in 2017

(A) Characteristics of Sellers

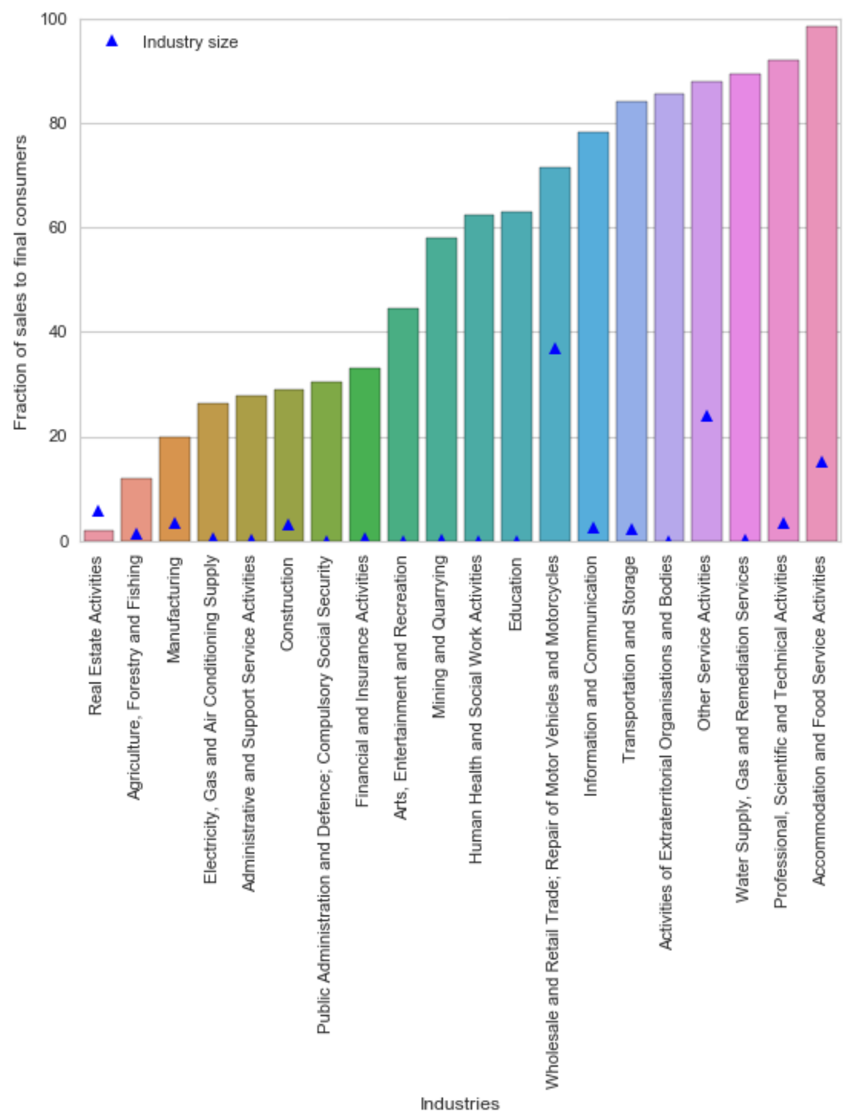
Statistic	Mean	Min	Pctl(25)	Median	Pctl(75)	Max	N
Number of Unique Items	4,894	1	25	194	1,594	3,759,201	11,873
Number of Receipts	2,359	1	19	134	928	1,781,001	11,873
Number of Unique Days	115	1	11	56	225	365	11,873
Number of Buyers	31	1	1	3	16	3,600	11,873
Number of 4-digit HS Codes	19	1	2	7	27	391	11,873
Number of 2-digit HS Codes	11	1	2	6	18	74	11,873

(B) Characteristics of Buyers

Statistic	Mean	Min	Pctl(25)	Median	Pctl(75)	Max	N
Number of Unique Items	1,596	1	2	8	43	55,637,447	36,416
Number of Receipts	789	1	1	5	27	27,221,828	36,416
Number of Unique Days	22	1	1	4	20	365	36,416
Number of Sellers	10	1	1	3	10	11,569	36,416
Number of 4-digit HS Codes	13	1	1	4	16	791	36,416
Number of 2-digit HS Codes	8	1	1	4	11	87	36,416

In each EBM receipt, a seller reports the identity of the customer's TIN (tax identification number) if the customer has a valid TIN. If the TIN is missing, the transaction is likely to be firm-to-consumers (or to the informal sector). Figure 15 reports this fraction by seller's industry. The figure captures intuitive patterns of the economic activity in Rwanda. Industries such as real estate, agriculture, or manufacturing have low fraction of firm-to-consumer sales, while accommodations or professional service sectors have high fraction of firm-to-consumer sales.[7]

Figure 15: Fraction of Sales to Final Consumers by Seller's Industry

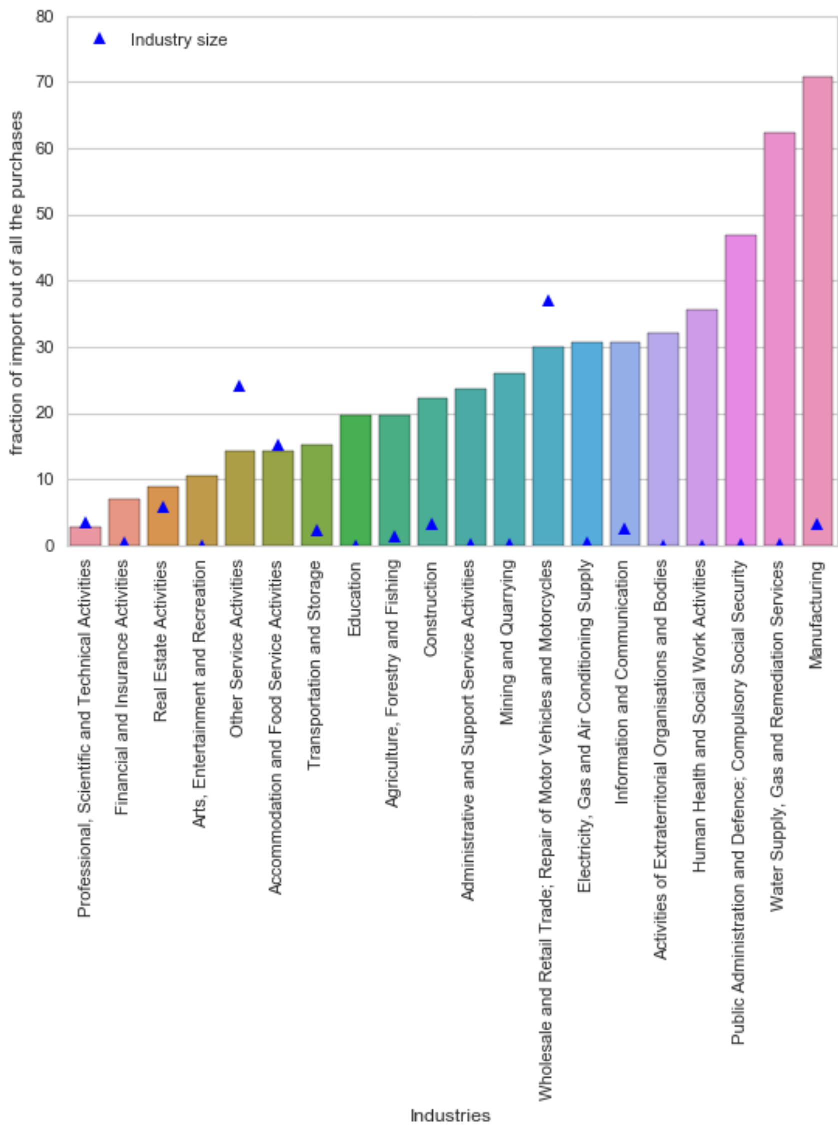


Note: Industry size indicates the number of firms in the EBM in the data set.

[7]Appendix Figure B.2 show the fraction of firm-to-firm sales disaggregated by the buyer's industry.

By merging the EBM receipt with the customs data, we can also capture how reliant firms in each industry are to imports. Figure 16 shows the fraction of import out of total purchases by industry. Intuitively, manufacturing is the sector most dependent on imports (70 % of total inputs are from imports). On the other hand, professional service, financial service and real estate activities have low share of imports.

Figure 16: Fraction of Imports out of Total Input Purchase by Seller's Industry



4 Impact of Exchange Rate Fluctuations on Imports

To examine the impact of exchange rate fluctuations on importers' import revenue, quantity and prices, we run the following regression specification:

$$lnY_{fikt} = \alpha + \beta lne_{kt} + \lambda_{ft} + \lambda_{fk} + \lambda_{ik} + \epsilon_{fikt} \tag{1}$$

where f indicates firm, i indicates HS-6 digit industry code, k indicates origin country and t indicates year. The sample period runs from 2012 to 2018. ft, fk and ik indicate firm-year, firm-country and industry-country fixed effects. The key outcome variables, lnY_{fikt}, include: (1) log import revenue (CIF amount), (2) log import quantity, measured in net weight (in kg), quantity (in various designated units) or the number of packages, and (3) log prices for each of the three quantity measures. For the key regressor of interest, we examine two types of exchange rate fluctuations: (1) the average nominal exchange rate between RWF and the currency of the origin country k in year t, and (2) the average nominal exchange rate between RWF and the invoice currency used for a given transaction.

Most of the literature has focused on invoice currency exchange rate (or at least conceptually). For example, when an important transaction is denominated in USD and RWF depreciates against USD, we would expect the import price in RWF to rise as the transaction amount in USD may only partially adjust. The idea of looking at origin country currency is more subtle but follows a similar rationale. Suppose a Rwanda importer buys from a Chinese exporter and the transaction is denominated in USD. When RMB, the Chinese currency, depreciates, the Chinese exporter would have the incentive to raise the dollar price in order to maintain the RMB value of the export revenue. This would result in an increase of the import price in RWF even though the transaction is not denominated in RMB.

The results are presented in Table 3. Panel A reports the results using origin country exchange rates and Panel B reports that for invoice currency exchange rates. We see that exchange rate depreciation against the origin country currency leads to significant reduction in import revenue (column 1) and import quantities (columns 2-4). The estimated quantity elasticity ranges from -0.28 to -0.47 depending on the measure used. The estimated pass-through rate ranges from 0.12 to 0.37 (columns 5-7), largely in line with the existing literature (Burstein and Gopinath, 2014).

Looking at Panel B, the results using invoice currency exchange rates are qualitatively similar. Note that the impact on import revenue becomes statistically insignificant (column 1 of Panel B). Theoretically, an increase in the exchange rate would lead to increases in border prices and reductions in quantity; the overall impact on revenue (price times quantity) is ambiguous. Overall, we think that policy makers should therefore focus on the impact on quantity and price (column 2 to 7).

4.1 Robustness Checks

We further examine the robustness of the estimated impacts. First, we look at the impact of exchange rate fluctuations at a monthly frequency. Specifically, we estimate Equation (1) with t defined at the monthly level. The results are presented in Table B.3. The main takeaways are similar to Table 3.

Next, we explore an alternative definition of "product" using HS-8 digit classification (instead of HS-6 digit). The results are shown in Table B.4. The coefficients are both qualitatively and quantitatively similar to the main estimates in Table 3. We also experiment with alternative fixed effect combinations, in particular controlling for firm-HS FE (instead of country-HS FE). The results, presented in Table B.5, are qualitatively similar to Table 3.

Table 3: Impact on Importers: Revenue, Quantity and Price

Dep. var: Revenue, Quantity and Price

	Ln (Revenue)	Ln (Net Weight)	Ln (Quantity)	Ln (Package)	$Ln(\frac{Revenue}{NetWeight})$	$Ln(\frac{Revenue}{Quantity})$	$Ln(\frac{Revenue}{Package})$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Origin Country Exchange Rates							
lne	-0.142*	-0.281***	-0.469***	-0.289***	0.119**	0.371***	0.159**
	(0.077)	(0.078)	(0.098)	(0.079)	(0.048)	(0.078)	(0.064)
Observations	622717	622712	598526	622718	622711	598526	622717
B. Invoice Currency Exchange Rates							
lne	0.053	-0.168*	-0.375***	-0.407***	0.201***	0.403***	0.432***
	(0.086)	(0.088)	(0.110)	(0.089)	(0.054)	(0.085)	(0.071)
Observations	722791	722784	695499	722793	722782	695499	722791
Firm-Country FE	✓	✓	✓	✓	✓	✓	✓
Firm-Year FE	✓	✓	✓	✓	✓	✓	✓
HS-Country FE	✓	✓	✓	✓	✓	✓	✓

4.2 Heterogeneity Analysis

One key advantage of the micro-level data is that it allows us to examine heterogeneous impact across different types of importers and importing activities. In this section, we present heterogeneity analysis across periods, sectors and firms. For the outcome variables, we focus on log revenue, log quantity measured in designated quantity units and the corresponding log price measure. We focus on origin country exchange rates in the main report. Results using invoice currency exchange rates can be found in the Appendix.

4.2.1 Heterogeneity Across Periods

Rwanda experienced a shock in foreign exchange reserve in the year of 2012 and 2013. Table 4 examines whether exchange rate fluctuations during that period had a differential impact on importers than the other years. Specifically, we define a *ReserveShock* dummy that equals to 1 for year 2012 and 2013. The key interaction term *lneXReserveShock* is significantly positive for log revenue (column 1) and log quantity (column 2), suggesting that the impact of exchange rate fluctuations appears to be smaller during this period. Having said that, the magnitude of the interaction term is relatively small compared to the main effect, and there doesn't appear to be any significant heterogeneity on the estimated pass-through rate with respect to the border price (column 3).

Table 4: Heterogeneity Across Period: Reserve Shock 2012-2013

Dep. var: Revenue, Quantity and Price

	Ln (Revenue)	Ln (Quantity)	$Ln(\frac{Revenue}{Quantity})$
	(1)	(2)	(3)
lne	-0.012	-0.404***	0.399***
	(0.082)	(0.105)	(0.083)
lneXReserveShock	0.024***	0.012*	0.005
	(0.005)	(0.006)	(0.005)
Observations	622717	598526	598526
Firm-Country FE	✓	✓	✓
Firm-Year FE	✓	✓	✓
HS-Country FE	✓	✓	✓

4.2.2 Heterogeneity Across Sectors

Next, we examine heterogeneity across sectors. Every import transaction is classified under one of the following categories: capital and raw materials, finished goods, intermediate goods and sensitive goods. Results are shown in Table 5. The intermediate goods sector appears to be more affected by exchange rate fluctuations compared to the other sectors. Having said that, we do not have enough statistical power to reject the equality of the coefficients across the different sectors.

Table 5: Heterogeneity Across Sectors

Dep. var: Revenue, Quantity and Price

	Ln (Revenue)	Ln (Quantity)	$Ln(\frac{Revenue}{Quantity})$
	(1)	(2)	(3)
lneXRaw	-0.131*	-0.453***	0.363***
	(0.078)	(0.100)	(0.079)
lneXFinished	-0.139*	-0.460***	0.364***
	(0.077)	(0.098)	(0.078)
lneXIntermediate	-0.167**	-0.525***	0.405***
	(0.078)	(0.099)	(0.079)
lneXSensitive	-0.127	-0.438***	0.339***
	(0.083)	(0.105)	(0.083)
Observations	622717	598526	598526
Firm-Country FE	✓	✓	✓
Firm-Year FE	✓	✓	✓
HS-Country FE	✓	✓	✓

Table B.7 and B.9 report the heterogeneity analysis across 2-digit ISIC sectors. The pass-through coefficients appear to be heterogeneous across ISIC sectors. However, the signs and magnitudes for some of the coefficients are rather difficult to interpret once we zoom into this finer level of industry classification.

4.2.3 Heterogeneity Across Firms

Finally, we examine heterogeneity across firms of different baseline size and importing frequency. We define the baseline years to be 2008 to 2011, prior to the beginning of our regression analysis sample (2012-2018). To calculate firm size, we sum up a firm's total import revenue from 2008 to 2011 and define "Big" firms to be those with total import revenue above the median and "small" to be those below the median. The results are shown in Table 6. The pass-through rate (column 3) appears to be smaller for big firms — the interaction coefficient *lneXBig* is negative, though standard errors are large.

This pattern is consistent with findings in Amiti et al. (2014) that big firms are less affected by exchange rate fluctuations than small firms and experience a lower pass-through rate. One explanation could be due to differential bargaining power: bigger firms may have stronger bargaining power against foreign exporters. When the RWF depreciates, they are able to negotiate the import price down and hence experience a smaller pass-through; similarly, when the RWF appreciates, they are able to maintain the price rather than letting it drop, again resulting in a smaller pass-through.[8]

Table 6: Heterogeneity By Firm Size

Dep. var: Revenue, Quantity and Price	Ln (Revenue) (1)	Ln (Quantity) (2)	$Ln(\frac{Revenue}{Quantity})$ (3)
lne	-0.033	-0.728	1.087***
	(0.425)	(0.528)	(0.418)
lneXBig	-0.085	0.172	-0.612
	(0.434)	(0.541)	(0.428)
Observations	338083	314596	314596
Firm-Country FE	✓	✓	✓
Firm-Year FE	✓	✓	✓
HS-Country FE	✓	✓	✓

One could also define "Big" and "Small" firms within the same sector: that is, allowing the median threshold to be sector specific. Table B.12 Panel A presents the results using the sector-specific size definitions. We can further allow the impact of firm size to be heterogeneous across sectors: for example, big firms in finished goods sector may be affected more or less than big firms in raw materials sector, relative to their small counterparts. Panel B examines this possibility. Overall, the main takeaways are similar to Table 6: big firms appear to have a lower pass-through rate, and this is true across different sectors; there does not appear to be any significant difference across sectors.

To investigate the impact of baseline importing frequency, we classify firms into high-frequency and low-frequency importers. To do so, we count the number of unique days or the number of unique months a firm has undertaken any import activity during the baseline period of 2008 to 2011.[9] A firm is defined

[8] However, surprisingly, the sign of the interaction coefficient flips when we look at invoice currency exchange rates (Table B.10). This may be due to the selection of firms, big and small, into using different invoice currencies.

[9] Ex ante, we do not have a strong prior on how to define a "transaction". For example, an importer may be receiving multiple batches of goods from a foreign exporter over several consecutive days. One may think of this as multiple transactions, as they are recorded on paper, or regard this as one single transaction from the perspective of the importers real business activity. Hence, we explore two definitions of importing frequency, one defined at the daily level and one defined at the monthly level.

to be a high-frequency importer if the number is greater than the median of all firms. Once again, we can allow the median threshold to be sector specific. Table 7 reports the results using a uniform median threshold across all sectors and Table B.14 reports the results using sector-specific thresholds. In all the regressions, we control for the interaction between firm size and exchange rate because a high-frequency importer, by definition, is also likely to be a big importer.[10] Hence, the coefficient on *lneXHighFrequency* captures the heterogeneous impact of importing frequency conditioning on importing volume (firm size). Column 3 suggests that high-frequency importers experience a higher pass-through rate: the coefficient is large and significantly positive when using the monthly frequency measure. The impact on quantity (column 2) is mixed, depending on whether daily frequency or monthly frequency is used. The latter suggests that high-frequency importers also suffer a bigger reduction in quantity. Results using sector-specific classifications are qualitatively similar (Table B.14).

4.3 Extensive Margin Responses and Potential Substitution Patterns

So far we have examined impact of exchange rate fluctuations on importers' revenue, quantity and price conditional on importing (i.e., the "intensive margin" responses). What about the "extensive margin" responses? Specifically, how do exchange rate fluctuations affect a firm's likelihood of importing? And how does it affect a firm's basket of importing countries and importing products? To examine these extensive margin responses, we first need to construct an exchange-rate exposure measure that is at the firm level. To do so, we use a firm f's baseline import revenue shares across countries as weights and construct an aggregate exchange rate measure for the firm f at a given year t:

$$lne_{ft} = \sum_{k} \frac{f\text{'s import revenue from } k \text{ during 2008-2011}}{f\text{'s total import revenue during 2008-2011}} lne_{kt} \tag{2}$$

where k is either origin country or invoice currency country. With this aggregate exchange-rate measure, we can run the following regression:

$$Y_{ft} = \alpha + \beta lne_{ft} + \lambda_f + \lambda_t + \epsilon_{ft} \tag{3}$$

where λ_f and λ_t are firm and time fixed effects. The key outcome variables include: a dummy for importing, number of countries and number of imported products conditional on importing. The results are shown in Table 8. Overall, increase in exchange rate seems to reduce the number of countries a firm sources from and the number of products a firm imports (not significant). The impact on importing probability is mixed and difficult to interpret for the origin country exchange rates.

[10] Table B.13 examines the correlation between baseline total import revenue (firm size) and importing frequency, measured at daily or monthly frequency. We see that size and frequency are positively correlated, especially for the frequency measure at monthly level.

Table 7: Heterogeneity By Importing Frequency

Dep. var: Revenue, Quantity and Price

	Ln (Revenue)	Ln (Quantity)	$Ln(\frac{Revenue}{Quantity})$
	(1)	(2)	(3)
A. Daily Frequency			
lne	-0.652	-0.733	0.528
	(0.563)	(0.704)	(0.557)
lneXHighFrequency	0.840*	0.007	0.758
	(0.502)	(0.631)	(0.499)
lneXBig	-0.285	0.170	-0.792*
	(0.451)	(0.561)	(0.444)
Observations	338083	314596	314596
B. Monthly Frequency			
lne	-0.320	0.348	-0.338
	(0.525)	(0.660)	(0.522)
lneXHighFrequency	0.393	-1.473***	1.951***
	(0.422)	(0.542)	(0.429)
lneXBig	-0.175	0.509	-1.059**
	(0.445)	(0.555)	(0.439)
Observations	338083	314596	314596
Firm-Country FE	✓	✓	✓
Firm-Year FE	✓	✓	✓
HS-Country FE	✓	✓	✓

Beyond the overall impact on the number of importing countries and products, there may be interesting substitution patterns in light of an exchange rate shock. For example, when RWF depreciates against one country's currency, firms which were previously importing certain products from that country may switch to other countries. One challenge of examining such substitution patterns is that we are in an environment where exchange rates against multiple countries are moving at the same time, and thus it's difficult to isolate one shock and trace its spillovers on other trading partners. To shed some light on this question, one strategy is to extend the baseline framework and control for firm-industry-year fixed effect. The idea is that if there is significant switching across origin countries, we would expect the estimated coefficients to be larger in magnitude compared to Table 3 due to the substitution.

Table 8: Extensive Margin Responses

	Importing (Dummy) (1)	Number of Countries (2)	Number of products (HS6) (3)
	A. Origin Country Exchange Rates		
Ln Aggregate Exchange Rate	0.027*	-0.109*	-0.767
	(0.015)	(0.056)	(0.657)
Observations	36994	18702	18902
	B. Invoice Currency Exchange Rates		
Ln Aggregate Exchange Rate	-0.012	-0.315	-2.980
	(0.044)	(0.199)	(2.316)
Observations	39324	19665	19880
Firm FE	✓	✓	✓
Year FE	✓	✓	✓

To illustrate this, suppose a firm imports textile from country A and B, and it imports electronics from country C and D. Suppose there is an exchange rate depreciation against country As currency. The specification in Table 2 compares imports from A to imports from all three other countries (taking out other fixed effects), whereas the specification in Table 8 compares imports from A to imports from B. Therefore, the estimates from these two specification will likely differ more when firms can more easily substitute across origin countries for a given product–that is, facing a depreciation against country As currency, the firm can import more textile from country B. In this case, the specification in Table 8 will give us a larger estimate (in magnitude) because of the substitution effect. Essentially the control group is changing as we control for different sets of fixed effects and in light of potential spillovers due to the substitution margin, we could get different estimates, which can in turn inform us about the magnitude of the substitution effects.

Results are presented in Table 9. While the estimated coefficients on quantity and price are larger compared to Table 3, suggesting that some substitutions may be happening, we cannot reject the equality of the estimates at the usual statistical significance levels. One reason again could be that there exists a lot of heterogeneity across firms in terms of the degree of substitution.

Table 9: Substitution Across Countries

Dep. var: Revenue, Quantity and Price

	Ln (Revenue)	Ln (Quantity)	$Ln(\frac{Revenue}{Quantity})$
	(1)	(2)	(3)
	A. Origin Country Exchange Rates		
lne	0.023	-0.702***	0.569***
	(0.136)	(0.189)	(0.141)
Observations	78478	76062	76062
	B. Invoice Currency Exchange Rates		
lne	0.434***	0.111	0.422***
	(0.139)	(0.193)	(0.142)
Observations	95458	93059	93059
Firm-HS-Year FE	✓	✓	✓
Firm-Country FE	✓	✓	✓
HS-Country FE	✓	✓	✓

5 Impacts of Exchange Rate Fluctuations on Importers' Domestic Behavior

Using the constructed EBM data set, we now proceed to examine the firm-level impacts of the exchange rate fluctuations on importers' domestic EBM purchases and sales, as well as their prices.

Unlike the customs data, the EBM data set only covers after 2014, with substantial missing months in 2015 and 2016 (see Figure 14). Furthermore, the coverage of firms in 2013 and 2014 are limited due to the phase-in period of EBM data. Due to this limitation, the following analysis use data in the first quarter of 2017 (the months of January, February, and March) and the first quarter of 2018. We study how the change of exchange rates during this time interval affects the outcome variables (domestic sales and purchase) at the firm level. We show that our results are robust by taking first quarter of 2016 and 2017.

In this section, we first investigate the impacts of exchange rate fluctuations on the domestic purchase and sales amount (Section 5.1). We then investigate the impact on prices, using the product classification developed in the previous section (Section 5.2).

5.1 Impacts on Domestic Purchase and Sales Amount

We first construct the measure of firm-level exposure to exchange rate fluctuations. In the baseline period (2017 first quarter), different firms have different intensities in the share of imports relative to the total expenditure (imports + domestic purchase). Moreover, conditional on importing, firms purchase different amount from different origin countries which may adopt different currencies. Hence, depending on the structure of imports, different firms are exposed to different degree of exchange rate fluctuations.[11]

Formally, our measure of firm-level exchange-rates exposure is defined as follows.

$$\begin{aligned}\Delta ExRateShock_f \quad \equiv \quad & \sum_{j \in OriginCountry} \Delta ExRate_{f,j} \frac{Import_{f,j}^{2017}}{\sum_{j \in origin} Import_{f,j}^{2017} + DomesticPurchase_f^{2017}} \\ & + \frac{DomesticPurchase_f^{2017}}{\sum_{j \in origin} Import_{f,j}^{2017} + DomesticPurchase_f^{2017}}\end{aligned}$$

where f is the firm, and j is the origin country. (We report the robustness of our results by defining j by invoice currencies, rather than origin countries.) $\Delta ExRate_{f,j}$ indicates the growth rate of the exchange rate of the currency of country j against RWF. The variables with superscript 2017 indicates

[11] Appendix Figure B.3 reports the distribution of the share of imports relative to total expenditure at the firm level. The mean of this measure is 0.16, with a strong bimodality at zero and one.

the observations in 2017 (baseline period), and the variables with Δ indicates that it is the growth from the 2017 till 2018.

Using the constructed exchange-rate exposure measure, our main regression specification is specified as follows:

$$\Delta Y_f \quad = \quad \beta \Delta ExRateShock_f + \eta_{Sector_f} + \epsilon_f$$

where ΔY_f indicates the growth rate of the outcome variable from 2017q1 to 2018q1. To make sure that the patterns are not driven by the sector-level macro-economic trend, we include the sector fixed effects (at the single-digit ISIC level). To incorporate the case where the outcome variable is zero for either of 2017 and 2018, we measure the percentage change in the outcome variable using arc-elasticity (Davis and Haltiwanger, 1992).[12]

5.1.1 Baseline Results

Table 10 presents our main results. The sample of the regression are all firms that pay corporate income tax during these periods. If firms import neither of 2017Q1 and 2018Q1, the outcome variable is defined as the mean of the outcome variables whose outcome variables are defined.

Table 10: Firm-level Impacts of Exchange Rates Fluctuations on Domestic Sales and Purchase

	Growth from 2017Q1 to 2018Q1			
	Imports	Domestic Purchase	Number of Domestic Sellers	Domestic Sales
	(1)	(2)	(3)	(4)
Exchange Rates Shock	-11.593^{***}	4.112^{***}	2.771^{***}	0.554
	(0.268)	(0.411)	(0.356)	(0.352)
Sector FE	X	X	X	X
Observations	14,447	14,447	14,447	14,447
Adjusted R^2	0.116	0.023	0.024	0.023

Note: *p<0.1; **p<0.05; ***p<0.01

Column 1 shows that exchange rate fluctuations reduce total imports. In terms of the magnitude, for firms which completely rely on imports and no domestic purchase, one percentage increase of the exchange rates reduces the imports by 11.5 percentage points.[13] The fact that the importers reduce imports as a response to the exchange rate increase is broadly consistent with the findings in Section

[12] Formally, it is defined as $\Delta Y_f \equiv \frac{Y_f^{Post} - Y_f^{Pre}}{\frac{1}{2}(Y_f^{Post} + Y_f^{Pre})}$.

[13] The average import expenditure share is 0.16 in the samples (see Appendix Figure B.3).

4.[14]

Column 2 shows that domestic purchase increases as a response to the increase of exchange rate. For each 11.5 percent reduction of imports, firms increase domestic purchase by 4.1 percent. In other words, about 30 percent of the reduced imports are substituted by the domestic purchase.

Column 3 shows the effect on the number of domestic sellers that firms source from. The coefficient is 3.0. By comparing with Column 2, 68 percent of the increase of domestic purchase is coming from the increased number of domestic sellers (extensive margin). By definition, the remaining fraction is explained by the increase of purchase per domestic seller (intensive margin).

Column 4 shows that there is no statistically significant impacts on the domestic sales (0.5 percent). Together with the results in Columns 1-3, the results indicate the limited impacts on the domestic buyers of the importers. We further investigate this results by studying the impacts on domestic prices in later subsection.

Using invoice currency to create the exchange-rate exposure provide qualitatively similar results (Appendix Table B.15). Using the growth from 2016Q1 to 2017Q1 also yield qualitatively similar results (Appendix Table B.16).

5.1.2 Heterogeneity by Firm Sector and Size

Table 11 documents the heterogeneous impacts with respect to firm sectors. For expositional purposes, we divide the sectors into "Commerce", "Manufacturing", and "Others" based on the ISIC industry classification of each firm. All the outcome variables are the same as in Table 10. Several comments are noted here. First, the reduction of imports is smaller for commerce and manufacturing, relative to other industries (column 1). More specifically, while the reduction of imports for Commerce is 8.6 percentage points and that of manufacturing is 7.2 percentage points, that of other industry is -12.4 percentage points. Second, the impacts on domestic purchase (Column 2) is smaller for Commerce (2.9 percentage point, relative to 4.3 percentage point for other industry). This is consistent with the fact that reduction of imports are smaller for commerce. As for manufacturing, coefficient is larger than other industries but not statistically significantly different. Lastly, the impacts of domestic sales is broadly small and close to zero.

Table 12 in turn documents the heterogenous impacts with respect to firm size. "Large" is the dummy variable that takes one if the total input purchase of the firm is above median in the baseline period (2017 first quarter). The regression also controls for the large dumy. Hence, the first row of the table indicates the impacts on small firms, and the second row indicates the differential impacts between small and large firms.

[14] Note, however, that the main specification in Section 4 is based on the variation of across origin countries (or invoice currencies) within firm and HS code. On the other hand, the analysis here is the comparison *across* firms with different exposure to exchange rate fluctuations.

Table 11: Firm-level Impacts of Exchange Rate Fluctuations on Domestic Sales and Purchase

	Growth from 2017Q1 to 2018Q1			
	Imports	Domestic Purchase	Number of Domestic Sellers	Domestic Sales
	(1)	(2)	(3)	(4)
Exchange Rates Shock x Commerce	-8.652^{***}	2.999^{***}	2.159^{***}	0.169
	(0.414)	(0.636)	(0.551)	(0.546)
Exchange Rates Shock x Manufacturing	-7.237^{***}	5.742^{**}	3.831^{*}	-0.243
	(1.470)	(2.258)	(1.957)	(1.936)
Exchange Rates Shock x Other Industry	-12.454^{***}	4.308^{***}	2.788^{***}	0.820^{*}
	(0.328)	(0.504)	(0.437)	(0.432)
Sector FE	X	X	X	X
Observations	14,447	14,447	14,447	14,447
Adjusted R^2	0.117	0.023	0.024	0.023
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 12: Firm-level Impacts of Exchange Rate Fluctuations on Domestic Sales and Purchase

	Growth from 2017Q1 to 2018Q1			
	Imports	Domestic Purchase	Number of Domestic Sellers	Domestic Sales
	(1)	(2)	(3)	(4)
Exchange Rates Shock	-13.682^{***}	6.244^{***}	7.529^{***}	0.682
	(1.200)	(1.841)	(1.576)	(1.563)
Exchange Rates Shock x Large	2.991^{**}	-2.617	-5.845^{***}	0.475
	(1.228)	(1.883)	(1.612)	(1.598)
Sector FE	X	X	X	X
Dummy Large	X	X	X	X
Observations	14,447	14,447	14,447	14,447
Adjusted R^2	0.114	0.024	0.047	0.042
Note:				*p<0.1; **p<0.05; ***p<0.01

The results from Table 12 indicate that large firms show smaller patterns of import substitution - they reduce imports less (2.9 percentage points, relative to the impacts on small firms of -13.6 percentage points). Large firms also reduce domestic purchase less (-2.6 percentage points, insignificant, relative to 6.2 percentage points of small firms). The impacts on the number of domestic sellers is also broadly consistent with this pattern (Column 3). Lastly, there are broadly no impacts on domestic sales, both for small and large firms.

5.2 Impacts on Domestic Prices and Markups

We now investigate the impacts of domestic sales prices and purchase prices. As described in Table 2, firms sell and purchase a wide range of products. More concretely, the median firm sells 7 categories of products and purchases 4 categories of products at the four-digit sectors. Given that different products have different unit of goods, it is important to control for the firm and product fixed effects when studying the impacts on prices.

Our regression is specified as follows:

$$Y_{jkft} \quad = \quad \beta ExRateShock_{ft} + \eta_{fk} + \nu_{t,Sector_f} + \epsilon_{jkft}$$

where t is the period (either of the 2017q1 and 2018q1), f is the firm, j is each transaction of the firm, and k is the HS code assigned for this transaction. The regression is run at the transaction level. The regression controls for η_{fk}, firm and and the four-digit HS code fixed effects, to control for the heterogeneity of the unit of prices within each product classification for each firm. The standard errors are clustered at the firm f level.

Table 13 presents the results. Columns 1 and 2 show the impacts on domestic sales prices, and 3 and 4 show the impacts on domestic purchase prices. For both outcome variables, we find no impacts of exchange rate fluctuations. Moreover, the magnitudes are small relative to the impacts on foreign and domestic purchases and domestic sales as documented in Table 10.

Lastly, Column 5 and 6 show the impacts on the log mark-up. The mark-up is defined by the difference between the average log sales price subtracted by the average log purchase price within the same (predicted) HS4 digit code. Partly because the cases where firms purchase and sell products in the same 4-digit HS code are relatively rare, and partly because the sample in this regression is aggregated at the 4-digit HS code for each time period, the sample size substantially decreases. With this specification, we find that there are no statistically significant impacts on mark-ups.

The lack of response of sales prices may be partly explained by the substitution to domestic imports (column 2 of Table 10). The lack of response of domestic purchase prices are consistent with the literature's finding that a large extent of incomplete pass-through of exchange rate shocks is explained by the presence of non-tradable cost, which does not respond directly to the exchange rate shocks (seeing the domestic purchase as nontradable goods). Using cross-country data, Goldberg and Hellerstein (2008) argue that the presence of non-tradable local cost is an important reason why we observe incomplete pass-through of exchange rates into domestic prices.

5.3 Interpretation

The takeaways from this section is summarized in the two points below.

Table 13: Firm-level Impacts of Exchange Rate Fluctuations on Domestic Prices

	Samples: 2017Q1 and 2018Q1					
	log Domestic Sales Prices		log Domestic Purchase Prices		log Mark-Up	
	(1)	(2)	(3)	(4)	(5)	(6)
Exchange Rates Shock	0.299	0.414	0.176	0.170	2.261	2.747
	(0.270)	(0.278)	(0.291)	(0.283)	(41.796)	(35.747)
Firm and 4-digit HS code FE	X	X	X	X	X	X
Quarter FE	X	X	X	X	X	X
Quarter and Sector FE		X		X		X
Observations	17,818,747	17,818,747	2,302,648	2,302,648	1,439	1,439
Adjusted R^2	0.741	0.741	0.629	0.629	0.329	0.283

Note: *p<0.1; **p<0.05; ***p<0.01

First, our results indicate the presence of import substitution, i.e., importers respond by increasing domestic purchases as a response to increase in exchange rates. However, this substitution is imperfect - for one percentage point reduction of import expenditure, the domestic purchase increases by about 0.3 percentage points (columns 1 and 2 of Table 10).

Second, the pass-through of exchange rate fluctuations to the domestic buyers of the importers are limited. There are no impacts of exchange rate fluctuations on sales prices (columns 1 and 2 of Table 13). This is consistent with the import substitution as indicated above. These results indicate that importers act as a "shock absorber" in mediating the pass-through of exchange rate fluctuations to the domestic economy and downstream consumers.

6 Conclusion

In this project, we have investigated the impact of exchange rate fluctuations on Rwanda's economy, both in terms of the direct impact on importing firms as well as the impact on the domestic economy through changes in the importers' domestic activities. The analysis takes advantage of two micro-level data sets, namely the Customs data and the newly available EBM data.

Using the Customs data, we estimate an exchange-rate pass-through rate of 10% to 40% to the import (border) prices, largely line with the existing estimates from the macro literature. One key advantage of the micro data is that it allows us to examine heterogeneous patterns across different types of importers and importing activities. We find that small firms and firms importing intermediate goods appear to be affected more (i.e. experience higher pass-through) by exchange rate shocks. On the extensive margins, we find suggestive evidence that firms reduce the number of products they import and the number of countries they source from in response to currency depreciation, and some degree of substitution may happen across the origin countries. Though some of the results are less precisely estimated, the data potentially point to rich underlying heterogeneity across firms and sectors. Finer cuts of the data may reveal more interesting patterns. We believe that more conversations with policy makers could help to provide helpful guidance to researchers to form sharper hypotheses and conduct further investigations using the granular data available in the future. We hope that our analysis in this report provides a first look into the potential heterogeneous responses and opens the way for broader policy discussions that target various sectors and firms.

Using the EBM data, we document evidence of import substitution: in light of exchange rate increases, importers reduce import expenditure and increase domestic purchases. However, the substitution is imperfect - for one percentage point reduction of import expenditure, domestic purchase increases by about 0.3 percentage point. We also find limited pass-through of exchange rate shocks to buyers of importers, partly due to the substitution and partly due to decreased profit margins by the importers. Taken together, these results suggest that importers act as a "shock absorber" in transmitting exchange-rate pass-through to the domestic economy. From a perspective of modelling and forecasting inflation, the results suggest that the nominal exchange rates may not be as significant factor as typically considered in the open-economy New Keynesian models.

One important caveat for our analysis is that our analysis is based on the customs data and VAT data, implying that informal sector is dropped from the samples. Studying how informal economy responds differently from the formal sector is left for future research.

The project presents a comprehensive understanding of the implications of the devaluation of Rwandan Franc on import and domestic activities using micro data. One important policy takeaway is that a weaker Rwandan Franc is not necessarily leading to higher domestic prices that Rwandan consumers face. Our findings also suggest that there is a large scope for import substitution policies (e.g. Made-in-Rwanda Initiative).

Our analysis also suggests that the detailed firm-to-firm and firm-to-consumer sales and price information contained in the EBM data can be a particularly useful resource for both academic researchers and policy makers. We have done substantial cleaning of the EBM data set, and we hope that will become useful for future research and policy analysis. To improve the future quality of such data set, we highly recommend tax authorities to enforce a strict compliance, as well as provide a clear guidance for precise data input to minimize the data noise. It is also recommended to report the product code directly in the EBM data rather than just a text entry of product names; this will significantly increase the value of the EBM data set for future policy and research purposes.

We conclude this report by several possible future research directions. First, further understanding market structure of Rwandan domestic economy is important. This includes the precise mechanism to explain why do importers have to absorb price shocks to a certain extent instead of passing them on to their customers. Second, creating an architecture to use EBM data and customs data for real-time policy analysis is highly awaited.

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A Details of the Item Text Classification using Customs Data

In this appendix, we detail the methodology to predict HS codes of each EBM receipt item, using customs data as a training data.

A.1 Methology

We used a text classification method proposed in Joulin et al. (2016), `fastText` algorithm, to assign HS code to each item name. `fastText` is a widely used open source library available in https://fasttext.cc/ and its classification performance is comparable with famous deep leaning based classifiers (Joulin et al. (2016)). How `fastText` algorithm assigns an HS code given the words showed up in an item name is the following.

1. Prepare the training and the prediction data set. The training set must include HS codes.
2. Convert each item name into a numeric vector. There are three sub-steps in this procedure.
   (a) List all words and bigrams (contiguous sequence of two words in a given text) that appears in item names in the training set (Figure A.1, 1 to 2).
   (b) Convert each word and bigram into a one-hot (indicator) numeric vector (Figure A.1, 2 to 3).
   (c) Obtain a numeric vector representation of an item name by averaging all one-hot vectors appeared in an item name (Figure A.1, 3 to 4).
3. Train the 3-layer linear neural network with training data set (Figure A.2). We adopt 100 dimensions (cells) for the hidden layer and the softmax function for converting an output vector of real numbers into a probability vector.
4. For each item name in the prediction set, get the classification probability the neural network outputs and assign the HS code whose probability is largest among all the labels (Table A.3).

Analitically the third step is equivalent to solve the following log-likelihood maximization problem.

$$\max_{\substack{A\in\mathbb{R}^{D\times K}\\ B\in\mathbb{R}^{L\times D}}} \frac{1}{N}\sum_{n=1}^{N} \mathbf{y}_n^{\mathrm{T}} \log(f(BA\mathbf{x}_n)) \tag{4}$$

Here N is the number of training data, K is the number of all possible words and bigrams (that ever appears in the training data), D is the dimension (the number of cells in the hidden layer of the 3-layer neural networks, see above), and L is all labels (HS codes). $\mathbf{x}_n \equiv (x_n^1, x_n^2, \ldots, x_n^K)^{\mathrm{T}} \in \mathbb{R}^K$ is an input vector (an average of all n-gram vectors in an item name) and $\mathbf{y}_n \equiv (y_n^1, y_n^2, \ldots, y_n^L)^{\mathrm{T}} \in \mathbb{R}^L$ is an 0-1 vector that takes $y_n^\ell = 1$ if the HS code of the item is ℓ and 0 otherwise. $f : \mathbb{R}^L \to \Delta_L$ is the multi-dimensional softmax (logistic) function

$$f((z_n^1, z_n^2, \ldots, z_n^L)^{\mathrm{T}}) = \left(\frac{e^{z_n^1}}{\sum_{\ell=1}^L e^{z_n^\ell}}, \frac{e^{z_n^2}}{\sum_{\ell=1}^L e^{z_n^\ell}}, \ldots, \frac{e^{z_n^L}}{\sum_{\ell=1}^L e^{z_n^\ell}} \right)^{\mathrm{T}}, \tag{5}$$

where Δ_L is the unit simplex in $\mathbb{R}^L$ and z_n^ℓ is the ℓ-th element of the vector (BAx_n).

Figure A.1: How to represent an item name as a numeric vector. First we create a set of words and bigrams from an item name. Then we convert each word and bigram into a one-hot (indicator) vector. Finally we obtain a numeric vector of an item name by averaging all one-hot vectors of the words and bigrams in it.

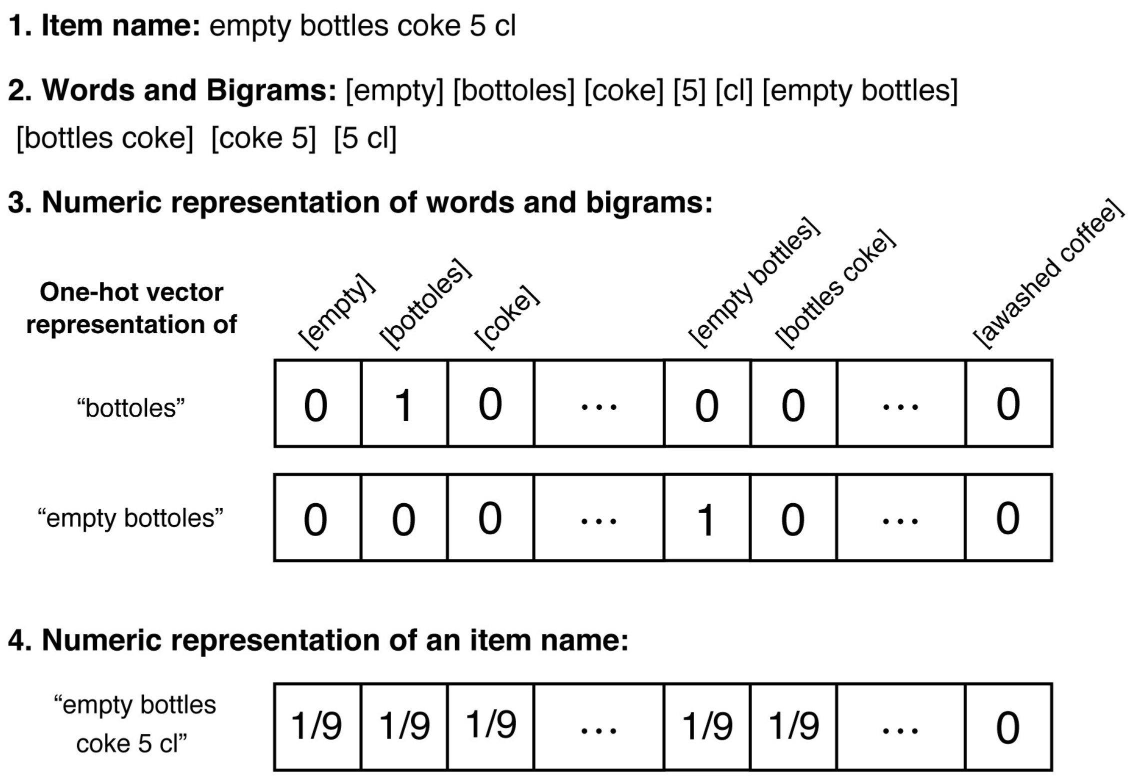
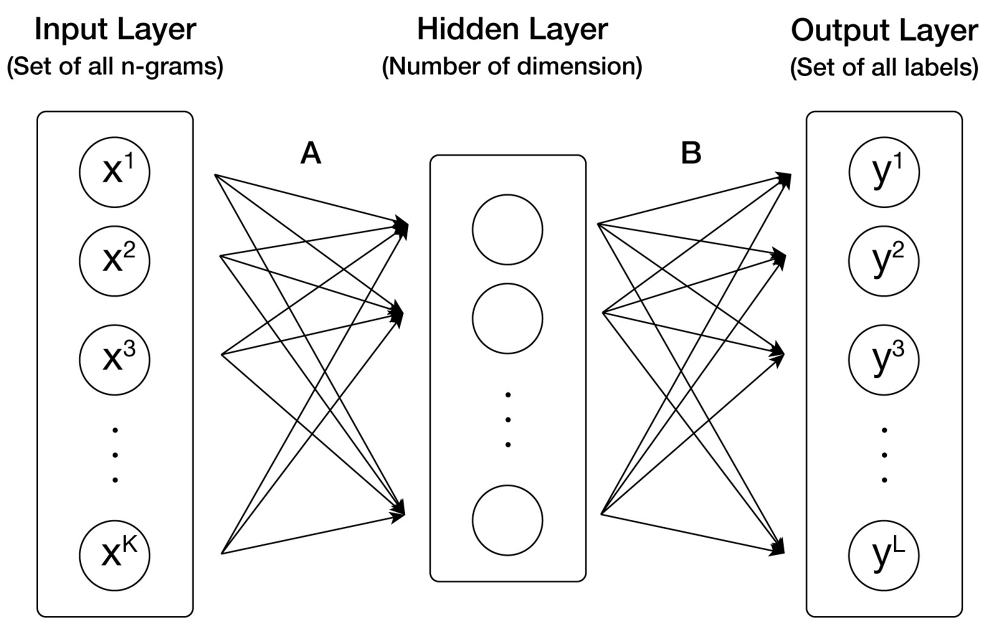


Figure A.2: The structure of the `fastText` model. K is the number of all words and bigrams in the item names and L is the number of labels. The number of cells (dimension) in the hidden layer is 100.



A.2 Training data: customs data

We train the above-mentioned algorithm to customs data. In the customs data, each firm reports the HS codes AND description of the item for each transactions. In our data, we have 3,998,106 transactions from 2008 until 2017, which is assigned to about 1,200 four-digit HS codes. Using customs data as a training data set has advantage than using manually-created training data set (Laterite (2018)), which cover only about 200 four-digit HS codes.

Before training the model, we first cleaned item names in the custom data in the following steps:

1. Eliminate some symbols (such as ?!"'$:;&()*@+) and special characters (such as newline characters and consecutive null characters).

2. Omit the items with less than 3 characters.

3. Convert all characters in item names to lowercase.

In this cleaning process, we dropped 5037 lines.

A.3 Prediction performance

In order to evaluate the accuracy of the predicted labels, we randomly split the remaining 3993069 items into training data (75%, 2994484 items) and test data (25%, 998585 items), train the model with the training data, assign estimated HS code to each item in test set, and then compute the proportion of items in the test data that the model correctly predicted their labels. When we evaluated the result, we used three types of sub-samples of the test data.

1. Sample 1: We used all the items in the test set.

2. Sample 2: We dropped the item names that have duplicates in the test set. For example, if the test set contains 100 rows of "item name: apple", we only used the first one row of item name: apple" and dropped other 99 duplicated rows when we evaluate the result.

3. Sample 3: Further we dropped item names that have duplicates in the training set. For example, if both the test set and training set contains a row of "item name: apple", we dropped that row in the test set. Note that all the predictions are extrapolation in this case.

A.3.1 Overall performance

The result is the following: in the full sample (sample 1), at the most disaggregated level (6-digit HS code) the method could match 60.2% of HS code. At the most aggregate level (2-digit HS code) it could assign 83.9% of HS code correctly. Even in sample 3, which only contains item names that are unique in the test set, the method could assign 44.5% of HS codes right at 6 digit level, and 72.2% at 2-digit level.

% of HS code = HS code assigned	6 digits	4 digits	2 digits
Sample 1 (# = 998585)	60.2%	73.6%	83.9%
Sample 2 (# = 345923)	46.7%	60.7%	74.7%
Sample 3 (# = 236159)	44.5%	58.2%	72.2%

A.3.2 Category-level performance (4-digits level, sample 1)

We compute the average accuracy rate among 4-digits HS codes with sample 1 (the probability that the item is classified in the correct category). Table A.1 and A.2 provide the best and the worst three HS codes with typical items in the category. The worst performers in Table A.2 tend to be the type of item which are hard to classify even manually. For example, at the four-digit HS codes, *dresses* has to be classified into finer categories of clothing based on the materials (e.g., cotton, silk). Clearly, we cannot tell the materials of the *dresses* by just looking at this text. It should be also noted that for worst performers, the classification probability (the probability that `fastText` assigns to the predicted HS code) is low. Roughly speaking, this probability indicates the certainty of the prediction. Therefore, the predictive performance generally increases by selecting subsamples whose classification probability is high.

Table A.1: Top 3 performers among 4-digits HS codes with more than or equal to 1000 data.

Best performers (with 1000 or more sample size)

HS code	Accuracy	Counts	Item name	Predicted	C. Prob
1107	99.72%	1085	malt	1107	99.05%
			malt pale c6 pt vialonga 5 kg bag	1107	96.21%
			bralirwa gis 7 7 ddcom s2374	1107	32.42%
8711	99.70%	26169	moto honda model 2 6	8711	98.43%
			motocycle	8711	91.43%
			tyres moto	4011	88.25%
102	99.60%	5498	fresian cattle	102	99.13%
			live cross breeding friesian cows	102	98.12%
			ankole long horned cattle	7308	4.56%

Note: "C. Prob" indicates the classification probability that `fastText` assigns to the predicted HS code. Note that we pick the HS code that has the highest classification probability.

Table A.2: Worst 3 performers among 4-digits HS codes with more than or equal to 1000 data.

Worst performers (with 1000 or more sample size)

HS code	Accuracy	Counts	Item name	Predicted	C. Prob
6114	0.00%	1097	baby socks	6115	52.19%
			dresses	6204	56.82%
			urutambi	6274	36.74%
6210	4.01%	1496	mixed clothes	6210	18.50%
			used clothes	6309	98.86%
			shirt12pant12jeans6jupe12charp3	6204	20.68%
6907	4.73%	1859	tiles	6908	54.76%
			ceramic floor tile	6901	39.61%
			carreaux	6908	51.01%

Note: "C. Prob" indicates the classification probability that `fastText` assigns to the predicted HS code. Note that we pick the HS code that has the highest classification probability.

Table A.3: Predicted classification probability of *empty bottles coke 5 cl* and *baracuda steak*. Our model predicts label 70 (glass and glassware) and 90 (optical, photographic, cinematographic, and so on) for each item. The correct 2-digit HS codes are 70 and 03 (fish and crustaceans, molluscs and other aquatic invertebrates).

empty bottles coke 5 cl

HS code	Classification probability
70	0.948784
39	0.047453
48	0.001020
76	0.000726
⋮	⋮
11	0.000010
23	0.000010

baracuda steak

HS code	Classification probability
90	0.027206
96	0.026762
73	0.025185
82	0.024442
⋮	⋮
52	0.000417
55	0.000307

B Additional Tables and Figures

Figure B.1: Different Types of EBM Receipt

Type 1 (75%):

```
- - - - - - - - - - - - - - - - -
Ikayi
20600.00 x   40      824000.00 B
Sante Savon
13200.00 x   2        26400.00 B
- - - - - - - - - - - - - - - - -
```

[1]

Type 2 (1%):

```
------------------------------------------
SIM CARD 32K PRE-PAID RWF 550
40     300                       12000A-EX
SIM CARD AIRT 400 FOR 550
160     300                         48000B
------------------------------------------
```

[2]

Type 3 (6%):

```
...........................................
Salt Bread-                   5      4500.00 B
900.00                         4500.00
...........................................
```

[3]

Type 4 (18%):

```
------------------------
AMAKAYE       20500.00 B
AMAVUTA       11000.00 B
------------------------
```

[4]

Table B.1: Top 50 Items by the Number of Unique Sellers

Item Name	Number of Unique Sellers (TIN)	Frequency of Transactions	Number of Unique Buyers
DEPT 01	4490	1828890	513843
DEPT 02	4425	520377	70641
DEPT 03	1246	7143	1152
FANTA	1183	3261636	464922
UMUNYU	996	395205	159237
AMAZI	901	372255	106695
OMO	855	224250	119052
DEPT 04	834	4524	633
KAWUNGA	816	462513	89718
UMUCERI	807	746253	271416
RED BULL	801	96213	28035
TRANSPORT	800	1428417	355347
	794	34887	31824
ISABUNE	776	581568	131136
ISUKARI	769	507921	204750
AMAVUTA	709	621690	243189
AMSTEL	691	340719	103074
JUS	684	376398	114618
HEINEKEN	666	407256	48801
INGUFURI	666	96345	30900
CIMENT	647	241308	78759
DEPT 06	609	2784	108
DEPT 12	608	4989	57
BAVARIA	590	60972	30441
ISUKA	587	65976	30312
VIM	584	66714	51843
SKOL LAGER	576	504891	102138
CONSTRUCTION	576	16872	18021
COTEX	571	101487	50148
CHIPS	553	417357	27735
BOMBO	549	351819	134574
DEPT 09	546	3771	339
JUICE	544	314097	78888
DP01	544	140493	28797
PRIMUS	538	596181	72708
PANACHE	538	214338	63918
IKIBIRITI	537	119868	63987
WATER	536	427923	55611
LEGEND	531	88950	24954
GUINESS	507	62670	18756
COLGATE	505	86673	31131
SERVIETTE	497	143823	101958
AMPOULE	480	42207	28362
SALSA	477	228312	171696
TRIPLEX	469	79647	37365
BAGUETTE	468	382608	114087
UMUHEHA	466	109878	64668
BISCUIT	457	369570	176706
IMISUMARI	449	71940	51219
BIC	444	44202	23517

Table B.2: Random 20 Items Sold by Only Two or One Unique Sellers

Item Name	Number of Unique Sellers (TIN)	Frequency of Transactions	Number of Unique Buyers
G MUTZ	2	384	0
ELLE &VIRE YAG GO ABRICOT 125GR	2	675	0
AMAVUTA Y IMASHINI	2	663	426
ALVITYL 150ML SIROP	2	444	372
ALUMINIUM PACKING BIG	2	1362	243
TUBES 16 X 16	2	885	1581
ACCESOIRE ELECTRIQUE	2	486	498
HAIR NO BASE RELAXER BIG	2	864	1053
DEBRIDAT 125ML BB SIROP	2	441	195
KIMBAP	2	891	498
MELAMINE CTN	2	1344	1938
USEDCLOTHES	2	3258	2244
CERES PASSION FRUIT 1L	2	405	129
UTUDOBO 6L	2	309	27
N2080270 SPACER PRIMARY DRIVEN GE	2	531	90
BILL PAYMENT	2	1260	453
20 L BOTTLE	2	471	72
YOGHAT	2	2892	3
RUDACO IKIVUGUTO 5L	2	726	6
RICE PAKISTAN 25 KG	2	411	561
100634655 BIO YOGHURT WITH REAL TROPICA	1	1941	45
SODA BIG CL50	1	576	21
BOTTLE 1.5 L	1	3429	45
C. ACTIVATOR	1	1725	42
2014914828054@FLOOR MATS NO.28054@	1	384	81
2014914815078@CERAMIC TABLELAMP24C	1	336	24
VASELINE BODY LOTION 4	1	939	18
SUGAR/BROWN 1KG	1	2019	831
MAHOGANY LANGUETTES	1	1911	870
SMX TRIPPLE H/C AT160 1	1	732	918
SUNSEED HUILE DE TOURNES	1	423	126
CARDIO ASPIRINE 100MG B	1	468	210
90*13 METAFOAM	1	312	9
6161100600294@SUN LIGHT 3.5KG	1	384	117
SLICED VANILLA CAKE SM	1	3678	114
TUBES 30	1	471	180
CHICKEN SCHINITZEL	1	1149	201
GOAT MEAT BROCHETTE	1	1329	18
BRONCALENE SP ADULTE 150ML(L001 - 2019-01-01)	1	1161	957
ZOE LOTION400ML	1	450	186

Figure B.2: Fraction of Sales to Different Industries and Final Consumers by Seller's Industry

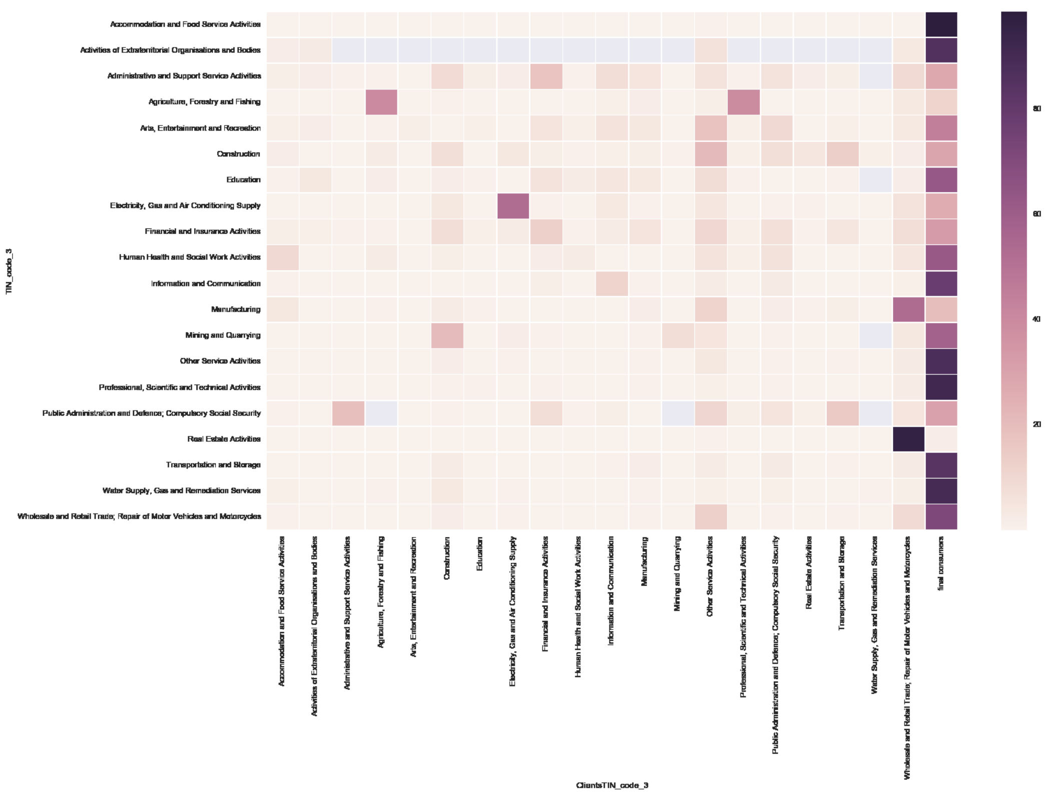
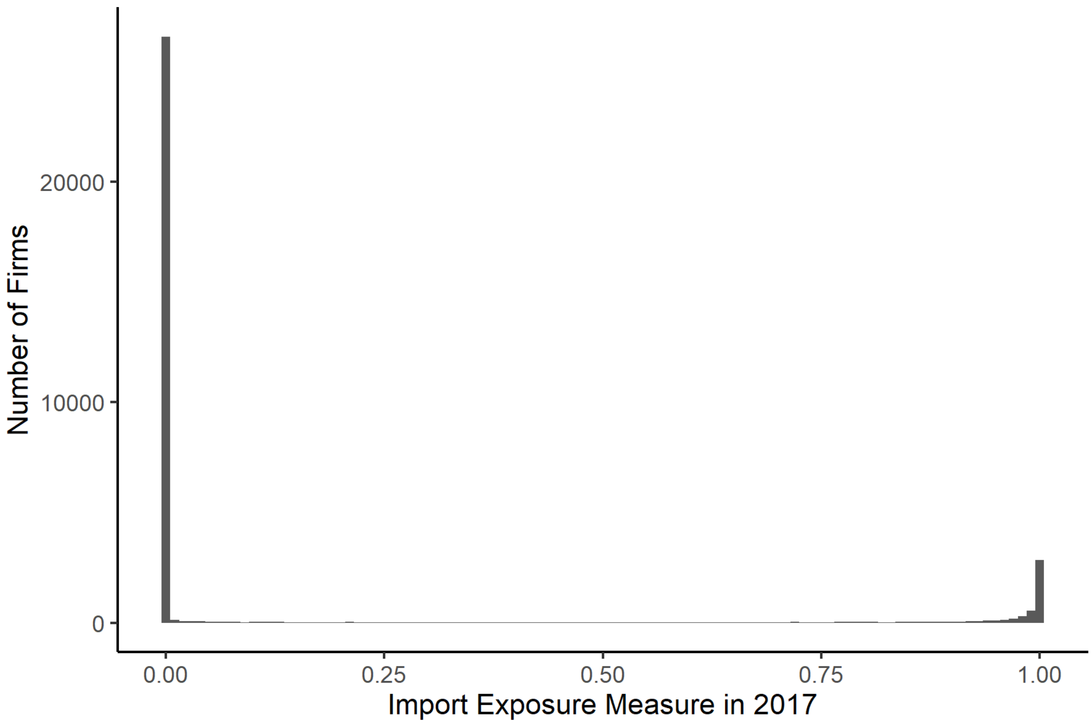


Figure B.3: Import Exposure



Note: The figure shows the distribution of the share of imports relative to the total expenditure (imports + domestic purchase) in 2017. Imports are from the customs data, and domestic purchase is from the EBM data.

Table B.3: Impact on Importers: Monthly Level Exchange Rate Shock

Dep. var: Revenue, Quantity and Price

	Ln (Revenue)	Ln (Net Weight)	Ln (Quantity)	Ln (Package)	$Ln(\frac{Revenue}{NetWeight})$	$Ln(\frac{Revenue}{Quantity})$	$Ln(\frac{Revenue}{Package})$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			A. Origin Country Exchange Rate Shock				
lne	-0.221***	-0.333***	-0.622***	-0.203***	0.104**	0.432***	0.009
	(0.068)	(0.068)	(0.086)	(0.069)	(0.046)	(0.073)	(0.059)
Observations	886264	886256	854200	886267	886253	854200	886264
			B. Invoice Currency Exchange Rates				
lne	-0.076	-0.213***	-0.621***	-0.428***	0.123**	0.451***	0.329***
	(0.076)	(0.077)	(0.095)	(0.078)	(0.051)	(0.079)	(0.066)
Observations	1070741	1070730	1032599	1070745	1070726	1032599	1070741
Firm-Country FE	✓	✓	✓	✓	✓	✓	✓
Firm-Year FE	✓	✓	✓	✓	✓	✓	✓
HS-Country FE	✓	✓	✓	✓	✓	✓	✓

Table B.4: Impact on Importers: HS 8 Digit Product Classification

Dep. var: Revenue, Quantity and Price

	Ln (Revenue)	Ln (Net Weight)	Ln (Quantity)	Ln (Package)	$Ln(\frac{Revenue}{NetWeight})$	$Ln(\frac{Revenue}{Quantity})$	$Ln(\frac{Revenue}{Package})$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				A. Origin Country Exchange Rate Shock			
lne	-0.150*	-0.302***	-0.508***	-0.273***	0.130***	0.397***	0.134**
	(0.077)	(0.078)	(0.098)	(0.079)	(0.048)	(0.078)	(0.064)
Observations	624921	624916	600628	624922	624915	600628	624921
				B. Invoice Currency Exchange Rates			
lne	0.062	-0.144	-0.353***	-0.375***	0.188***	0.394***	0.410***
	(0.086)	(0.088)	(0.109)	(0.089)	(0.054)	(0.085)	(0.071)
Observations	725722	725715	698296	725724	725713	698296	725722
Firm-Country FE	✓	✓	✓	✓	✓	✓	✓
Firm-Year FE	✓	✓	✓	✓	✓	✓	✓
HS-Country FE	✓	✓	✓	✓	✓	✓	✓

Table B.5: Impact on Importers: Alternative Fixed Effects

Dep. var: Revenue, Quantity and Price

	Ln (Revenue)	Ln (Net Weight)	Ln (Quantity)	Ln (Package)	$Ln(\frac{Revenue}{NetWeight})$	$Ln(\frac{Revenue}{Quantity})$	$Ln(\frac{Revenue}{Package})$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Origin Country Exchange Rate Shock							
lne	-0.026	-0.121	-0.537***	-0.219***	0.077	0.504***	0.220***
	(0.077)	(0.080)	(0.105)	(0.084)	(0.052)	(0.083)	(0.068)
Observations	316057	316053	301554	316058	316052	301554	316057
B. Invoice Currency Exchange Rate Shock							
lne	-0.006	-0.147	-0.499***	-0.261***	0.152***	0.512***	0.268***
	(0.087)	(0.091)	(0.118)	(0.096)	(0.059)	(0.093)	(0.076)
Observations	370709	370704	354149	370710	370703	354149	370709
Firm-Country FE	✓	✓	✓	✓	✓	✓	✓
Firm-Year FE	✓	✓	✓	✓	✓	✓	✓
Firm-HS FE	✓	✓	✓	✓	✓	✓	✓

Table B.6: Heterogeneity Across Period: Reserve Shock 2012-2013
Using Invoice Currency Exchange Rates

Dep. var: Revenue, Quantity and Price

	Ln (Revenue)	Ln (Quantity)	$Ln(\frac{Revenue}{Quantity})$
	(1)	(2)	(3)
lne	0.083	-0.418***	0.442***
	(0.094)	(0.120)	(0.093)
lneXReserveShock	0.004	-0.006	0.005
	(0.005)	(0.007)	(0.005)
Observations	722791	695499	695499
Firm-Country FE	✓	✓	✓
Firm-Year FE	✓	✓	✓
HS-Country FE	✓	✓	✓

Table B.7: Heterogeneity Across ISIC Sector
Using Origin Country Currency Exchange Rate Shock

Dep. var: Revenue, Quantity and Price

	Ln (Revenue)	Ln (Quantity)	$Ln(\frac{Revenue}{Quantity})$
	(1)	(2)	(3)
lneXISIC1	1.762***	0.490	1.824***
	(0.521)	(0.663)	(0.523)
lneXISIC2	1.028	5.642***	-4.929***
	(1.164)	(1.474)	(1.164)
lneXISIC3	-0.245	-2.039*	2.517***
	(0.865)	(1.163)	(0.918)
lneXISIC4	-0.701	0.413	-0.947
	(1.130)	(1.421)	(1.122)
lneXISIC5	-0.064	3.350	-3.179
	(2.653)	(3.256)	(2.571)
lneXISIC6	-0.108	-0.115	-0.075
	(0.305)	(0.388)	(0.306)
lneXISIC7	0.289	-1.168	1.157
	(1.118)	(1.460)	(1.152)
lneXISIC8	-2.825***	-3.442***	-0.030
	(0.595)	(0.748)	(0.590)
lneXISIC9	1.836*	-0.857	3.437***
	(1.066)	(1.443)	(1.139)
lneXISIC10	0.929	0.563	-0.120
	(0.674)	(0.885)	(0.698)
lneXISIC11	-1.104**	0.010	-0.444
	(0.484)	(0.625)	(0.493)
lneXISIC12	-0.300	-0.606*	0.455*
	(0.267)	(0.348)	(0.275)
lneXISIC13	4.377*	5.351*	0.310
	(2.377)	(3.022)	(2.386)
lneXISIC14	-0.441**	-0.695***	0.507***
	(0.194)	(0.241)	(0.190)
lneXISIC15	0.662	-0.933	2.324**
	(1.070)	(1.370)	(1.082)
lneXISIC16	0.308	-0.718	0.902**
	(0.455)	(0.575)	(0.454)
lneXISIC17	1.180*	0.801	0.572
	(0.672)	(0.832)	(0.657)
lneXISIC18	0.967*	2.349***	-1.088**
	(0.514)	(0.644)	(0.508)
lneXISIC19	-6.041***	-8.434***	1.784
	(1.218)	(1.527)	(1.206)
lneXISIC20	-0.080	-0.534***	0.394***
	(0.114)	(0.145)	(0.114)
Observations	563291	540860	540860
Firm-Country FE	✓	✓	✓
Firm-Year FE	✓	✓	✓
HS-Country FE	✓	✓	✓

Table B.8: Heterogeneity Across Sector
Using Invoice Currency Exchange Rates

Dep. var: Revenue, Quantity and Price

	Ln (Revenue)	Ln (Quantity)	$Ln(\frac{Revenue}{Quantity})$
	(1)	(2)	(3)
lneXRaw	0.121	-0.313***	0.402***
	(0.087)	(0.110)	(0.086)
lneXFinished	0.014	-0.406***	0.395***
	(0.087)	(0.110)	(0.086)
lneXIntermediate	0.078	-0.350***	0.411***
	(0.087)	(0.110)	(0.086)
lneXSensitive	0.087	-0.398***	0.439***
	(0.089)	(0.113)	(0.088)
Observations	722791	695499	695499
Firm-Country FE	✓	✓	✓
Firm-Year FE	✓	✓	✓
HS-Country FE	✓	✓	✓

Table B.9: Heterogeneity Across ISIC Sector
Using Invoice Currency Exchange Rate Shock

Dep. var: Revenue, Quantity and Price

	Ln (Revenue)	Ln (Quantity)	$Ln(\frac{Revenue}{Quantity})$
	(1)	(2)	(3)
lneXISIC1	0.260	-0.926	1.294**
	(0.615)	(0.772)	(0.598)
lneXISIC2	-0.454	3.758*	-2.911*
	(1.615)	(2.040)	(1.581)
lneXISIC3	2.273**	2.614**	-0.117
	(0.907)	(1.176)	(0.911)
lneXISIC4	-2.257**	-0.004	-1.962**
	(0.945)	(1.166)	(0.903)
lneXISIC5	0.794	-1.382	2.299
	(1.940)	(2.397)	(1.858)
lneXISIC6	1.458***	-0.017	1.484***
	(0.415)	(0.534)	(0.414)
lneXISIC7	-0.558	-1.789	0.729
	(0.996)	(1.271)	(0.985)
lneXISIC8	-1.121	-2.261**	0.232
	(0.725)	(0.897)	(0.695)
lneXISIC9	1.939*	2.243*	-0.045
	(1.004)	(1.309)	(1.014)
lneXISIC10	-1.051	-0.806	0.357
	(0.685)	(0.906)	(0.702)
lneXISIC11	-1.039	-1.154	0.745
	(0.731)	(0.947)	(0.734)
lneXISIC12	-1.434***	-3.079***	1.571***
	(0.320)	(0.412)	(0.319)
lneXISIC13	6.829***	0.387	5.479***
	(2.172)	(2.708)	(2.098)
lneXISIC14	0.061	-0.274	0.336*
	(0.201)	(0.249)	(0.193)
lneXISIC15	2.482**	0.667	1.912*
	(1.139)	(1.450)	(1.123)
lneXISIC16	-1.609**	-1.462*	-0.260
	(0.652)	(0.813)	(0.630)
lneXISIC17	-0.874	-2.438*	0.785
	(1.095)	(1.353)	(1.048)
lneXISIC18	1.518***	-0.698	1.934***
	(0.542)	(0.679)	(0.526)
lneXISIC19	-1.810	-0.869	-0.707
	(1.919)	(2.402)	(1.861)
lneXISIC20	0.085	-0.021	0.072
	(0.126)	(0.160)	(0.124)
Observations	650039	624733	624733
Firm-Country FE	✓	✓	✓
Firm-Year FE	✓	✓	✓
HS-Country FE	✓	✓	✓

Table B.10: Heterogeneity Across Firm Size
Using Invoice Currency Exchange Rates

Dep. var: Revenue, Quantity and Price

	Ln (Revenue)	Ln (Quantity)	$Ln(\frac{Revenue}{Quantity})$
	(1)	(2)	(3)
lne	0.943**	1.425***	-0.365
	(0.380)	(0.474)	(0.367)
lneXBig	-1.135***	-2.145***	0.824**
	(0.394)	(0.493)	(0.382)
Observations	387138	360555	360555
Firm-Country FE	✓	✓	✓
Firm-Year FE	✓	✓	✓
HS-Country FE	✓	✓	✓

Table B.11: Heterogeneity Across Importing Frequency
Using Invoice Currency Exchange Rates

Dep. var: Revenue, Quantity and Price

	Ln (Revenue)	Ln (Quantity)	$Ln(\frac{Revenue}{Quantity})$
	(1)	(2)	(3)
A. Daily Frequency			
lne	0.695	1.831***	-0.703
	(0.526)	(0.657)	(0.509)
lneXHighFrequency	0.346	-0.567	0.471
	(0.507)	(0.635)	(0.492)
lneXBig	-1.223***	-2.001***	0.704*
	(0.414)	(0.518)	(0.402)
Observations	387138	360555	360555
B. Monthly Frequency			
lne	1.866***	2.276***	-0.605
	(0.472)	(0.615)	(0.477)
lneXHighFrequency	-1.324***	-1.224**	0.345
	(0.402)	(0.565)	(0.438)
lneXBig	-0.807**	-1.824***	0.734*
	(0.406)	(0.514)	(0.399)
Observations	387138	360555	360555
Firm-Country FE	✓	✓	✓
Firm-Year FE	✓	✓	✓
HS-Country FE	✓	✓	✓

Table B.12: Heterogeneity Across Firm Size: Sector-Specific Classification

Dep. var: Revenue, Quantity and Price

	Ln (Revenue)	Ln (Quantity)	$Ln(\frac{Revenue}{Quantity})$
	(1)	(2)	(3)
A. Sector-Specific Size			
lneXBig	0.001	0.400	-0.674
	(0.439)	(0.547)	(0.433)
lneXRaw	-0.093	-0.896*	1.120***
	(0.430)	(0.535)	(0.423)
lneXFinished	-0.114	-0.931*	1.137***
	(0.430)	(0.534)	(0.423)
lneXIntermediate	-0.164	-1.047*	1.191***
	(0.430)	(0.535)	(0.423)
lneXSensitive	-0.067	-0.894*	1.131***
	(0.431)	(0.536)	(0.425)
Observations	338083	314596	314596
B. Sector X Size			
lneXRaw	-0.117	-0.889*	1.089**
	(0.430)	(0.535)	(0.424)
lneXFinished	-0.112	-0.933*	1.140***
	(0.430)	(0.534)	(0.423)
lneXIntermediate	-0.168	-1.040*	1.183***
	(0.430)	(0.535)	(0.423)
lneXSensitive	-0.092	-0.895*	1.108***
	(0.431)	(0.536)	(0.425)
lneXRawXBig	0.028	0.393	-0.642
	(0.439)	(0.547)	(0.433)
lneXFinishedXBig	-0.002	0.403	-0.678
	(0.439)	(0.547)	(0.433)
lneXIntermediateXBig	0.005	0.392	-0.666
	(0.439)	(0.547)	(0.433)
lneXSensitiveXBig	0.029	0.401	-0.649
	(0.439)	(0.547)	(0.433)
Observations	338083	314596	314596
Firm-Country FE	✓	✓	✓
Firm-Year FE	✓	✓	✓
HS-Country FE	✓	✓	✓

Table B.13: Correlation Between Baseline Firm Size and Importing Frequency

Dep. var: ln (total import revenue) at baseline (2008-2011)

	(1)	(2)	(3)	(4)	(5)	(6)
Daily Frequency	0.023***	0.023***	0.023***			
	(0.000)	(0.000)	(0.000)			
Monthly Frequency				0.133***	0.133***	0.150***
				(0.001)	(0.001)	(0.002)
Observations	27000	27000	18028	27000	27000	18028
Sector FE		✓			✓	
ISIC FE			✓			✓

Note: Daily (Monthly) frequency is defined as the number of unique days (months) a firm has undertaken any import activity during the baseline period of 2008 to 2011. Column 2 controls for sector fixed effect (based on the internal sector classification) and column 3 controls for 2-digit ISIC industry fixed effect.

Table B.14: Heterogeneity Across Importing Frequency: Sector-Specific Classification

Dep. var: Revenue, Quantity and Price

	Ln (Revenue)	Ln (Quantity)	$Ln(\frac{Revenue}{Quantity})$
	(1)	(2)	(3)
A. Daily Frequency			
lneXHighFrequency	0.547	-0.541	0.874*
	(0.474)	(0.598)	(0.473)
lneXBig	-0.129	0.528	-0.882**
	(0.453)	(0.565)	(0.447)
lneXRaw	-0.493	-0.500	0.480
	(0.553)	(0.691)	(0.547)
lneXFinished	-0.515	-0.535	0.497
	(0.552)	(0.691)	(0.547)
lneXIntermediate	-0.565	-0.651	0.552
	(0.552)	(0.691)	(0.547)
lneXSensitive	-0.468	-0.498	0.492
	(0.554)	(0.692)	(0.548)
Observations	338083	314596	314596
B. Monthly Frequency			
lneXHighFrequency	0.453	-1.172**	1.598***
	(0.388)	(0.500)	(0.396)
lneXBig	-0.101	0.666	-1.037**
	(0.448)	(0.559)	(0.442)
lneXRaw	-0.421	-0.048	-0.036
	(0.514)	(0.646)	(0.511)
lneXFinished	-0.442	-0.083	-0.019
	(0.513)	(0.645)	(0.511)
lneXIntermediate	-0.492	-0.199	0.035
	(0.514)	(0.645)	(0.511)
lneXSensitive	-0.396	-0.046	-0.025
	(0.515)	(0.647)	(0.512)
Observations	338083	314596	314596
Firm-Country FE	✓	✓	✓
Firm-Year FE	✓	✓	✓
HS-Country FE	✓	✓	✓

Table B.15: Firm-level Impacts of Exchange-Rates Shock on Domestic Sales and Purchase: Using Invoice Currency for Exchange Rates

	Growth from 2017Q1 to 2018Q1			
	Imports	Domestic Purchase	Number of Domestic Sellers	Domestic Sales
	(1)	(2)	(3)	(4)
Exchange Rates Shock (Invoice Currency)	-13.253^{***}	4.113^{***}	3.001^{***}	0.126
	(0.362)	(0.547)	(0.474)	(0.469)
Sector FE	X	X	X	X
Observations	14,447	14,447	14,447	14,447
Adjusted R^2	0.086	0.020	0.022	0.023
Note:				*p<0.1; **p<0.05; ***p<0.01

Table B.16: Firm-level Impacts of Exchange-Rates Shock on Domestic Sales and Purchase: From 2016 to 2017

(A) Exchange Rate Shock Defined by Origin Country

	Growth from 2016Q1 to 2017Q1			
	Imports	Domestic Purchase	Number of Domestic Sellers	Domestic Sales
	(1)	(2)	(3)	(4)
Exchange Rates Shock	-12.438^{***}	8.358^{***}	6.683^{***}	0.190
	(0.367)	(0.552)	(0.472)	(0.409)
Sector FE	X	X	X	X
Observations	9,020	9,020	9,020	9,020
Adjusted R^2	0.115	0.047	0.032	0.008
Note:				*p<0.1; **p<0.05; ***p<0.01

(B) Exchange Rate Shock Defined by Invoice Currency

	Growth from 2016Q1 to 2017Q1			
	Imports	Domestic Purchase	Number of Domestic Sellers	Domestic Sales
	(1)	(2)	(3)	(4)
Exchange Rates Shock (Invoice Currency)	-12.121^{***}	8.319^{***}	6.444^{***}	0.430
	(0.302)	(0.461)	(0.395)	(0.343)
Sector FE	X	X	X	X
Observations	9,020	9,020	9,020	9,020
Adjusted R^2	0.154	0.057	0.039	0.008
Note:				*p<0.1; **p<0.05; ***p<0.01