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# 3 Exchange Rate Volatility and Global Food Supply Chains

Sandro Steinbach

## 3.1 Introduction

Most countries have moved from a fixed exchange rate system to a floating or soft-pegged regime since the disintegration of the Bretton Woods system in the 1970s (Clark et al. 2004). The fixed system's dismissal allowed monetary policy makers to pursue independent monetary policy and ensure free capital movement. Simultaneously, the move to a floating exchange rate system implies a significant increase in exposure to foreign market forces. Studies have shown that high variability of foreign exchange correlates with a rise in uncertainty regarding the terms of trade (McKenzie 1999). Not surprisingly, the consequences of exchange volatility remain a primary source of concern for monetary policy makers worldwide but are of particular relevance in countries with relatively low financial development levels. Therefore, many developing countries use soft-pegged exchange regimes to reduce their exposure to foreign exchange risk.[1] Still, there is no consensus

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1. I use the terms *exchange rate risk* and *exchange rate volatility* interchangeably throughout the paper. Exchange rate volatility is a primary measure of currency exchange risk (Viaene and de Vries 1992).

about the impact of exchange volatility on economic outcomes and how they vary for different industries along the food supply chains. The implications for international trade are poorly understood, and the related empirical literature is mostly inconclusive (Auboin and Ruta 2013).

The theoretical literature has developed several explanations for a causal relationship between exchange rate volatility and international trade. The conventional wisdom is that an increase in exchange rate uncertainty causes an increase in revenue uncertainty, which will hamper the exchange of goods and services across international borders. This uncertainty is the result of risk aversion and irreversible investment in productive capital (Ethier 1973; Demers 1991). Market imperfections can lead to imperfect and costly hedging, a primary source of exchange risk avoidance that is of particular relevance in less developed countries. Therefore, it is likely that international trade correlates negatively with exchange rate volatility due to risk aversion of economic agents (Mundell 2000). The work of Johnson (1969) challenges this view, since he argues that arbitrage between spot and forward markets and speculation would tend to keep the cost of forward exchange cover within reasonable bound in a flexible exchange rate system. Due to these characteristics of financial markets, neither appreciation nor depreciation would harm trade badly. Still, it would benefit economic agents, since policy makers would no longer need to pursue otherwise irrational and difficult policy objectives for the sake of improving the balance of payments. Franke (1991) showed that an increase in exchange rate volatility could have a positive effect on trade. He argues that a multinational monopolist with a trading strategy that factors in exchange rate uncertainty may increase international trade due to growing exchange rate volatility. As pointed out by Grauwe (1988), exchange rate volatility can have a negative or positive effect on trade flows, depending on the shape of the expected marginal utility of income function specific to different sectors of the economy.

The substantial uncertainty regarding the impact of exchange rate risk is echoed in the empirical literature on international trade (for an extensive review, see Auboin and Ruta 2013). Most earlier studies provide evidence for an adverse effect of exchange rate volatility on manufacturing trade (Thursby and Thursby 1987; Koray and Lastrapes 1989; Rose 2000). The empirical evidence for the agricultural and food industry is mostly in line with the assertion for manufacturing trade (Pick 1990; Cho, Sheldon, and McCorriston 2002; Kandilov 2008). Tenreyro (2007) challenged this view by arguing that the negative and significant effect estimates are the result of endogeneity and heteroskedasticity issues neglected so far. She outlined an identification strategy that addresses both identification issues and accounts for reverse causality. Her findings indicate that an increase in short-run exchange rate volatility does not affect international trade. These findings find support in the work of Klaassen (2004), who shows that the maximal effect of exchange rate volatility on international trade occurs with a delay of one year. Therefore, long-term (about one year) risk for trade flows is constant over time, with only short-term deviations from average presenting a risk for global supply chains. Broda and Romalis (2011) introduced a structural estimation approach to account for reverse causality. They argue that the insignificant estimates in Tenreyro (2007) result from aggregation bias and that exchange rate volatility depresses trade mainly for differentiated products. It is reasonable to assume that an agent's reaction to short-run uncertainty differs from the response to long-run uncertainty, which is a possible explanation for the largely insignificant estimates presented in Tenreyro (2007). The lack of consensus about the impact of exchange volatility in light of increasingly integrated global food supply chains represents a significant challenge for understanding better the functioning of agricultural and food markets.

This paper provides three distinct contributions to the ongoing academic debate on the impact of exchange rate volatility on global food supply chains. First, I add to the ongoing discussion by testing for a causal relationship at the product level. I consider 781 agricultural and food products in my analysis and categorize these products according to the liberal product classification of Rauch (1999) into homogenous, reference-priced, and differentiated products and Regmi et al's (2005) classification into aquaculture, bulk, horticulture, semi-processed, and processed products. Second, I study the effect of both short-run and long-run exchange rate volatility. Agents may react differently to these sources of uncertainty. I extracted daily exchange rate data for 25,122 currency pairs and 22 years from the Thomson Reuters database to calculate the volatility measures. The exchange rate measures are assigned to bilateral export data for 159 countries covering 2001 to 2017. I divert from the literature and use daily instead of end-month exchange rate data to calculate the short-run and long-run exchange rate volatility measures following the methods outlined in Rose (2000) and Tenreyro (2007). The end-month volatility measures are likely biased, as they do not accurately represent the distribution of exchange rates within a month. Third, my identification strategy simultaneously addresses the following identification issues: Endogeneity, heteroskedasticity, zero trade flows, sampling, and reverse causality. Using a Poisson count data regression, I account for high-dimensional fixed effects, heteroskedasticity, and zero trade flows (Silva and Tenreyro 2006; Correia, Guimarães, and Zylkin 2020). The multilateral trade resistance terms that may cause an endogeneity issue are accounted for with time-varying fixed effects for importers and exporters (Anderson and van Wincoop 2003). I also include standard gravity control variables such as distance, economic integration agreements, contiguity, and others in my baseline and consider country-pair fixed effects in my preferred regression specification. The sampling issue is addressed by analyzing trade flows for all available country pairs. Lastly, since I conduct my analysis at the product level, I can deal with the reverse causation, since agents operating in these markets do not influence the exchange rate regime (Tenreyro 2007; Broda and Romalis 2011).

I estimate the gravity model at the product level and summarize the parameter estimates according to product and industry characteristics for short-run and long-run volatility measures. The results are analyzed using both mean and trade-weighted effect estimates, providing considerable evidence for a heterogeneous exchange rate volatility effect on global food supply chains. My elasticity estimates indicate that the short-run effects are smaller than the long-run for the overall volatility impact. More specifically, I find that bulk products are positively affected by short-run exchange rate volatility, whereas aquaculture products are negatively impacted by short-run and long-run exchange rate volatility. I observe similar results for horticulture products, which indicates an adverse effect of exchange rate volatility. These findings imply that the impact of exchange rate volatility can vary significantly depending on the product and industry characteristics. The results also indicate that products produced by industries with high upstreamness have positive trade effects, while lower downstreamness of an industry correlated with larger trade effects. I find that export prices correlate positively with trade effects for long-run but not for short-run volatility. The findings do not indicate any relevant correlation between trade effects of exchange rate volatility and both product sophistication and product complexity. I also find no evidence of differences in the trade effects according to the economic development stage of trading partners. Several robustness checks are deployed to explain why my results divert from earlier work. These estimations confirm that gravity model misspecification, aggregation bias, exchange rate measurement errors, and treatment misspecification are the primary causes for significant and negative estimates in these earlier studies (see, for example, Rose 2000, Tenreyro 2007). I conclude that both short-run and long-run exchange rate volatility have limited trade effects, but the average trade effects hide significant heterogeneity between agricultural and food products. There is substantial heterogeneity between different products along the global food supply chain. These estimates enhance the understanding of the implications of exchange rate volatility, which is a primary source of concern for monetary policy makers worldwide.

The remainder of this paper is organized as follows. Section 3.2 presents the empirical model, explains data sources, and details my estimation strategy. Section 3.3 summarizes the regression results, discusses heterogeneity in the trade effect estimates, and explains sources of estimation bias in earlier work. Section 3.4 concludes with a review of my findings and sorts them into the broader literature.

## 3.2 Identification Strategy

I rely on a sectoral gravity-type regression specification to estimate the impact of exchange rate volatility on global food supply chains (Hallak 2010;

Costinot, Donaldson, and Komunjer 2012; Anderson and Yotov 2016). The baseline regression model accounts for multilateral trade resistance terms with country-time specific fixed effects for importers and exporters (Anderson and van Wincoop 2003). The sectoral gravity model is specified in its general form as follows:

$$X_{ij,t}^{s} = \exp(e_{i,t}^{s} - \theta \log \tau_{ij,t}^{s} + m_{j,t}^{s})\eta_{ij,t}, \tag{1}$$

where $X_{ij,t}^{s}$ stands for bilateral export flows of product $s$ from country $i$ to country $j$ in year $t$. The time-variant multilateral resistance terms for exporters are denoted by $e_{i,t}^{s}$ and for importers by $m_{j,t}^{s}$. The trade cost function is denoted by $\tau_{ij,t}^{s}$ (symmetric and of the iceberg form) and includes measures of exchange rate volatility and common gravity-type control variables. I measure nominal exchange rate variability ($\delta_{ij,t}$) by the standard deviation ($\sigma$) of the first difference of the logarithmized bilateral exchange rate ($e_{ij,k}$) as follows:

$$\delta_{ij,t} = \sigma[\ln(e_{ij,k}) - \ln(e_{ij,k-1})]. \tag{2}$$

I extracted exchange rate data for 25,122 currency pairs and 22 years from the Thomson Reuters database. The exchange rate volatility measures were calculated based on daily exchange rate data for 159 countries and the period from 1996 to 2017 (Thomson Reuters 2019). Table 3A.1 provides the list of sample countries. I divert from the literature and use daily exchange rate data to calculate the short-run and long-run exchange rate volatility measures. This decision is informed by concerns about spurious breaks in the exchange rate volatility measures (Rose 2000; Tenreyro 2007). These measures are likely biased as they do not represent the distribution of exchange rates within a month accurately. I define short-run exchange rate volatility $\alpha_{\delta}^{S}$ according to Tenreyro (2007) based on the preceding year and long-run exchange rate volatility $\alpha_{\delta}^{L}$ according to Rose (2000) based on the five preceding years.

The trade cost function $\tau_{ij,t}^{s}$ includes additional control variables that vary at the country-pair level over time. The covariates in my regression model are the log of weighted distance, common legacy, economic integration, WTO membership, shared border, and common language. I also include the log of GDP and the log of the population in a partial model that only includes importer, exporter, and time fixed effects and serves as a comparison to the literature (see, e.g., Tenreyro 2007). I obtained data on GDP and population from the World Development Indicators database (World Bank 2021). The GDP variable is measured in the current US$. I also constructed a variable for multilateral economic integration with membership information from the World Trade Organization (WTO 2021). The bilateral economic integration variable was obtained from the Economic Integration Agreement Dataset (Bergstrand 2016). This data set indexes the amount of trade openness on a scale from 0 to 6, where 0 stands for no economic integration and 6 for an economic union. The remaining gravity control variables are from the GeoDist Database by Mayer and Zignago (2011). I extracted information on geographical distance, common legacy, shared border, and common language from this database. My preferred model specification accounts for multilateral trade resistance terms with country-time specific fixed effects for importers and exporters, controls for time-invariant trade costs with country-pair fixed effects, and includes time-variant covariates to control for trade cost changes over time. The descriptive statistics of all regressors are provided in table 3A.2.

I denote the outcome variable in my preferred regression specification by $X_{ij,t}$. The variable represents the non-negative integer count of bilateral trade flows at the product level. The trade data were obtained from the Comtrade Database and cover the period from 2001 to 2017 (United Nations 2021). I use the reconciled export flows published in BACI (CEPII 2021). I consider 781 food products in my analysis and categorize these products according to the liberal trade product classification of Rauch (1999) into homogenous (202), reference-priced (303), and differentiated products (231). I also use Regmi et al's (2005) classification of agricultural sectors to classify the food products into aquaculture (104), bulk (63), horticulture (238), semi-processed (121), and processed products (255). Although I could transform the outcome variable and then estimate the relationship using a linear regression model, I believe that this approach is inappropriate for the data because the outcome variable is a count. A linear regression model is incapable of identifying the relationship of primary interest because the model does not ensure positivity of the predicted values for the count outcome (Wooldridge 1999). Moreover, the discrete nature of the count outcome makes it difficult to find a transformation with a conditional mean that is linear in parameters. This issue is further exaggerated in the presence of heteroskedasticity as the transformed errors correlate with the covariates. Such correlation can result in an inconsistent identification of the treatment effect. Even if the transformation of the conditional mean is correctly specified, it would be impossible to obtain an unbiased measure of the relationship. Therefore, I model the relationship between the outcome and the trade cost variables directly. I ensure the positivity of the covariates by employing a nonlinear regression model which uses an exponential form equation.

I use the Poisson pseudo-maximum likelihood (PML) estimator to identify the relationship between the treatment variable and the count outcome (Gong and Samaniego 1981; Gourieroux, Monfort, and Trognon 1984).[2]

2. Although I could also rely on the standard Poisson regression model to estimate the relationship, this estimator has two properties that could complicate the identification of the exchange rate volatility treatment effect. First, this regression is known to suffer from convergence problems which can result in spurious estimation results. Second, it is sensitive to numerical difficulties, which is a particular issue for regressions with high-dimensional fixed effects and highly disaggregated data (Silva and Tenreyro 2010). Therefore, I use the PML estimator as it allows me to circumvent these cavities of the standard Poisson regression.

The estimator is unbiased and consistent in the presence of heteroskedasticity. Even if the conditional variance is not proportional to the conditional mean, the estimator is still consistent (Wooldridge 1999; Cameron and Trivedi 2013). Note that because the estimator does not make any specific assumption on the dispersion of the fitted values, I do not have to test for this aspect of the data. A further advantage of the Poisson PML estimator is that the scale of the dependent variable has no effect on the parameter estimates, which is a particular concern for the Negative Binomial PML estimator. As long as the conditional mean is correctly specified, the Poisson PML estimator yields parameter estimates that have a similar magnitude to the estimates of both the Gaussian and Negative Binomial PML estimators. I account for high-dimensional fixed effects using the approach outlined in Correia, Guimarães, and Zylkin (2020). Lastly, I suspect the presence of residual correlation at the country-pair level. Therefore, I address the potential heteroskedasticity in the error term using a robust variance estimator that accounts for clustering at the country-pair level (Cameron and Miller 2015).

## 3.3 Results

### 3.3.1 Baseline Results

Table 3.1 summarizes the baseline regression results for agricultural and food products (columns 2–3) and compares these estimates to all other

**Table 3.1 Parameter estimates for baseline model**

| | Agriculture and food | | All other products | |
|---|---|---|---|---|
| | $\alpha_\delta^S$ | $\alpha_\delta^L$ | $\alpha_\delta^S$ | $\alpha_\delta^L$ |
| *Sign of parameter estimates* | | | | |
| Positive estimates | 51.54 | 52.27 | 51.50 | 53.89 |
| Negative estimates | 48.46 | 47.73 | 48.50 | 46.11 |
| *Significance of parameter estimates* | | | | |
| Significant at 1% level | 15.90 | 13.33 | 12.83 | 14.34 |
| Significant at 5% level | 24.87 | 29.60 | 24.12 | 26.86 |
| Significant at 10% level | 34.36 | 37.87 | 33.25 | 35.52 |
| *Magnitude of parameter estimates* | | | | |
| Mean estimate | 0.008 | 0.115 | 0.002 | −0.068 |
| Median estimate | −0.050 | −0.105 | −0.033 | −0.167 |
| % percentile estimate | −0.800 | −1.554 | −0.659 | −1.343 |
| % percentile estimate | 0.767 | 1.631 | 0.623 | 1.147 |

*Note:* The table summarizes the parameter estimates of the short-run and long-run exchange rate volatility. Columns 2–5 summarize the estimates for $\alpha_\delta^S$ and $\alpha_\delta^L$. The arithmetic mean effects are presented for agricultural and food products in columns 2–3 and all other products in columns 4–5.

products (columns 4–5). I indicate the parameter estimates for short-run volatility with $\alpha_\delta^S$ and the ones for long-run volatility with $\alpha_\delta^L$. The table presents summary statistics for the sign, significance, and magnitude of parameter estimates. All estimations incorporate dyadic importer-exporter fixed effects and control for multilateral resistance terms with importer-year and exporter-year fixed effects. I also include time-variant covariates potentially correlated with the volatility measures.

The sign of the parameter estimates for short-run and long-run volatility indicate an almost equal distribution of positive and negative volatility effects: 51.54 percent of short-run and 52.27 percent of long-run volatility estimates have a positive sign. The distribution is similar for all other products. In terms of the significance of parameter estimates, I find that 34.36 percent of short-run and 37.87 percent of long-run volatility parameter estimates are significant at the 10 percent confidence level. The distribution for all other products looks similar to that for agricultural and food products. The magnitude of parameter estimates indicates a mean positive effect that is larger for the long-run than for the short-run exchange rate volatility. The mean is 0.008 for short-run and 0.115 for long-run volatility estimates. The estimates for all other products show a different picture. The mean estimate of long-run volatility is negative, and the short-run volatility estimate is similar to that for agricultural and food products. Note that the median estimates are negative for short-run and long-run volatility. The results indicate that the long-run volatility effect is more pronounced than the short-run volatility effect. The wide distribution of volatility estimates is striking. I find a wider spread for the long-run than for the short-run elasticity estimates for agricultural and food products and all other products.

Table 3.2 provides a summary of the baseline regression results according to different agricultural and food products and Rauch's product classification. The table compares mean and trade-weighted effects for short-run $\alpha_\delta^S$ and long-run volatility $\alpha_\delta^L$ based on the preferred model specification.[3] I distinguish between aquaculture, bulk, horticulture, semi-processed, and processed products. The product distribution at the HS-6 level indicates that most products are either processed or horticulture products. Bulk products have the lowest share. I find that apart from bulk products, all mean and trade-weighted short-run volatility estimates have a negative sign. The largest volatility effects are found for processed and semi-processed agricultural and food products. The short-run volatility estimates for bulk products are positive, with a parameter estimate of 0.095 for the mean and 0.075 for the trade-weighted effects. The picture is different for long-run volatility estimates, where I find that several product groups (aquaculture, horticulture, and semi-processed products) record a positive volatility effect. This effect is

3. I weigh the parameter estimates by the total export value of the specific HS-6 product for 2001 to 2017.

**Table 3.2** **Trade effects for baseline model**

| | # | Mean effect | | Trade-weighted effect | |
|---|---|---|---|---|---|
| | | $\alpha_\delta^S$ | $\alpha_\delta^L$ | $\alpha_\delta^S$ | $\alpha_\delta^L$ |
| *Agriculture and food products* | | | | | |
| Aquaculture | 101 | −0.038 | 0.037 | −0.031 | 0.040 |
| Bulk | 58 | 0.095 | −0.021 | 0.075 | −0.005 |
| Horticulture | 208 | −0.016 | 0.054 | −0.010 | 0.038 |
| Semi-processed | 120 | −0.043 | 0.056 | −0.038 | 0.045 |
| Processed | 250 | −0.041 | −0.026 | −0.035 | −0.024 |
| *Product differentiation* | | | | | |
| Homogenous | 222 | −0.055 | 0.029 | −0.043 | 0.023 |
| Reference-priced | 314 | 0.001 | 0.036 | −0.001 | 0.031 |
| Differentiated | 186 | −0.004 | −0.002 | −0.003 | −0.005 |

*Note:* The table summarizes the parameter estimates of the exchange rate volatility measures by product category. The upper part of the table presents the trade effects according to Regmi's (2005) classification of agricultural and food products, while the lower part summarizes the trade effects according to Rauch's (1999) goods classification. Column 2 shows the number of parameters used for calculation in each category. Columns 3–6 summarize the estimates for $\alpha_\delta^S$ and $\alpha_\delta^L$. The arithmetic mean effects are presented in columns 3–4 and trade-weighted effects in columns 5–6.

present for mean and trade-weighted effects. I find that bulk and processed product exports are negatively affected by exchange rate volatility, but this effect is comparably small for mean and trade-weighted estimates. According to Rauch's product classification, the parameter estimates indicate adverse short-run volatility effects for homogenous products and positive long-run volatility effects for homogenous and reference-priced products. They do not show short-run and long-run volatility effects for differentiated products. The mean and trade-weighted effects are similar in magnitude and have the same parameter signs.

Figure 3.1 illustrates the ranked distribution of trade effects for a one standard deviation change in short-run and long-run exchange rate volatility for agricultural and food products. Subfigure (a) presents the estimates for the short-run and subfigure (b) the ones for the long-run volatility. The dashed lines indicate pooled estimates. The trade effects are calculated by the formula $\beta^* = sd_x / sd_y * \hat{\beta}$. The pooled estimates for the preferred regression specification indicate no evidence for a significant impact of short-run and long-run exchange rate volatility on agricultural and food exports. The disaggregated trade effects at the HS-6 product level indicate a different picture. I find for short-run and long-run exchange rate volatility strong evidence for heterogeneity between different products. This heterogeneity effect is more pronounced for the long-run than for short-run volatility, with the trade effects ranging between –2.95 and 3.64 per one standard deviation change in exchange rate volatility.

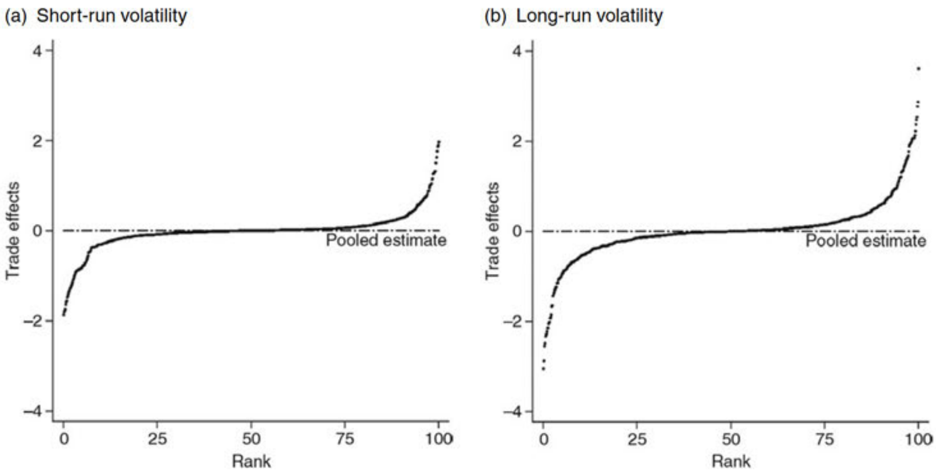


**Figure 3.1 Ranked trade effects of exchange rate volatility**

*Note:* The figure shows the ranked trade effects of a one standard deviation change in short-run and long-run exchange rate volatility for agricultural and food products. The trade effects are calculated by the formula $\beta^* = sd_x / sd_y * \hat{\beta}$.

## 3.3.2 Product and Industry Characteristics

### *3.3.2.1 Supply Chain*

Figure 3.2 shows the link between supply chain characteristics and trade effects of exchange rate volatility. I measure trade effects according to one standard deviation change in short-run and long-run exchange rate volatility and indicate piecewise cubic spline interpolations with dashed lines. Subfigures (a) and (b) shows the results for upstreamness and subfigures (c) and (d) the ones for downstreamness. Upstreamness measures the distance between the production stage and final demand (Antràs et al. 2012).[4] Upstreamness is measured based on a production function:

$$y(s) = c(s) + \sum_{t} d(s,t)c(t) + \sum_{t}\sum_{u} d(s,t)d(s,u)c(t) + \ldots, \tag{3}$$

where $c(s)$ represents the final consumption of good $s$ and $d(s, t)$ represents the amount of input $s$ needed to produce good $t$. This definition allows us to derive upstreamness ($U$) as follows:

$$U(s) = 1 + \sum_{t=1}^{N} \frac{d(s,t)y(t)}{y(s)} U(t), \tag{4}$$

4. I convert NAICS classification into HS-92 classification using conversion tables provided by the United Nations.

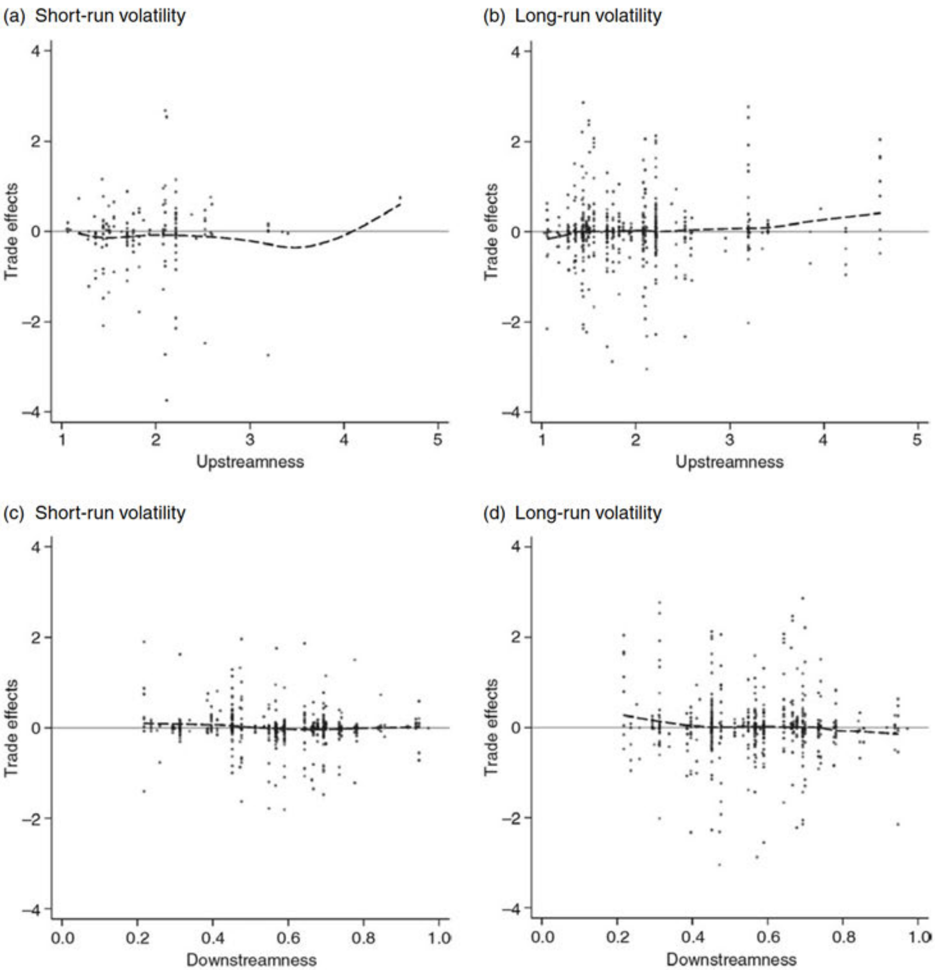


**Figure 3.2 Supply chain and trade effects of exchange rate volatility**

*Note:* The figure shows the relationship between supply chain position and trade effects of exchange rate volatility. The supply chain length is measured by upstreamness and downstreamness. The trade effects are expressed as one standard deviation change in short-run and long-run exchange rate volatility for agricultural and food products. The dashed lines indicate piecewise cubic spline interpolations.

where $[d(s, t)y(t)]/y(s)$ is the share of $s$ purchased by $t$. If the upstreamness measure is equal to one, then the entire output is directly consumed. The larger the upstreamness measure, the more upstream the industry is. The piecewise cubic spline interpolations indicate a weak positive relationship between upstreamness and the trade effects of exchange rate volatility. The effects are more pronounced for the long-run than for the

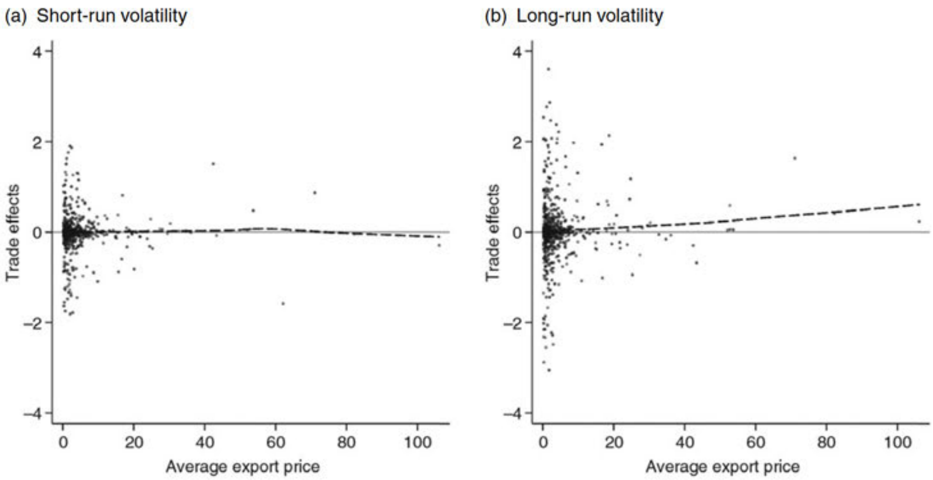


**Figure 3.3 Export prices and trade effects of exchange rate volatility**

*Note:* The figure shows the relationship between average export prices and trade effects of exchange rate volatility. The average export price is defined as the total value of exports divided by the total quantity of exports overall years within the sample. The trade effects are calculated by the formula $\beta^* = sd_x / sd_y * \hat{\beta}$.

short-run volatility measures. The results indicate that the upstreamness of the supply chain has a minor impact on the magnitude of the exchange rate volatility effects. I also use the downstreamness measure to investigate supply chain effects (Antràs and Chor 2013). The downstreamness measure is a weighted index of the average position in the value chain at which an industry's output is used, with the weights given by the ratio of the use of that industry's output in that position relative to the total production of that industry. Antràs and Chor (2013) calculate the downstreamness measure from 2002 US input-output tables. The piecewise cubic spline interpolations indicate a weak negative association between downstreamness and the trade effects of exchange rate volatility. These effects are more pronounced for the long-run than for the short-run volatility measure. The results indicate that an industry's position in the supply chain has no impact on the magnitude of the exchange rate volatility effects.

### *3.3.2.2 Export Prices*

Figure 3.3 shows the relationship between the average export price of agricultural and food products and the trade effects of short-run and long-run exchange rate volatility. The average export price is calculated as the unit value at the HS-6 product level, and the trade-weighted average unit value is used to illustrate the relationship. The presented trade effects are measured according to one standard deviation change in short-run and long-run exchange rate volatility. I indicate piecewise cubic spline interpolations with dashed lines. The results show no significant relationship between export prices and trade effects of short-run exchange rate volatility for agricultural and food products. I find evidence for a positive association between the average export price and the trade effects of long-run exchange rate volatility. The higher the unit value, the more likely it is that exchange rate volatility has a positive trade effect. However, the statistical evidence for such a relationship remains weak, being driven by few products with positive trade effects.

#### *3.3.2.3 Product Sophistication*

To measure the impact of product sophistication on the link between exchange rate volatility and agricultural and food trade, I implement the framework outlined by Hausmann, Hwang, and Rodrik (2007) and calculate a product-level sophistication index. The rationale underlying the sophistication index is that products exported by highly developed countries will have characteristics that allow high-wage producers to compete globally. These characteristics include technology as an essential determinant, but they are also related to other factors such as marketing, logistics and proximity, fragmentability, information and familiarity, natural resources, infrastructure, and value chain organization (Lall, Weiss, and Zhang 2006). The index measures the level of sophistication associated with product $k$ as follows:

(5) $$S_k = \sum_j \frac{x_{jk} / X_j}{\sum_j x_{jk} / X_j} Y_j ,$$

where the numerator stands for the value-share of product $k$ in country $j$'s overall export basket and the denominator represents the aggregated value-shares of all countries exporting product $k$. The index is calculated by year, and the grand mean is used to illustrate the relationship between product sophistication and the trade effects of exchange rate volatility. I measure trade effects according to one standard deviation change in short-run and long-run exchange rate volatility and indicate piecewise cubic spline interpolations with dashed lines. The results show no relationship between product sophistication and the trade effects of short-run and long-run exchange rate volatility. Although there is a downward trend for the cubic spline estimates, the association is weak and provides insufficient evidence for a significant relationship. These estimates imply that the trade effects caused by exchange rate volatility are not affected by product sophistication.

#### *3.3.2.4 Product Complexity*

Product complexity correlates with income inequality, which is strongly associated with exchange rate volatility (Galí and Monacelli 2005). To account for the role of product complexity, I use the Product Complexity Index (PCI) developed by Hartmann et al. (2017). The PCI derives from the

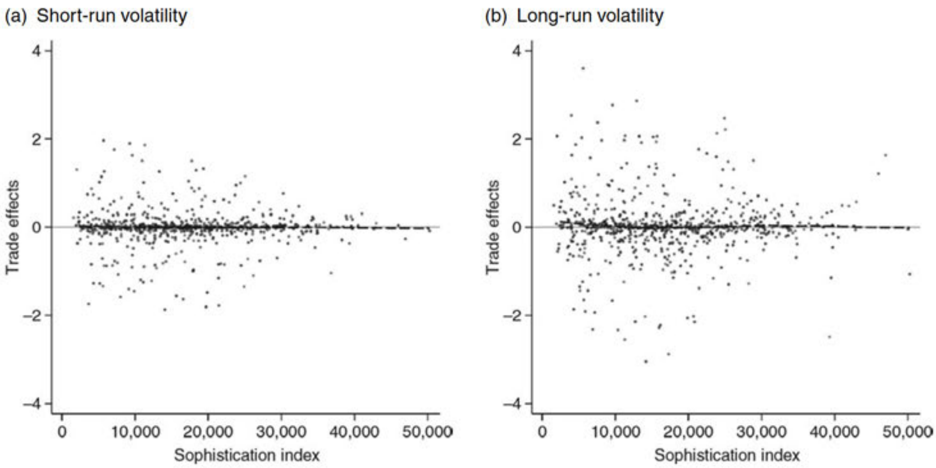


**Figure 3.4 Product sophistication and trade effects of exchange rate volatility**
*Note:* The figure shows the relationship between product sophistication and trade effects of exchange rate volatility. The product-level sophistication index is calculated using the approach outlined by Hausmann, Hwang, and Rodrik (2007). The trade effects are calculated by the formula $\beta^* = sd_x / sd_y * \hat{\beta}$.

Economic Complexity Index, which is a holistic measure of the productive capabilities of large economic systems. I relate the PCI with the trade effects of short-run and long-run exchange rate volatility in figure 3.5. The PCI ranges between −2 and 2. I measure trade effects according to one standard deviation change in exchange rate volatility and indicate piecewise cubic spline interpolations with dashed lines. The spline estimates indicate no significant relationship between exchange rate volatility and the PCI. These results imply that the product complexity does not correlate with the ability to hedge exchange rate risk.

### *3.3.2.5 Economic Development*

The economic development stage of an economy could impact its ability to hedge exchange rate risk (CITE). I interact the short-run and long-run volatility measures with a dyadic variable for OECD membership to measure differences in the trade effects according to economic development. I estimate the directional trade effects for North-North, North-South, South-North, and South-South. The results of this analysis are illustrated in figure 3.6. I show the trade effects for agricultural and food products and use box-and-whisker plots to summarize the findings. The figures indicate no differences in the average trade effects for short-run and long-run exchange rate volatility based on the economic development stage. All average trade effects are close to zero. An interesting observation is the wider spread of trade effects for North-South and South-South trade.

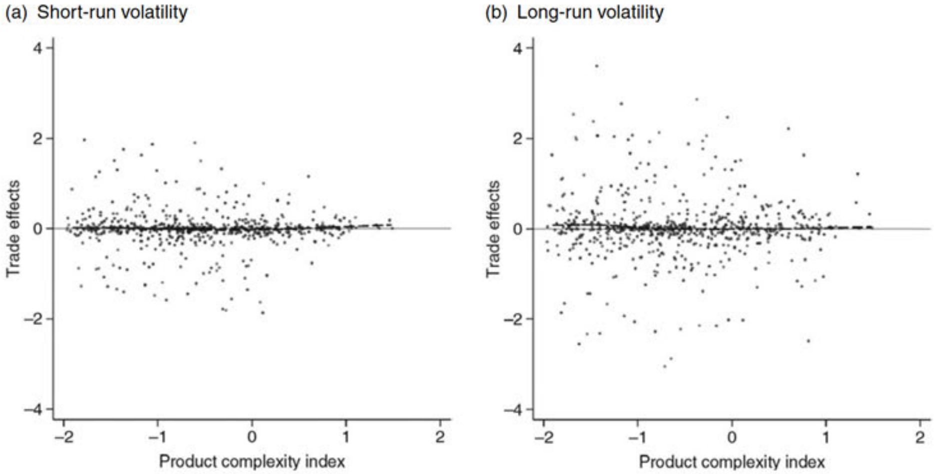


**Figure 3.5 Product compexity and trade effects of exchange rate volatility**

*Note:* The figure shows the relationship between product complexity and trade effects of exchange rate volatility. The product-level sophistication index is calculated using the approach outlined by Hartmann et al. (2017) (CITE). The trade effects are calculated by the formula $\beta^* = sd_x / sd_y * \hat{\beta}$.

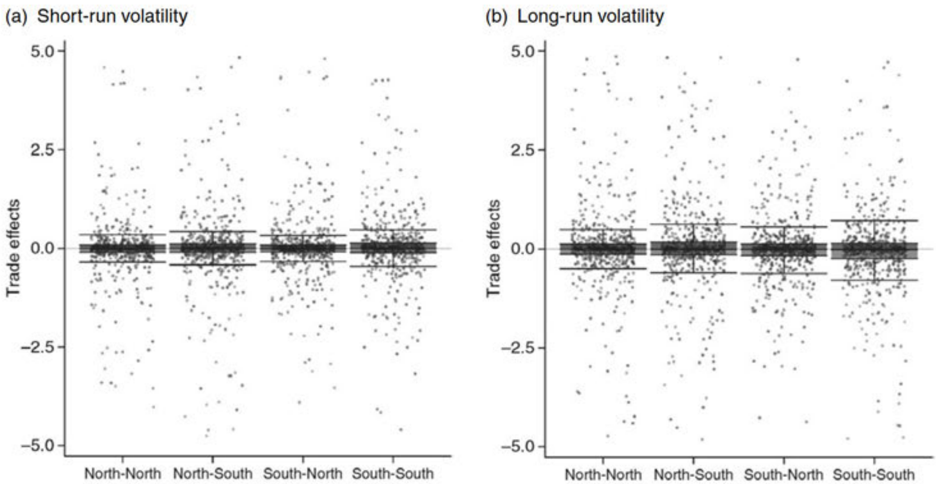


**Figure 3.6 Economic development and trade effects of exchange rate volatility**

*Note:* The figure shows the relationship between economic development and trade effects of exchange rate volatility. The directional trade effects are measures by interacting a dyadic development stage dummy with the short-run and long-run volatility measures. The trade effects are calculated by the formula $\beta^* = sd_x / sd_y * \hat{\beta}$.

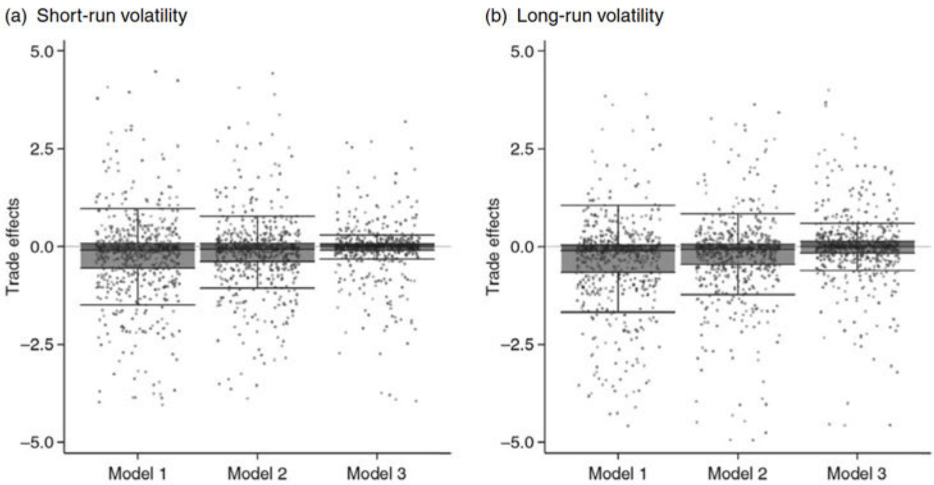


**Figure 3.7 Gravity model specification and trade effects of exchange rate volatility**
*Note:* The figure shows the impact of the gravity model specification on the trade effects of exchange rate volatility. The trade effects are calculated by the formula $\beta^* = sd_x / sd_y * \hat{\beta}$.

## 3.3.3 Identification Challenges

### *3.3.3.1 Gravity Model Specification*

A potential explanation for the starkly different results in this analysis compared to earlier work relates to the gravity model specification. In addition to aggregation bias, earlier studies also suffer from model misspecification issues by either exploring the relationship using cross-sectional data only or not accounting for multilateral resistance terms and time-invariant trade cost. Figure 3.7 shows the distribution of trade effects for three model specifications. Model 1 includes time-invariant importer and exporter as well as year fixed effects. This specification suffers from the "gold medal mistake" by not accounting accurately for the multilateral resistance terms. Model 2 represents a theoretically justified gravity specification with time-varying importer and exporter fixed effects. A potential concern relates to the correlation between time-invariant trade costs and the exchange rate volatility measures. To account for this issue, Model 3 includes time-varying importer and exporter and dyadic importer-exporter fixed effects. This specification is my preferred gravity model specification as it accounts for any correlation between the volatility measures and time-invariant trade costs. To illustrate the consequences of gravity model misspecification, I use a box-and-whisker plot for the trade effects of short-run and long-run exchange rate volatility. The results provide clear evidence for an adverse effect of gravity model misspecification on the reliability of the exchange rate volatility estimates. I find strong evidence that model misspecification has an adverse impact on the exchange rate volatility estimates for agricultural and food exports, both for short-run and long-run volatility measures.

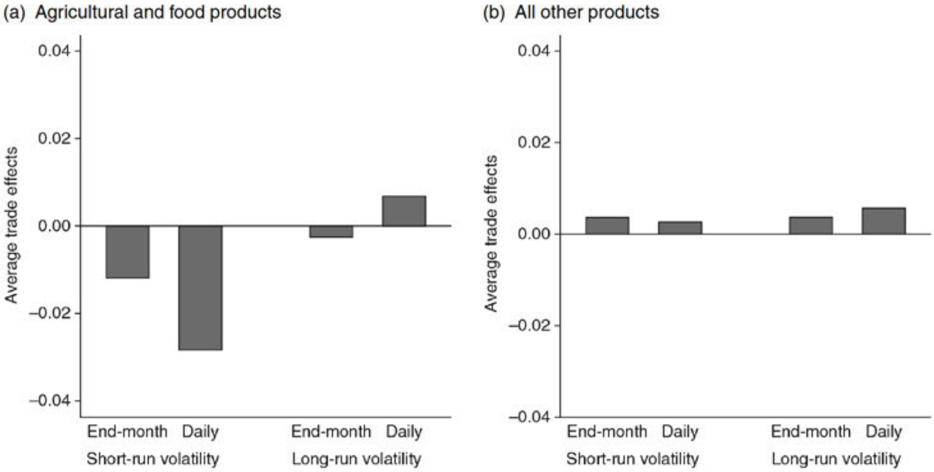


**Figure 3.8 Exchange rate measure and trade effects of exchange rate volatility**

*Note:* The figure shows the impact of the exchange rate measure on the trade effects of exchange rate volatility. The average trade effect represents the arithmetic mean of the individual trade effects calculated by the formula $\beta^* = sd_x / sd_y * \hat{\beta}$.

### *3.3.3.2 Exchange Rate Measure*

A further issue related to earlier studies is the use of end-month instead of daily volatility measures. Figure 3A.1 shows the exchange rate quotation USD/CAD for 2010. Earlier studies solely rely on end-month quotations to calculate volatility measures. This choice can introduce substantial bias in the estimation as the end-month quotations are not representative of the experienced volatility for exchange rate time series. To illustrate the impact of this issue, I compare average trade effects for short-run and long-run volatility based on end-month and daily exchange rate quotations in figure 3.8. These estimates are based on the preferred model specification. Subfigure (a) shows the estimates for agricultural and food products and subfigure (b) the estimates for all other products. The estimates indicate a larger average trade effect for daily than for end-month exchange rate volatility measures. The short-run volatility effect is twice as large for daily than for end-month volatility, while the average trade effect turns positive for the long-run volatility measures. These results indicate that the choice of the exchange rate measure has a significant impact on the gravity estimation results.

### *3.3.3.3 Treatment Specification*

A further concern relates to the joint inclusion of short-run and long-run volatility measures. Most earlier studies measure either the effects of short-run or long-run volatility. The Pearson correlation coefficient between both measures is 0.3382, indicating only limited multicollinearity concerns for both variables. Figure 3.9 shows the average trade effects for short-run and long-run exchange rate volatility by estimating the preferred model specifica-

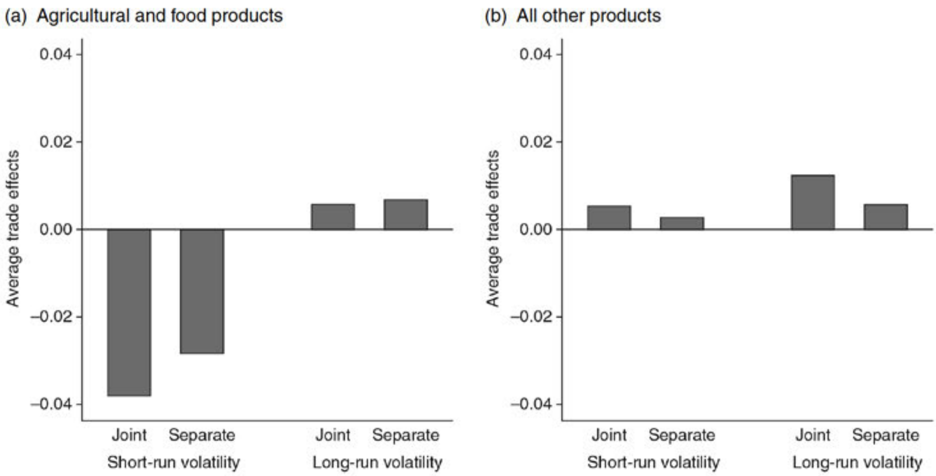


**Figure 3.9 Treatment specification and trade effects of exchange rate volatility**
*Note:* The figure shows the impact of the treatment specification on the trade effects of exchange rate volatility. I compare the joint estimation with the separate estimation for short-run and long-run volatility estimates. The average trade effect represents the arithmetic mean of the individual trade effects calculated by the formula $\beta^* = sd_x / sd_y * \hat{\beta}$.

tion with short-run and long-run volatility measures jointly and separately. The average trade effects are larger for the joint specification than for the separate specification, indicating some correlation between short-run and long-run volatility effects. These effects are small for the long-run volatility measure and more pronounced for the short-run volatility measure. The results indicate that separate or joint estimation of trade effects for short-run and long-run exchange rate volatility has a limited impact on the average trade effects.

### *3.3.3.4 Non-linearity*

Non-linearity could have an impact on the trade effects of short-run and long-run exchange rate volatility. The rationale is that higher volatility levels associate with non-linear treatment effects. To account for these effects, I include linear and quadratic exchange rate volatility measures in the preferred regression specification. The results of this analysis are presented in figure 3.10. Subfigures (a) and (b) show the change in the rank for all agricultural and food products comparing the linear to the quadratic specification. The arrows indicate the movement in rank and trade effects. For the majority of agricultural and food products, the inclusion of quadratic exchange rate volatility measures has a limited impact on the trade effects. This observation applies to short-run and long-run volatility effects. Subfigures (c) and (d) compare the absolute change in the trade effects for one-standard deviation change in exchange rate volatility. The figures indicate that most agricultural and food products show a minor change in trade effects. However, some

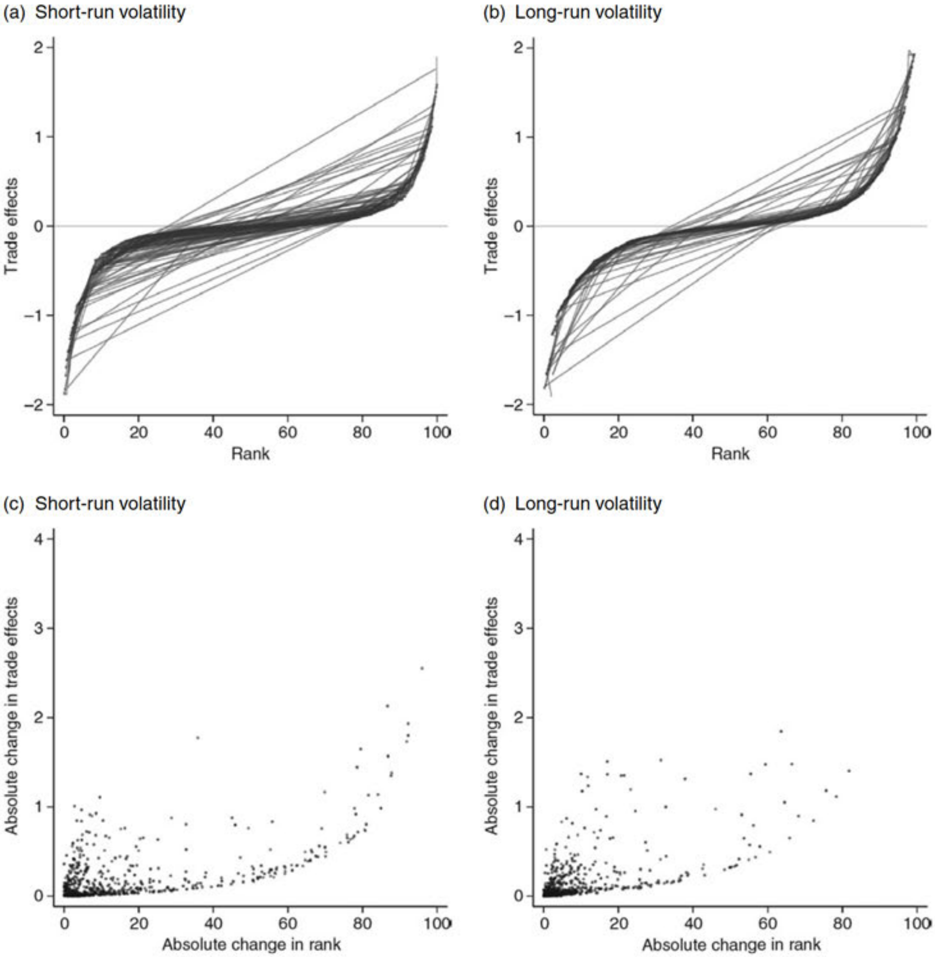


**Figure 3.10 Non-linearity and trade effects of exchange rate volatility**
*Note:* The figure shows the impact of the model specification on the trade effects of short-run and long-run exchange rate volatility. I compare the joint with the separate trade effect estimates.

product are strongly impacted by non-linearity indicated by significant rank movement and change in trade effects.

## 3.4 Conclusion

This paper contributes to the ongoing academic debate on the impact of exchange rate volatility on global food supply chains. I estimate a theoretically consistent sectoral gravity model to measure the effects of short-run and long-run exchange rate volatility on agricultural and food trade at the product level. Earlier studies are characterized by several sources of misspecification and measurement error that are addressed in my analysis. I consider 781 food products and categorize them according to the liberal product classification of Rauch (1999) into homogenous, reference-priced, and differentiated products. My estimates indicate significant differences between product categories and industries. I find some evidence for an adverse effect of short-run and a positive impact of long-run exchange rate volatility on global food supply chains. The results indicate that products produced by industries with high upstreamness have positive trade effects, while low downstreamness of an industry correlated with larger and positive trade effects. I also find that export prices correlate positively with trade effects for the long-run but not for short-run volatility measures. The estimates do not indicate any relevant correlation between trade effects of exchange rate volatility and both product sophistication and product complexity. I also find no evidence of differences in the trade effects according to the economic development stage. Several robustness checks are conducted to explain why my results divert from common wisdom in the international trade literature. These checks confirm that gravity model misspecification, aggregation bias, exchange rate measurement errors, and treatment misspecification are the leading causes for the significant and negative estimates in earlier studies (see, for example, Rose 2000; Tenreyro 2007). Both short-run and long-run exchange rate volatility have a limited mean impact on agricultural and food trade. There is substantial heterogeneity between different products along the global food supply chain that requires a product-level analysis to be unmasked.

## Appendix

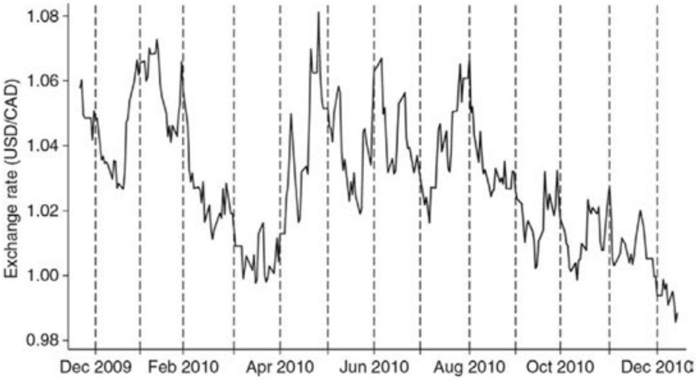


**Figure 3A.1 Temporal resolution of the exchange rate data**

*Note:* The figure shows the exchange rate quotation for the USD/CAD pair for 2010. Red vertical lines indicate end-month exchange rate quotations.

**Table 3A.1** **Sample countries**

| Country name | ISO code | Country name | ISO code |
|---|---|---|---|
| Angola | AGO | Djibouti | DJI |
| Albania | ALB | Dominica | DMA |
| United Arab Emirates | ARE | Denmark | DNK |
| Argentina | ARG | Dominican Rep. | DOM |
| Antigua and Barbuda | ATG | Algeria | DZA |
| Australia | AUS | Ecuador | ECU |
| Austria | AUT | Egypt | EGY |
| Benin | BEN | Spain | ESP |
| Burkina Faso | BFA | Estonia | EST |
| Bangladesh | BGD | Finland | FIN |
| Bulgaria | BGR | Fiji | FJI |
| Bahrain | BHR | France | FRA |
| Bahamas | BHS | Gabon | GAB |
| Belarus | BLR | United Kingdom | GBR |
| Belize | BLZ | Ghana | GHA |
| Bolivia | BOL | Guinea | GIN |
| Brazil | BRA | Gambia | GMB |
| Barbados | BRB | Guinea-Bissau | GNB |
| Central African Republic | CAF | Greece | GRC |
| Canada | CAN | Grenada | GRD |
| Switzerland | CHE | Guatemala | GTM |
| Chile | CHL | Guyana | GUY |
| China | CHN | China, Hong Kong SAR | HKG |
| Cote d'Ivoire | CIV | Honduras | HND |
| Cameroon | CMR | Croatia | HRV |
| Congo | COG | Haiti | HTI |
| Colombia | COL | Hungary | HUN |
| Comoros | COM | Indonesia | IDN |
| Cape Verde | CPV | India | IND |
| Costa Rica | CRI | Ireland | IRL |
| Cyprus | CYP | Iran | IRN |
| Czech Republic | CZE | Iceland | ISL |
| Germany | DEU | Israel | ISR |
| Italy | ITA | Pakistan | PAK |
| Jordan | JOR | Peru | PER |
| Japan | JPN | Philippines | PHL |
| Kazakhstan | KAZ | Poland | POL |
| Kenya | KEN | Portugal | PRT |
| Cambodia | KHM | Paraguay | PRY |
| Rep. of Korea | KOR | Russian Federation | RUS |
| Kuwait | KWT | Rwanda | RWA |
| Lebanon | LBN | Saudi Arabia | SAU |
| Liberia | LBR | Senegal | SEN |
| Libya | LBY | Singapore | SGP |
| Saint Lucia | LCA | Sierra Leone | SLE |
| Sri Lanka | LKA | El Salvador | SLV |
| Lithuania | LTU | Suriname | SUR |
| Latvia | LVA | Slovakia | SVK |
| Morocco | MAR | Slovenia | SVN |

(*continued*)

**Table 3A.1** **(continued)**

| Country name | ISO code | Country name | ISO code |
|---|---|---|---|
| Moldova | MDA | Sweden | SWE |
| Madagascar | MDG | Seychelles | SYC |
| Mexico | MEX | Syria | SYR |
| Mali | MLI | Chad | TCD |
| Malta | MLT | Togo | TGO |
| Mozambique | MOZ | Thailand | THA |
| Mauritania | MRT | Tonga | TON |
| Mauritius | MUS | Trinidad and Tobago | TTO |
| Malawi | MWI | Tunisia | TUN |
| Malaysia | MYS | Turkey | TUR |
| Niger | NER | Tanzania | TZA |
| Nigeria | NGA | Uganda | UGA |
| Nicaragua | NIC | Ukraine | UKR |
| Netherlands | NLD | Uruguay | URY |
| Norway | NOR | USA | USA |
| Nepal | NPL | Saint Vincent and Grenadines | VCT |
| New Zealand | NZL | Venezuela | VEN |
| Oman | OMN | Vietnam | VNM |
| Vanuatu | VUT | South Africa | ZAF |
| Yemen | YEM | | |

*Note:* The table reports the list of sample countries. I report the country name and ISO code.

**Table 3A.2** **Descriptive statistics**

| | | Standard deviation | | | |
|---|---|---|---|---|---|
| Variables | Mean | Overall | Between | Within | Trend |
| Log of weighted distance | 8.76 | 0.80 | 0.00 | 0.80 | 0.00 |
| Log of market size | 26.31 | 1.78 | 0.19 | 1.77 | 0.10 |
| Log of income difference | 9.25 | 1.39 | 0.08 | 1.39 | 0.05 |
| Economic integration | 0.61 | 1.25 | 0.15 | 1.24 | 0.11 |
| WTO membership | 0.63 | 0.48 | 0.17 | 0.46 | −0.05 |
| Common colonizer | 0.01 | 0.11 | 0.00 | 0.11 | 0.00 |
| Shared border | 0.02 | 0.12 | 0.00 | 0.12 | 0.00 |
| Common language | 0.16 | 0.36 | 0.00 | 0.36 | 0.00 |
| Common legacy | 0.01 | 0.10 | 0.00 | 0.10 | 0.00 |

*Note:* The table presents the descriptive statistics. The calculation are based on data by country-pair for 2001 to 2017.

## References

Anderson, J., and Y. Yotov. 2016. "Terms of Trade and Global Efficiency Effects of Free Trade Agreements, 1990–2002." *Journal of International Economics* 99: 279–98.

Anderson, J. E., and E. van Wincoop. 2003. "Gravity with Gravitas: A Solution to the Border Puzzle." *American Economic Review* 93: 170–92.

Antràs, P., and D. Chor. 2013. "Organizing the Global Value Chain." *Econometrica* 81: 2127–2204.

Antràs, P., D. Chor, T. Fally, and R. Hillberry. 2012. "Measuring the Upstreamness of Production and Trade Flows." *American Economic Review* 102: 412–16.

Auboin, M., and M. Ruta. 2013. "The Relationship between Exchange Rates and International Trade: A Literature Review." *World Trade Review* 12: 577–605.

Bergstrand, J. H. 2016. *Economic Integration Agreement Dataset*. https://kellogg.nd.edu/faculty/fellows/bergstrand.

Broda, C., and J. Romalis. 2011. "Identifying the Relationship Between Trade and Exchange Rate Volatility." In *Commodity Prices and Markets*, NBER-East Asia Seminar on Economics, Volume 20, edited by Takatoshi Ito and Andrew K. Rose, 79–110. Chicago, IL: University of Chicago Press.

Cameron, C., and D. Miller. 2015. "A Practitioner's Guide to Cluster-Robust Inference." *Journal of Human Resources* 50: 317–72.

Cameron, C., and P. Trivedi. 2013. *Regression Analysis of Count Data*. Cambridge: Cambridge University Press.

CEPII. 2021. *BACI*. http://www.cepii.fr/CEPII.

Cho, G., I. M. Sheldon, and S. McCorriston. 2002. "Exchange Rate Uncertainty and Agricultural Trade." *American Journal of Agricultural Economics* 84: 931–42.

Clark, P., S. J. Wei, N. Tamirisa, A. Sadikov, and L. Zeng. 2004. *A New Look at Exchange Rate Volatility and Trade Flows*. Occasional Papers. USA: International Monetary Fund.

Correia, S., P. Guimarães, and T. Zylkin. 2020. "Fast Poisson Estimation with High-Dimensional Fixed Effects." *The Stata Journal* 20: 95–115.

Costinot, A., D. Donaldson, and I. Komunjer. 2012. "What Goods Do Countries Trade? A Quantitative Exploration of Ricardo's Ideas." *Review of Economic Studies* 79: 581–608.

Demers, M. 1991. "Investment under Uncertainty, Irreversibility and the Arrival of Information Over Time." *Review of Economic Studies* 58: 333–50.

Ethier, W. 1973. "International Trade and the Forward Exchange Market." *American Economic Review* 63: 494–503.

Franke, G. 1991. "Exchange Rate Volatility and International Trading Strategy." *Journal of International Money and Finance* 10: 292–307.

Galí, Jordi, and T. Monacelli. 2005. "Monetary Policy and Exchange Rate Volatility in a Small Open Economy." *The Review of Economic Studies* 72: 707–34.

Gong, G., and F. J. Samaniego. 1981. "Pseudo Maximum Likelihood Estimation: Theory and Applications." *Annals of Statistics* 9: 861–69.

Gourieroux, C., A. Monfort, and A. Trognon. 1984. "Pseudo Maximum Likelihood Methods: Applications to Poisson Models." *Econometrica* 52: 701–20.

Grauwe, P. D. 1988. "Exchange Rate Variability and the Slowdown in Growth of International Trade." *IMF Staff Papers* 35: 63–84.

Hallak, J. C. 2010. "A Product-Quality View of the Linder Hypothesis." *Review of Economics and Statistics* 92: 453–66.

Hartmann, D., M. R. Guevara, C. Jara-Figueroa, M. Aristarán, and C. A. Hidalgo.

2017. "Linking Economic Complexity, Institutions, and Income Inequality." *World Development* 93: 75–93.
Hausmann, R., J. Hwang, and D. Rodrik. 2007. "What You Export Matters." *Journal of Economic Growth* 12: 1–25.
Johnson, H. G. 1969. "The Case for Flexible Exchange Rates." In *Federal Reserve Bank of St. Louis Review*. St. Louis: MI, 12–24.
Kandilov, I. T. 2008. "The Effects of Exchange Rate Volatility on Agricultural Trade." *American Journal of Agricultural Economics* 90: 1028–1043.
Klaassen, F. 2004. "Why Is It So Difficult to Find an Effect of Exchange Rate Risk on Trade?" *Journal of International Money and Finance* 23: 817–39.
Koray, F., and W. D. Lastrapes. 1989. "Real Exchange Rate Volatility and U.S. Bilateral Trade: A Var Approach." *The Review of Economics and Statistics* 71: 708–12.
Lall, S., J. Weiss, and J. Zhang. 2006. "The 'Sophistication' of Exports: A New Trade Measure." *World Development* 34: 222–37.
Mayer, T., and S. Zignago. 2011. "Notes on CEPII's Distances Measures: The GeoDist Database." In *CEPII Working Paper 2011–25*.
McKenzie, M. D. 1999. "The Impact of Exchange Rate Volatility on International Trade Flows." *Journal of Economic Surveys* 13: 71–106.
Mundell, R. 2000. "Currency Areas, Exchange Rate Systems and International Monetary Reform." *Journal of Applied Economics* 3: 217–56.
Pick, D. H. 1990. "Exchange Rate Risk and U.S. Agricultural Trade Flows." *American Journal of Agricultural Economics* 72: 694–700.
Rauch, J. E. 1999. "Networks versus Markets in International Trade." *Journal of International Economics* 48: 7–35.
Regmi, A., M. J. Gehlhar, J. Wainio, T. L. Vollrath, P. V. Johnston, and N. Kathuria. 2005. "Market Access For High-Value Foods." Agricultural economic reports No. 33999, United States Department of Agriculture, Economic Research Service.
Rose, A. K. 2000. "One Money, One Market: The Effect of Common Currencies on Trade." *Economic Policy* 15: 08–45.
Silva, J. M. C. S., and S. Tenreyro. 2006. "The Log of Gravity." *The Review of Economics and Statistics* 88: 641–58.
Silva, J. M. C. S., and S. Tenreyro. 2010. "On the Existence of the Maximum Likelihood Estimates in Poisson Regression." *Economics Letters* 107: 310–12.
Tenreyro, S. 2007. "On the Trade Impact of Nominal Exchange Rate Volatility." *Journal of Development Economics* 82: 485–508.
Thomson Reuters. 2019. *Datastream*. https://infobase.thomsonreuters.com.
Thursby, J. G., and M. C. Thursby. 1987. "Bilateral Trade Flows, the Linder Hypothesis, and Exchange Risk." *The Review of Economics and Statistics* 69: 488–95.
United Nations. 2021. *UN Comtrade Database*. https://comtrade.un.org.
Viaene, J. M., and C. G. de Vries. 1992. "International Trade and Exchange Rate Volatility." *European Economic Review* 36: 1311–1321.
Wooldridge, J. 1999. *Handbook of Applied Econometrics Volume II: Quasi-Likelihood Methods for Count Data*. Oxford: Blackwell Publishing Inc.
World Bank. 2021. *World Development Indicators Database*. http://data.worldbank.org/data-catalog/world-development-indicators.
WTO. 2021. *Understanding the WTO*. https://www.wto.org.