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The Uncertain Cost of Uncertainty: An Inquiry into Exchange Rate Volatility and Bilateral Trade Flows

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The Uncertain Cost of Uncertainty:

An Inquiry into Exchange Rate Volatility and Bilateral Trade Flows

A senior thesis presented by

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Abstract

The literature on exchange rate volatility and trade burgeoned following the collapse of the post-World War II Bretton Woods monetary system. After five decades of study, the relationship between currency fluctuations and bilateral trade remains unclear. This paper seeks to contribute to that literature by studying exchange rate volatility from several perspectives. The objective is to present findings that will be of interest both to academics and to policymakers. Controlling for several factors that explain variability in trade, this thesis finds that longer-term exchange rate volatility has a substantial negative effect, while shorter-term fluctuations have an ambiguous effect, if any. Specialized manufactured goods are found to be more susceptible to volatility than homogenous goods, although the result may not be robust to model specification. Countries with deeper foreign exchange derivatives markets experience substantially lower currency volatility and higher trade, but the interaction between hedging and volatility appears reliant on country-specific initial conditions. While currency misalignments are not correlated with volatility, a depreciated real exchange rate is found to considerably benefit exporters—that said, competitive devaluations may not mitigate the negative trade effect of high volatility. Policy implications and proposals for further study are included throughout.

Acknowledgements

This has been a challenging and gratifying project. I owe an immense debt of gratitude to my adviser, Professor Frieden, for his guidance and unfailing patience. I began my senior thesis with a limited understanding of the topic and without a firm grasp of how to tackle a research project of this scale. Prof. Frieden's advice was invaluable, and his encouragement and good cheer made the research process that much more enjoyable. Many thanks as well to Johnny Tang, my Economics 985 seminar classmates, and Asher—whose knowledge of statistics I greatly benefit from. I cannot thank Mama (Deepti Mehra) and Dada (Gautam Bardoloi) enough for their unconditional love and support. Mama, in particular, for diligently encouraging me to pursue research. And thank you to the many wonderful people in my life for their warmth, humor, and company—none of this would have been possible without you.

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1 Introduction

Addressing the nation on August 15, 1971, President Nixon announced that he had "directed Secretary Connally to suspend temporarily the convertibility of the dollar into gold" (Nixon 1971). The Nixon Shock, as the event came to be known, reverberated across global financial markets: Twenty-seven years after the famous conference of Allied Powers at the Mount Washington Hotel, the Bretton Woods system was now no more. International economists are fond of saying that the exchange rate is the most important price in an economy. That price, the price of the domestic currency relative to foreign ones, determines all other prices in the country. With the curtains drawn on the Bretton Woods era, volatility in exchange rates—something which, among the major trading economies, had been largely nonexistent for decades—suddenly became a salient topic. In the half-century since, there have been a number of theoretical and empirical treatments of this subject. Broadly, these studies have been inconclusive on the relationship between exchange rate volatility and trade. There have few wide-ranging studies on the matter since the rapid growth of trade in the first decade-plus of the twenty-first century, and there remain important unanswered questions about the impact of volatility on trade across differing time horizons, product categories, levels of market development and other economic variables. This thesis attempts to take an empirical approach to filling some of these gaps.

This study analyzes 528 bilateral trading partnerships; the 33 countries represented in this sample are among the world's largest economies, and account for 77% of global trade in goods over the period studied. The two decades covered are a deeply significant time in the modern history of global trade—a period that saw a massive expansion in international trade, economic upheaval, and anti-globalization backlash. Important events include: the adoption of the Euro, the accession of China to the World Trade Organization, the Global and European Financial

Crises and the subsequent ascendance of populist forces in Western democracies (including the Brexit vote in the UK and the election of Donald Trump in the US). This study also follows several countries—notably, China and India—through a period of especially rapid growth, while previous empirical studies tended to focus on a narrower group of countries, particularly developed Western nations.

Exchange rate volatility can be viewed transaction cost, inserting noise in the price signal, making it more costly for importers and exporters to determine whether a particular trading agreement is an appropriate match, and therefore reducing the volume of trade (IMF, 2004). For managers of firms, increases in exchange rate volatility create uncertainty about domestic currency revenue from foreign sales, lowering the expected marginal utility of trade. And while Boz, et al. (2020) notes the vast majority of trade is invoiced in US dollars and Euros, volatility remains relevant because of producers ultimately convert revenues into their domestic currency to pay wages and distribute profits, among other expenses.

This paper begins by investigating whether using exchange rate volatility as a regressor adds explanatory power to the gravity model of trade. The gravity model, which posits that trade between two countries varies proportionally to their GDPs and inversely to the square of their distance, is a central model in international trade. As a preliminary task, I test the explanatory power of the gravity model against my dataset and observe trends in trade across the sample period. The gravity model is found to be highly predicted of bilateral trade flows, explaining over two-thirds of variability. Trailing twelve months' volatility is found to have a strong, statistically significant negative relationship with trade. The gravity model is then expanded using regressors that are established in the literature as meaningfully explaining variability in bilateral trade. After accounting for this expanded set of controls in addition to the gravity

model, I test whether exchange rate volatility still maintains significant explanatory power over bilateral goods trade. Although the relationship remains negative, these results are no longer statistically significant. These findings are part of this paper's attempt to add to previous empirical studies assessing the high-level impact of currency volatility on trade.

We then examine how different measures of volatility impact trade. First, volatility across different time horizons, from twelve-month volatility to extended periods of volatility up to five years. Firms may not respond on an immediate basis to exchange rate volatility, especially given that investments in capital goods and supply chains are longer-term decisions involving considerable sunk costs. While firms may not enter and/or exit a market on the basis of a year's volatility, perhaps the likelihood increases over time: countries with persistently high volatility look like unattractive destinations for further investment, while countries with persistently low volatility appear safe. On the other hand, year-by-year changes in levels of trade, resulting from increased volatility, are not unreasonable. Given a fixed capital structure, firms may dynamically adjust output in response to changes in volatility levels, without entirely exiting the market. The degree to which they do so may be related to their risk aversion and the structure of the market they are selling into. I find a statistically significant negative relationship between the timespan of volatility and the volume of trade, after controlling for expanded gravity model regressors and then for country fixed effects. The sensitivity of trade to the term of volatility is an important consideration for policymakers weighing the costs and benefits of a mitigatory intervention into foreign exchange markets. Further, I investigate the impact on trade of nominal versus real exchange rate volatility, discussing the theoretical justifications for using one or the other as the basis for analysis. The two tend to move in tandem, although real volatility is generally favored as an analytical tool because it more directly reflects changes in competitiveness. Mean real

volatility is observed to be less than mean nominal volatility—a result that is discussed in the section. And while both real and nominal volatility exhibit a similar form in their relationship to trade volumes, the negative effect on trade of nominal volatility exceeds that of real volatility.

In the following section, I investigate the differential impact of exchange rate volatility on trade in strongly homogenous goods versus trade in strongly differentiated goods (together referred to as polarized goods). This is a primary area of focus and could contribute to a more nuanced understanding of the economic circumstances under which exchange rate volatility may be harmful. Homogenous goods are largely comprised of commodities and standardized manufactured products—broadly, those for which "brand" would not be a material consideration for a customer or purchasing manager (Rauch 1999). Differentiated goods are specialized manufactures that are non-interchangeable with other goods in their category and often produced by contract for specific customers. Aircraft, furniture and clothing are among those goods classified as differentiated. Theory would predict that differentiated goods are more sensitive to exchange rate volatility than homogenous goods: producers of specialized manufactures do not have the ability to hedge their production in forwards markets the way producers of homogenous goods do, and the higher "search costs" associated with establishing supply chains for differentiated goods may make them more sensitive to an increase in transaction costs (Rauch 1999, Broda and Romalis 2003). This study largely affirms that hypothesis, although the results are not always robust to variations in the analytical approach—and there is a surprising positive relationship between volatility and trade in homogenous goods, the possible causes of which are considered.

In an effort to address the literature on foreign exchange hedging, I investigate the relationship been the depth of foreign exchange derivatives markets and the sensitivity of trade to

nominal exchange rate volatility. In countries with well-developed foreign exchange derivatives markets, firms may be able to effectively mitigate the impact of currency volatility. This would suggest that, for any given level of currency volatility, a deepening of foreign exchange markets would blunt the negative impact on trade. There are potential identification problems here and these are discussed, along with a consideration of how this research might be extended with the availability of more granular, firm-level data. One of the main findings here is that there is a strong negative relationship between the depth of a country's foreign exchange markets the and the level of exchange rate volatility it experiences, even after controlling for the country's GDP. There is also some relationship between the depth of foreign exchange markets and the influence of volatility on trade, but with nuances that will be discussed further.

I then address misalignments in the level of real exchange rates. More specifically: the impact on trade of the interaction between, 1) exchange rate volatility and, 2) trends toward undervaluation or overvaluation across time. This notion has relevance in both the international and domestic political economy. Countries with a weak real exchange rate confer an advantage onto their exporting sector by increasing its competitiveness in the international market. Thus, we may expect that countries with weakening real exchange rates increase their level of exports relative to imports, all else equal. Conversely, countries with a strengthening real exchange rate substitute in favor of increased imports. The results presented in Section 8 strongly corroborate this hypothesis. Following from this, a decline in the real value of the currency may mitigate—or even outweigh—the negative impact on exports of an increase in exchange rate volatility. From a domestic perspective, this analysis may be relevant to understanding interest group support for a given exchange rate regime. Exporting firms may, for instance, prefer a floating exchange rate that can be adjusted for competitiveness to a fixed exchange rate that does not provide flexibility,

even if it the latter imposes transaction costs through volatility (Frieden, Ghezzi and Stein 2001). This study, however, finds that there is 1) no direct correlation between exchange rate volatility and misalignments in the real exchange rate and 2) there is not much evidence to support the notion that the interaction between volatility and currency misalignments has a significant impact on trade volume.

Finally, a note on the data and empirical work: A meaningful portion of the work done for this thesis involved the preparation and analysis of data from several sources. Fairly little of the data required for this thesis was available in a form immediately useful for the analyses I sought to conduct. This process will be elucidated in the Data section and, as necessary, in the substantive sections. Appendices will present samples of the computer programming and analytical methods that were part of this thesis.

2 Literature Review

The relationship between exchange rate volatility and trade became a topic of particular interest after the collapse of the Bretton Woods monetary system and is a widely studied topic in the international economics and political economy literature. The most fundamental model for these interactions, developed by Clark (1973), involves a firm operating in a perfectly competitive market, without imported inputs and purely for sales to the export market. The firm is paid in foreign currency, which it immediately exchanges for domestic currency. Production decisions are made in the period prior to the realization of the exchange rate and the firm does not have the ability to hedge currency exposure, so it is exposed to all subsequent variability in the exchange rate. Under these circumstances, and assuming the existence of risk aversion, the model predicts a strong, negative relationship between exchange rate volatility and trade. This stylized model

can be refined and extended by inserting considerations of importers' attitudes toward volatility and permitting for varying levels of risk aversion. Hooper and Kohlhagen (1978) present such a model and find a strongly negative relationship between volatility and trade, much as Clark (1973) did. However, for a very risk averse manager, a rise in volatility could increase the expected marginal utility of export revenues, stemming from a desire to avoid "catastrophic" losses. DeGrauwe (1988) concludes that this implies a decision to increase, not decrease, output when faced with meaningful uncertainty about per unit domestic currency revenues. This model is grounded in parameters similar to those used in the earlier literature, but with the degree of risk aversion displayed by firm managers cast as the central determinant of output levels in the face of exchange rate variability. Essentially, there is ambiguity about whether the substitution effect (reduce exports due to the currency risk) or the income effect (increase exports to be assured of sufficient revenues) will dominate the decision-making process for any given firm. All considered, early theoretical models take a highly stylized approach to the problem, assuming perfect competition, an inability to hedge currency risk, high risk aversion, and only one type of product sold, among others. These assumptions were considerably relaxed in the later literature.

The capacity to hedge exchange rate risks in forwards markets has been an area of keen study. Perfect forwards markets would nullify the relationship between exchange rate volatility and trade, through the ability of firms to hedge all their risk costlessly (Baron 1976). This is an important theoretical baseline, but the assumption of perfect forwards markets has been substantially relaxed in later models to better reflect empirical realities. In particular, the IMF (1984) observes in its study that forwards markets are not reliably available in many countries—and when these hedging opportunities are available, large contract sizes, high fees, and coverage of a limited range of outcomes are common features. This means the arrangements are

inaccessible to smaller exporting firms and provide limited benefits to larger ones. Risk-averse firms will tend to take hedging opportunities if available to minimize uncertainty, but the costs involved flow through to higher export prices and lower levels of trade, according to an empirical study conducted by Obstfeld and Rogoff (1998). While the volume of foreign exchange derivatives activity has increased considerably over the last few decades, it continues to be true that access is far from universal (BIS 2021). Less economically developed countries tend to have poorer availability of currency hedges and less mature of forwards markets, which may lead to a larger negative relationship between exchange rate volatility and trade for developing countries relative to developed ones (Arize and Bahmani-Oskooee 2020). Where forwards markets do exist, the literature points to the importance of considering that high contracting costs for hedging instruments can mitigate their potential benefit to trading volumes.

Adding further nuance to the literature is the observation that, when firms establish a presence in international markets, they are often subject to "search costs" (Rauch 1999). These are sunk costs incurred in establishing the relationships required to build supply chains and marketing systems, the long-term investment in physical capital, and so on. Rauch presents evidence that an increase in these costs has a more pronounced impact on the producers of differentiated goods relative to homogenous goods, suggesting a possible relationship between the costs of exchange rate volatility and a decreased volume of trade in differentiated goods. This paper seeks to empirically test this result against a large and current set of data. Rauch also develops a methodology by which to classify goods as differentiated or homogenous, and his classification is employed in this paper: One of his main strategies is to draw from purchasing manager surveys to determine whether the brand of a product was a relevant consideration (differentiated products) or not (homogenous products). Associated with some of Rauch's ideas

about entry costs is the "option value" approach, which investigates whether multinational firms exhibit inertia in market entry and exit decisions due to the sunk costs associated with establishing a presence in the market. This work has been developed, in particular, by Krugman (1989), Dixit (1989) and Franke (1991). The notion is that the uncertainty caused by exchange rate volatility means firms make fewer entry or exit decisions, ergo, firms that are already in the market are likely to stay while new firms are unlikely to enter. This underscores a possible difference between volatility in the short run, where fixed costs are salient, and volatility over the longer-term, where firm decision-making is not influenced by sunk costs.

Misalignments in the real exchange rate, and the mechanism by which this is associated with currency volatility and trade, has also been an important topic of consideration. Much of the initial interest in exchange rate volatility was driven by the desire of the international trading community to understand how this variability might affect the real economy. In particular, whether volatility was associated with misalignments in the real exchange rate, as this had the potential to cut against the reductions in trading barriers that had been negotiated through GATT (Auboin and Ruta 2011). The IMF (1984) study emphasizes the role of volatility-induced exchange rate misalignments in distorting market price signals and causing dislocations in international trade flows. Associated with the international trade impacts, there are domestic political economy implications of the interaction between volatility and real prices. Countries with larger tradable goods sectors as a share of total economic activity are likelier to have floating instead of fixed exchange rates (Frieden, Ghezzi and Stein 2001). Although floating exchange rates can result in costly volatility, Frieden et al. argue that they are also more likely than fixed rates to deliver the depreciated exchange rates which make exporters more

internationally competitive. This is especially the case when exporters comprise a large share of the economy and/or wield significant political power.

A large number of studies on exchange rate volatility, especially those over the past decade and a half, have taken a primarily empirical focus; the gravity model has been an important component of several such studies, and this paper is no different. The model explains the volume of bilateral trade between countries as varying positively with the product of their GDPs and negatively with the square of their distance. First introduced into trade theory by Walter Isad (1954), it has been a fixture in papers seeking to understand trade between countries. The first major empirical study of exchange rate volatility and trade was conducted by the IMF in 1984 at the request of the General Agreements on Tariffs and Trade (GATT), the precursor to the World Trade Organization, in an effort to understand the role of currency variability in the post-Bretton Woods trading order. The IMF found limited direct evidence to support the conclusion that exchange rate volatility negatively impacted trade, but it presented a host of mechanisms by which such a link could exist, including the commercial uncertainty generated by short-term and long-term volatility, incorrect price signals that might be sent by volatility-induced misalignments in the real exchange rate, and inter-sectoral reallocation within an economy due to perceived shifts in competitiveness. A study of EU 15 Members and Switzerland over a twenty-year period ending in the mid-1990s found a statistically significant negative relationship between exchange rate variability and trade, concluding that a reduction of volatility to zero would increase trade from 10 to 13 percent (Del'Arricia 1998). Empirical studies seeking to explain the impact of an "outside" factor—such as volatility, the adoption of a common currency, etc.—regularly use the gravity model as a benchmark against which to test the additional regressor. The adoption of a common currency, which reduces nominal exchange rate

volatility to zero, is an example of interest. Rose (2000) finds an especially strong result, with his research estimating that members of a currency union trade up to three times more with each other after accession than they did prior. These studies, and others like them, suggested a potentially strong link between exchange rate volatility (at least, in nominal terms) and bilateral trade flows. That said, the robustness of these results has been questioned by scholars calling attention to several potential estimation and identification problems, including omitted variables that may have boosted trade upon a country's adoption of the Euro (Tenreyro 2003). In a follow-up to its previously mentioned 1984 study, the IMF conducted a renewed analysis of exchange rate volatility in 2004, including a comprehensive survey of the extant literature. The empirical component evaluated trade data from 1975 to 2000. Much as in the study 20 years earlier, the IMF found no "obvious negative relationship between aggregate exchange rate volatility and aggregate trade." However, it did find evidence that bilateral exchange rate volatility is negatively associated with bilateral trade, although the effect was determined not to be "robust to alternative ways of controlling for factors that could affect trade."

Broadly, the literature remains undecided on the overall nature of the relationship between exchange rate volatility and trade. To this author's knowledge, there have not been recent, large scale studies of the effect of volatility on bilateral trade between the world's leading trading nations. This paper attempts to contribute toward a deeper understanding of that question by studying several potentially salient factors, including by building on much of the research cited in this literature review.

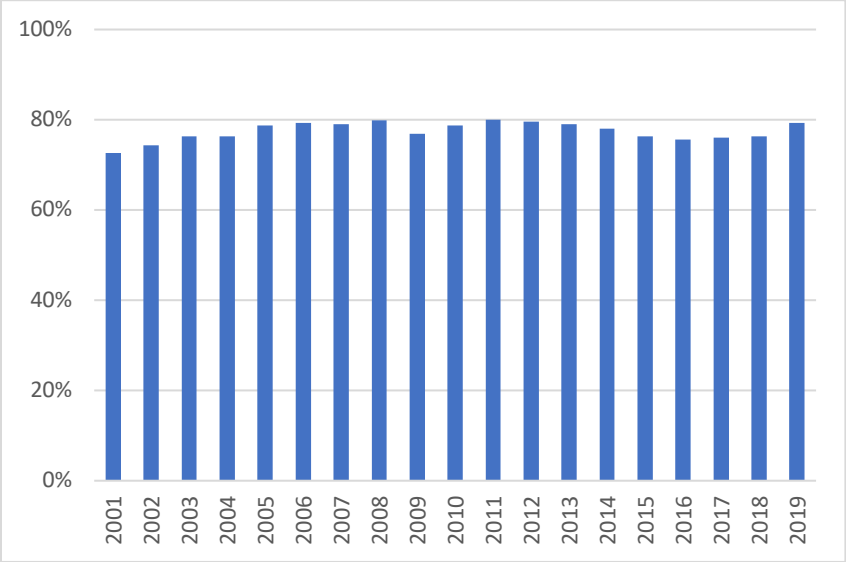
3 Data

The consolidated dataset contains 1,056 country-pair observations across 33 countries for each year from 2001 to 2019. Each country-pair observation represents the dollar volume of exports from one country to the other, not total trade between the countries. This is important because some factors have opposite effects on imports and exports (e.g., relative currency competitiveness), and an aggregate measure would not be able to parse this. As noted in the Introduction, constructing the data required for this thesis was one of the major tasks for this thesis project. Data sources include: United Nations Comtrade database on international trade, the IMF's International Financial Statistics, the Bank for International Settlements and the World Bank's World Development Indicators. Software used include, among others: the Jupyter Notebook environment for Python, Pandas data frames, Matplotlib and NumPy libraries, API tools for database queries, Excel for coding functions, and Stata. Please refer to the Appendix for selected samples of the programming / quantitative work involved.

3.1 Aggregate, Differentiated and Homogenous Trade

Data on bilateral trade is extracted from the UN Comtrade database using an API query run through Python's Jupyter notebook. Other trade data are extracted from the World Bank Group's World Development Indicators. Details are in Appendix 11.1. This thesis focusses on trade in goods. Although the last several decades have seen a sharp rise in the services share of GDP in the world's leading economies, a large and stable majority of international trade remains concentrated in goods.

Figure 1 – Goods Trade as a Share of All Trade



Most bilateral pairings of countries trade relatively little with each other, while there is a very high volume of trade between a small number of large economies. Mean aggregate bilateral trade over 2001 to 2019 is $7.9bn, with a standard deviation of $23bn. A log distribution of the variable provides a far clearer visualization of the data.

Figure 2 – Distribution of Bilateral Goods Trade Obs.

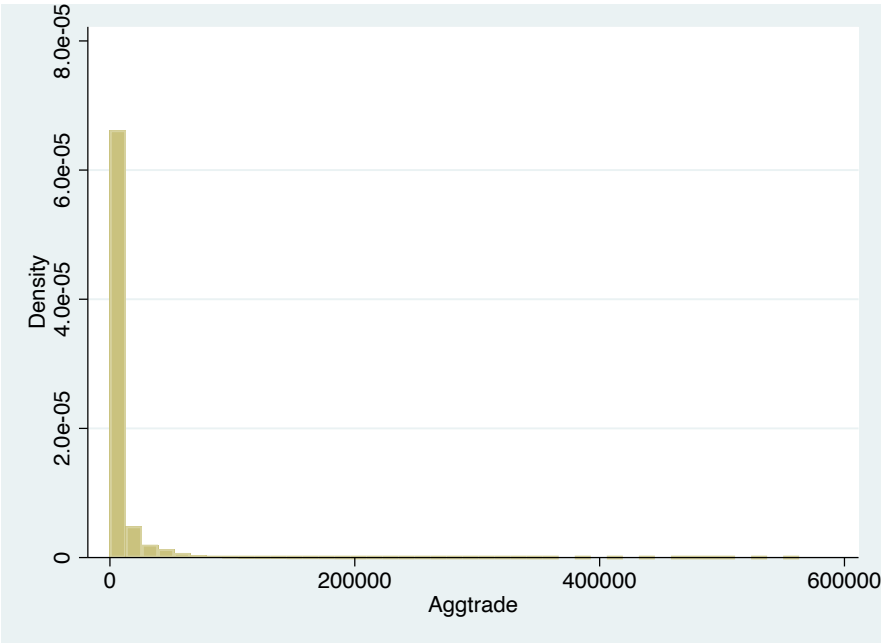
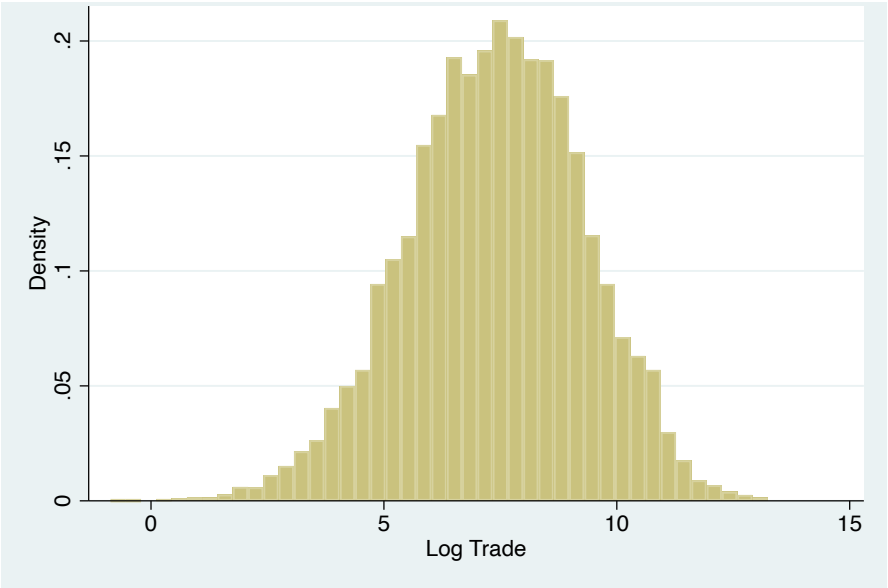


Figure 3 – Distribution of Log Bilateral Goods Trade Obs.

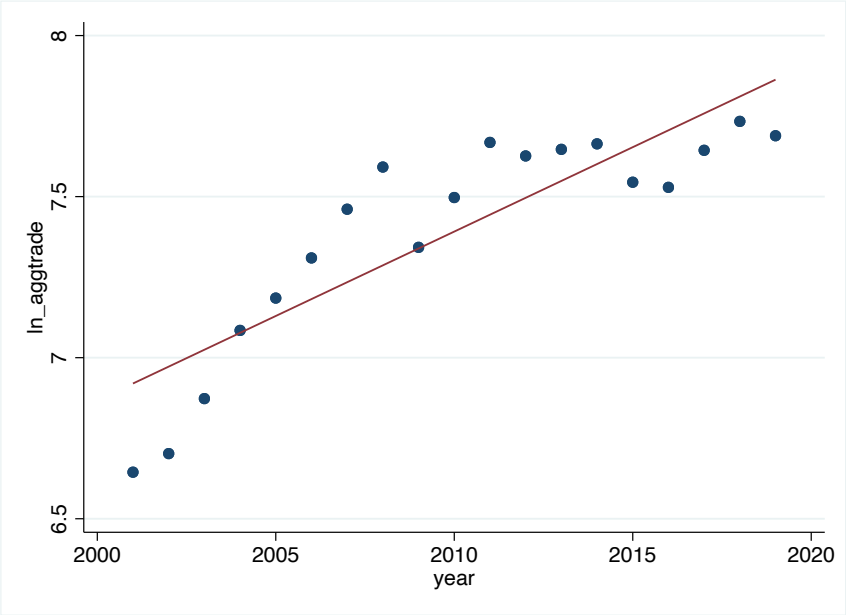


Using the Standard International Trade Classification (SITC) system, and with reference to Rauch's (1999) delineation of strongly differentiated and strongly homogenous goods, product-level data on trade in polarized goods is extracted from the UN Comtrade database with API queries and then aggregated across the two categories (as outlined in Appendix 11.1). Trade in polarized goods is about 45% of total bilateral trade between countries; this starts at 54% in 2001 and slides down to 26% by 2019, a trend that is discussed in Section 6. There is a clear upward trend in the total volume of bilateral trade across the sample period, but there is a fair bit of nuance in this relationship, which is explored in Section 4 and in Section 6.

Table 1 – Summary Statistics on Trade Data

Variable	Obs	Mean	Std. Dev.	Min	Max
aggtrade	20,058	7916.238	23005.01	.419	563000
homg. trade	20,064	646.7158	3192.23	0	121771.4
diff. trade	20,064	2799.543	9498.774	0	247118.9

Figure 4 – Log Goods Trade by Year



3.2 The Real Exchange Rate (RER) Index

This paper constructs a monthly RER index from 2001 to 2019, encompassing all 528 country-pairs. These data are constructed using monthly Consumer Price Index (CPI) data from the IMF and national bureaus of statistics[1] combined with bilateral nominal exchange rate data from the IMF's International Financial Statistics (IFS) database. CPI data are used instead of Producer Price Index (PPI) data or other measures to align with standard practice in the literature (Clark, et al. 2004, Auboin and Ruta 2011). Matching these raw data with the trading pairs in the dataset required coding a unique ID for each country pair (to ensure that countries get matched both when they are the exporter in the pair and when they are the importer) in Python, and then using a 3-way Index-Match function in Excel. The programming required to construct this index can be found in Appendix 11.1. Hopefully, this database can be of use to future researchers as well.

[1] This is for Australia and New Zealand, neither of which report monthly CPI data to the IMF.

The nominal exchange rate, expressed as the units of Country B's currency per unit of Country A's currency, is:

$$NER_{A,B} = \frac{NER_{USD,B}}{NER_{USD,A}}$$

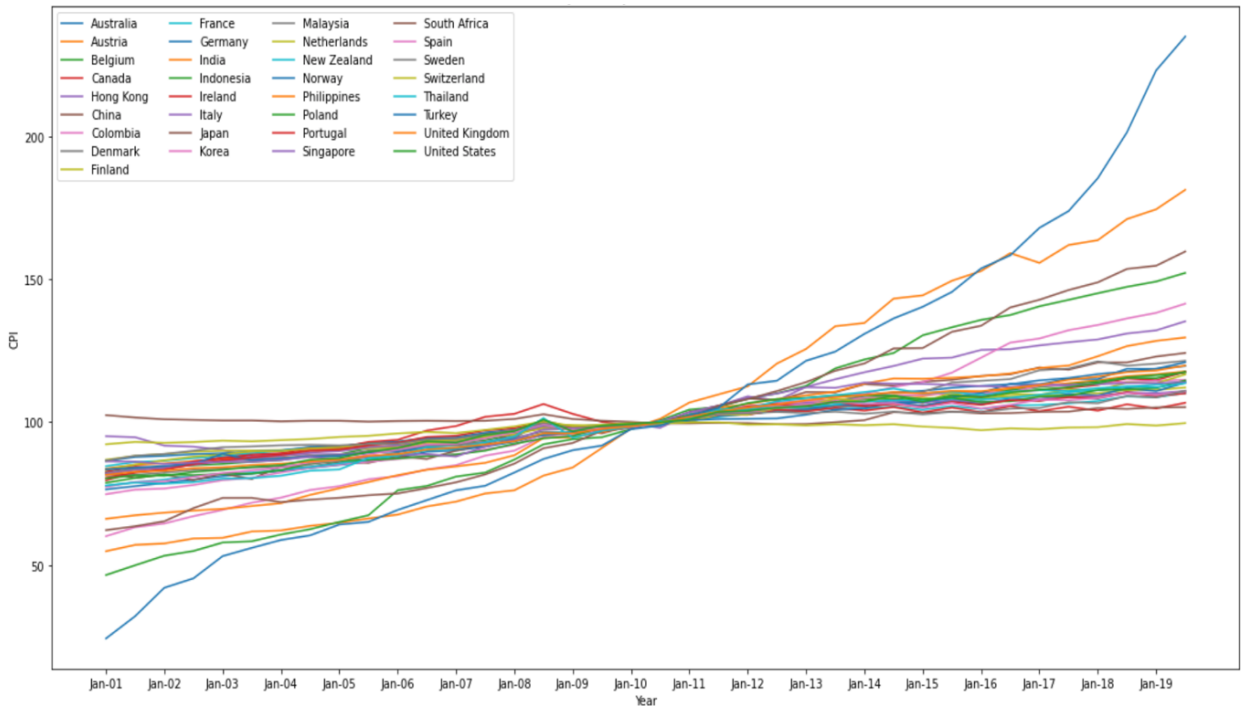
where we use the units of currency per USD for Country B and Country A, respectively. This is a monthly measure. The real exchange rate index, expressed as the price of Country A's goods in terms of Country B's goods, is:

$$RER_{A,B} = NER * \frac{CPI_A}{CPI_B}$$

where we use the Consumer Price Index level for Country A and Country B, respectively. This is a monthly measure, indexed to 100 in 2010. Although it does not represent absolute differences in real price levels, only changes over time, the latter is of more use in this thesis—as will be explained later.

To visualize inflation across countries and time, please see below for a chart produced using Python's matplotlib library. This dataset is comprised primarily of larger, more developed economies, all of which have experienced relatively low inflation over the past couple decades, and especially since the Global Financial Crisis. This is reflected in the clustering of lines near the indexed level of 100. The major outlier is Turkey, which has consistently experience high inflation.

Figure 5 – CPI Data by Country (Indexed to 100 in 2010)



3.3 Constructing Measures of Volatility

Annual real exchange rate volatility for year *m* is calculated as the standard deviation of the monthly real exchange rate index, for each bilateral trading pair, over the preceding twelve months:

$$RERVol_{TTM,m} = \sigma\left(RER_{Jan,m}, \ldots, RER_{Dec,m}\right)$$

TTM signifies trailing twelve months for year *m* (i.e., from January to December that year, inclusive). Constructing volatility as a standard deviation within country-pairs ensures that results are adjusted for the "typical" level of currency volatility in a given bilateral trading partnership. With this measure, a one-point movement in a more stable pair (say, the USD–GBP) is directly comparable—in terms of deviation from the prior conditions—to a one point move in a more volatile pair (say, the INR–THB).

The distribution of volatility data is strongly right tailed—the extent of which is clear from the histogram below. This is not an unexpected result, given that currencies typically trade with relative stability against each other—while periods of crisis, dislocation or fundamental shifts in economic and political policy tend to cause large, sudden shifts in values. Taking the log of the variable results in a more normal distribution of the observations.

Figure 6 – Distribution of Bilateral RER Volatility Obs.

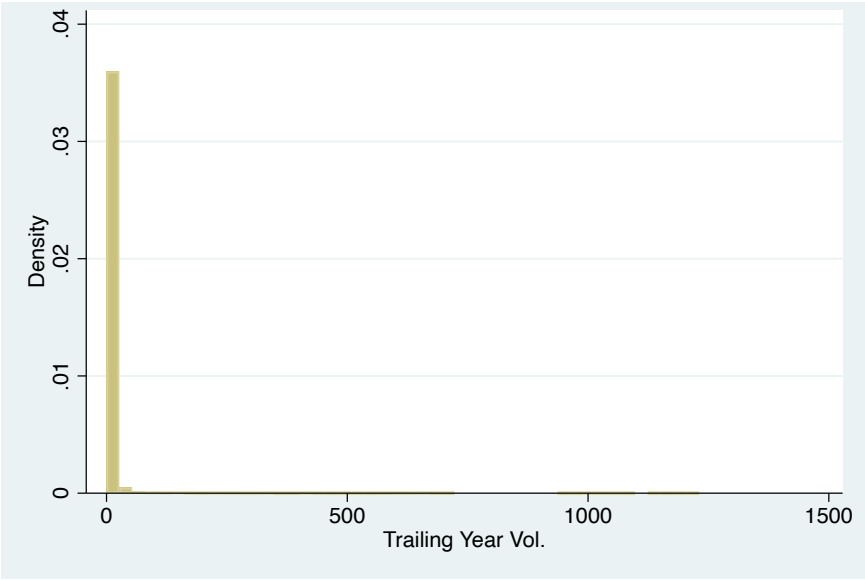
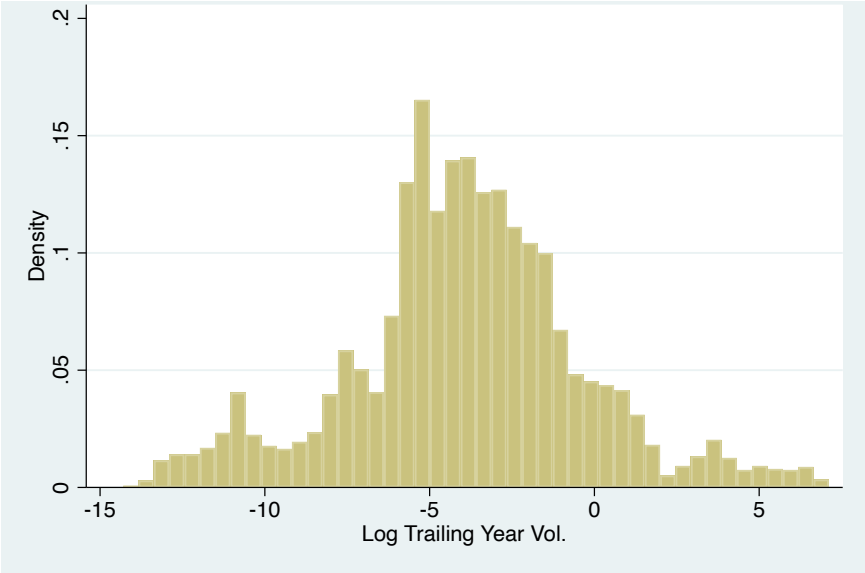


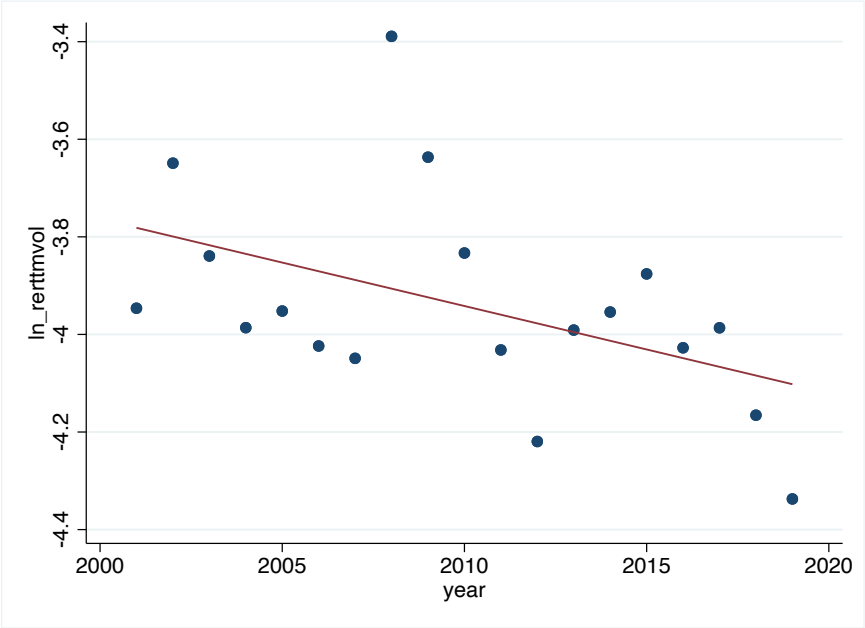
Figure 7 – Distribution of Log Volatility Observations



Real exchange rate volatility over two- to five-year periods for year *m* are calculated as the average of the past *n* years' (inclusive of the year *m*) calculations of $RERVol_{TTM}$. Nominal exchange rate volatility is calculated using the same methodology, but with *NER* instead of *RER* data. The formula is as follows:

$$RERVol_{TnM,m} = \overline{RERVol_{TTM,m}, RERVol_{TTM,m-1}, \dots, RERVol_{TTM,m-n+1}}$$

Figure 8 – Exchange Rate Volatility Over Time



There is a steady decline in real exchange rate volatility over the two decades covered in the sample. As there is also a positive time trend in trade, it follows that a simple regression of trade on volatility would yield a negative relationship between the two. That said, there is nothing inherent to the year itself that should define the level of trade or the relationship between real exchange rate volatility and trade; any relationship embedded within the variable "year" should be attributable to economic, geographic, or other trade-related variables.

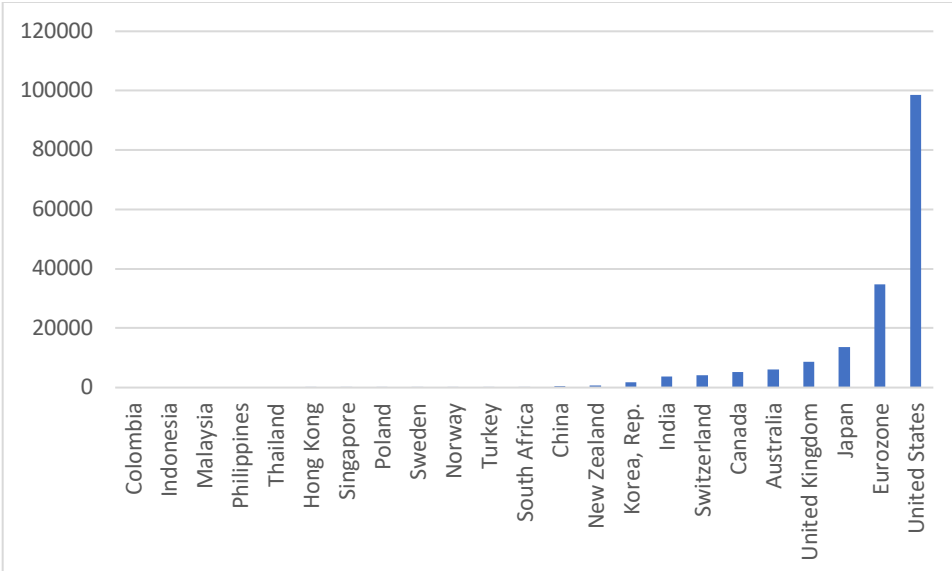
3.4 Hedging and Foreign Exchange Derivatives Markets

As a proxy for the availability of hedging, I use Bank for International Settlements data on the average daily turnover, in terms of notional principal value, of exchange-traded currency futures and options. Ideally, hedging data would be available at a firm level, and would include the cost of entering these hedges as well as the range of outcomes covered by each given contract. This would allow for a nuanced analysis of the effects of hedging across countries and across types of firms. Firm-level data would also enable a study of how the rise of multinational corporations and global supply chains interact with the impact of exchange rate volatility. Notional principal value is a somewhat blunt proxy for the accessibility of currency hedges. That said, it should be well-correlated with the ease of securing hedges in any given currency, which makes it quite useful for my analytical efforts. There is clear reason to believe that currencies with deeper markets in exchange-traded derivatives will permit for more cost-effective access to these instruments.

For each country-pair-year observation, the *avgfxdepth* variable is constructed as the mean of the two countries' forex derivatives market turnover. It may be the case that the currency with lower derivatives volume is the constraining factor, but it seemed more appropriate to balance that against the notion that there is, intuitively, a nonzero benefit to one partner in the pairing having an especially deep currency market. There are several interesting observations relating to these data—please refer to Section 7.

Variable	Obs	Mean	Std. Dev.	Min	Max
avgfxdepth	40,128	15946.39	18367.69	0	110305

Figure 9 – Notional Principal ($mn) Avg. Daily Turnover of Forex Derivatives (2001-2019)



3.5 Real Exchange Rate Misalignments

This variable is constructed from existing data by taking the difference, in standard deviations, between the RER Index value for a given year and the average RER Index value for that country-pair across the 19 years in the sample period. The mean of this variable is thus zero, and its purpose is not so much to suggests that a currency is misaligned in real terms on a point-in-time basis, but rather to measure the evolution of any such misalignment over time. This has a relevance to trade patterns and volatility which will be discussed in Section 8.

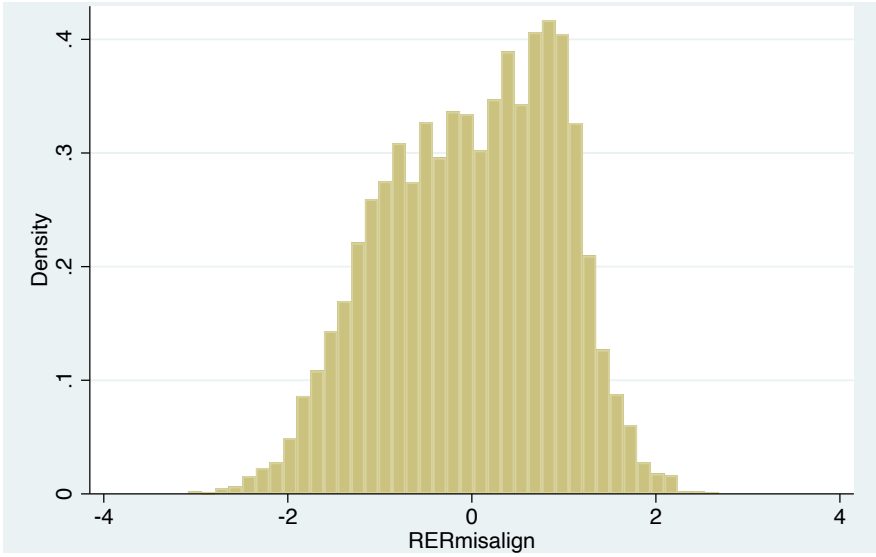
The *rermisalign* score for the pair of countries *A* and *B*, at year *t*, is calculated as:

$$RERmisalign_{t,AB} = \frac{RERIndex_{t,AB} - \overline{RERIndex_{2001,AB}, \ldots, RERIndex_{2019,AB}}}{\sigma(RERIndex_{AB})}$$

Summary statistics for the variable, as well as the distribution of observations:

Variable	Obs	Mean	Std. Dev.	Min	Max
rermisalign	9,481	9.49e-08	.9397598	-3.0878	2.6841

Figure 10 – Distribution of RER Misalignment Observations



4 Understanding Volatility Using the Gravity Model

4.1 The Gravity Model of Trade

Countries with larger economies can be expected to trade more with each other, while distance between trading partners imposes exponentially increasing costs upon trade. These two premises, drawn directly from the forces governing celestial bodies, form the gravity model of trade. Since its introduction into the trade literature by Isard (1954), the gravity model has been a workhorse model for international economists seeking to understand the dynamics of bilateral trade. The model is especially useful in testing the significance of variables hypothesized to have a significant effect on bilateral trade, in this instance, volatility. We can confidently run a pooled analysis of bilateral trade data, relying on the gravity model to control for differences between country-pairs that may be associated with trade volume.

The standard gravity model, for trade in year *t*, is specified as:

$$lntrade_{\mathrm{t},I,\mathrm{j}} = \beta_0 + \beta_1 GravDist_{I,\mathrm{j}} + \beta_2 lrgdp_{I,\mathrm{t}} + \beta_3 lrgdp_{\mathrm{j,t}} + u_{I,\mathrm{j,t}}$$

For year t, I = *Country 1, …, Country 33* and j = *Country 1, …, Country 33* where $I \neq j$.

The predictions of the gravity model align strongly with the bilateral trade data assembled for this thesis. A basic implementation, including only the log of each partner's GDP and the log of their distance, is able to explain 66% of the variation in bilateral trade levels, with trade declining significantly with distance and increasing significantly with GDP.

Figure 11 – Goods Trade by Distance, GDP Controls (Gravity Model)

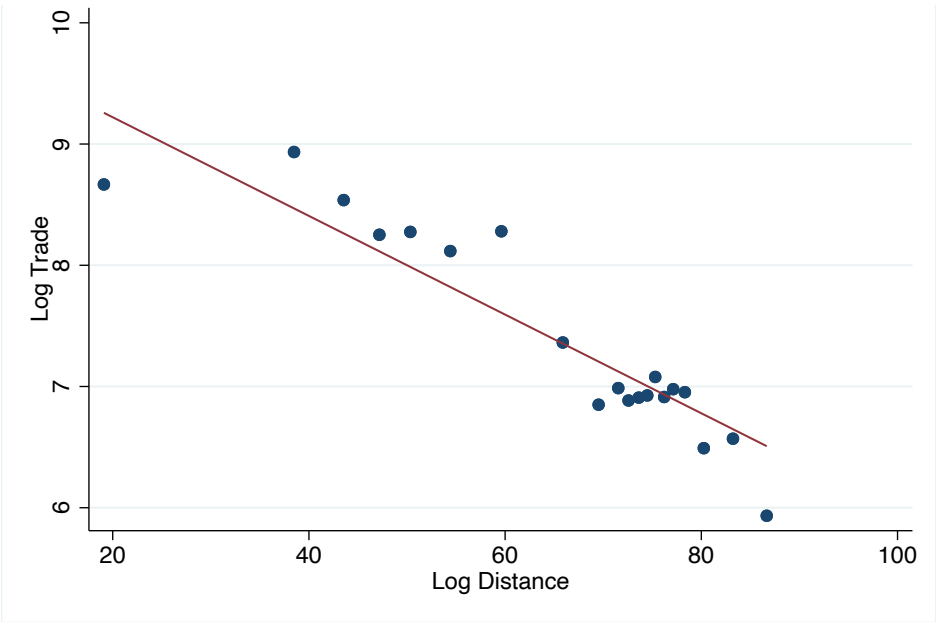


Table #: Regression Output: Trade on Standard Gravity Model

Source	SS	df	MS			
				Number of obs	=	19,887
				F(3, 19883)	=	12895.24
Model	47427.5128	3	15809.1709	Prob > F	=	0.0000
Residual	24375.9426	19,883	1.22596905	R-squared	=	0.6605
				Adj R-squared	=	0.6605
Total	71803.4554	19,886	3.61075407	Root MSE	=	1.1072

ln_aggtrade	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
gravdist	-.0406948	.0004506	-90.31	0.000	-.0415781	-.0398116
lrgdp1	1.827058	.0150847	121.12	0.000	1.797491	1.856626
lrgdp2	1.799566	.0150942	119.22	0.000	1.76998	1.829152
_cons	-32.82213	.2488017	-131.92	0.000	-33.3098	-32.33445

4.2 Time Trends in Trade, Controlling for Gravity

In the Data section, it was observed that aggregate bilateral trade increased consistently across the sample period. I was interested in taking a look at how bilateral trade evolved over time, after adjusting the economic growth of trading partners. The results are striking, and perhaps surprising. Controlling for the gravity model's predictions, trade decreases by around 3.6% each year from 2001 to 2019.

Figure 12 – Goods Trade by Year, Gravity Model Controls

This regression is specified as:

$$lntrade_{t,I,j} = \beta_0 + \beta_1 Year_t + \beta_2 GravDist_{I,j} + \beta_3 lrgdp_{I,t} + \beta_4 lrgdp_{j,t} + u_{I,j,t}$$

For year *t*, *i* = *Country 1, …, Country 33* and *j* = *Country 1, …, Country 33* where $I \neq j$.

Table 2 – Regression Output: Trade on Year, Gravity Model Controls

Source	SS	df	MS			
				Number of obs	=	19,887
				F(4, 19882)	=	10098.61
Model	48119.3118	4	12029.828	Prob > F	=	0.0000
Residual	23684.1436	19,882	1.19123547	R-squared	=	0.6702
				Adj R-squared	=	0.6701
Total	71803.4554	19,886	3.61075407	Root MSE	=	1.0914

ln_aggtrade	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
year	-.0361876	.0015016	-24.10	0.000	-.0391309	-.0332442
lrgdp1	1.916107	.0153218	125.06	0.000	1.886075	1.946139

```
       lrgdp2 |   1.888558   .0153302   123.19   0.000     1.858509    1.918606
     gravdist |  -.0406555   .0004442   -91.53   0.000    -.0415261   -.0397848
        _cons |   37.80845   2.941147    12.86   0.000     32.04356    43.57335
------------------------------------------------------------------------------
```

The result is highly significant, both statistically and economically, and persists across the entire period, calling into question the dominant narrative that the first decade and a half of the 21st century was a time of unusually rapid globalization and expansion in trade. Although bilateral trade in absolute terms certainly increased rapidly through the time period, this rise was easily and consistently outpaced by GDP growth in the world's largest trading nations—China being the most notable contributor to this effect. As observed in the figure above, the downtrend was less pronounced from 2011 to 2015 after a particularly steep decline between 2010 and 2011, but from 2016 onward, trade again declined sharply relative to expectations. This finding is consistent with the contemporary rise in populism and the associated erection of tariff and non-tariff barriers to trade.

4.3 Expanding the Gravity Model of Trade

The standard gravity model provides impressive explanatory power with just three variables. However, there a number of factors that trade economists have empirically linked to deviations from the gravity model's results. Some of these factors, such as sharing a common currency, are intuitively connected with bilateral currency volatility (of course, assuming we are studying real exchange rates; with nominal exchange rates, there would be no volatility) in a way that could be meaningful to results. Others, such as whether countries share a border, are less likely sources of omitted variable bias. Nonetheless, to more rigorously study the effect of volatility on bilateral trade, all additional factors cited by the IMF (2004) and World Trade Organization (2011) are included in the analysis. The following are the regressors with which the expanded gravity model was constructed, along with a brief justification for each.

Table 3 – Additional Regressors for the Expanded Gravity Model

Variable	**Description**	**Justification**
landl	Number of landlocked countries in the country pair.	Landlocked countries do not have direct access to ports, and overland trade is less efficient at scale than maritime trade.
commoney	Dummy for countries with a common currency.	Countries with a common currency face reduced transaction costs and no exchange rate risk in trading with each other.
border	Dummy for shared border.	Countries with a shared border trade with each other more than would be predicted by their proximity, in part due to the convenience of trade that can pass directly from one jurisdiction to the other.
comlang	Dummy for common language.	Trading partnerships may be more easily established between countries that share a common language. Proxy for cultural similarity, which also promotes trade.
comcol	Dummy for countries with the same colonizer after 1945.	Countries with a common colonizer may have cultural similarities and trading networks that enable higher trade.

colony	Dummy for countries that were ever in a colony-colonizer relationship.	These countries may have cultural similarities and trading networks that enable higher trade.
curcol	Dummy for countries that are currently in a colony-colonizer relationship.	These countries would likely have cultural similarities and trading networks that enable higher trade.
island	Number of island countries in the country pair.	Decreases likelihood that a country trades more with proximate partners than with all other countries.
comctry	Dummy for countries that are part of the same nation.	Countries in the same nation trade more with each other than otherwise predicted.

The expanded gravity model performs better than the standard model, as anticipated, and explains nearly 71% of the variance in bilateral trade. The additional regressors have the effects that were predicted, with a shared border, shared language and shared colonizer having among the strongest effects on trade. Strikingly, countries with a common post-World War II colonizer have bilateral trade 200% higher than otherwise predicted by the gravity model, and a common language boosts trade by 46%.

The regression is specified as:

$$lntrade_{t,I,j} = \beta_0 + \beta_1 GravDist_{I,j} + \beta_2 lrgdp_{I,t} + \beta_3 lrgdp_{j,t} + \beta_4 commoney_{j,t} + \beta_5 landl_{j,t} + \beta_6 island_{j,t} + \beta_7 border_{j,t} + \beta_8 comlang_{j,t} + \beta_9 comcol_{j,t} + \beta_{10} comctry_{j,t} + \beta_{11} colony_{j,t} + \beta_{12} curcol_{j,t} + u_{i,j,t}$$

For year t, i = *Country 1, …, Country 33* and j = *Country 1, …, Country 33* where $I \neq j$.

Table 4 – Regression Output: Trade on Expanded Gravity Model Controls

Source	SS	df	MS			
				Number of obs	=	19,887
				F(11, 19875)	=	4351.66
Model	50737.253	11	4612.47755	Prob > F	=	0.0000
Residual	21066.2024	19,875	1.05993471	R-squared	=	0.7066
				Adj R-squared	=	0.7065
Total	71803.4554	19,886	3.61075407	Root MSE	=	1.0295

ln_aggtrade	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
gravdist	-.0362726	.0004959	-73.14	0.000	-.0372447	-.0353005
landl	-.1948745	.0224917	-8.66	0.000	-.23896	-.1507889
island	.1865533	.0159438	11.70	0.000	.1553021	.2178045
border	.890023	.0383546	23.21	0.000	.8148449	.9652011
comlang	.4578144	.0197958	23.13	0.000	.419013	.4966157
comcol	2.012338	.0694854	28.96	0.000	1.87614	2.148535
comctry	0	(omitted)				
colony	.1918759	.0459219	4.18	0.000	.101865	.2818867
curcol	.736682	.1728768	4.26	0.000	.3978292	1.075535
commoney	.4312914	.028633	15.06	0.000	.3751683	.4874144
lrgdp1	1.83362	.0141794	129.32	0.000	1.805828	1.861413
lrgdp2	1.809302	.0141779	127.61	0.000	1.781512	1.837092
_cons	-33.53735	.2365022	-141.81	0.000	-34.00091	-33.07378

4.4 Exchange Rate Volatility and the Gravity Model of Trade

The next step is simply to add volatility as a regressor to the gravity model, which I do both for the standard controls and for the expanded controls. A statistically significant negative coefficient on trailing volatility would lend support to the notion that exchange rate volatility reduces trade flows. However, statistical significance is not sufficient. Economic significance is as important: if a one standard deviation increase in volatility reduces trade by, say, 1%, this would suggest that policymakers need not greatly concern themselves about fluctuations in the domestic currency. If volatility is an important determinant of trade, we should also see the adjusted-R^2 values of the models increase.

Table 5 – Regression Output: Trade on Volatility, Standard Gravity Model Controls

Source	SS	df	MS			
				Number of obs	=	19,887
				F(4, 19882)	=	9682.58
Model	47446.8628	4	11861.7157	Prob > F	=	0.0000
Residual	24356.5926	19,882	1.22505747	R-squared	=	0.6608
				Adj R-squared	=	0.6607
Total	71803.4554	19,886	3.61075407	Root MSE	=	1.1068

ln_aggtrade	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]

rerttmvol	-.000521	.0001311	-3.97	0.000	-.000778	-.0002641
gravdist	-.0405534	.0004519	-89.75	0.000	-.0414391	-.0396677
lrgdp1	1.82669	.0150794	121.14	0.000	1.797133	1.856247
lrgdp2	1.799305	.0150887	119.25	0.000	1.769729	1.82888
_cons	-32.81986	.2487098	-131.96	0.000	-33.30735	-32.33236

Table #: Regression Output: Trade on Volatility, Expanded Gravity Controls

Source	SS	df	MS			
				Number of obs	=	19,887
				F(12, 19874)	=	3989.09
Model	50738.2605	12	4228.18838	Prob > F	=	0.0000
Residual	21065.1949	19,874	1.05993735	R-squared	=	0.7066
				Adj R-squared	=	0.7064
Total	71803.4554	19,886	3.61075407	Root MSE	=	1.0295

ln_aggtrade	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rerttmvol	-.0001194	.0001225	-0.97	0.330	-.0003596	.0001207
gravdist	-.0362298	.0004979	-72.77	0.000	-.0372057	-.035254
landl	-.1942951	.0224995	-8.64	0.000	-.2383961	-.1501941
island	.1855382	.0159778	11.61	0.000	.1542205	.216856
border	.8904249	.0383568	23.21	0.000	.8152424	.9656075
comlang	.456974	.0198146	23.06	0.000	.4181358	.4958122
comcol	2.012256	.0694855	28.96	0.000	1.876058	2.148453
comctry	0	(omitted)				
colony	.1914868	.0459237	4.17	0.000	.1014725	.2815012
curcol	.7361098	.172878	4.26	0.000	.3972546	1.074965
commoney	.430736	.0286387	15.04	0.000	.3746017	.4868702
lrgdp1	1.833473	.0141802	129.30	0.000	1.805678	1.861267
lrgdp2	1.809187	.0141784	127.60	0.000	1.781396	1.836978
_cons	-33.53565	.2365089	-141.79	0.000	-33.99923	-33.07207

We see a statistically significant effect, with $p<0.001$ for trade on volatility with the standard gravity model controls; the effect is not statistically significant once expanded gravity model controls are added.[2] To explore the cause of this, I regress exchange rate volatility on the expanded gravity model controls. Notably, being landlocked is highly positively correlated with exchange rate volatility, and negatively with aggregate trade; further, sharing a common language is very negatively correlated with currency volatility and positively correlated with aggregate trade. The omission of these factors from the standard gravity model negatively biased the effect of trade on volatility. That said, the underlying driver of these associations—positive

[2] Excluding countries with a common currency does not significantly change the results, with the p-value for the rerttmvol coefficient updating to 0.306.

for being landlocked and having a volatility currency, negative for having a common language—is not entirely clear.

Table 6 – Regression Output: Volatility on Expanded Gravity Controls

```
note: comctry omitted because of collinearity

      Source |       SS           df       MS      Number of obs   =    39,786
-------------+----------------------------------   F(8, 39777)     =     38.82
       Model |   1111451.3         8  138931.413   Prob > F        =    0.0000
    Residual |   142350301    39,777  3578.70882   R-squared       =    0.0077
-------------+----------------------------------   Adj R-squared   =    0.0075
       Total |   143461752    39,785  3605.92565   Root MSE        =    59.822

------------------------------------------------------------------------------
   rerttmvol |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       landl |   4.185147   .9179812     4.56   0.000     2.385882    5.984412
      island |  -5.494113   .6317007    -8.70   0.000    -6.732261   -4.255965
      border |  -5.018495   1.501322    -3.34   0.001    -7.961122   -2.075868
     comlang |   -6.48364   .8115729    -7.99   0.000    -8.074342   -4.892938
      comcol |  -5.371968   2.832576    -1.90   0.058    -10.92388    .1799474
     comctry |          0  (omitted)
      colony |  -1.933356   1.875925    -1.03   0.303    -5.610213    1.743501
      curcol |  -2.983748   7.101752    -0.42   0.674    -16.90335    10.93585
    commoney |  -10.41551   1.128199    -9.23   0.000    -12.62681   -8.204217
       _cons |   11.40407   .4152939    27.46   0.000     10.59008    12.21805
------------------------------------------------------------------------------
```

It is important to note that, even for the standard controls, the addition of real exchange rate volatility as an explanatory variable does not improve the performance of the model—the share of trade explained is essentially unchanged. Economic significance is also absent, with a one standard deviation increase in trailing one-year real exchange rate volatility resulting in a nearly negligible decrease in bilateral trade. These results do not lend support to the conclusion that exchange rate volatility—at least in the short run—has a significant and meaningful impact on bilateral trade volumes. In Section 5, I look further into this model by testing it against measures of volatility beyond the trailing twelve months.

5 Further Analytical Approaches to Volatility

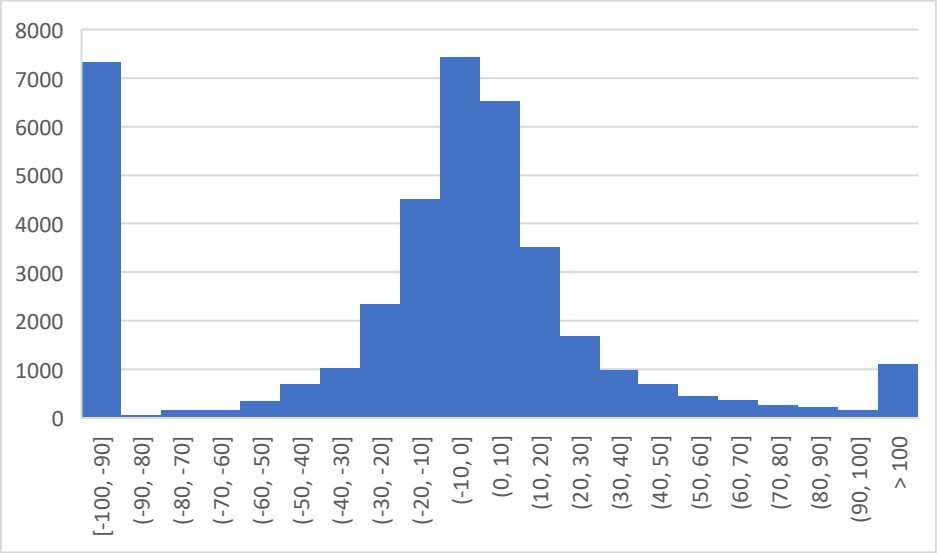
5.1 Nominal vs Real ER Volatility

The exchange rate volatility literature tends to prefer real over nominal volatility as an analytical tool. While nominal exchange rate volatility captures the observed fluctuations in a country's currency, volatility is usually considered impactful (Huchet-Bourdon and Korinek 2011) for the impact it has on trading partners' relative competitiveness and domestic purchasing power, both of which are governed by real price levels. Furthermore, nominal and real volatility should, in most cases, track each other: local currency prices tend to be "sticky" in the short run (McKenzie and Brooks 1997). The underlying mechanism for price stickiness is the presence of non-tradables (i.e., services and non-tradable goods) and low pass-through goods—typically more differentiated goods, for which prices are less sensitive to changes in input costs—in the economy. This effect is more pronounced for developed countries, in which primary commodity trade (high pass-through) tends to constitute a relatively low share of economic activity. Perfect price stickiness would mean that a change in the currency's international price is not reflected by changes in domestic price levels, in which case nominal volatility is mechanically transmitted to real volatility of equivalent magnitude.

This paper looks at both nominal and real measures for two reasons. The first is as a robustness check: this is a common best practice in the currency volatility literature. If a statistically significant relationship between trade and volatility is not robust to an analysis with nominal volatility, this could bring into question the validity and/or strength of any conclusion. A common exception to the concordance between nominal and real volatility is found in countries experiencing periods of hyperinflation: the sharp and simultaneous increase in a country's goods prices and depreciation in its currency mean that nominal exchange rate volatility usually

exceeds real volatility. (By definition, price stickiness does not exist during an episode of hyperinflation.) This provides a concrete reason to examine whether the impact on trade differs between the two measures. The second is to aid in analyzing the relationship between volatility, trade and foreign exchange market depth, because hedging contracts are set in nominal, not real, terms. This will be covered in a subsequent section.

Figure 13 – Histogram of Percentage Differences Between TTM NER Vol. and RER Vol.



The [-100, -90] bin consists exclusively of currencies that share a common currency (e.g., members of the Eurozone) or have a hard peg to a trading partner's currency (e.g., the Hong Kong dollar's peg to the US dollar). Under a common currency or currency peg, nominal exchange rate volatility is zero, while real exchange rates vary on an annual basis along with changes in relative consumer prices. Ergo, real volatility exceeds nominal volatility. The overflow bin largely represents instances of high inflation, as noted earlier. (In particular, periods of high inflation in Turkey and the Philippines; the reader may refer to Section 3.7 for CPI data by country over time, for a clear illustration.) Overall—excluding the observations in which there is no nominal volatility due to a common currency or a currency peg—volatility in the nominal exchange rate is 8.31% greater than volatility in the real exchange rate. Indeed, because

prices are not perfectly sticky—especially so when nominal volatility persists and is not mean-reverting—some of the volatility in the nominal exchange rate is compensated for by changes in relative price levels, which drives down real exchange rate volatility.

5.2 Short-term and Long-term Exchange Rate Volatility

It would be reasonable to expect volatility of different durations to have divergent impacts on trade. Firms that have already invested in a market may not wish to exit or alter production on the basis of short-term volatility, which could be viewed as transient. And for firms deciding whether to enter the market, volatility over a shorter time span may not weigh heavily in decision-making. However, as volatility persists, it is less likely to be dismissed as a transient phenomenon and more likely to be salient consideration for firms seeking to enter a market; over the long run, sunk costs become a weaker constraint on exit decisions for firms that are in the market. These hypotheses are tested with data on trailing one-year through five-year volatility. This is also discussed further in the subsection on Future Directions. These gravity model regressions are specified as described in the previous section.

Another analytical benefit of looking at longer-term volatility is the ability to mitigate reverse causality issues: i.e., the possibility that a negative relationship between volatility and trade exists because higher levels of trade dampen volatility, instead of decreased volatility supporting trade. A failure to resolve this would pose clear problems for my analytical framework. By using realized volatility on a trailing basis of up to five years, and trade for the year just passed, the potential for reverse causality is mitigated: higher trade in the past year could not have caused lower volatility in the years preceding.

Table 7 – Regression Output: Trade, Real Volatility (1yr to 5yr), Exp. Gravity Model Controls

	(1) ln_aggtrade	(2) ln_aggtrade	(3) ln_aggtrade	(4) ln_aggtrade	(5) ln_aggtrade
rerttmvol	**-0.000119**				
	(-0.97)				
rert2yvol		**-0.000265**			
		(-1.95)			
rert3yvol			**-0.000356***		
			(-2.49)		
rert4yvol				**-0.000392****	
				(-2.67)	
rert5yvol					**-0.000424****
					(-2.82)
gravdist	-0.0362***	-0.0363***	-0.0364***	-0.0364***	-0.0365***
	(-72.77)	(-71.42)	(-69.91)	(-68.16)	(-66.46)
landl	-0.194***	-0.190***	-0.188***	-0.185***	-0.179***
	(-8.64)	(-8.29)	(-8.00)	(-7.66)	(-7.22)
island	0.186***	0.182***	0.177***	0.168***	0.161***
	(11.61)	(11.13)	(10.59)	(9.82)	(9.14)
border	0.890***	0.887***	0.884***	0.882***	0.877***
	(23.21)	(22.64)	(22.06)	(21.43)	(20.74)
comlang	0.457***	0.452***	0.446***	0.441***	0.436***
	(23.06)	(22.35)	(21.55)	(20.74)	(19.96)
comcol	2.012***	2.034***	2.054***	2.066***	2.071***
	(28.96)	(28.67)	(28.29)	(27.73)	(27.06)
comctry	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)
colony	0.191***	0.174***	0.158***	0.146**	0.137**
	(4.17)	(3.70)	(3.29)	(2.96)	(2.70)
curcol	0.736***	0.755***	0.775***	0.788***	0.796***
	(4.26)	(4.27)	(4.29)	(4.25)	(4.18)
commoney	0.431***	0.424***	0.420***	0.422***	0.427***
	(15.04)	(14.51)	(14.04)	(13.73)	(13.53)
lrgdp1	1.833***	1.857***	1.880***	1.898***	1.915***
	(129.30)	(126.78)	(123.92)	(120.69)	(117.66)
lrgdp2	1.809***	1.835***	1.861***	1.883***	1.905***
	(127.60)	(125.28)	(122.67)	(119.77)	(117.10)
_cons	-33.54***	-34.14***	-34.72***	-35.20***	-35.68***
	(-141.79)	(-138.42)	(-134.70)	(-130.87)	(-127.57)
N	19887	18842	17798	16751	15705

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 8 – Regression Output: Trade, Nominal Volatility (1y to 5y), Exp. Gravity Model Controls[3]

	(1) ln_aggtrade	(2) ln_aggtrade	(3) ln_aggtrade	(4) ln_aggtrade	(5) ln_aggtrade
nerttmvol	**-0.000315***				
	(-2.33)				
nert2yvol		**-0.000431****			
		(-2.92)			
nert3yvol			**-0.000496****		
			(-3.23)		
nert4yvol				**-0.000532*****	
				(-3.36)	
nert5yvol					**-0.000559*****
					(-3.45)
gravdist	-0.0362***	-0.0363***	-0.0364***	-0.0364***	-0.0364***
	(-72.67)	(-71.34)	(-69.85)	(-68.10)	(-66.41)
lrgdp1	1.834***	1.858***	1.880***	1.898***	1.915***
	(129.33)	(126.82)	(123.96)	(120.73)	(117.69)
lrgdp2	1.809***	1.836***	1.861***	1.883***	1.905***
	(127.63)	(125.32)	(122.70)	(119.80)	(117.13)
_cons	-33.54***	-34.15***	-34.73***	-35.21***	-35.69***
	(-141.84)	(-138.47)	(-134.74)	(-130.91)	(-127.61)
N	19887	18842	17798	16751	15705

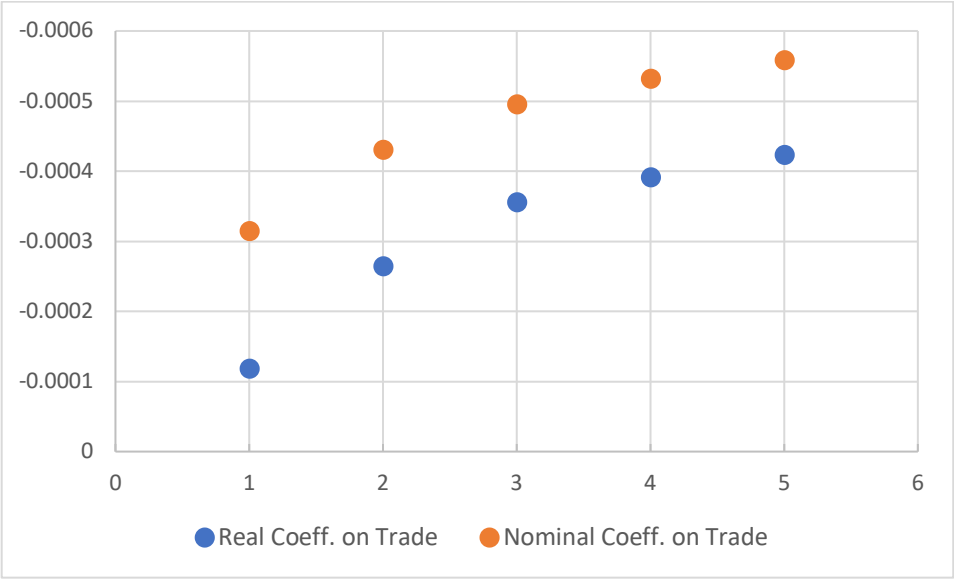
t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Regressing trade and real volatility, we see a significant negative relationship for volatility across three to five years, with statistical significance (and the coefficients) increasing as the term of volatility increases. With nominal volatility, the results are significant across the board. The real and nominal coefficients on volatility take the same form, increasing in magnitude but at a decreasing pace as we extend the timespan of volatility. This comports with the expectation that longer-term volatility is more damaging to trade than short-term volatility. Under the volatility salience paradigm, it is reasonable to expect that the magnitude of the coefficient increases sharply at first—when volatility transitions from being perceived as "random" to being seen as more endemic—and then more gradually as firms adjust over time

[3] Expanded gravity model regressors omitted in the interest of preserving space. The coefficients on these regressors are nearly identical to the coefficients for the regression on real volatility.

and make marginal decisions to reduce production and/or investment on the basis of more persistent volatility.

Figure 14 – Trailing n Year Real and Nominal Volatility, Gravity Model Controls (rev. y-axis)



Real volatility coefficients are shifted down in magnitude, relative to nominal coefficients. This may be a result of zero nominal volatility among Eurozone members and countries with currencies pegged to each other'; these observations would be represented in the regression for real volatility but not in the nominal regression. Countries with a common currency (or a hard peg) tend to trade with each other more than would be predicted with standard trade model variables, as Rose (2000) finds—it would thus be very reasonable to suspect that trade between such countries is also less sensitive to volatility than trade between other countries. I test this hypothesis by running the real volatility regression on countries that share a common currency. And indeed, the results show that countries sharing a common currency are less susceptible to real exchange rate volatility — there is no statistically significant relationship between volatility and aggregate bilateral trade at any volatility time horizon. That said, there the t-statistic does indicate greater significance for longer-term volatility, which

suggests there could be value in a study that uses a longer volatility time series to explore these effects.

Table 9 – Regression Output: Trade, Nominal Volatility (1y to 5y), Exp. Gravity Model Controls[4]

	(1)	(2)	(3)	(4)	(5)
	ln_aggtrade	ln_aggtrade	ln_aggtrade	ln_aggtrade	ln_aggtrade
rerttmvol	**2.678**				
	(0.49)				
rert2yvol		**2.859**			
		(0.42)			
rert3yvol			**-6.480**		
			(-0.84)		
rert4yvol				**-11.29**	
				(-1.35)	
rert5yvol					**-15.15**
					(-1.68)
gravdist	-0.0808***	-0.0809***	-0.0810***	-0.0816***	-0.0824***
	(-33.43)	(-32.86)	(-32.33)	(-31.74)	(-31.15)
lrgdp1	1.788***	1.822***	1.848***	1.856***	1.859***
	(59.07)	(57.97)	(56.98)	(55.22)	(53.51)
lrgdp2	1.600***	1.639***	1.675***	1.692***	1.704***
	(52.86)	(52.15)	(51.62)	(50.36)	(49.04)
_cons	-27.88***	-28.77***	-29.46***	-29.71***	-29.84***
	(-46.71)	(-45.75)	(-44.98)	(-43.54)	(-42.12)
N	1710	1620	1530	1440	1350

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

5.3 Country Fixed Effects Analysis of Volatility

It can be argued that the pooled approach in my other regressions overlooks idiosyncratic aspects of country-pair variability that are not appropriately accounted for by the "extended gravity model" regressors. A country fixed effects approach is an alternative to the gravity model as a method for holding constant characteristics that differ between country pairs. While the gravity

[4] Expanded gravity model regressors omitted in the interest of preserving space.

model pools observations and seeks to control for relevant factors, the fixed effects approach explicitly interrogates the relationship between exchange rate volatility and trade for a given bilateral trading relationship. It warrants mention that a drawback of the fixed effects approach is that the typical country-pair experiences relatively low levels of real exchange rate volatility over time, potentially limiting the usefulness of this approach. I regress trade on real exchange rate volatility with country-pair fixed effects, with these generated for each of the 1,056 trading pairs contained within the dataset.[5] A unique pairing ID is created for each of the country-pairs in the dataset. (The coding behind this can be found in Appendix 11.1.)

The fixed-effects regression takes the form:

$$\text{Log Volatility: } lntrade_{i,j,t} = \beta_1 lnrervol_{(n),t,i,j} + \alpha_{i,j} + u_{i,j,t}$$

$$\text{Linear Volatility: } lntrade_{i,j,t} = \beta_1 rervol_{(n),t,i,j} + \alpha_{i,j} + u_{i,j,t}$$

For year *t*, *i = Country 1, …, Country 33*, *j = Country 1, …, Country 33* where $i \neq j$ and $n = 1, \ldots,$ 5 years of trailing volatility (five separate regressions).

Table 10 – Regression Output: Fixed Effects Regression of Trade on Log Real ER Volatility

	(1) ln_aggtrade	(2) ln_aggtrade	(3) ln_aggtrade	(4) ln_aggtrade	(5) ln_aggtrade
ln_rerttmvol	-0.110***				
	(-17.11)				
ln_rert2yvol		-0.191***			
		(-23.53)			
ln_rert3yvol			-0.203***		
			(-21.66)		
ln_rert4yvol				-0.173***	
				(-17.15)	
ln_rert5yvol					-0.150***
					(-13.55)
_cons	6.957***	6.692***	6.694***	6.849***	6.967***
	(271.46)	(211.48)	(184.70)	(176.41)	(164.00)
N	20058	19004	17951	16895	15840

t statistics in parentheses

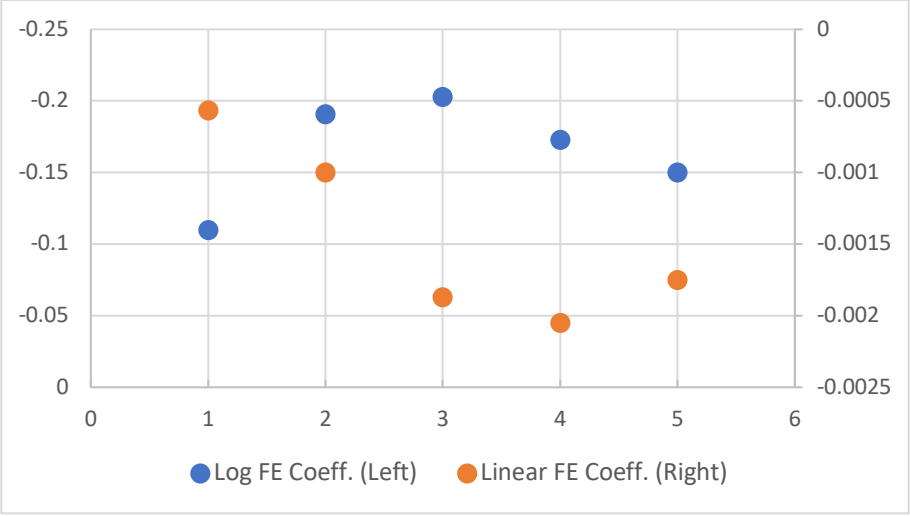
[5] There are 33 countries in the dataset, resulting in 528 unique pairings. For each pairing of Country A and Country B, there is one set of entries where Country A is the importer and Country B the exporter, and vice versa.

```
* p<0.05, ** p<0.01, *** p<0.001
```

Table 11 – Regression Output: Fixed Effects Regression of Trade on Real ER Volatility

	(1) ln_aggtrade	(2) ln_aggtrade	(3) ln_aggtrade	(4) ln_aggtrade	(5) ln_aggtrade
rerttmvol	-0.000564***				
	(-4.97)				
rert2yvol		-0.000999***			
		(-6.11)			
rert3yvol			-0.00187***		
			(-8.37)		
rert4yvol				-0.00205***	
				(-8.23)	
rert5yvol					-0.00175***
					(-6.73)
_cons	7.396***	7.442***	7.492***	7.531***	7.557***
	(2060.87)	(2102.52)	(2108.80)	(2145.71)	(2175.97)
N	20058	19004	17951	16895	15840

Figure 15 – Trailing n Year Log and Linear Volatility, Fixed Effects Model



This regression yields a highly statistically significant relationship between exchange rate volatility within a bilateral trading pair and a reduction in the level of trade. There is a marked divergence in the relationship between term of volatility and fixed-effect coefficients for the log versus linear explanatory variable, the cause of which is not entirely clear, but it does not affect the statistical significance of the results. It is interesting that, while the expanded gravity model

does not yield a statistically significant effect on a one-year horizon, the fixed effects model does, and at a level of $p<0.001$. The fixed effects model does not directly control for changes in the GDP of trading partners, but with GDP increasing over time and volatility decreasing,[6] this omission should not bias the results in the direction of a strong effect from volatility. Regardless, the effect is not economically significant aside from at very high levels of volatility: for log exchange rate volatility, a one percent increase in volatility reduces trade by no more than 0.20%,[7] while for linear exchange rate volatility, the maximum effect is a 0.21% decrease in trade for a one standard deviation increase in volatility.

5.4 Future Directions

From a domestic policymaker's perspective, firm entry/exit is a particularly salient outcome. Reductions in trade related to increases in exchange rate volatility would be more worrying to a policymaker if associated with a permanent withdrawal from the market. Data on the entry and exit of specific firms—and the conditions associated with this activity—is difficult to access or not available at all, and it is beyond the scope of this thesis. However, as an exercise, I propose that regressing changes in planned capital expenditures for exporting firms on exchange rate volatility could more directly link volatility to firm-level decision-making. For publicly listed firms in many countries, such data would be available in annual reports and earnings releases. This data could also be gleaned from Foreign Direct Investment (FDI) statistics, and it would be relevant, from a government's perspective, to determine whether any relationship exists between exchange rate volatility and changes in FDI levels. A related method might be surveys of

[6] Refer to the Data section for this analysis.
[7] Exchange rate volatility is measured in standard deviations, and an "x% increase" refers to a percentage increase in the value of the volatility variable.

managers, inquiring as to their leading business concerns, with exchange rate volatility among the categories surveyed. One could then track whether there is a relationship between increased concerns about volatility and decreased investment in fixed assets related to the export market, or an increased probability that the firm exits the market.

A future analysis may also seek to regress trade against the difference between discounted and realized volatility. Discounted volatility can be imputed for major currencies through pricing on forwards markets, but these data are either analytically unreliable or entirely unavailable for currencies that have thinly exchange-traded derivatives markets (or none at all). That is not to say that there is no economic significance of high expected volatility followed by equally high realized volatility: from an analytical perspective, a negative relationship between volatility and trade that persists despite the absence of unexpected volatility might be particularly insightful, suggesting an inherent cost associated with market volatility. For instance, when hedging is not available or is prohibitively expensive, the anticipation of volatility may well accelerate firm exit or production decreases *in advance of* realized volatility. It could then be instructive to study the differential impact on trade of discounted, below-discounted and above-discounted volatility given an expectation of high volatility (or an expectation of low volatility).

6 Trade in Polarized Goods

Much of the early literature on trade and exchange rate volatility neglected to sufficiently consider how volatility might have divergent effects on trade in different sorts of goods. A more nuanced understanding of these dynamics emerged as the literature developed and, in this section, I use a wide-ranging and up-to-date dataset in an attempt to understand the divergent effects, to the extent they exist. Rauch (1999) argues that there are higher "search costs"

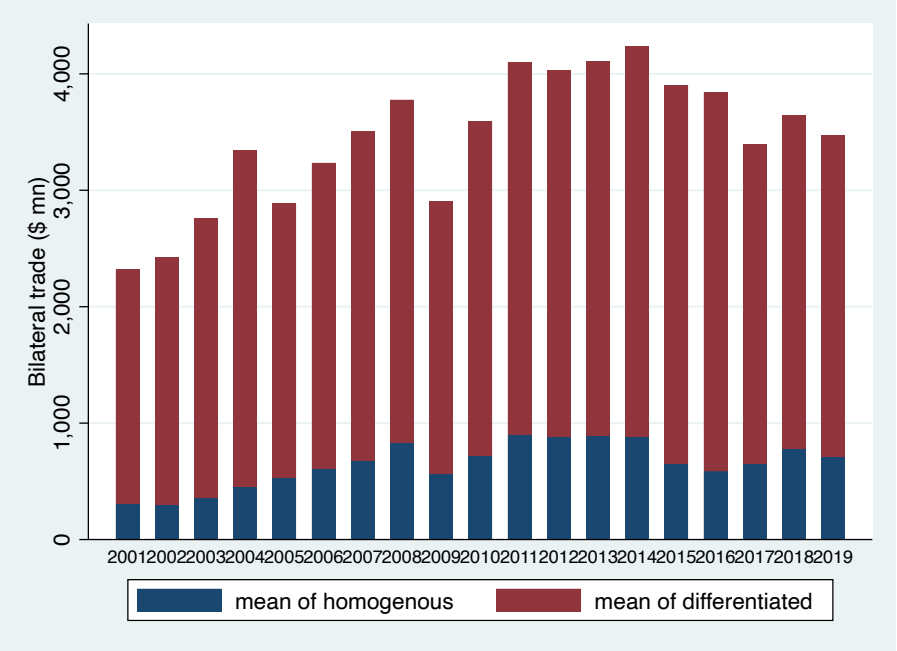
associated with exporting differentiated goods because these are not traded on organized exchanges, relying instead on a costly process of establishing a match between buyers and sellers. The absence of a well-defined market clearing price in the trade of "branded" goods means producers are sensitive to the search costs required for the completion of a trade—and higher transaction costs, of which currency volatility is a component, may reduce trade. However, sunk costs that are more pronounced for differentiated goods, such as adapting products to foreign markets and establishing distribution and marketing networks, may indeed reduce a producer's sensitivity to short-run exchange rate volatility (Clark 2004). There is some evidence from Byrne et al.'s (2008) analysis of US bilateral trade that differentiated goods are more sensitive to increases in currency volatility, but no recent studies have investigated a similarly large cross-section of global bilateral trade.

If there is a meaningful difference in the impact of high currency volatility on the trade of one type of good relative to the other, the domestic mix of good exports would be a relevant consideration for policymakers weighing the relative costs and benefits of intervening in foreign exchange markets to stabilize their currency. Should differentiated goods be more sensitive to volatility, a country concentrated in primary goods trade may not need to be as attentive to volatility as a country with a large share of secondary goods trade. Further, countries frequently seek to adjust their production mix toward more differentiated goods as they develop—these goods offer higher margins and are more capital-intensive rather than low-wage labor-intensive (Clark 2004). The sensitivity of such trade to currency fluctuations would be pertinent to policymakers deciding which leg of the Mundell-Fleming trilemma to select in structuring their exchange rate regime.

6.1 Patterns in the Trade of Polarized Goods

Mean annual bilateral trade in polarized goods is $3.5bn in 2019, peaking above $4bn in 2015. Trade in strongly differentiated goods comprising roughly four-fifths of total trade represented in the dataset. One of the major industrial commodities, oil, is relatively underrepresented in this dataset due to the exclusion of major producers like Saudi Arabia and Russia.

Figure 16 – Mean annual bilateral trade in differentiated and homogenous goods

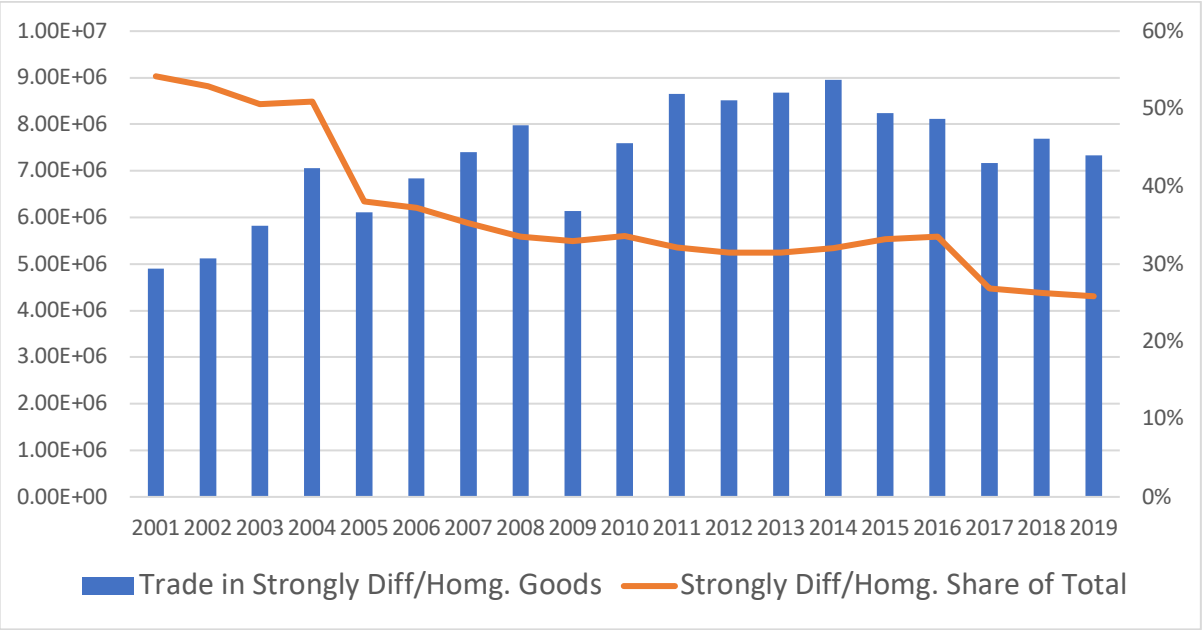


The share of total bilateral trade that is classified as either strongly homogenous or strongly differentiated falls almost consistently from 54% in 2001 to 26% in 2019, even as the absolute volume of trade in these categories increases by roughly 50% across the time period (Figure 17). This is because total bilateral trade across the 528 country-pairs increases by a factor of 3 across the time span: essentially, trade in "intermediate" goods — those that are neither commodities nor specialized manufactures — rose sharply over the first two decades of the 21st century. These would include goods such as intermediate inputs for manufacturing and standardized industrial machinery and equipment. Indeed, recent work by Antràs and Chor

(2021) underscore the extent to which value chains in production have been "sliced up" across countries.

The secular decline in the trade share of polarized goods should not undermine the analytical validity of the subsequent results, as they remain a nontrivial portion of trade, producers in the sector will continue to be impacted by volatility, and there is relatively little overlap between producers in polarized sectors and producers in other sectors (fundamentally different production processes). That said, if trade in these goods is progressively less significant as a share of total trade, then the policy and political economy implications of these results might be less significant.

Figure 17 – Trade in Polarized Goods Over Time and as a Share of Aggregate Bilateral Trade



6.2 Regressing Trade in Polarized Goods on Volatility

This regression is specified as:

$$lntrade_{t,I,j} = \beta_0 + \beta_a lnrerttmvol + \beta_1 GravDist_{I,j} + \beta_2 lrgdp_{I,t} + \beta_3 lrgdp_{j,t}$$
$$+ \beta_4 commoney_{j,t} + \beta_5 landl_{j,t} + \beta_6 island_{j,t} + \beta_7 border_{j,t} + \beta_8 comlang_{j,t}$$
$$+ \beta_9 comcol_{j,t} + \beta_{10} comctry_{j,t} + \beta_{11} colony_{j,t} + \beta_{12} curcol_{j,t} + u_{i,j,t}$$

For year *t*, *i = Country 1, …, Country 33* and *j = Country 1, …, Country 33* where *i ≠ j* and for *differen = 0* to run on homogenous goods, and *differen = 1* to run on differentiated goods. The first regression is on trade as a linear response variable, while the second regression takes the log of trade. Both regressions are run on nominal volatility in addition to real volatility, as a robustness check.

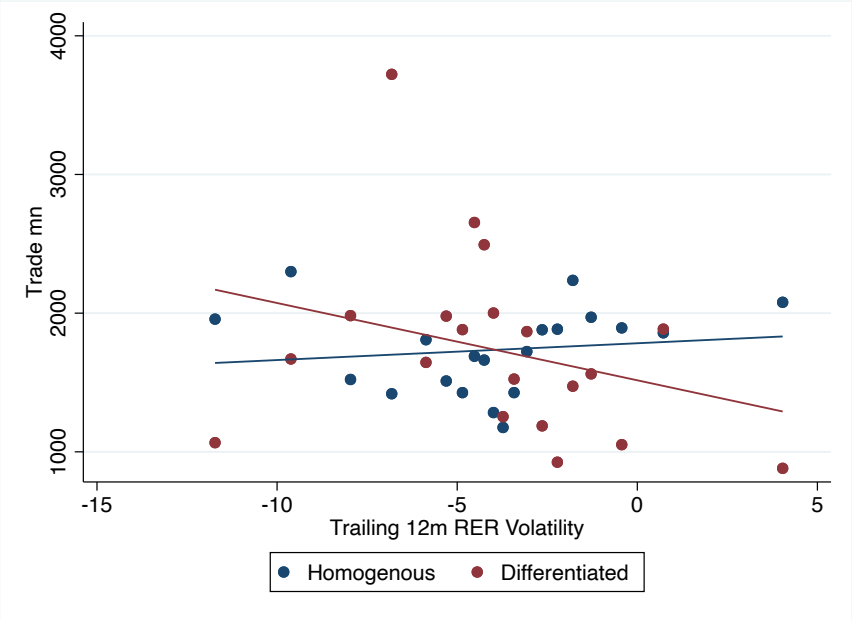
Table 12 – Regression Output: Volatility and Trade in Differentiated v. Homogenous Goods

	(1) trade (diff_rer)	(2) trade (diff_ner)	(3) trade (homg_rer)	(4) trade (homg_ner)
ln_rerttmvol	**-41.02***		**14.87***	
	(-2.20)		**(2.35)**	
ln_nerttmvol		**-16.88***		**3.200**
		(-2.50)		**(1.28)**
importer	1.428***	1.353***	0.268**	0.495***
	(5.34)	(5.18)	(2.95)	(5.12)
gravdist	-7.596	-14.53***	-11.88***	-9.567***
	(-1.73)	(-3.43)	(-7.95)	(-6.09)
landl	-1644.4***	-1644.6***	-632.2***	-653.0***
	(-8.27)	(-8.14)	(-9.37)	(-8.74)
island	-3.805	207.9	186.1***	207.0***
	(-0.03)	(1.54)	(3.87)	(4.14)
border	3119.0***	4707.7***	2466.2***	3443.2***
	(9.20)	(11.69)	(21.44)	(23.10)
comlang	1924.5***	1458.0***	445.6***	408.3***
	(11.00)	(8.67)	(7.51)	(6.56)
comcol	5328.7***	5444.1***	879.1***	911.3***
	(8.68)	(9.52)	(4.22)	(4.30)
comctry	0	0	0	0
	(.)	(.)	(.)	(.)
colony	-2968.8***	-2149.1***	-95.97	-856.6***
	(-7.27)	(-4.68)	(-0.69)	(-5.04)
curcol	14488.6***	14327.8***	188.6	886.7
	(9.51)	(9.94)	(0.36)	(1.66)

commoney	1143.0***	0	18.35	0
	(4.20)	(.)	(0.20)	(.)
lrgdp1	2893.0***	2862.0***	667.1***	806.6***
	(21.80)	(21.84)	(14.81)	(16.63)
lrgdp2	1385.2***	1357.9***	331.6***	376.7***
	(10.44)	(10.37)	(7.36)	(7.77)
_cons	-49562.6***	-48341.5***	-10836.5***	-13297.8***
	(-21.34)	(-21.15)	(-13.75)	(-15.72)
N	19893	17320	19893	17320

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Figure 18 – Goods Trade and Currency Volatility, Expanded Gravity Controls



An approximately one percent increase in real exchange rate volatility[8] decreases annual trade in differentiated goods by $41mn, with significance at a 5% level—this is relative to mean annual differentiated goods trade of $2.8bn. Trade in homogenous goods *increases* by $14mn, also at a 5% significance—mean annual homogenous goods trade is $647mn. This puzzling effect of volatility on homogenous goods might be, at its root, a story of reverse causation. Certain countries have a concentrated economic exposure to the commodities trade and,

[8] See Footnote 4 for clarity

relatedly, constitute a disproportionate share of total trade in commodities. These countries may also have increased variability in real price levels due to fluctuations in revenues from the (potentially) highly variable prices of commodities on world markets. When commodities prices are high, importers need to buy more of the exporter's currency to purchase a given quantity of commodity (thus pushing up the value of the exporter's currency) and elevated revenues in the sector means higher spending in the economy, leading to a bump in domestic price levels. Together, these factors increase the real strength of the currency, with the opposite effect should commodity prices fall. If commodity prices are volatile, so are these countries' currencies. Thus, the positive relationship between volatility and trade in homogenous goods may just be a reflection of these countries' predominance in the commodities trade and their economies' sensitivity to fluctuations in commodity prices. Corroborating this hypothesis, the data show that, of the 528 trading pairs represented, just 1% (5) account for 34% of total trade in homogenous goods.

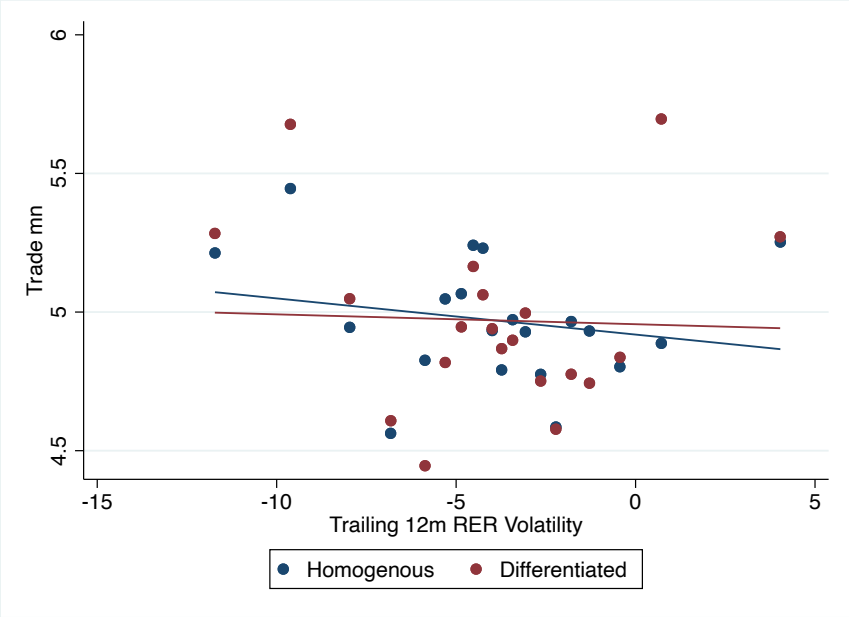
Table 13 – Regression Output: Volatility, Log Trade in Differentiated v. Homogenous Goods

	(1) ln_trade (diff_rer)	(2) ln_trade (diff_ner)	(3) ln_trade (homg_rer)	(4) ln_trade (homg_ner)
ln_rerttmvol	**-0.00351**		**-0.0130****	
	(-0.86)		**(-2.62)**	
ln_nerttmvol		**-0.00841*****		**-0.00334**
		(-5.18)		**(-1.76)**
gravdist	-0.0286***	-0.0309***	-0.0416***	-0.0437***
	(-29.47)	(-30.42)	(-35.35)	(-36.60)
landl	-0.295***	-0.187***	-0.831***	-0.820***
	(-6.68)	(-3.84)	(-15.61)	(-14.38)
island	-0.114***	-0.0663*	-0.297***	-0.294***
	(-3.62)	(-2.04)	(-7.81)	(-7.71)
border	-0.335***	-0.425***	-0.353***	-0.417***
	(-4.46)	(-4.38)	(-3.90)	(-3.67)
comlang	0.431***	0.466***	0.734***	0.857***
	(11.11)	(11.50)	(15.66)	(18.05)

comcol	2.268***	2.275***	2.901***	2.914***
	(16.65)	(16.50)	(17.64)	(18.06)
comctry	0	0	0	0
	(.)	(.)	(.)	(.)
colony	0.592***	1.062***	0.343**	0.617***
	(6.55)	(9.66)	(3.15)	(4.80)
curcol	2.801***	2.401***	1.506***	1.188**
	(8.28)	(6.91)	(3.69)	(2.92)
commoney	0.461***	0	0.0826	0
	(7.75)	(.)	(1.15)	(.)
avgfxdepth	0.0000228***	0.0000259***	0.0000161***	0.0000164***
	(24.42)	(25.53)	(14.25)	(13.80)
lrgdp1	0.728***	0.710***	0.966***	1.012***
	(24.70)	(22.49)	(27.09)	(27.33)
lrgdp2	0.418***	0.381***	0.831***	0.920***
	(14.19)	(12.06)	(23.25)	(24.79)
_cons	-6.173***	-5.490***	-14.88***	-16.37***
	(-12.00)	(-10.01)	(-23.91)	(-25.42)
N	19887	17316	19808	17237

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Figure 19 – Goods Trade and Currency Volatility, Expanded Gravity Model Controls



With a log response variable, the statistical significance of the earlier results no longer holds; in fact, there is now a statistically significant negative relationship between increased volatility and trade in homogenous goods. However, with nominal volatility as the explanatory variable, there continues to be a statistically significant negative relationship with trade, although the coefficient is small enough to be economically insignificant. While it is unclear what in the data may have caused this wide divergence in effects, this general inconsistency calls into the question the robustness of the results. One could argue that it is inappropriate to assume a multiplicative relationship between the explanatory variables in this expanded regression and the response variable (taking the log of the response variable implies that such a relationship exists). This would be a dubious claim, however, because regressions with the log of aggregate trade were successfully implemented in previous sections. Thus, I cannot conclude that there is a significant difference in the impact of exchange rate volatility on trade in differentiated goods versus trade in homogenous goods, although there is some evidence in support of that result.

A future analysis could explicitly incorporate commodity price data, constructing a weighted basket of commodity goods for large exporters, and testing the concordance of their currency's volatility with the volatility of that commodity basket. It would also be illuminating to disaggregate the products within the differentiated goods category, in an effort to analyze the sensitivity of individual goods to exchange rate volatility. This could have relevance to the literature on exchange rate pass-through, insofar as we may expect that consumption of more differentiated goods with lower pass-through is less susceptible to currency volatility.

6.3 Trade in Polarized Goods with Volatility of Varying Terms

Firms selling into commodity markets may have a greater ability to adjust output on a shorter time scale relative to firms selling specialized manufactures. Trading in homogenous goods

usually takes place on organized exchanges, and firms can dynamically adjust their output on the spot market and through hedging contracts. With differentiated goods, it is likelier that the producer has contractual obligations to deliver a particular volume of product regardless of market conditions; spot markets and forwards markets certainly are not an option (Rauch 1999). This may dampen sensitivity to short-run volatility—that which takes place within the term of existing contracts—but may increase sensitivity to sustained volatility, with firms hesitating to assume the risks associated with fixed supply contracts. Regressions similar to the ones in the previous subsection are implemented, with trailing volatility of one year through to five years

Table 14 – Regression Output: Diff. Goods, Varying Time Horizons, Exp. Gravity Controls[9]

	(1) trade	(2) trade	(3) trade	(4) trade	(5) trade
ln_rerttmvol	-41.02*				
	(-2.20)				
ln_rert2yvol		-42.29*			
		(-2.17)			
ln_rert3yvol			-43.19*		
			(-2.12)		
ln_rert4yvol				-43.62*	
				(-2.05)	
ln_rert5yvol					-42.59
					(-1.93)
_cons	-49562.6***	-49628.6***	-49568.9***	-48800.8***	-47183.5***
	(-21.34)	(-20.20)	(-19.05)	(-17.76)	(-16.39)
N	19893	18846	17799	16752	15705

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 15 – Regression Output: Homg. Goods, Varying Time Horizons, Exp. Gravity Controls[10]

	(1) trade	(2) trade	(3) trade	(4) trade	(5) trade
ln_rerttmvol	14.87*				
	(2.35)				
ln_rert2yvol		15.54*			

[9] Gravity model regressors omitted in the interest of preserving space. The coefficients on these regressors are not much changed from the earlier regressions.
[10] See Footnote 3.

		(2.33)			
ln_rert3yvol			16.25*		
			(2.31)		
ln_rert4yvol				17.43*	
				(2.35)	
ln_rert5yvol					18.63*
					(2.38)
_cons	-10836.5***	-11263.1***	-11729.2***	-12143.0***	-12457.1***
	(-13.75)	(-13.41)	(-13.06)	(-12.67)	(-12.21)
N	19893	18846	17799	16752	15705

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Notwithstanding this hypothesis, the tables above indicate that increasing the time span of the trailing volatility does not lead to a statistically significant difference in the impact of volatility on the trade of differentiated and homogenous goods. As I noted in Section 5.4, this is not firm evidence of an absence of such a relationship: five years does not constitute the "long run" in the context of firms' investments in supply chains and real assets—the latter are often depreciated across ten- to twenty-year time scales or longer. It is possible that with a longer time series of data we would observe a significant increase in the impact of volatility.

7 The Availability of Hedging

Volatility would have no adverse effect on the volume of trade if it were possible to perfectly and costlessly hedge exposure to currency fluctuations. However, such hedging is far from universally available and, when it is, certainly not costless. For a given level of volatility, we may expect any associated impact on trade to be negatively related to firms' ability to hedge currency risk (i.e., with access to hedging, volatility is less deleterious to trade). With access to currency hedges, firms mitigate the need to adjust output and blunt the impetus to reconsider investment decisions. Deeper foreign exchange markets may also be related to less expensive hedges for any given level of volatility, through the mechanism of higher levels of liquidity and

greater competition among providers of hedging contracts. That said, extended periods of volatility may increase the cost of hedging such that it becomes less attractive to engage in international trade. For a risk-averse firm, however, the defined cost of an expensive hedge would be a superior outcome to the wide cone of uncertainty it may face in the absence of hedging (De Grauwe 1988).

To measure the depth of foreign exchange markets, I use Bank for International Settlements data on the average daily turnover—in terms of notional principal value—of exchange-traded derivatives (data are available on futures and options contracts) for every included currency. Data on over-the-counter trades (OTC) are not used; however, this should not pose an analytical problem for my purposes, given that OTC trading volumes for a currency are likely well-correlated with exchange-traded volumes. The regressor used is the average of foreign exchange market depth for each of the currencies represented in the country-pair.[11] The measure selected, although the best available to me, is an imperfect one: ideally, it would be possible to aggregate firm-level data on the availability and cost of hedging. Regressions including foreign exchange depth could be confounded by the possibility that such a market deepened precisely in response to volatility or anticipation of further volatility—with that volatility in turn depressing trade—in which case we may see a false negative relationship between foreign exchange market depth and trade.

7.1 Contextualizing the Availability of Hedging

The distribution of foreign exchange derivatives volume is highly uneven: over the sample period, Dollar derivatives average over 2.5 times the turnover of Euro derivatives (the

[11] Kindly refer to the Data section for more detail.

second-most traded), which in turn is over 2.5 times the turnover of Yen derivatives.[12] Of course, volume in derivatives, especially in these currencies, is not attributable entirely to trade: Assets denominated in these currencies are popular holdings among foreign investors, and hedging is much in demand for this reason too, among others. That said, the increased liquidity undoubtedly benefits exporters seeking to hedge their production. Importantly, the predominance of dollar invoicing in global trade, as reinforced by Boz (2020), means that a large share of dollar derivatives volume will also be driven by the hedging needs of trading partnerships that do not include the US (e.g., a forward contract entered into by a Chinese exporter to convert into yuan the dollar revenues from an Indian importer).

Figure 20 – Distribution of Avg. FX Derivatives Market Depth Obs.

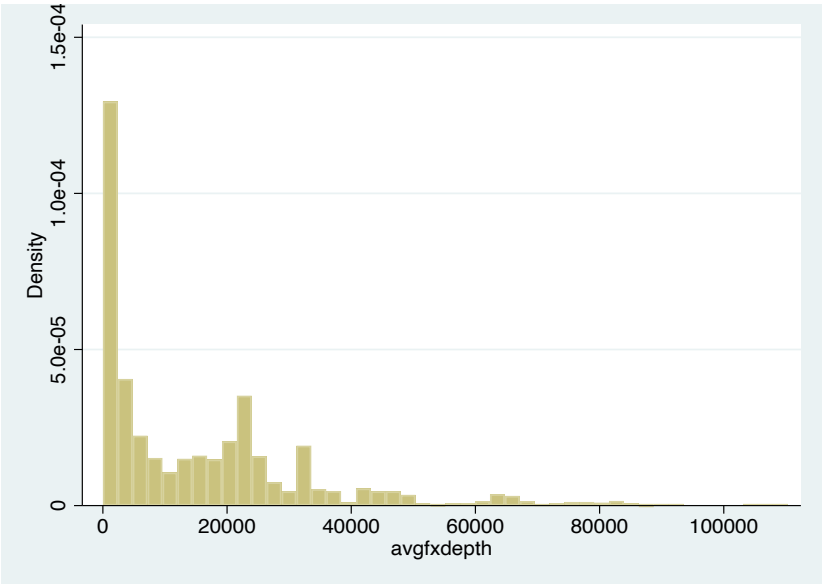


Table 16 – Regression Output: Forex Depth on GDP

```
      Source |       SS           df       MS      Number of obs   =    40,128
-------------+----------------------------------   F(2, 40125)     =   4865.85
       Model |  2.6425e+12         2  1.3212e+12   Prob > F        =    0.0000
    Residual |  1.0895e+13    40,125   271532898   R-squared       =    0.1952
-------------+----------------------------------   Adj R-squared   =    0.1952
       Total |  1.3538e+13    40,127   337372203   Root MSE        =     16478

------------------------------------------------------------------------------
```

[12] Refer to Footnote 11.

avgfxdepth	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lrgdp1	10796.72	158.2173	68.24	0.000	10486.61	11106.83
lrgdp2	10796.72	158.2173	68.24	0.000	10486.61	11106.83
_cons	-239219.5	2587.902	-92.44	0.000	-244291.9	-234147.2

The GDP of trading partners explains 20% of the variation in the depth of foreign exchange markets. Large economies are likelier to have more developed capital markets and are also likelier to be a more substantial share of world trade (naturally, these are broad generalizations). Some of the unexplained variance is undoubtedly due to 1) China's restrictions on capital flows, which meant that a derivatives market developed late relative to economic growth, and remains small, and 2) Eurozone countries with large derivatives markets relative to GDP because of the common currency.

Next, I regress aggregate trade on average forex market depth, using the expanded gravity model. Exchange rate volatility is left out of this equation: the objective is to study the impact of foreign exchange depth alone, after controlling for other factors that influence trade. There is a positive relationship between derivatives market depth and aggregate bilateral trade, significant at a $p<0.001$ level. Controlling for other factors, a $10 billion increase in daily foreign exchange derivatives turnover (mean turnover is $15.9 billion, with a standard deviation of $18.4 billion) is associated with a $566 million increase in bilateral trade, which is a 7.2% increase on average bilateral trade.[13] This is a stronger result than the regression of volatility on trade levels, conducted in Section 4. One possible explanation is that the availability of hedging, by reducing currency risk for trading partners, is driving excess trade beyond the predictions of the gravity model. There is probably reverse causality here: countries that engage in high levels of trade develop deeper foreign exchange derivatives markets in response to the demand for hedging; the existence of these markets is not exogenous.

[13] Kindly refer to the data section for summary statistics on these variables.

Table 17 – Regression Output: Trade on Forex Depth, Expanded Gravity Controls (excl. Vol)

Source	SS	df	MS			
				Number of obs	=	19,887
				F(12, 19874)	=	698.00
Model	3.1439e+12	12	2.6199e+11	Prob > F	=	0.0000
Residual	7.4597e+12	19,874	375349040	R-squared	=	0.2965
				Adj R-squared	=	0.2961
Total	1.0604e+13	19,886	533219033	Root MSE	=	19374

aggtrade	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
avgfxdepth	.0565917	.0089607	6.32	0.000	.039028	.0741553
gravdist	-73.93063	9.342559	-7.91	0.000	-92.24282	-55.61843
lrgdp1	12870.01	283.4711	45.40	0.000	12314.38	13425.63
lrgdp2	12825.63	283.4597	45.25	0.000	12270.03	13381.24
landl	-3958.163	423.8684	-9.34	0.000	-4788.981	-3127.346
island	1837.434	302.0946	6.08	0.000	1245.303	2429.564
border	28062.68	722.1863	38.86	0.000	26647.13	29478.23
comlang	1945.989	373.0831	5.22	0.000	1214.715	2677.263
comcol	10211.02	1309.022	7.80	0.000	7645.231	12776.82
comctry	0	(omitted)				
colony	-4158.242	864.8392	-4.81	0.000	-5853.399	-2463.085
curcol	703.1435	3254.777	0.22	0.829	-5676.491	7082.778
differen	0	(omitted)				
commoney	1763.257	569.3692	3.10	0.002	647.2457	2879.268
_cons	-293771.9	4945.313	-59.40	0.000	-303465.2	-284078.7

7.2 The Interaction of Hedging and Volatility

To begin, I take a simple look at the relationship between currency market depth and currency volatility. There is a strong, negative relationship, even after controlling for the GDP of trading partners. The control is necessary to adjust for the fact that larger economies are less susceptible to exchange rate volatility than smaller ones.[14] Causality with this regression likely flows in both directions: deep derivatives markets counteract volatility by distributing exchange rate risk across market participants, and lower currency volatility supports the development of financial markets by reducing the risks of conducting market activities in that currency.

Table 18 – Regression Output: Volatility on Trade Depth

Source	SS	df	MS			
				Number of obs	=	40,128
				F(1, 40126)	=	53.12
Model	683.566879	1	683.566879	Prob > F	=	0.0000
Residual	516382.986	40,126	12.8690372	R-squared	=	0.0013
				Adj R-squared	=	0.0013
Total	517066.553	40,127	12.8857516	Root MSE	=	3.5873

[14] The negative relationship between the GDPs of trading partners and their level of exchange rate volatility is significant to a p<0.01 level.

```
------------------------------------------------------------------------------
ln_rerttmvol |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  avgfxdepth |  -7.11e-06   9.75e-07    -7.29   0.000    -9.02e-06   -5.19e-06
       _cons |  -3.828424   .0237155  -161.43   0.000    -3.874907   -3.781941
------------------------------------------------------------------------------
```

I then look to study whether the interaction of hedging availability and volatility has any explanatory power on the volume of trade. As discussed earlier, we may expect to see derivative market depth correlate positively with trade for a given level of volatility. First, 25 buckets are created, each containing country-pair observations corresponding to the intersection of a given quintile rank for exchange rate volatility and foreign exchange market depth. There are at least (roughly) 1,000 observations in each bucket, lending validity to a regression using these interaction terms. Aggregate trade is then regressed on these interaction terms, with the expanded gravity model as controls.

The regression is specified as:

$$\begin{aligned} lntrade_{t,i,j} = \beta_0 &+ \beta_a avgfxcat + \beta_b volcat + \beta_c avgfxcatvolcat + \beta_1 GravDist_{I,j} \\ &+ \beta_2 lrgdp_{I,t} + \beta_3 lrgdp_{j,t} + \beta_4 commoney_{j,t} + \beta_5 landl_{j,t} + \beta_6 island_{j,t} \\ &+ \beta_7 border_{j,t} + \beta_8 comlang_{j,t} + \beta_9 comcol_{j,t} + \beta_{10} comctry_{j,t} + \beta_{11} colony_{j,t} \\ &+ \beta_{12} curcol_{j,t} + u_{i,j,t} \end{aligned}$$

For year t, i = *Country 1, …, Country 33* and j = *Country 1, …, Country 33* where $i \neq j$.

Figure 21 – Count of Observations in each Interaction Bucket

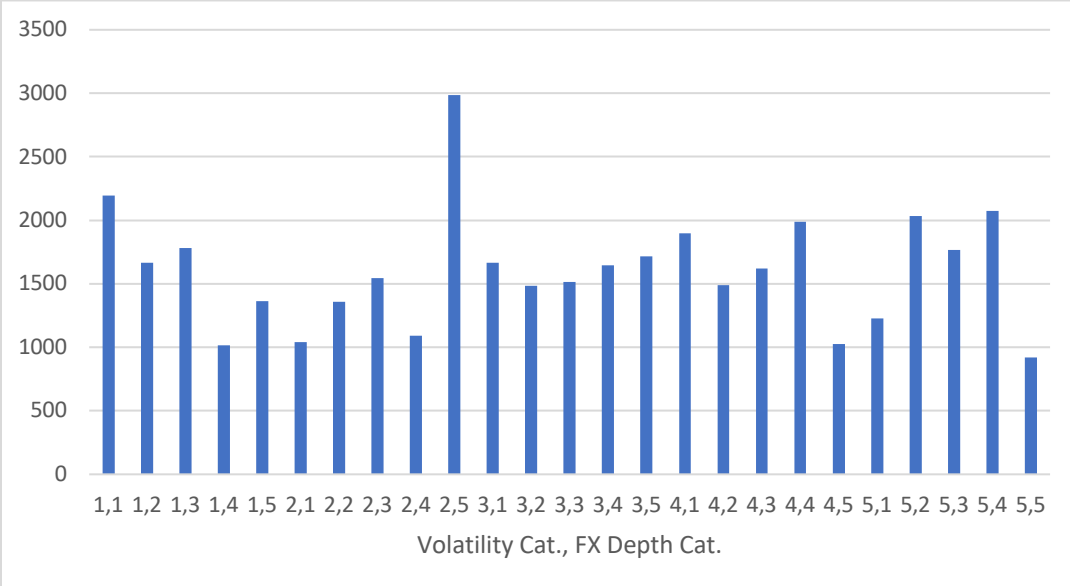


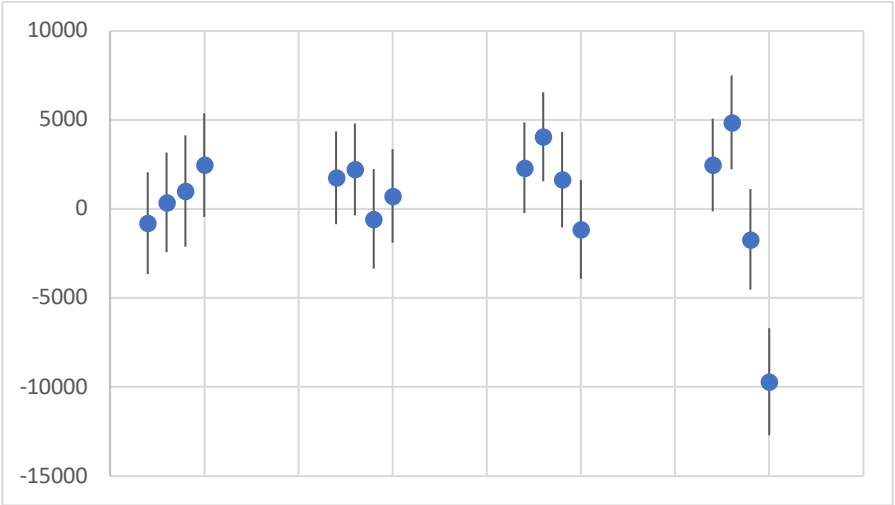
Table 19 – Regression Output: Trade on the Interaction of Forex Depth and Volatility

Source	SS	df	MS			
				Number of obs	=	19,887
Model	3.2920e+12	37	8.8973e+10	F(37, 19849)	=	241.54
Residual	7.3116e+12	19,849	368359938	Prob > F	=	0.0000
				R-squared	=	0.3105
Total	1.0604e+13	19,886	533219033	Adj R-squared	=	0.3092
				Root MSE	=	19193

aggtrade	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rerttmvol	-4.210145	2.371222	-1.78	0.076	-8.857938	.437649
importer	1.810797	.5751007	3.15	0.002	.6835511	2.938042
gravdist	-54.99308	9.50836	-5.78	0.000	-73.63026	-36.3559
landl	-2820.042	436.9108	-6.45	0.000	-3676.423	-1963.66
island	1672.248	305.3003	5.48	0.000	1073.833	2270.662
border	27904.6	720.8765	38.71	0.000	26491.62	29317.58
comlang	1326.886	375.6734	3.53	0.000	590.5348	2063.237
comcol	7940.231	1338.344	5.93	0.000	5316.965	10563.5
comctry	0	(omitted)				
colony	-3339.91	872.9015	-3.83	0.000	-5050.87	-1628.95
curcol	836.588	3242.197	0.26	0.796	-5518.388	7191.564
differen	0	(omitted)				
commoney	-718.491	780.344	-0.92	0.357	-2248.03	811.0485
lrgdp1	14033.89	284.6583	49.30	0.000	13475.93	14591.84
lrgdp2	13985.44	284.3786	49.18	0.000	13428.03	14542.84
vol_cat						
2	2563.774	1048.186	2.45	0.014	509.2428	4618.305
3	736.5742	902.509	0.82	0.414	-1032.419	2505.567
4	116.9189	858.2721	0.14	0.892	-1565.366	1799.204
5	2020.06	979.6302	2.06	0.039	99.90311	3940.217
avgfx_cat						
2	-4049.538	901.7734	-4.49	0.000	-5817.09	-2281.987
3	-7132.863	903.1672	-7.90	0.000	-8903.146	-5362.58
4	-5854.948	1067.132	-5.49	0.000	-7946.617	-3763.28
5	-1338.51	981.2881	-1.36	0.173	-3261.917	584.8962

vol_cat#avgfx_cat						
2 2	-789.9246	1458.074	-0.54	0.588	-3647.871	2068.022
2 3	378.6623	1425.979	0.27	0.791	-2416.376	3173.701
2 4	1016.472	1594.969	0.64	0.524	-2109.801	4142.744
2 5	2475.828	1484.133	1.67	0.095	-433.1961	5384.853
3 2	1757.743	1328.679	1.32	0.186	-846.5798	4362.066
3 3	2228.361	1314.388	1.70	0.090	-347.9498	4804.673
3 4	-547.4751	1425.125	-0.38	0.701	-3340.839	2245.889
3 5	739.6478	1338.797	0.55	0.581	-1884.505	3363.801
4 2	2321.769	1299.964	1.79	0.074	-226.269	4869.807
4 3	4064.576	1275.932	3.19	0.001	1563.643	6565.509
4 4	1650.164	1369.994	1.20	0.228	-1035.139	4335.467
4 5	-1138.52	1417.457	-0.80	0.422	-3916.853	1639.814
5 2	2474.628	1329.348	1.86	0.063	-131.0056	5080.261
5 3	4872.553	1344.202	3.62	0.000	2237.804	7507.302
5 4	-1700.679	1442.606	-1.18	0.238	-4528.307	1126.949
5 5	-9694.859	1534.404	-6.32	0.000	-12702.42	-6687.299
_cons	-320211.3	4979.382	-64.31	0.000	-329971.3	-310451.3

Figure 22 – Coefficient on Vol, FX Interaction Terms with Std. Error Bars



The figure above takes the coefficients on the interaction terms generated from the regression above. Each cluster represents a quintile of volatility, from the second quintile to the fifth. Each point in the cluster represents a quintile of foreign exchange market depth, also from the second quintile to the fifth. For the second quintile of volatility, results are as expected, with trade increasing across the cluster, although the differences are not significant. For fourth and fifth quintiles of volatility, we have a significant and peculiar pattern, in which highest quintile of foreign exchange depth is associated with a substantial reduction in trade relative to the lowest quintile within that volatility category. One possible explanation is as follows: high volatility is

not discounted into firms' expectations in countries with deep foreign exchange markets. As a consequence, firms respond more negatively to the emergence of volatility in these instances, which is why we see a strongly negative coefficient on trade when countries experience high volatility despite having deep foreign exchange markets. This hypothesis could be directly tested with data on discounted vs. realized volatility.

7.3 Future Directions

Firm-level data would be exceedingly helpful in a further study of this topic. This is especially the case for multinational corporations (MNCs), which in generate cash flows in several, potentially mutually offsetting, currencies (i.e., many MNCs are "operationally hedged" against exchange rate volatility). The extent to which a country's trade flows are related to MNCs that may be able to internalize exchange rate volatility is likely related to the overall linkages beings studied in this section, and in the paper more broadly. Further, firm-level data pertaining to the cost of derivatives contracts, including the cost of OTC contracts would provide further color to this analysis. Larger importing and exporting firms likely benefit from their scale when negotiating currency hedges with brokers, and it would be instructive to study how firm size in the tradable goods sector is associated with bilateral trade volume's sensitivity to volatility.

Finally, regarding the positive association between derivatives market depth and trade, it would be useful to temporally delink one from the other so that we can establish the direction in which causality flows. One way to do this could be an event study of countries adopting the Euro as their currency. After controlling for the trade effect of adopting a common currency—as well as the expanded gravity model controls used in this thesis—researchers can study the residual effect on trade of accession, in an attempt to isolate the impact of access to the Euro derivatives market.

8 Misalignments in the Real Exchange Rate

The determinants and consequences of shifts in the real exchange rate are topics of great interest both to academics and to practitioners. Indeed, some of the earliest studies of exchange rate volatility, such as IMF (1984), were motivated by a desire to study the effects of volatility on trading partners' relative competitiveness. This paper's approach focuses on changes in real price levels, as opposed to absolute price levels. For a given country-pair-year observation, I construct a variable for the difference, in standard deviations, between the RER Index for that year and the average reading of the RER index across the sample period.[15] Because the RER measure is indexed and not absolute, we cannot directly assess the real value of an exporter's currency relative to an importer's currency for a given country pair. However, changes in *rermisalign* represent increases or decreases in exchange rate competitiveness, and this provides the desired analytical capability. Indeed, changes in the RER index may be more instructive than the absolute level of the real exchange rate. Countries can, and often do, have sustained undervaluations and overvaluations in their real currencies for several reasons, including cross-national differences in the productivity of the non-tradable goods sector. Those matters are outside the scope of this thesis, but the crux of the matter is: A static real undervaluation of a country's currency might be less indicative of export competitiveness than a real depreciation relative to earlier levels.

As constructed, increases in *rermisalign* correspond to an increase in the exporting partner's competitiveness, and lower *rermisalign* values correspond to a decrease in the exporting partner's competitiveness. We may anticipate a positive relationship between

[15] Kindly refer to the Data section for details.

rermisalign and the trade response variable, which represents exports of Country B to Country A in a given year, not total trade between the two countries. The mean of *rermisalign* is zero because of how it represents a given observation's deviation from the mean real exchange rate index over the sample period; values range from -3.09 to 2.68 standard deviations from the mean.

8.1 The Relationship Between Volatility and RER Misalignment

Investigating whether such a relationship exists is relevant because of concerns that volatility may lead to misalignments that lend a competitive advantage to certain exporting nations with a devalued currency. With reference to the figures below, there is no relationship between misalignments in the real exchange rate and volatility for the trailing year. However, there is a somewhat negative relationship between 5-year volatility and real misalignments (i.e., *decreased* export competitiveness as volatility increases), which is significant at the 15% level.

Figure 23 – Volatility and RER Misalignment

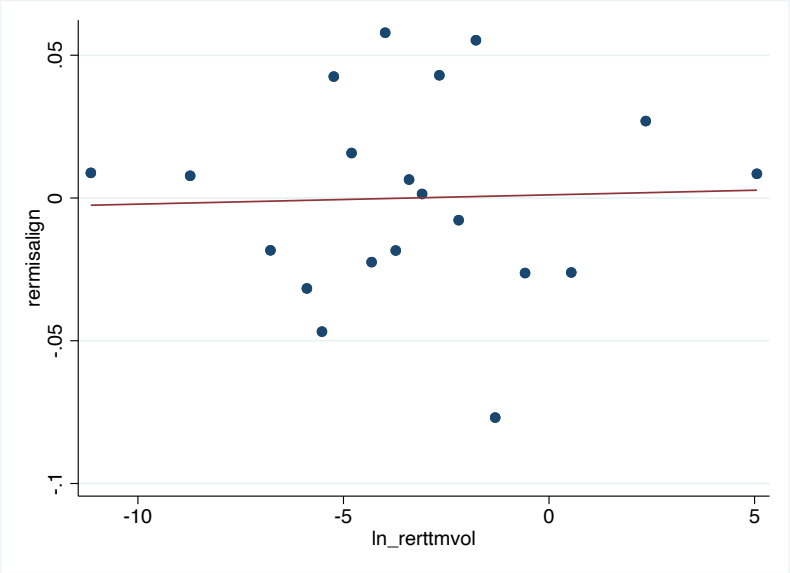
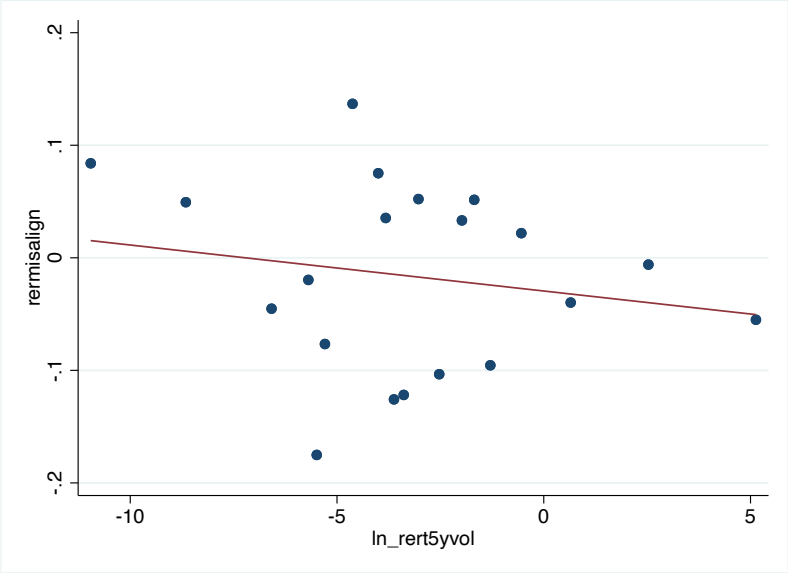


Figure 24 – Volatility (5 years) and RER Misalignment



It is possible that, with data on a longer time scale, increases in volatility may correspond to a more appreciated real exchange rate. If that were to be the case, it raises a potential identification problem: the negative relationship between exchange rate volatility and trade may instead be driven by exchange rate misalignments, associated with high volatility, that are reducing the competitiveness of exports and driving down trade volumes. The absence of a significant correlation between volatility and currency misalignments suggests that this is not a problem. Further, one would expect that: 1) more volatile currencies are less valuable (in nominal terms), all else equal, as investors demand a greater risk premium for holding the currency, and 2) that, combined with the relative stickiness of domestic prices, this would result in currency depreciation, *not* appreciation.

Regardless, the relationship, to the extent that it exists, appears to be a negative one. This cuts against the concerns in the literature, highlighted by Auboin and Ruta (2011), that increased volatility may be correlated with a competitive advantage for exporters. And while Frieden, et al. (2011) find that countries with large tradable goods sectors are likelier to have floating exchange rates (i.e., more volatile exchange rates) than similar countries with smaller tradable goods

sectors, these results suggest that exporters may not have an inherent reason to favor more volatility currency regimes. Granted, this sample is restricted to major exporting countries, and the results do not preclude the possibility that exporters favor floating exchange rate regimes in some countries, especially when they have political heft and so a reason to believe that, once the rate is floating, they will be successful in lobbying the government to depreciate the currency in real terms.

8.2 Trade and RER Misalignment

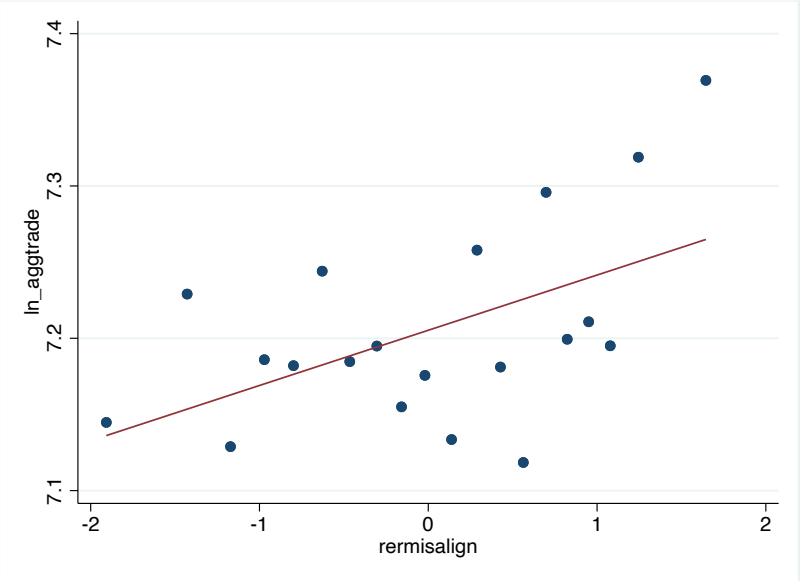
The relationship between trade and real exchange rate misalignment is as anticipated, with increases in exporter competitiveness—signified by an increase in *rermisalign*—leading to a statistically significant (at a 1% level) increase in exports. A one standard deviation decrease in the value of a currency, relative to its average value, results in a 3.62% annual increase in the dollar value of exports that year: all else equal, an exporter with a two standard deviation increase in competitiveness can expect trade to increase 14.5% year-on-year, relative to an exporter with an equally-sized decrease.

Table 20 – Regression Output: Trade on RER Misalignments, Exp. Gravity Model Controls

Source	SS	df	MS			
Model	12830.2345	10	1283.02345	Number of obs	=	4,654
Residual	3755.64587	4,643	.808883453	F(10, 4643)	=	1586.17
Total	16585.8804	4,653	3.56455628	Prob > F	=	0.0000
				R-squared	=	0.7736
				Adj R-squared	=	0.7731
				Root MSE	=	.89938

ln_aggtrade	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
rermisalign	.0362498	.0140373	2.58	0.010	.0087301	.0637695
gravdist	-.0612681	.0011477	-53.38	0.000	-.0635182	-.0590181
landl	-.3934357	.0345587	-11.38	0.000	-.4611871	-.3256842
island	.3830734	.0303069	12.64	0.000	.3236575	.4424893
border	.3691234	.0726415	5.08	0.000	.2267116	.5115353
comlang	.1147911	.0367241	3.13	0.002	.0427943	.1867878
comcol	0	(omitted)				
comctry	0	(omitted)				
colony	.4826907	.0997747	4.84	0.000	.2870848	.6782965
curcol	0	(omitted)				
commoney	.1992693	.048623	4.10	0.000	.103945	.2945935
lrgdp1	2.145221	.028047	76.49	0.000	2.090236	2.200207
lrgdp2	1.643045	.0261305	62.88	0.000	1.591816	1.694273
_cons	-33.56975	.4468038	-75.13	0.000	-34.4457	-32.69381

Figure 25 – Trade and RER Misalignment, Expanded Gravity Model Controls



Note that this is misalignment and trade over a one-year period, and that misalignments are relative to average real price levels over the sample period, not an absolute measure. Although we can reasonably conclude that there is a short-run relationship between a competitive exchange rate and increased exports, we cannot comment on longer-term effects. For that, we would need a reliable measure of a country's true real exchange rate, with data covering a longer time scale.

8.3 Interaction between Volatility and RER Misalignment

The previous subsection established a short-run relationship between competitiveness and increased trade. Earlier in this thesis, we concluded that there may be a negative relationship between exchange rate volatility and trade. Bringing these two threads together, I now investigate whether the interaction of volatility and RER misalignment has an impact on trade. Specifically, whether an increase in currency competitiveness offsets the negative impact on trade of high volatility (note that we established there is no correlation between volatility and

misalignments alone). Categorical variables *misaligncat* and *volcat* are coded for the regression, with each splitting the continuous variables into quintiles for the interaction terms.[16]

The regression is specified as:

$$lntrade_{t,i,j} = \beta_0 + \beta_a misaligncat + \beta_b volcat + \beta_c misaligncatvolcat + \beta_1 GravDist_{I,j}$$
$$+ \beta_2 lrgdp_{I,t} + \beta_3 lrgdp_{j,t} + \beta_4 commoney_{j,t} + \beta_5 landl_{j,t} + \beta_6 island_{j,t}$$
$$+ \beta_7 border_{j,t} + \beta_8 comlang_{j,t} + \beta_9 comcol_{j,t} + \beta_{10} comctry_{j,t} + \beta_{11} colony_{j,t}$$
$$+ \beta_{12} curcol_{j,t} + u_{i,j,t}$$

For year *t*, *i* = *Country 1, …, Country 33* and *j* = *Country 1, …, Country 33* where $i \neq j$.

Table 21 – Regression Output: Interaction of Volatility and Exchange Rate Misalignment[17]

Source	SS	df	MS			
Model	13076.7742	43	304.111027	Number of obs	=	4,654
Residual	3509.10621	4,610	.761194405	F(43, 4610)	=	399.52
				Prob > F	=	0.0000
				R-squared	=	0.7884
				Adj R-squared	=	0.7865
Total	16585.8804	4,653	3.56455628	Root MSE	=	.87246

ln_aggtrade	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
gravdist	-.0609891	.0011269	-54.12	0.000	-.0631984	-.0587798
lrgdp1	2.02598	.0289102	70.08	0.000	1.969302	2.082658
lrgdp2	1.638848	.0256759	63.83	0.000	1.588511	1.689185
vol_cat	.2154875	.0949016	2.27	0.023	.0294349	.4015402
misaligncat	.0062347	.0874106	0.07	0.943	-.165132	.1776013
misaligncat						
-2-	-.2685279	.2675645	-1.00	0.316	-.7930825	.2560267
-1-	-.1144996	.2594335	-0.44	0.659	-.6231134	.3941143
-.5-	-.0500018	.2744911	-0.18	0.855	-.5881356	.4881321
0-	-.1527966	.3123825	-0.49	0.625	-.7652159	.4596227
1-	.0262963	.3776685	0.07	0.944	-.7141147	.7667073
2-	0	(omitted)				
vol_cat						
2	.3927501	.3165906	1.24	0.215	-.227919	1.013419
3	-.0402585	.3075259	-0.13	0.896	-.6431564	.5626395
4	.0961452	.2884552	0.33	0.739	-.4693652	.6616556
5	0	(omitted)				
misaligncat#vol_cat						
-2-#2	.1765747	.3807944	0.46	0.643	-.5699647	.9231141
-2-#3	.3304019	.3943872	0.84	0.402	-.4427857	1.10359
-2-#4	.2415088	.3774997	0.64	0.522	-.4985714	.981589
-2-#5	-.125805	.3945132	-0.32	0.750	-.8992397	.6476296
-1-#2	.003577	.3843095	0.01	0.993	-.7498536	.7570076
-1-#3	.2543965	.3956817	0.64	0.520	-.521329	1.030122
-1-#4	-.0642384	.3782321	-0.17	0.865	-.8057545	.6772776
-1-#5	-.1036792	.3955034	-0.26	0.793	-.8790553	.6716969

[16] Kindly refer to the Data section for more detail.
[17] Expanded gravity model regressors previously excluded in the interest of preserving space.

-.5-#2	-.0666221	.3785702	-0.18	0.860	-.808801	.6755568
-.5-#3	.2185178	.3925974	0.56	0.578	-.551161	.9881966
-.5-#4	-.037639	.3758016	-0.10	0.920	-.77439	.699112
-.5-#5	-.4186592	.3926666	-1.07	0.286	-1.188474	.3511554
0-#2	.0560581	.3715552	0.15	0.880	-.6723681	.7844842
0-#3	.283357	.3855556	0.73	0.462	-.4725167	1.039231
0-#4	-.05324	.3673707	-0.14	0.885	-.7734624	.6669824
0-#5	-.1160694	.3858921	-0.30	0.764	-.8726027	.6404638
1-#2	-.0928194	.381555	-0.24	0.808	-.8408498	.655211
1-#3	.0565693	.3947567	0.14	0.886	-.7173428	.8304815
1-#4	-.0065726	.3781754	-0.02	0.986	-.7479774	.7348322
1-#5	-.3189794	.3953206	-0.81	0.420	-1.093997	.4560383
2-#2	.6613107	.7595868	0.87	0.384	-.8278431	2.150464
2-#3	.9523724	.6971269	1.37	0.172	-.41433	2.319075
2-#4	.27367	.668824	0.41	0.682	-1.037545	1.584885
2-#5	-.3437585	.6654168	-0.52	0.605	-1.648294	.96077
_cons	-32.7575	.572959	-57.17	0.000	-33.88078	-31.63423

There is clearly no relationship between trade and the interaction of volatility and exchange rate misalignment, with the regression's adjusted-R^2 of 77% attributable to the gravity model and the effect of inserting volatility and exchange rate misalignment in their own right. What might have been expected is that, for every given level of volatility, an increase in the exporter's competitiveness would result in a higher positive coefficient of the interaction term on aggregate trade. Although we certainly cannot prove the negative, there is nothing in these data to suggest that such a compensatory effect exists. Perhaps the underlying issue here is that quintile-on-quintile slicing, which cuts the data into 25 buckets, results in cross sections of the pooled data that are not appropriate units for regression analysis due to inherent differences between the country-pair-year observations represented. A country-pair fixed-effects version of this regression—which would determine the interaction within each given trading partnership and then average across all 1,056 of them—might be more appropriate. Unfortunately, the 19 years of annual trade data do not contain a sufficient number of observations with which to conduct this analysis.

9 Conclusion and Future Directions

The relationship between exchange rate volatility and trade has intrigued international economists for over half a century; this paper cannot claim to provide an authoritative resolution to the questions it set out to answer. However, my hope is that the treatment of the subject contained in this thesis contributes substantively to the extant literature, provides useful findings for policymakers and suggests fruitful directions for further research.

A number of notable results are produced. There are also many notable *non*-results. Granted, this does not prove the negative. Nonetheless, the absence of strong evidence supporting some of the theoretical presuppositions about volatility has the potential to guide some policy recommendations. Policies, after all, are about tradeoffs: if trade-dependent countries observe that, under certain conditions, increased volatility does not harm bilateral trade, this widens the policy space to implement other measures—perhaps floating exchange rate arrangements, interest rate changes, etc.— that may be politically or economically desirable but liable to induce a measure of volatility into the currency. To that end, this study does not find convincing evidence that short-run volatility has a deleterious effect on trade. Whether through its limited salience to corporate decisionmakers or because sunk costs constrain entry/exit by firms, even large currency fluctuations over a trailing twelve-month period do not seem to drive firms' decisions about output levels.

Among the clearest results, robust both to an expanded set of gravity model controls and to a country fixed effects analysis, is that volatility over long time spans is a greater impediment to trade than short-term volatility. This holds across several model specifications, including the expanded gravity model, nominal exchange rates and country fixed effects. It also appears that differentiated goods are weakly more susceptible to volatility than homogenous goods,

particularly over longer time horizons. While this lends support to the "search costs" hypothesis put forth by Rauch (1999), further analysis is required to determine which differentiated goods are driving the divergence. Countries seeking to move up the manufacturing value chain may consider implementing a more stable exchange rate regime in light of these results. An analysis of homogenous goods further suggests that policymakers in commodity dependent economies may not need to directly concern themselves with exchange rate variability; volatility in commodity prices appears to outweigh exchange rate volatility as a determinant of trade. Taking a step back, it is worth observing that trade in polarized goods has experienced secular decline, as a share of total trade since 2001, and future research may benefit from a focus on trade in the intermediate goods that have become dominant in global value chains.

Countries with deeper foreign exchange markets exhibit less exchange rate volatility, even controlling for other relevant factors, lending support to the notion that a well-developed financial market can assist in the promotion of international trade. However, the results of this paper's analysis cannot confidently determine the degree to which hedging defrays the negative impact of volatility on trade. This is a matter that may well depend on how volatility evolves relative to discounted future expectations—and on firm-level differences in access to derivatives instruments.

Depreciations in the real exchange rate have a clear positive effect on a country's export volumes. However, contrary to some expectations in the literature, it does not appear that there is any relationship between increased currency volatility and a depreciated real exchange rate. Further, controlling for the competitive advantage of an undervalued currency, there is no evidence that the negative effect of increased currency volatility is mitigated by a further depreciation of the real exchange rate.

My thesis has several limitations and presents numerous opportunities for further inquiry, discussed in "Future Directions" subsections and within the analysis elsewhere. One broader point is that my dataset consists of 33 large trading nations—together accounting for over three-quarters of global trade. Although this sample well-represents world trade, it would be valuable to conduct a set of analyses, similar to those in this thesis, on a dataset containing a number of smaller, less economically advanced economies. Although the macro implications might be less wide-ranging, these countries are likely more susceptible to volatility than those included in my analysis. Understanding the implications of this currency volatility may be a relevant topic for development economists. However, expanding the set of countries considered may also introduce substantial complexity of political instability, the effects of which may be difficult to disaggregate from the effects of currency volatility alone. (This goes for the countries in my dataset too, though usually to a lesser extent.) The role of multinational corporations is not directly studied in this country-level analysis, but the ambiguity of certain results suggests strongly that the involvement of operationally hedged MNCs, their decisions around FDI and the structure of their global supply chains, are important explanatory variables in the relationship between exchange rate volatility and trade.

Several questions this thesis set out to answer are, indeed, answered—so too are a number of questions that were not initially asked. That said, many more remain unresolved, and many new questions appeal for response.

Uncertain remains the cost of uncertainty.

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11 Appendix

11.1 Coding Samples for Data Preparation and Analysis

Most of this work was done in Pandas for Python, using the Jupyter Notebook programming environment. Skills applied were learned in classes including CS109a, AM10 and AM120, as well as self-thought methods, as necessary. This is a small sample of the coding work, selected as it represents several of the major programming tasks.

Creating and applying labels for homogenous and differentiated goods

```
def homodiff(code):
    if code in SITCdiff:
        val=1
    else:
        val=0
    return val

def apply_homodiff(df):
    df['Diff. Good'] = df.apply(
        lambda row: homodiff(
            code=row['Commodity Code']),
        axis=1)
```

Aggregating across product categories to determine total trade, for each country-pair-year, in polarized goods

```
fulltrade_df[fulltrade _df['Partner Code'].isin(countrycodes)]
fulltrade _diff = fulltrade2_df[fulltrade2_df['Diff. Good']==1]
fulltrade _homo = fulltrade2_df[fulltrade2_df['Diff. Good']==0]

dat = {'Year':[], 'Importer':[],'Partner':[],'Trade':[]}
ConsolTrade_df1 = pd.DataFrame(data=dat)
columns = list(ConsolTrade_df1)
data = []

for importer in countrycodes:
    subset_df = FULLtrade_diff[FULLtrade_diff['Importer Code'] == importer]
    for partner in countrycodes:
        subset2_df = subset_df[subset_df['Partner Code'] == partner]
        for year in years:
            subset3_df = subset2_df[subset2_df['Year'] == year]
            trade = subset3_df['Trade Value (US$)'].sum()
            values = [year, importer, partner, trade]
            zipped = zip(columns, values)
            dictionary = dict(zipped)
            data.append(dictionary)

ConsolTrade_diff = ConsolTrade_df1.append(data, True)

dat = {'Year':[], 'Importer':[],'Partner':[],'Trade':[]}
ConsolTrade_df2 = pd.DataFrame(data=dat)
```

```
columns = list(ConsolTrade_df2)
data = []

for importer in countrycodes:
    subset_df = FULLtrade_homo[FULLtrade_homo['Importer Code'] == importer]
    for partner in countrycodes:
        subset2_df = subset_df[subset_df['Partner Code'] == partner]
        for year in years:
            subset3_df = subset2_df[subset2_df['Year'] == year]
            trade = subset3_df['Trade Value (US$)'].sum()
            values = [year, importer, partner, trade]
            zipped = zip(columns, values)
            dictionary = dict(zipped)
            data.append(dictionary)

ConsolTrade_homo = ConsolTrade_df2.append(data, True)

# Remove obvs where importer and partner are the same
ConsolTrade_diff0 = ConsolTrade_diff[ConsolTrade_diff['Importer'] !=
ConsolTrade_diff['Partner']]
ConsolTrade_homo0 = ConsolTrade_homo[ConsolTrade_homo['Importer'] !=
ConsolTrade_homo['Partner']]
```

Creating unique markers for each country-pair (necessary for further analysis)

```
l1 = l2 = codearr
RERVol_Consol = pd.DataFrame(list(product(l1, l2)), columns=['Importer',
'Partner'])
RERVol_Consol = RERVol_Consol[RERVol_Consol['Importer'] !=
RERVol_Consol['Partner']]
RERVol_Consol['RER TTMvol'] = np.ones(len(RERVol_Consol['Importer']))
RERVol_Consol['Marker'] = np.sqrt(RERVol_Consol['Importer']) *
np.sqrt(RERVol_Consol['Partner'])
# Verify
len(RERVol_Consol.Marker.unique()) == 528
```

Coding the RER Index

```
countries = nercpi_df['Country'].unique()
country1 = countries
country2 = countries

from itertools import product
countrycombos_raw = pd.DataFrame(list(product(country1, country2)),
columns=['country1', 'country2'])
countrycombos = countrycombos_raw[countrycombos_raw.country1 !=
countrycombos_raw.country2]

def makemarker(c1, c2):
    a = c1 + c2
    mark = ''.join(sorted(a))
    return mark
def apply_marker(df):
    df['marker'] = df.apply(
        lambda row: makemarker(
            c1=row['country1'],
            c2=row['country2']),
        axis=1)
```

```
# Applying functions to the dataframe
apply_marker(countrycombos)
countrycombos_unique = countrycombos.drop_duplicates(subset=['marker'])
pairs = countrycombos_unique.drop(columns=['marker'])
tradevolWIP = pairs
tradevolWIP_2 = pd.DataFrame(np.repeat(tradevolWIP.values,19,axis=0))
tradevolWIP_2.columns = tradevolWIP.columns

years = []
for i in range(len(tradevolWIP)):
    for j in range(2001,2020):
        years.append(j)
len(years)

tradevolWIP_2['year'] = years
tradevolWIP_2 = tradevolWIP_2.reindex(columns=['year','country1','country2'])
tradevolWIP_2['c1 CPI'] = np.ones(len(tradevolWIP_2))
tradevolWIP_2['c2 CPI'] = np.ones(len(tradevolWIP_2))
tradevolWIP_2['c1 USD NER'] = np.ones(len(tradevolWIP_2))
tradevolWIP_2['c2 USD NER'] = np.ones(len(tradevolWIP_2))
tradevolWIP_2['NER_c2perc1'] = np.ones(len(tradevolWIP_2))
tradevolWIP_2['RER Index'] = tradevolWIP_2['NER_c2perc1'] * tradevolWIP_2['c1
CPI'] / tradevolWIP_2['c2 CPI']

country1_name (eg HK), country2_name (eg India), country1_CPI, country2_CPI
NER_c2perc1 = country2_NER / country1_NER
RER Index = NER_c2perc1 * country1_CPI / country2_CPI

tradevolWIP_3 = pd.DataFrame(np.repeat(tradevolWIP_2.values,12,axis=0))
tradevolWIP_3.columns = tradevolWIP_2.columns

months =
['Jan','Feb','Mar','Apr','May','Jun','Jul','Aug','Sep','Oct','Nov','Dec']
tradevolWIP_3['month year'] = months*int(len(tradevolWIP_3)/len(months))
tradevolWIP_3 = tradevolWIP_3.reindex(columns=['month year','year',
'country1', 'country2', 'c1 CPI', 'c2 CPI', 'c1 USD NER',
       'c2 USD NER', 'NER_c2perc1', 'RER Index'])

tradevolWIP_3 = tradevolWIP_3.reindex(columns=['Month Year', 'country1',
'country2', 'c1 CPI', 'c2 CPI', 'c1 USD NER','c2 USD NER', 'NER_c2perc1',
'RER Index'])

tradevolWIP_3.to_csv('RER vol WIP.csv')
```

Generating Annual Misalignments Data from Monthly Data

```
step = 228
df2 = misalign.groupby(misalign.index // step).std()
df2_full = df2.loc[df2.index.repeat(df2.times)].reset_index(drop=True)
misalign_fin[12::12].to_csv()
```

Generating API Queries for the UN Comtrade Database

```
# Generating UN COMTRADE queries
years = np.linspace(2001,2019,19)
```

```
countrycodes =
[36,40,56,124,156,170,208,246,251,276,344,699,360,372,381,392,410,458,528,554
,579,608,616,620,702,710,724,752,757,764,792,826,842]
SITCcodes =
[1121,1124,1222,2517,3214,3310,3321,3411,5121,5122,5811,6411,6412,6415,6516,6
732,6748,6821,6822,6841,6842,7291,2432,5417,5530,5999,6291,6429,6522,6537,655
4,6942,6952,6981,6989,7114,7115,7143,7149,7151,7171,7182,7184,7191,7192,7193,
7195,7196,7197,7199,7222,7231,7241,7242,7249,7250,7293,7294,7295,7299,7321,73
23,7328,7331,7341,7349,7353,8210,8310,8411,8414,8510,8616,8617,8619,8624,8911
,8912,8921,8942,8944]
start_str = 'https://comtrade-un-org.ezp-
prod1.hul.harvard.edu/api/get?max=100000&type=C&freq=A&px=S1&'
SITC =
'cc=1121%2C1124%2C1222%2C2517%2C3214%2C3310%2C3321%2C3411%2C5121%2C5122%2C581
1%2C6411%2C6412%2C6415%2C6516%2C6732%2C6748%2C6821%2C6822%2C6841'
end_str = 'uitoken=017ccb98c1d528632dd9f09674f50b1f&fmt=csv'
for country in countrycodes:
      print(f'{start_str}ps=2004%2C2003%2C2002%2C2001&r={country}&p=all&rg=1&
      {SITC}&{end_str}\n')
```

Creating the Figure for CPI By Country Over Sample Period

```
plt.figure(figsize=(20,10))
for c in CPItrends.country1.unique():
    CPItrends_c = CPItrends[CPItrends.country1==c]
    plt.plot(CPItrends_c['Month Year'].iloc[::6], CPItrends_c['c1
CPI'].iloc[::6], label=c)
    plt.xticks(CPItrends_c['Month Year'].iloc[::12])
    plt.ylabel('CPI')
    plt.xlabel('Year')
plt.plot(CPItrendsUS['Month Year'].iloc[::6], CPItrendsUS['c2
CPI'].iloc[::6], label='United States')
plt.title(f'CPI Data by Country (Indexed to 100 in 2010)')
plt.legend(ncol=4)
plt.show()
```

Generic example of index-match methodology for Excel

```
=INDEX(J2:J20065,match(1,(B2=H2:H20065)*(C2=i2:i20065)*(A2=g2:g20065),0))
```

11.2 Lists of Countries and Products

Table 22 – Appendix: List of Countries Included in the Empirical Analysis

Country Name	**ISO Code[1/]**
Australia	36
Austria	40
Belgium	56
Canada	124
China	156
Colombia	170
Denmark	208

Finland	246
France	251
Germany	276
Hong Kong, China	344
India	699
Indonesia	360
Ireland	372
Italy	381
Japan	392
Korea, Rep. of	410
Malaysia	458
Netherlands	528
New Zealand	554
Norway	579
Philippines	608
Poland	616
Portugal	620
Singapore	702
South Africa	710
Spain	724
Sweden	752
Switzerland	757
Thailand	764
Turkey	792
United Kingdom	826
United States	842

Table 23 – Appendix: List of Strongly Homogeneous Products. SITC, Rev. 1

4-Digit Code	**Product Name/Description**
1121	Wine of fresh grapes including grape must
1124	Distilled alcoholic beverages
1222	Cigarettes
2517	Sulphate wood pulp
3214	Coal /anthracite, bituminous/
3310	Petroleum,crude & partly refined
3321	Motor spirit, gasolene and other light oils
3411	Gas, natural
5121	Hydrocarbons and their derivatives

5122	Alcohols,phenols,phenol-alcohols,glycerine
5811	Prods of condensation, polycond. & polyaddition
6411	Newsprint paper
6412	Other printing and writing paper, machine-made
6415	Machine-made paper & paperboard, simply fnshd
6516	Yarn and thread of synthetic fibres
6732	Bars and rods of iron or steel, ex wire rod
6748	Oth. coated iron or steel plates etc under 3 mm
6821	Copper and alloys, unwrought
6822	Copper and alloys of copper, worked
6841	Aluminium and aluminium alloys, unwrought
6842	Aluminium and aluminium alloys, worked
7291	Batteries and accumulators

Table 24 – Appendix: List of Strongly Differentiated Products. SITC, Rev. 1

4-Digit Code	**Product Name/Description**
2432	Lumber, sawn, planed, etc. - conifer
5417	Medicaments
5530	Perfumery & cosmetics,dentifrices etc.
5999	Chemical products and preparations,nes
6291	Rubber tyres & tubes for vehicles and aircraft
6429	Art. of paper pulp,paper or paperboard
6522	Cotton fabrics, woven, other than grey
6537	Knitted or crochd fabrics not elast nor rubberd
6554	Coated or impregnated textile fabrics & prod.
6942	Nuts, bolts, screws, rivets, washers, etc.
6952	Other tools for use in the hand or in machines
6981	Locksmiths wares
6989	Articles of base metals, nes
7114	Aircraft - incl jet propulsion - engines
7115	Internal combustion engines, not for aircraft
7143	Statistical machines-cards or tapes-
7149	Office machines, nes
7151	Machine-tools for working metals
7171	Textile machinery
7182	Printing and bookbinding machinery
7184	Construction and mining machinery, nes
7191	Heating and cooling equipment

7192	Pumps and centrifuges
7193	Mechanical handling equipment
7195	Powered-tools, nes
7196	Other non-electrical machines
7197	Ball, roller or needle-roller bearings
7199	Parts and accessories of machinery, nes
7222	Apparatus for electrical circuits
7231	Insulated wire and cable
7241	Television broadcast receivers
7242	Radio broadcast receivers
7249	Telecommunications equipment nes
7250	Domestic electrical equipment
7293	Thermionic valves and tubes, transistors, etc.
7294	Automotive electrical equipment
7295	Electrical measuring & controlling instruments
7299	Electrical machinery and apparatus, nes
7321	Passenger motor cars, other than buses
7323	Lorries and trucks, including ambulances, etc.
7328	Bodies & parts motor vehicles ex motorcycles
7331	Bicycles & other cycles, not motorized, & parts
7341	Aircraft, heavier-than-air
7349	Parts of aircraft,balloons airships
7353	Ships and boats, other than warships
8210	Furniture
8310	Travel goods,handbags & similar articles
8411	Clothing of text fabric, not knitted crocheted
8414	Clothing and accessories,knitted or crocheted
8510	Footwear
8616	Photographic & cinematographic equipment nes
8617	Medical instruments, nes
8619	Measuring,controlling & scientific instruments
8624	Photo. film etc & develpd film other than cine.
8911	Phonographs, tape & other sound recorders etc.
8912	Phonograph records,recorded tapes,oth.sound rec
8921	Books and pamphlets,printed
8942	Childrens toys, indoor games, etc.
8944	Other sporting goods