Exchange-Rate Volatility and Trade: A Semiparametric Approach

Debasri Mukherjee
Assistant Professor
Department of Economics
Western Michigan University
Kalamazoo, MI 49008

Susan Pozo
Professor
Department of Economics
Western Michigan University
Kalamazoo, MI 49008

Abstract:
We use a gravity model to analyze the impact of exchange-rate volatility on the volume of bilateral international trade. Semiparametric regression methods are applied to pooled data for over 200 countries. Our results indicate that volatility affects trade negatively although at very high level of volatility the effect diminishes and eventually becomes statistically indistinguishable from zero. Countries apparently find avenues to mitigate the detrimental impact of exchange rate uncertainty when volatility attains very high levels. These results help reconcile the contradictory findings often found in the literature on the impact of exchange-rate uncertainty on trade volume.

Keywords: international trade, semiparametric regression, volatility

JEL Classification: F40, C14

June 29, 2007

1 Corresponding author: Debasri Mukherjee, Economics Department, Western Michigan University, Kalamazoo, MI 49008. Fax: (269)3875637. Email: debasri.mukherjee@wmich.edu
1. Introduction:

Despite the completion of a great number of studies on the impact of exchange-rate volatility on the volume of international trade, there is still little consensus on how uncertainty in currency values affects trade flows. Theoretical and empirical studies can be cited to support a host of conclusions; that exchange-rate volatility depresses trade, that it induces increases in the level of international trade, or that it has no impact on trade flows. Researches have tried to reconcile these differences by slicing the data in a myriad of ways. Our own solution to the reconciliation of the numerous results on the impact of exchange-rate volatility on trade is to use a gravity equation and apply a semiparametric regression technique because it does not superimpose any a priori functional form restriction on the relationship under scrutiny. We examine (1) whether the trade-volatility relation is negative; (2) whether the rate at which volatility affects trade is constant; (3) and if not, at what levels of volatility it is nonlinear/non-constant; and finally (4) whether we can derive any meaningful economic conclusion from these statistical estimates.

Using a pooled sample for over 200 countries (with a total of 121,501 observations) we find that exchange-rate volatility affects trade negatively and the effect remains more or less constant for a wide range of values of exchange-rate volatility. However, at relatively high levels of volatility, the negative effect becomes very strong, then subsequently weakens and finally gradually adjusts to zero. What may explain this behavior? Countries may respond to higher levels of volatility by reducing their volume of trade but after a certain point the countries find avenues to mitigate the harmful impact of exchange-rate uncertainty. For example countries might informally dollarize when
exchange-rate volatility attains “unbearably” high levels, thereby insulating the country from most of the harmful impacts of very high volatility. Section 2 provides background and a literature review, section 3 explains the methodology used and section 4 describes the data. Results are analyzed in section 5 while section 6 discusses the implications and limitations of our findings.

2. Background and Literature Review

While most inquiries into the effects of exchange-rate volatility on trade conclude that uncertainty reduces trade, there are enough exceptions to raise doubts with respect to the universality of this conclusion. The lack of consensus exists with respect to both theoretical and empirical studies. While theoretical models were derived early on showing that increases in currency volatility will induce risk-averse traders to reduce the level of international trade that takes place (e.g. Hooper and Kohlhagen, 1978), later models demonstrated the possibility of the converse. Firms might reorganize production and ultimately increase their share of international trade in response to increases in exchange risk (e.g. De Grauwe, 1988). Lack of consensus on the impact of exchange-rate volatility also arises with respect to the numerous empirical studies that have been conducted. While many studies link exchange-rate volatility to decreases in the level of trading (e.g. Kenen and Rodrik, 1986; Dell’Ariccia, 1999), others fail to find conclusive evidence that volatility negatively impacts on trade flows (e.g. Hooper and Kolhagen, 1978; Tenreyro, 2004) and a few concur with the theoretical models attributing increased trade to increases in volatility in exchange rates (e.g. Baum, et al, 2004).

Several avenues have been pursued in an attempt to reconcile the differing conclusions about exchange-rate uncertainty on trade. One approach has been to
disaggregate trade by type of good traded. Differentiated products are found to be much more susceptible to exchange-rate volatility relative to less differentiated products or commodities (Broda and Romalis, 2004). Other attempts have been made by considering the development status of trading partners, or the region in which trade is taking place. Sauer and Bohara (2001) find that while developing countries’ exports fall with exchange-rate volatility, the exports of developed countries’ are not affected. They also find regional variations in the effect of exchange risk, with Africa and Latin America displaying high susceptibility and Asia no susceptibility to exchange-rate risk. But these disaggregations have not led to a consistent generalization aside from concluding that whether exchange-rate volatility's impact is negative or not "depends" on specific circumstances. As such these disaggregations have not succeeded in bringing us any closer to a comprehensive understanding of the impact of exchange-rate volatility on trade.

Alternative approaches to obtaining consistent results revolve around correcting for econometric problems and experimenting with alternative specifications. Export supply and import demand functions (e.g. Cushman, 1983) have given way to the gravity model (e.g. Rose, 2000). Studies have also tended to move from focusing on a relatively small number of countries (e.g. Thursby and Thursby, 1987 with a sample of 17 countries) to studies consisting of very large samples (e.g. Rose, 2000 and Sauer and Bohara, 2001 with 186 and 91 countries respectively). Pozo (1992) examined historical data from the early 1900s and Dell’Ariccia (1999) experimented with different specifications for the volatility variable. In addition to using both nominal and real exchange rates, he constructed proxies for exchange-rate instability using the standard
deviation of returns, the sum of squares of the forward errors, and the range of the nominal spot exchange rate. Baum, Caglayan and Ozkan (2004) introduce dynamics to the relationship between volatility and trade by applying various lag structures to volatility.

Our paper offers an alternative approach to the empirical literature on the impact of exchange-rate volatility on trade by using a semiparametric model of trade flows. This model considers a general nonlinear (nonparametric) relationship between volatility and trade, avoiding the need to superimpose any linearity restriction on the underlying relationship between exchange-rate volatility and trade. Hence our approach is free from any bias due to misspecification of the functional form in the aforementioned relationship. The results indicate that increase in the level of volatility depresses trade. We also find that although the rate at which volatility depresses trade is more or less constant for a wide range of volatility, the rate changes very substantially at very high levels of volatility. While the negative effect increases when the volatility is very high, after a point the negative impact actually weakens. At the highest levels of volatility we find no significant effect of volatility on trade. We offer explanations for why this non-linear impact is observed and for why the impact fades to zero as volatility rises. The non-linear nature of the impact of exchange risk on trade that we uncover provides an explanation for some of the contradictory findings present in the literature.

3. Methodology

The overall plan for tracking how volatility impacts trade is to use a gravity model of international trade. Gravity models have been very successful at explaining trade
volume and as discussed earlier have been increasing in popularity when testing for the impact of exchange risk on said flows. The gravity model specifies that the log of the value of real bilateral trade at time $t$ between countries $i$ and $j$ ($T_{ijt}$) can be expressed as:

$$\ln(T_{ijt}) = \alpha_1 + \alpha_2 \ln (GDP_i \times GDP_j)_t + \alpha_3 \ln((GDP_i/Pop_i)(GDP_j/Pop_j))_t + \alpha_4 \ln(D_{ij}) + \varepsilon_{ijt}$$  \hspace{1cm} (1)$$

$Pop_i$ and $Pop_j$ are populations in $i$ and $j$ and $D_{ij}$ is the distance between $i$ and $j$. The product of real GDP and real GDP per capita are presumed to positively impact trade volume.

As has been common in the literature, this equation has been augmented with a series of dummy variables that are thought to further explain variations in the level of trade.

$$\ln(T_{ijt}) = \alpha_1 + \alpha_2 \ln (GDP_i \times GDP_j)_t + \alpha_3 \ln((GDP_i/Pop_i)(GDP_j/Pop_j))_t + \alpha_4 \ln(D_{ij}) + \alpha_5 Border_{ij} + \alpha_6 ComLang_{ij} + \alpha_7 Regional_{ij} + \alpha_8 Colony_{ij} + \alpha_9 CUStrict_{ij} + \varepsilon_{ijt}$$  \hspace{1cm} (2)$$

Countries sharing borders ($Border_{ij} = 1$) or languages ($ComLang_{ij} = 1$) are expected to trade more with one another. Countries in the some trade integration arrangement ($Regional_{ij} = 1$) and countries who are either currently in a colonial relationship or in the past maintained a colonial relationship ($Colony_{ij} = 1$) are also expected to engage in more trade. Trade is expected to be enhanced when the trading partners share a single currency.
(CUStrict\(_{ij}=1\)) and trade is expected to be disrupted and diminished when either partner experiences a currency crisis (Crisis=1).\(^2\)

To test for the impact of exchange rate uncertainty, the gravity equation is augmented once more with a continuous variable that proxies for uncertainty in the exchange rate and is denoted as \(\sigma_{ijt}\).

\[
\ln(T_{ijt}) = \alpha_1 + \alpha_2 \ln(GDP_i \times GDP_j) + \alpha_3 \ln((GDP_i/Pop_i)(GDP_j/Pop_j)) + \alpha_4 \ln(D_{ij}) + \alpha_5 \text{Border}_{ij} + \alpha_6 \text{ComLang}_{ij} + \alpha_7 \text{Regional}_{ij} + \alpha_8 \text{Colony}_{ij} + \alpha_9 \text{CUStrict}_{ij} + \alpha_{10} \text{Crisis}_{ijt} + \alpha_{11} \sigma_{ijt} + \varepsilon_{ijt} \tag{3}
\]

Unlike the dummy variables we do not have a prior expectation on the sign of the coefficient \(\alpha_{11}\). There has been much discussion in the literature on the methodology that should be employed to measure the latent exchange rate uncertainty variable (e.g. Pozo, 1992; Dell’Arricia, 1999). Following Rose (2000), we take a simple approach, computing the standard deviation of monthly real exchange rate returns over the preceding year to construct the volatility of the exchange-rate (\(\sigma_{ijt}\)) -- exchange-rate volatility in the period before \(t\). One may be concerned with the potential issue of endogeneity between exchange-rate volatility and trade volume. Using disaggregated data on bilateral trade for different types of products, Broda and Romalis (2004) find evidence of endogeneity by reporting a substantial impact of trade on exchange-rate volatility.

\(^2\) In this paper we consider four different currency crisis episodes. The Asian currency crisis is presumed to have taken place during 1997 and 1998. All trade flows including an Asian country are assigned a crisis dummy value of 1 in 1997 and in 1998. We assign a crisis dummy variable value of 1 to any trading pair that includes a Latin American nation during 1981 through 1986 and again in 1994 through 1998 to capture the 2 currency crises believed to have impacted the Latin American nations and their trading partners. Finally, we assigned a dummy variable value of 1 for all trade taking place from 1971 through 1974 to account for the breakdown of the Bretton Woods Monetary system.
Rose (2000) addresses this issue by using instrumental variables to account for the possible issue of endogeneity, and has shown that correcting for the endogeneity of exchange-rate volatility does not change the results (as long as volatility itself is measured with a one period lag). We follow Rose and use a one period lagged volatility variable to account for the possible endogeneity of exchange-rate volatility and trade.

The novelty in our estimation is to use semiparametric methods to explain the effect of volatility (our main variable of interest) on trade volume. This is justified given that Ramsey’s RESET test rejects linearity in the overall model with an associated p-value of 0.000. It is well known that misspecification of the functional relationship can lead to biased estimation and hypothesis testing. It is in this regard, that nonparametric regression, which does not impose functional form restrictions, has been increasingly popular in studying economic phenomena.

However, a pure nonparametric approach has several costs (sometimes double-edged) associated with it. The computational problem, on the one hand, and the problem of dimensionality, on the other, are major concerns. A fully nonparametric regression technique that incorporates both continuous and categorical variables has been discussed in the classic paper by Racine and Li (2004), where they also discuss the well-known computational challenge of any fully nonparametric technique. Given our sample size of 121,501 observations and given our rich set of explanatory variables we too face a computational challenge, given that the challenge increases not only with the sample size, but also with the number of regressors modeled nonparametrically. However our focus is to use as much information as possible in terms of the sample size and we do not want to
reduce the number of regressors as this may possibly result in an omitted variable bias problem. Thus we resort to a simple, more conventional and easily computable partially linear (semiparametric) framework with only volatility (our main variable of interest) being treated nonparametrically.\(^4\)

One might be concerned with the possible remaining bias in the estimated semiparametric coefficient of the exchange-rate volatility variable (our main variable of interest) due to the linearity assumptions in the other variables, which could be misspecified as well. However, we find that the correlation coefficients between exchange-rate volatility and the other regressors are very low in our sample. (See Table 1 for details.) Therefore, any possible misspecification due to a linearity assumption for the other regressors would not considerably impact the coefficient on volatility -- our main variable of interest. However, in an attempt to provide some robustness testing we also consider a randomly chosen sub-sample from our sample and estimate and compare the results from a fully nonparametric model (see, Racine and Li (2004)) and a partially linear model with only volatility being modeled nonparametrically (as in ours). The goodness of fit gain turns out to be less than half of a percent - 68% for our partially

---

\(^3\) Henderson and Millimet (forthcoming) mentions about the same computational challenges in the context of a fully nonparametric model. In order to deal with the problem they consider a much smaller sub-sample from Rose’s data set and use a limited number of regressors.

\(^4\) Interestingly, Henderson and Millimet (forthcoming) does not find any evidence of nonlinearity in their gravity equation itself, although they do not include the exchange-rate volatility variable in their framework. Using a fully nonparametric model, they conclude that gravity is mostly linear. However, in our case, when we include the volatility variable, trade-volatility relation not only displays some nonlinearity (as clearly shown by the plots at the end of the paper), but the pattern of nonlinearity is consistent with an interesting economic phenomenon. Note that Herwartz (2003) also considers nonlinearity in trade flows and exchange-rate volatility relation among the Group of Seven.
linear model with only volatility being nonlinear (equation 4 below), as opposed to 68.22% for a fully nonparametric model.\(^5\)

One may also be concerned with the effects of time invariant country specific heterogeneities in the regression. To our knowledge, \textit{fixed effect unbalanced panel} regression results are not yet developed for the nonparametric/semiparametric framework. A Hausman-type test that would help one choose between fixed vs. random effects in a semiparametric framework has not yet been developed. As mentioned earlier, our objective is to use as much data information as possible. Hence we estimate an unbalanced panel. Otherwise, the loss of observations will be quite substantial. We have used Li and Stengos (1996) type pooled semiparametric regression (without any fixed or random effect heterogeneity) technique. The Li and Stengos (1996) approach incorporates both predetermined and strictly exogenous regressors which is compatible with our set of covariates. To compensate for the inability to estimate a fixed effects regression, we augment the gravity models one additional time with region specific dummy variables. Based on economic and geographical criteria, we consider seven broad regional categories in our sample, namely Africa, Asia, the former socialist countries, Latin America, Middle East, Oceania, and OECD. There are two sets of regional dummies for each country pair. Thus we have two sets of regressions, one with, and one without the regional dummies. Our main conclusion is however, quite robust to the use of regional dummies.\(^6\) We also have six other dummy variables, (as discussed earlier) which are mainly time invariant in nature. We reason that these regional and the other dummy variables should capture the country specific characteristics to a considerable extent.

While Herwartz also uses a semiparametric approach to explore how exchange-rate volatility impacts trade, our approach and his differ in a variety of ways. Most importantly, he uses mainly time series data, while we use pooled data with large \(n\)

\(^5\) The in-sample average prediction error shows the same picture as well. This is consistent with Henderson et al (forthcoming) finding in the sense that the other regressors do not have significantly nonlinear impact on trade.

\(^6\) We get similar coefficients for the continuous as well as for the other dummy variables, as far as the signs and the significances are concerned. The graphs depicting the relationship between volatility and trade (to be discussed later) look very similar as well.
(number of cross sectional observations) and small $T$ (time dimension). In this respect, our approach is similar to Rose (2000) who also considers a pooled sample with large $n$ and small $T$. Herwartz estimates export supply and import demand equations separately while in our approach we employ the gravity model. Herwartz (2003) concentrates on the growth of trade among the Group of Seven while we use trade flows from over 200 countries. He constructs exchange-rate volatility by using a GARCH (1,1) model while we use the standard deviation of exchange rate movement over the previous year. Our intent in the paper is to focus on the nonlinear relationship using a very large pooled data with a fixed time period (small yearly observations) with the number of cross sections going to infinity.  

The details of our approach are as follows. First we assume that our true model is a pooled partially linear semiparametric model. We allow our primary variable of interest, (exchange-rate volatility) to affect trade volume in a general nonlinear fashion (nonparametrically, so that there is no pre-assigned functional form) whereas the other control covariates are assumed to affect the dependent variable in a linear fashion. The partially linear (semiparametric) model that we have used can be written as

$$Y_{ijt} = X_{ijt} \beta + g(Z_{ijt}) + \varepsilon_{ijt}$$

(4)

Where $Y_{ijt}$ denotes the dependent variable ($\ln(T_{ijt})$), $Z_{ijt}$ denotes our main variable of interest, ($\sigma_{ijt}$), $X_{ijt}$ captures all other control variables (as listed in (3)), and $g(.)$ denotes the

---

7 A recent paper by Silva and Tenreyro (2006) criticizes the existing approaches for estimating a log-linear gravity model. They suggest an alternative estimation approach - Poisson pseudo maximum likelihood (PML) – even if the dependent variable is not strictly discrete. Using a RESET test they show that the PML is appropriate, though OLS and parametric nonlinear least squares are not adequate for modeling a gravity equation. Following their suggestion, we also use PML estimation for our data and perform the same RESET test as they recommend. But we strongly reject the null hypothesis of PML being appropriate and the corresponding RESET test $p$-values turn out to be 0.000 for both of our regression models (with and without regional dummies). Hence PML, as suggested by Silva et al (2006) is not suitable for our dataset and the variables.
unknown (nonparametric) functional form. The basic estimation method is a standard
kernel based semiparametric estimation (as described below). It is similar to that in Li
and Stengos (1996) which is similar to the one in Robinson (1988) and the approach is

From (4) we get:

\[
Y_{ijt} - E(Y_{ijt} | Z_{ijt}) = [X_{ijt} - E(X_{ijt} | Z_{ijt})] \beta + [g(Z_{ijt}) - E(g(Z_{ijt}) | Z_{ijt})] + [\varepsilon_{ijt} - E(\varepsilon_{ijt} | Z_{ijt})] 
\]

(5)

Let \( \hat{m}_{ij}^1 \) and \( \hat{m}_{ij}^2 \) denote the kernel based estimators of \( E(Y_{ijt} | Z_{ijt}) \) and \( E(X_{ijt} | Z_{ijt}) \)
respectively and \( E(\varepsilon_{ijt} | Z_{ijt}) = 0 \). Also note that \( [g(Z_{ijt}) - E(g(Z_{ijt}) | Z_{ijt})] = 0 \).

Rewriting (5) in matrix form we can then present the typical semiparametric
estimator of \( \beta \) as

\[
\hat{\beta} = [(X - \hat{m}^2)'(X - \hat{m}^2)]^{-1}[(X - \hat{m}^2)'(Y - \hat{m}^1)]
\]

Where \( Y \) is an \( nT \times 1 \) vector of \( Y_{ijt} \), \( X \) is an \( nT \times K \) matrix capturing the control variables
\((K \) being the number of control variables) and \( \hat{m}^1 \) and \( \hat{m}^2 \) are the vector and matrix
generated from \( \hat{m}_{ij}^1 \) and \( \hat{m}_{ij}^2 \) respectively.

After obtaining \( \hat{\beta} \), we can then rewrite (4) as

\[
(Y_{ijt} - X_{ijt} \hat{\beta}) = Y_{ijt}^* = g(Z_{ijt}) + \varepsilon_{ijt}
\]

(6)

It is now a pure nonparametric regression model and we apply nonparametric kernel
weighted least square regression estimation at this final stage.\(^8\) Following the usual
practice, \( \frac{\partial g}{\partial Z} \) can be interpreted as the point wise partial effect of exchange-rate volatility

\(^8\) See Robinson, 1988, Pagan and Ullah, 1999 and Fan and Yao (2003) and Li and Racine (2007) for more
details on such semiparametric and nonparametric regressions, their asymptotic properties as well as some
applications. We have used standard Gaussian kernel, exact binning and optimal as well as cross validated
bandwidths. Our conclusion is robust to the choice of bandwidths.
on trade volume. Our final stage of estimation is similar to the final stage estimation in Herwartz (2003) in the sense that he also uses nonparametric kernel weighted least square regression method to estimate the effect of volatility on export/import. Overall, Herwartz’s approach can tease out variations in the response across countries as countries may respond differently to exchange-rate risk. In our case, we derive an overall conclusion backed by the results from a large number of countries. As such we are able to better generalize about the impact of exchange risk on trade.

Our partially linear model will not only take care of any possible functional-form misspecification in our main variable of interest; but will also shed some lights on how volatility affects trade at various levels of volatility. Importantly, the model provides information on the extent to which the underlying relationship between these two variables is linear. This can only be achieved by using a general functional form.

4. Data

The data set used in this estimation is very large. We began with the data compiled and used by Rose (2004) to study the impact of WTO membership on trade stability. While many follow-ups to Rose’s (2000) widely cited study of the currency union effect have been undertaken using Rose’s currency union database, it only contains 5-year intervals of data. We wished to use annual data to better capture the nonlinearities in functional form that may be present in the data. We supplemented Rose's WTO database with annual observations for real exchange-rate volatility. The volatility of the exchange rate is constructed by first constructing monthly real exchange rate returns. These returns are computed as log differences in the month to month exchange rate. Twelve monthly returns are then used to compute a standard deviation for the year.
These standard deviations are then matched to the appropriate yearly observation so that the volume of trade between two countries is presumed to be influenced by the previous year’s real exchange-rate volatility. International Financial Statistics data on bilateral exchange rates with their appropriate CPIs are used to construct the real exchange rates used in the computation.

The original Rose data set includes observations, when available, from 1948 to 2000. Monthly exchange rate data were available in an easily accessible format only since 1957, hence our database does not contain observations earlier than 1957. There are a total of 214 countries in our sample and we use yearly data. Since all countries do not trade with one another and since there are some missing observations our sample consists of a total of 121501 observations.9

5. Results

We present the results with and without regional dummies for both parametric and semiparametric regressions in Table 2. It is clear that the results are robust to the use of regional dummies. These results are, broadly speaking, in line with results from Rose (2000). The forces of attraction -- the product of real GDPs and of GDP per capita -- increase trade, as do the various dummy variables specifying the existence of common borders, current or former colonial ties, trade integration agreements, and common language. In contrast and as expected, the log of distance reduces trade flows while the common currency variable promotes trade. The estimated value of the coefficient on the common currency variable is similar to Rose's value of 1.25 implying that countries with
common currencies trade about 3 times more than do countries that do not share common currencies ($\exp(1.1) = 2.99$). The coefficient of the crisis variable turns out to be negative and significant, as expected.

Of particular interest to us is the coefficient associated with the exchange-rate volatility variable. As in any typical semiparametric regression, we obtain point wise partial effects of volatility on trade (the conditional first derivatives or $\partial g(Z_{ijt})/\partial Z_{ijt}$). The median of these point wise partial effects are reported in Table 2.\(^9\) These median values (-0.87 for the regression without regional dummies and -1.46 for the regression with regional dummies) indicates that on an average\(^{10}\) real exchange-rate volatility depresses the volume of trade, thereby concurring with the segment of the empirical and theoretical literature that concludes that uncertainty in the exchange rate will depress the amount of trade taking place. However, more comprehensive are the plots of these partial effects, i.e., the plot of the conditional first derivatives (measured on the vertical axis) against volatility (measured on the horizontal axis) as shown in Figure 1 and Figure A (in the Appendix) for the entire range of observations on volatility. Figure 1 corresponds to the semiparametric regression without the regional dummies. The corresponding plot is very similar for the regression with the regional dummies, as is shown in Appendix Figure A. While such plots allow us to observe how the partial effects vary with the level of volatility, it is important to recall that not all levels of volatility are equally represented.

\(^9\) Note that our data set is a pooled one with large cross sections. The time dimension varies from about 10 to 40 annual observations per cross section. Thus the nonstationarity issues are not of major concern for us because our data set, although pooled, contains large $n$. See Phillips and Moon (1999).

\(^{10}\) We have used STATA, Gauss and Nonparametric software NP package at various stages of our computations. For more information on NP package, see http://www.mcmaster.ca/economics/racine/

\(^{11}\) The mean values are also negative and larger than the median values.
In fact most of the values of volatility (97.4%) are between 0 and 0.05 and are thus clustered in the first section of the graphs.

To better understand how trade, in practice, is impacted by exchange-rate volatility, we focus on different ranges of volatility separately. We first “blow up” the initial segment which contains 97.4% of total observations and display it in Figure 2. Interestingly, we find that when volatility assumes values from around 0 to 0.025 the plotted values appear almost as a horizontal line (though slightly downward sloping). As volatility increases, trade seems to be depressed at a fairly constant rate. However, at higher volatility (above 0.025 and up to about 0.05, containing about 3000 observations), the relationship becomes noticeably nonlinear. The partial effects drop sharply implying that volatility’s detrimental impacts become noticeably greater. Hence we can conclude that exchange-rate volatility does depress trade and the depressing impact increases with the level of volatility. Furthermore, at very high levels of volatility the “penalty” increases at a rapidly increasing rate, practically pushing the volume of trade towards zero.

In Figure 3 we plot how volatility impacts trade when volatility assumes even greater values, specifically values between 0.05 and 0.07. This range contains about 750

---

12 It is noteworthy that we observe a sharp and large hump (for volatility level roughly around 0.025-0.07). This hump does not disappear even if we use much larger bandwidths. We have tried up to 12 times larger than the optimal (mean-square error minimizing bandwidth which is usually the default bandwidth) one. However, the other relatively smaller humps appearing to the right (beyond this volatility level) get smoothened out when we use larger bandwidths. The coefficients associated with this large hump are always highly significant. This hump can also be explained by an interesting economic phenomenon. We therefore, focus on this part of the graph in Figures 2 and 3.

13 However, this rate is not really constant. A distinction between the partial effects for nonparametric vs. parametric (constant partial effect, hence horizontal) regressions is shown in Figure 5 (for the range of volatility up to 0.015) which depicts a steadily downward sloping partial effects for the nonparametric model as opposed to the parametric model.
observations.\textsuperscript{14} Here we observe a curious phenomenon. As volatility grows further, the detrimental impact on trade weakens. Greater exchange-rate uncertainty no longer elicits an even greater penalty on trade volume. Instead the detrimental impact weakens (though it is still negative.) What might explain such? We argue that after some point, as the level of exchange-rate uncertainty grows, countries learn to adapt to volatility, lessening its harmful impacts. Countries employ hedging strategies that might otherwise be too expensive to employ when volatility is relatively low. But when volatility surpasses a point (and our data seem to indicate that point to be approximately a level of volatility of 0.05) it becomes cost-effective to employ these strategies\textsuperscript{15}. Eventually (when volatility reaches about 0.07 or 0.08) trade is no longer depressed by exchange-rate volatility. When volatility is this high countries have fully adjusted to the volatility employing one means or another to mitigate its effect on trade.

In Figure 4 we show that at the highest range of volatility (around 0.07 and above) the partial effect becomes noisy around the value zero.\textsuperscript{16} This noisy range contains about 2\% percent of the observations. It is difficult to know exactly what is taking place in this “noisy tail region”\textsuperscript{17} but it is noteworthy that almost all the insignificant coefficients fall in this range.

Overall these plots seem to be suggesting that for the most part exchange-rate volatility depresses trade and that the negative impact grows with the level of volatility.

\textsuperscript{14} Pakistan falls consistently in this range for the year 1973. This is basically the year after Bangladesh gained its independence from Pakistan (the official date of independence was December 16\textsuperscript{th} 1971). So it is natural to observe some unusual exchange rate and trading behavior for Pakistan economy which just experienced a considerable partitioning during that time.

\textsuperscript{15} As shown in Appendix Figure B, the story remains almost same for the regression with the regional dummies as far as the shape of the graph and its location (values in the horizontal axis) is concerned, although the steepness of the graphs differs.

\textsuperscript{16} It is 0.08 and above for the regressions with the regional dummies.

\textsuperscript{17} This may simply be the noisy tail behavior.
However, after a point countries seem to get a handle on the volatility and in one way or another learn to diminish its impact. Figure 3 shows the weakening impact and suggests that by the time exchange-rate volatility reaches around 0.07 countries have learned to totally mitigate volatility’s negative impact on trade. How might this happen? Take for example the case of trade between say the U.S. and the Dominican Republic (DR). Suppose that exchange-rate volatility between the peso and the dollar becomes very large. This will result in diminished trade. But over time with increasing levels and persistence of volatility traders may protect themselves by informally dollarizing, defining all of their transactions and assets in dollars, creating a mini "dollar economy." Official levels of exchange-rate volatility will be recorded as high given our tracking of the peso/dollar exchange rate, when in fact these traders are not affected to a great extent by the peso/dollar exchange rate due to their operations in a "dollar" economy. This is one manner by which traders may be mitigating the harmful impacts of exchange-rate volatility and may explain what we are observing in the highest volatility ranges.

An examination of observations in the region of volatility running from roughly 0.0488 and 0.07/0.08 (where countries impact of volatility is weakening with greater volatility) is supportive of this supposition. While a large cross-section of countries is represented, ten countries show up repeatedly (with each consisting from 2.5 to 6 percent of total observations). These are Argentina, Bolivia, Chile, Costa Rica, Ethiopia, Guatemala, Pakistan, Nigeria, Sri Lanka, and Uruguay. We examined inflation series for these countries in relation to the other countries in their respective geographic region. In the case of the Latin American nations, all of these countries have experienced inflation rates well in excess of the average for the region over extended periods of time. The
incidence of informal (and formal) dollarization for many of these countries is well known (e.g. Argentina, Uruguay, and Bolivia). The Asian nations represented in this group have also experienced relatively high inflation rates (in relation to neighboring nations) over various periods in time. Nigeria has experiences periods of run-away inflation, and Ethiopia’s inflation series is noteworthy in its variability, from high inflation to deflation. As such, for each of these nations, domestic money, as a unit of account, has suffered. Over time, countries that suffer from declines in the usefulness of money tend to develop alternative methods to effectuate and to define transactions including informal dollarization. It is conceivable that this region of observations is picking up some of that adjustment to high and variable inflation which accompanies very high exchange-rate volatility.

The question then arises, how do our results compare with Herwartz (2003)? He finds that the impact of exchange-rate volatility on trade (growth) is non-linear and as such our findings coincide. However, Herwartz does not find that trade is as consistently negatively impacted as we find. The seven countries that he examines appear in some cases to experience positive growth in trade on account of increased uncertainty, while other countries experience the converse. His results appear to be country-specific. Our larger sample, on the other hand, seems to point to an overall negative impact of volatility on trade volume.

6. Discussions and Limitations:

To our knowledge, this is the first attempt to explore the relationship between exchange-rate volatility and trade using a very large sample in a semiparametric framework. A fully linear parametric model is a special case of a partially linear model, i.e., our
semiparametric model is a more generic one. Unless one estimates a more general model it is not possible to assess to what extent a linear model is an appropriate one. Using a data-driven estimation strategy (where we do not superimpose any a priori functional form restriction in the trade-volatility relation), we try to investigate (1) if there is any non-constancy in the rate at which volatility affects trade; (2) if so, at what levels of volatility; (3) and whether we can derive any meaning economic conclusion from there.

We find that the detailed expositions of the relationship reveals nonlinearities and those nonlinearities seem to get accentuated at higher levels of volatility (see Figures 2,3 and 5). This observed “U” (at a high level of volatility as shown in Figures 2 and 3) remains present even if we use different bandwidths and try to smooth it out. Although our parametric and semiparametric results are quite similar for the other control variables, our semiparametric model gives us some additional economic information on how volatility affects trade at various levels of volatility and this information has an intuitive appeal.18

Overall our results can be interpreted as a reconciliation of the alternative findings on the impact of exchange-rate volatility on trade volume. We find that by and large exchange-rate volatility depresses trade, which is in accord with what has been found in the bulk of the empirical literature. We also find that the negative impact of volatility on trade strengthens as the level of uncertainty increases. Greater uncertainty increases the costs of trade (and hedging) and in accordance the volume of trade is further reduced. That is, there is some nonlinearity in the way that volatility impacts trade. More interesting however, is our finding that at very high levels of exchange-rate volatility the

---

18In particular, the behavior of the data around the “U” (Figures 2 and 3) could never be revealed in a linear framework where we just obtain a single coefficient.
impact of uncertainty on trade volume fades and eventually trade volumes are unaffected by increases in volatility. This provides us with an explanation for the less common, yet bothersome occasional result in the empirical literature suggesting no impact of volatility on trade. We find that at very high levels of volatility countries adjust or somehow eliminate the harmful impact of volatility on trade. Informal dollarization is suggested as one avenue that traders may be using to mitigate high levels of volatility.
References


Table 1: Descriptive Statistics and Correlation Coefficients with Volatility

<table>
<thead>
<tr>
<th>Variables</th>
<th>Minimum</th>
<th>Mean</th>
<th>Maximum</th>
<th>Standard Deviation</th>
<th>Correlation Coefficients of other Regressors With Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>LTrade</td>
<td>-2.922</td>
<td>10.354</td>
<td>20.889</td>
<td>3.300</td>
<td>-</td>
</tr>
<tr>
<td>Volatility</td>
<td>1.08E-06</td>
<td>0.006</td>
<td>0.953</td>
<td>0.032</td>
<td>-</td>
</tr>
<tr>
<td>Border</td>
<td>0</td>
<td>0.027</td>
<td>1</td>
<td>0.163</td>
<td>-0.021</td>
</tr>
<tr>
<td>Colony</td>
<td>0</td>
<td>0.119</td>
<td>1</td>
<td>0.324</td>
<td>-0.015</td>
</tr>
<tr>
<td>Crisis</td>
<td>0</td>
<td>0.272</td>
<td>1</td>
<td>0.445</td>
<td>0.046</td>
</tr>
<tr>
<td>Custrict</td>
<td>0</td>
<td>0.011</td>
<td>1</td>
<td>0.106</td>
<td>-0.018</td>
</tr>
<tr>
<td>LDdistance</td>
<td>3.684</td>
<td>8.167</td>
<td>9.421</td>
<td>0.811</td>
<td>0.003</td>
</tr>
<tr>
<td>LGDP</td>
<td>22.369</td>
<td>35.446</td>
<td>44.804</td>
<td>2.595</td>
<td>-0.0004</td>
</tr>
<tr>
<td>LGDPPTC</td>
<td>11.423</td>
<td>17.043</td>
<td>21.007</td>
<td>1.414</td>
<td>-0.084</td>
</tr>
<tr>
<td>ComLang</td>
<td>0</td>
<td>0.211</td>
<td>1</td>
<td>0.408</td>
<td>-0.005</td>
</tr>
<tr>
<td>RTA</td>
<td>0</td>
<td>0.018</td>
<td>1</td>
<td>0.135</td>
<td>-0.018</td>
</tr>
</tbody>
</table>

Note: LTrade denotes log of the value of real bilateral trade. Volatility denotes exchange-rate volatility. Border is a dummy variable (=1, if the trading partners are sharing a common border). Colony is a dummy variable (=1, if the trading partners are in a colonial relationship or had such relationship in the past). Crisis denotes a dummy variable (=1, if either partner is experiencing a currency crisis). Custrict is a dummy variable (=1, if the trading partners are sharing a single currency). LDdistance denotes log of distance between two trading partners, LGDP is the product of real GDPs of the trading partners and LGDPPC is the product of real per capita GDPs of the two countries. ComLang is a dummy variable (=1, if the countries are sharing a language) and RTA is a dummy variable (=1, if the countries are engaged in some trade integration arrangement). To measure the correlation coefficient between a dummy variable and the volatility variable, we use point-biserial correlation measure which is mathematically equivalent to the Pearson (product moment) correlation measure.
Table 2: Parametric and Semiparametric Results

<table>
<thead>
<tr>
<th>Variables</th>
<th>Parametric Coefficients</th>
<th>Semiparametric Coefficients</th>
<th>Parametric Coefficients</th>
<th>Semiparametric Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.0000)</td>
<td>(&lt;0.000)</td>
</tr>
<tr>
<td>Volatility</td>
<td>-1.759</td>
<td>-0.873</td>
<td>-0.634</td>
<td>-1.461</td>
</tr>
<tr>
<td></td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
</tr>
<tr>
<td>Border</td>
<td>0.465</td>
<td>0.472</td>
<td>0.432</td>
<td>0.436</td>
</tr>
<tr>
<td></td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
</tr>
<tr>
<td>Colony</td>
<td>0.848</td>
<td>0.844</td>
<td>0.747</td>
<td>0.751</td>
</tr>
<tr>
<td></td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
</tr>
<tr>
<td>Crisis</td>
<td>-0.136</td>
<td>-0.149</td>
<td>-0.117</td>
<td>-0.124</td>
</tr>
<tr>
<td></td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
</tr>
<tr>
<td>Custrict</td>
<td>1.097</td>
<td>1.053</td>
<td>1.166</td>
<td>1.143</td>
</tr>
<tr>
<td></td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
</tr>
<tr>
<td>LDistance</td>
<td>-1.116</td>
<td>-1.116</td>
<td>-1.215</td>
<td>-1.214</td>
</tr>
<tr>
<td></td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
</tr>
<tr>
<td>LGDP</td>
<td>0.883</td>
<td>0.884</td>
<td>0.807</td>
<td>0.809</td>
</tr>
<tr>
<td></td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
</tr>
<tr>
<td>LGDPCC</td>
<td>0.554</td>
<td>0.544</td>
<td>0.465</td>
<td>0.462</td>
</tr>
<tr>
<td></td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
</tr>
<tr>
<td>ComLang</td>
<td>0.341</td>
<td>0.341</td>
<td>0.332</td>
<td>0.331</td>
</tr>
<tr>
<td></td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
</tr>
<tr>
<td>RTA</td>
<td>0.606</td>
<td>0.592</td>
<td>0.227</td>
<td>0.218</td>
</tr>
<tr>
<td></td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
<td>(&lt;0.000)</td>
</tr>
<tr>
<td>Regional dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>121501</td>
<td>121501</td>
<td>121501</td>
<td>121501</td>
</tr>
</tbody>
</table>

Note: Dependent variable is the log of real bilateral trade. P-values are in the parentheses. All the coefficients are significant at 1% level. Note, for the nonparametric part, medians of the nonparametric point-wise estimates are reported. For details about nonparametric conditional first derivatives (partial effects of volatility on logarithm of trade volume), refer to the graphs. For variable descriptions, refer to Table 1.
Note: The Horizontal straight line represents the constant partial effects (-1.76) from the parametric regression. The downward sloping curve represents the varying partial effects from the semiparametric regression.
Appendix:

Figure A

Partial Effects (with Regional Dummies)

Note: In all these graphs we have not presented the upper and the lower confidence intervals because they were very close to each other (small confidence intervals) and especially with too many observations, it was heard to distinguish them visually in some regions. However for volatility level up to 0.08, all the coefficients are significant at 1% level.

Figure B

Partial Effects (with Regional Dummies)
(for volatilities 0.01 to 0.08)