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Exchange Rate Volatility and Real Exports: A Sensitivity Analysis

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Abstract. We investigate the sensitivity of real exports to exchange rate volatility by applying Leamer's Extreme Bound Analysis to US exports to five major trading partners. Various volatility measures, ranging from ad hoc measures to a nonparametric one, are used to investigate whether results depend upon the measure chosen. The main conclusion is that the relationship between real exports and exchange rate volatility is not robust across measures of volatility used and across countries.

JEL Codes: F11, F17.
Key Words: Exchange Rate Risk, Trade Flows, Sensitivity Analysis.

1. Introduction

Does higher exchange rate volatility reduce the volume of international trade? After the adoption of flexible exchange rates in the 1970s, this question received considerable attention in the international economics literature. In particular, the higher exchange rate volatility observed under flexible exchange rates was in conflict with expectations, implying that the financial environment for international transactions had become riskier.

The increase in the risk of international transactions led researchers to investigate the exchange rate volatility-trade flows

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connection. Microtheory suggests that price uncertainty[1] causes a perfectly competitive firm to produce less than it would under certainty (see, Sandmo, 1971; Baron, 1970; Holthausen, 1979). Furthermore, a mean preserving increase in uncertainty decreases output even further, *ceteris paribus*. This result is the main theoretical justification for the impact of exchange rate risk on trade volumes (see, Clark, 1973, Ethier, 1973; Hooper and Kohlhagen; 1978, Cushman, 1986). Even though most models imply a negative relationship between trade flows and exchange rate risk, there are also models providing necessary and sufficient conditions for a positive or ambiguous relationship (see, Neumann, 1995; Franke, 1991; Viaena and Vries, 1992). In addition, empirical studies have not been able to provide clear evidence in favor of one model over the others. While some studies find a negative relationship between volatility and trade (for example, Pozo, 1992; De Grauwe, 1988; Savvides, 1992), others find a positive or no relationship (for example, Assery and Peel, 1991).

This paper also studies the relationship between exchange rate risk and trade flows. However, our approach differs from previous studies in two ways. First, we investigate this relationship by measuring exchange rate risk with a wider range of proxies, ranging from ad hoc measures to a nonparametric measure. Various measures of exchange rate risk are used in order to investigate whether the results depend upon the measure chosen. Second, instead of presenting one set of results, the robustness of the results is tested by the use of extreme bound analysis as an alternative to standard econometric techniques. That is, we address the question of how much confidence we should have in the results of empirical studies on this issue.

The remainder of the paper is organized as follows. Section 2 briefly reviews Extreme Bound Analysis (EBA) and the differences among past studies on exchange rate volatility and trade flows. Section 3 gives the model specification, followed by the empirical implementation of the sensitivity analysis in section 4. Finally, section 5 reports our main conclusions and suggestions for further research.

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[1] In this study, we used risk, uncertainty, and volatility terms interchangeably.

2. Methodology and the Data

Most of the time economic theory does not clearly specify which variables should be included in the set of conditioning variables while conducting statistical inference on the relationship investigated by the researcher. This is also true for investigating the relationship between trade flows and exchange rate risk. The lack of consensus on the theoretical framework often leads to a diverse and sometimes unwieldy empirical literature.

The work of Leamer (1978, 85) and Leamer and Leonard (1983) offers a procedure, namely Extreme Bound Analysis (EBA), that tests the sensitivity of coefficient estimates to alterations in the set of conditioning variables. For this procedure, the researcher identifies the family of alternative models and summarizes the range of inferences implied by each model. For a broad enough family, if the range of inferences is small enough, the researcher might conclude that inferences from these data are robust. Otherwise, she/he might conclude that inferences are too fragile to be useful. Consider an equation of the form;

$$Y_t = \mathbf{X}_t\boldsymbol{\beta} + M_t\gamma + \mathbf{Z}_t\boldsymbol{\delta} + \varepsilon_t$$

where Y is the response variable, X is a set of variables always included in the regression (free variables), M is the focus variable, and Z is a subset of doubtful variables. The objective of EBA is to find the upper and lower bounds on the coefficient estimates on the focus variable M by varying the subset of doubtful variables **Z** included in the regression. If the distance between the minimum and maximum coefficient estimates is short in comparison to sampling uncertainty[2], the ambiguity in the model is irrelevant since all models lead to the same inferences. McAleer *et. al.* (1985) calls this definition Type A fragility. Alternatively, the interval between extreme bounds is short if all values in the interval lead to essentially the same decision. In other words, this type B fragility occurs if there is a sign change in the bounds. In this study, we will use the latter definition of fragility.

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[2] Sampling uncertainty can be measured as k times the estimated standard deviation of the focus coefficient, where k is a predetermined constant (see, McAleer *et. al.*;1985).

One problem with this approach, as noted by Leamer and Leonard, is its concentration on point estimation and its neglect of hypothesis testing or interval estimation. Levine and Renelt (1992) modified the definition of fragility to deal with this problem. They considered the range of coefficient estimates that standard hypothesis tests do not reject. We will report extreme bounds both for the modified and original definitions of fragility. For the modified definition, the extreme bounds will be defined as the highest and lowest values for the coefficient on the variable of interest that cannot be rejected at the 0.10 significance level[3]. Contrary to the analysis of Levine and Renelt (1992), we will not take the significance of the coefficient in the base regression as an implication of robustness or fragility. This is due to the fact that the literature on the relationship between trade flows and exchange rate risk finds insignificant estimates most of the time. This has led some researchers to infer the direction of effect from the sign of the coefficient, independent of its significance. Therefore, we will call a result robust if the estimated coefficient has the same sign at the extreme bounds. On the other hand, if the estimated coefficient changes sign at the extreme bounds, we will conclude that inferences from these data are too fragile to be useful.

Table 1 provides a brief but not exhaustive summary of the studies that examine the relationship between export volume and exchange rate risk. Most of the studies concentrate on the recent flexible exchange rate period and there is little consensus on the empirical findings. The major differences between these studies can be grouped into four categories. The first category is the frequency of the data. Monthly, quarterly and annual data are used in both time series and time series and cross section analysis. The choice of real or nominal exchange rate is the second category that differentiates these studies from each other. The third, and perhaps the most important category, is the wide range of volatility measures used. The fourth difference is the variety of conditioning variables, which is not presented in this table. It is also worth mentioning that studies differ with respect to trade flows. Studies that find negative effects on trade flows of exchange rate volatility mostly employ bilateral trade flows rather than aggregate trade flows.

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[3] The null hypothesis is that the coefficient is zero.

3. Specification Analysis

Empirical studies to date have not been consistent, as researchers have used both multilateral and country-level trade data[4], as well as real and nominal exchange rates. In this study, we use only unilateral trade data – the US trade with five major trading partner countries. Past studies suggest that it is easier to find a relationship between exchange rate volatility and trade flows using country-level trade flows. This is due to the trade diverting effect of exchange rate risk in the case of unilateral trade flows. If exchange rate risk leads only to a reallocation of resources but does not affect the trade flows at aggregate levels, we expect to see a significant impact of volatility with the country-level data, but not with the aggregate data.

The choice of exchange rate measure appears more important for low frequency data. For monthly data, Mark (1990) reports that changes in real and nominal exchange rates are highly correlated and correlations at non-zero leads and lags are close to zero. Table 2 presents cross-correlations from two lags to two leads for changes in real and nominal exchange rates and relative prices and nominal exchange rates for our data. This table reveals that exchange rate changes and relative price level changes are, by and large, uncorrelated at these lags and leads. In addition, contemporaneous changes in real and nominal exchange rates are highly correlated, while correlations at non-zero leads and lags are close to zero. Therefore, we can conclude that in the short run real exchange rate movements are dominated by nominal exchange rate movements since nominal exchange rate changes are not offset by changes in relative price levels. Thus, we decided to use monthly data since this will eliminate one other category and make the sensitivity analysis more informative.

The slow decay of the autocorrelation function (ACF) for exchange rates implies that the data are nonstationary. In addition, conventional unit root tests do not reject the null hypothesis of a unit root. The same hypothesis is rejected for the differenced series. The ACFs of the differenced series die off quickly but the null of white noise in the residuals is rejected by Ljung-Box Q-statistics. An MA(1) specification, chosen by the BIC criterion, is fitted to the exchange rates and then the

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[4] With multilateral trade data, we mean aggregate trade data, and with country-level or unilateral trade data, we mean one country's trade with another country.

residuals are found to be white noise. Therefore, we specified the following exchange rate relationship:

$$\Delta s_t = \mu + e_t + \theta e_{t-1}$$

where s is defined as the foreign currency per U.S. dollar, μ is a constant, and θ is the coefficient on the MA(1) term.

In choosing proxy measures for exchange rate risk, we have used two different sources. Some of the proxies are chosen from this particular literature. We also looked at the literature investigating the predictive power of alternative volatility measures and included some measures that have not been used in the literature investigating the relationship between trade flows and exchange rate risk (see, West and Cho, 1995; Jorion, 1995; Pagan and Schwert, 1990). Table 3 lists the measures we used in this study.

Early studies investigating the relationship between exchange rate volatility and trade flows mostly employed ad hoc measures of volatility. The first three measures, the absolute percentage change in the differenced exchange rate series, and the moving standard deviations for 4 and 8 periods, are chosen to represent this early literature. Several recent studies measured exchange rate risk by a function of the conditional variance from a GARCH process, introduced by Engle (1982) and Bollerslev (1986). By definition, the conditional variance of a series is the predictable component of volatility in that series and this predictable component is an important determinant of the risk premium in financial markets. Furthermore, West and Cho (1995) compare the predictive ability of several models and find that the GARCH(1,1) specification performs slightly better than other models[5]. Therefore, the conditional variance from an estimated GARCH process and its square root are included as two other volatility measures[6].

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[5] The finding of West and Cho does not represent the standard view in this literature. For instance, Jorion (1995) finds that the volatility implied in option prices outperforms the GARCH(1,1) in prediction.

[6] Some studies using GARCH models have tried alternative functional forms of conditional variance, ranging from a log function to a square root function (for example, Kroner and Lastrapes, 1993). We want to see whether or not using different functional forms can affect the sensitivity results.

We also included an autoregressive model for e_t^2. Because $E(e_t^2| I_t)= \sigma_t^2$, where I_t is the information set available at time t, a simple two-step estimator of conditional variance can be found as the predictions from the regression of $\hat{e}_t^2$ against $\{\hat{e}_{t-1}^2, \cdots, \hat{e}_{t-6}^2\}$. For this autoregression, the lag-length of 6 was chosen because for all series our specification tests indicated that such a lag-length was sufficient to produce Q-statistics that implied white noise residuals. As another measure, we included a recursive variance estimate[7]. This measure estimates the unconditional variance at each time t, but when observed for entire sample, it is in fact an estimate of conditional variance at time t.

We also tried a nonparametric estimator.

$$\hat{\sigma}_t^2 = \sum_{j=1}^{T} w_{jt} \hat{e}_j^2 , \quad \sum_{j=1}^{T} w_{jt} = 1$$

The weights are made to depend on the information set It and Ij in such a way that, if It and Ij are far apart, wjt is close to zero. This makes the estimate equivalent to the sample variance of $\hat{e}_t^2$ using only the observations that are close to It. The weights are given by,

$$w_{jt} = K_{jt} / \sum_{k=1}^{T} K_{kt} \quad \text{and}$$

$$K_{jt} = (2\pi b^2)^{-0.5} \exp(-0.5(e_t - e_j)^2 / b^2)$$

where K is the Gaussian Kernel and has the properties that it is nonzero, integrates to unity, and is symmetric. The bandwidth, b, is set to $\hat{\sigma} T^{-1/5}$ where $\hat{\sigma}$ is the sample standard deviation of e_t. As in West and Cho (1995), and Pagan and Schwert (1990), we did not try any other kernel. In addition, we did not experiment with different bandwidths and weighting schemes. As a last measure of volatility, monthly standard deviations of differenced daily exchange rates are also included in this study. Our

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[7] The recursive variance estimates give the sample variance at time t. In calculating the sample variance, the starting date does not move together with the end date. That is, the sample window does not move as t moves, as in moving average measures.

objective is to see whether using higher frequency exchange rate data will affect the information contained in the volatility measure.

The investigation of the ACFs for the squared residuals from estimation of the exchange rate equation showed that all exchange rate series display time-varying conditional variances, except for the Canada-US exchange rate. This finding is supported by the Q-statistic and LM test. This is a surprising result since the Caporale and Doroodian (1994) study estimates a GARCH(1,1) model for the Canada-US exchange rate over the flexible exchange rate period. As a second test, a GARCH(1,1) model was fit to the exchange rate series but all the parameters, except for the constant, in the conditional variance equation turned out to be statistically insignificant. Therefore, we dropped the measures based on the GARCH model for the Canada-US exchange rate series. In choosing the best fitting ARCH class of models to the exchange rate series, the BIC criterion is used. The MA(1)-GARCH(1,1) specification is the best fitting model for exchange rates. Parameter estimates of this model are provided in Table 4.

For the countries in our sample, the calculated cross-correlations for the volatility measures are presented in Table 5. As expected the correlations between ms(4) and ms(8) are above 0.6 for all countries. It is also evident that moving average measures, and especially ms(8), have a close association to g(1,1) and ar(6) measures. In addition, the correlations between ar(6) and g(1,1) are high, except for the Japanese Yen-U.S. Dollar exchange rate. There seems to be a strong association between g(1,1) and rvar only in the case of the Yen/US Dollar exchange rate.

Furthermore, we conducted a standard efficiency test to compare our measures from a different perspective by estimating the following OLS regression with heteroscedasticity-consistent standard errors (e.g., Pagan and Schwert (1990), West and Cho (1995))

$$\hat{e}_t^2 = \alpha + \beta \hat{h}_t + u_t$$

where $\hat{h}_t$ is the predicted volatility. If the forecasts are unbiased, one should find $\alpha=0$, $\beta=1$, and one should also find that u_t is serially uncorrelated. The results are presented in Table 6. The existence of serial correlation implies that there is additional persistence in volatility that is not captured by this measure. It is rarely the case that this condition is satisfied. The Ljung-Box statistics for 4 lags of the residual autocorrelation Q(4), corrected for heteroscedasticity, are large for ac, ms(4), ms(8), rvar and dvol especially.

Of the 39 tests of $H_o : \alpha=0, \beta=1$ presented in Table 6, 29 are rejected at the 0.05 level. The exceptions are the g(1,1) and ar(6) measures[8]. This test has good power as indicated by Monte Carlo simulations and noted by West and Cho (1995). More encouraging is the fact that all of the estimates of β are significantly different from zero at the 0.05 level. In addition, 13 of the α estimates are not significantly different from zero at the 0.05 level, 9 of these being for ar(6) and g(1,1) models. This shows that there is some predictive power in the estimated conditional variances.

4. Empirical Implementation

We test the impact of exchange rate risk on international trade by estimating a model using U.S. real exports to five major trading partners, namely France, Japan, Germany, the U.K., and Canada, over the flexible exchange rate period. Examination of real exports shows that levels of the series are nonstationary. Therefore, first differencing is applied and nonstationarity is tested by conventional unit root tests and by plotting autocorrelation functions. Furthermore, the raw data are seasonally adjusted by subtracting the monthly means from the raw series. All the other series are tested for stationarity in the same way. The model used in the estimations can be written as

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[8] Since $h_t=e_t^2$ for ar(6) measure, we should fail to reject the null, and also we should get white noise residuals.

$$\begin{aligned}
\Delta Q_t = {} & a_0 + a_1\Delta RP_t + a_2\Delta Y_t^* + a_3\Delta S_t + a_4\Delta Q_{t-1} \left.\vphantom{Y_t^*}\right\} \textit{FreeVariables}\\
& + \theta\, f(\hat{\sigma}_t^2) \left.\vphantom{\hat{\sigma}_t^2}\right\} \textit{Focus Variable}\\
& \left.\begin{aligned}
& + \sum_{i=2}^{k} b_i \Delta Q_{t-i} + \sum_{i=1}^{p} c_i \Delta RP_{t-i} + \sum_{i=1}^{p} d_i \Delta Y_{t-i}^* + \sum_{i=1}^{p} e_i \Delta S_{t-i}\\
& + \sum_{i=0}^{p} f_i \Delta r_{t-i} + \sum_{i=0}^{p} g_i \Delta r_{t-i}^*\\
& + \sum_{i=0}^{p} h_i \Delta UC_{t-i} + \sum_{i=0}^{p} j_i \Delta UC_{t-i}^*\\
& + \sum_{i=0}^{p} k_i \hat{\sigma}_t^{2^*} + \sum_{i=0}^{p} l_i \Delta S_{t-i}^* + \sum_{i=0}^{p} m_i \operatorname{cov}(S_{t-i}, S_{t-i}^*)
\end{aligned}\right\} \textit{Doubtful Variables}\\
& + \varepsilon_t
\end{aligned}$$

where Q_t denotes real exports, S_t is the price of the US dollar in terms of foreign currencies, RP_t is the relative price variable expressed as the ratio of foreign to domestic prices, and Y_t^* is the level of foreign income. The focus variable $f(\hat{\sigma}_t^2)$ is denoted as a function of the conditional volatility at time t. The doubtful variables include a measure of unit cost and real interest rates in the foreign and domestic country. We also included 'third country' effects as doubtful variables in the analysis. Instead of picking out one or two trading partners, we used the trade-weighted exchange rate as a measure of the average exchange rate. Third country variables, therefore, are the trade weighted exchange rate (S_t^*), the conditional volatility of S_t^*, and the covariance between S_t and S_t^*. Except in the case of Canada, the conditional covariance and variance for third country effects are measured with a multivariate GARCH model[9]. In the case of

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[9] That is, we jointly estimated

$$\Delta S_t = \mu_1 + e_t + \theta_t e_{t-1}$$

$$\Delta S_t^* = \mu_1 + u_t + \phi_t u_{t-1}$$

with the following form for the covariance matrix of residuals.

$\varepsilon_t |\ \varepsilon_{t-1} \sim N(0, H_t)$, where $\varepsilon_t = (e_t\ u_t)'$, and $H_t = \begin{pmatrix} \sigma_{s,t}^2 & \sigma_{s,s^*,t} \\ \sigma_{s,s^*,t} & \sigma_{s^*,t}^2 \end{pmatrix}$.

$$\sigma^2_{s,t} = \alpha_0 + \alpha_1 e_{t-1}^2 + \alpha_2 \sigma^2_{s,t-1}$$

$$\sigma^2_{s^*,t} = \beta_0 + \beta_1 u_{t-1}^2 + \beta_2 \sigma^2_{s^*,t-1}$$

$$\sigma_{s,s^*,t} = \pi_0 + \pi_1 e_{t-1} * u_{t-1} + \alpha_2 \sigma_{s,s^*,t-1}$$

Canada, recursive variance and covariance estimates are used. As in the Kroner and Lastrapes' study, lagged values of the dependent variable are also included as right hand side variables to account for the short run conditional mean dynamics. The first lag is included as a free variable while the rest are included in the set of doubtful variables. We have chosen k=4, and p=4 as the lag lengths[10]. All of the variables are selected from the empirical literature on trade flows and exchange rate volatility.

We estimated extreme bounds using U.S. exports to France, Germany, Japan, the United Kingdom and Canada. The data are monthly and range from 1974:01 to 1996:05, except for Germany for which the latest available data end at 1994:12. Because of lags, actual estimation starts at 1974:06. The volatility measures are normalized to 1 at 1975:01.

Trade volume is estimated by dividing nominal trade flows by the unit price index for U.S. exports. Consumer price indices are used in calculating relative price variables. We used industrial production indices to proxy foreign income. All the data are taken from the IMF's *International Financial Statistics Database*, the *Citibase Database*, *Datastream International* and the *St. Louis Federal Reserve Bank's Web Site*.

We limit the EBA in two ways. First, we restrict the number of lags to be the same in the equation if more than one doubtful variable enters with a lag, except the lagged dependent variable. Second, we restrict the third country variables, real interest rate variables, and unit cost variables to enter as a group in any one regression. That is, we do not let EBA search inside the groups.

In Table 7, we present the coefficient estimates for the focus variable in the base regression and the extreme bounds[11]. The first set of extreme bounds, denoted as LB(A) and UB(A), are the lower and upper bounds with no restrictions on statistical significance. The second set of

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We used $\sigma^2_{s*,t}$ and $\sigma_{s,s*,t}$ as our measures of third country effect, together with ΔS_t^*.

[10] We also estimated extreme bounds with p=6 but the results were qualitatively the same. Including an MA(1) term also did not change the results.

[11] We are well aware of the generated regressors problem, as discussed by Pagan (1984). However, even after the restrictions put on the EBA, the total number of regressions run for one volatility measure is 1260. Therefore, it is not feasible to pursue joint estimation.

lower and upper bounds, denoted as LB(B) and UB(B), on the other hand, present the coefficient estimates significant at the 0.10 level. Of the 43 volatility coefficients, 28 are negative, though insignificant, in the base regressions. This has led some researchers to conclude that there is weak support for the hypothesis that exchange rate risk has adverse effects on trade flows.

Of the 86 extreme bounds, only 20 are robust. That is, only in 20 cases do coefficient estimates on the focus variable have the same sign at the extreme bounds. In addition, only 17 of these robust coefficients imply a negative relationship between volatility and real exports. That is, most of the coefficient estimates on the focus variable are not robust, and when they are robust, they do not always lead to the same decision. Thus, one can conclude that there is no negative relationship between volatility and real exports. However, this conclusion might be misleading if we don’t investigate the country data separately. Most of the coefficient estimates are fragile for U.S. exports to France. The same is also true for U.S. exports to UK and Canada. However, we have some robust relationships between volatility and real exports for US exports to Germany and Japan. The relationship is robust and negative for seven of the measures for exports to Germany and for four of the measures for exports to Japan.

Furthermore, one might criticize the use of a measure of the current exchange rate risk for the analysis. Because of transportation lags and the structure of trade contracts, the volume of trade might, in fact, be affected not in the current period but in future periods. For that reason, we performed the EBA for 1 to 6 lags and present the results in Table 8 only for coefficient estimates significant at 0.10 level. The results in table 8 are not contrary to the results in table 7: overall, the results are best characterized as mixed.

These results somewhat support the evidence provided by past studies that the relationship between exchange rate volatility and trade flows cannot be generalized to all countries. In other words, the direction of this effect and its significance varies across the countries investigated. In addition, the measures used for exchange rate risk have direct effects on the results. If we use only the robustness criterion that depends on significant coefficient estimates, and investigate the countries separately, our results get more informative. For US exports to France, it is clear that either there is no relationship, or if there is, we can’t extract this information with the measures or statistical model we used. For the ar(6) measure, we have a robust and positive association only in the case of US exports to UK, but the rest of the measures lead to fragile results. On the other hand, the robust and negative association between real exports and exchange rate volatility has been documented by more than one measure in the case of US exports to Japan, Germany, and Canada. This finding, by itself, weakly favors the hypothesis that a negative association is more dominant than a positive or no association between exchange rate volatility and real exports, at least for these countries[12].

One possible reason for finding few robust relationships is that the volatility of exchange rates is not systematically correlated with real exports. Another explanation, however, is that the test is too strong for volatility measures to pass it. One way to see whether the test is too strong is to look at the entire distribution of the estimator of θ, the coefficient on the volatility measure. That is, if 90 percent of the density function for the estimates of θ lies to the left of zero, then we might think that the volatility measure is negatively correlated with real exports. Following Sala-i-Martin (1997), we construct the mean estimate of θ_i, for measure i, as the weighted average of all point estimates θ_{ij}, where j is the coefficient estimate in the individual regression. That is,

$$\theta_i = \sum_{j=1}^{N} w_{ij}\theta_{ij}$$

The reason for using a weighting scheme is to give more weight to the regressions with a better fit. The weight is calculated as[13],

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[12] One other finding is the effect of functional form on the results. We used conditional variance from a GARCH process and its square root to see whether we get the same results. Only in two cases (in Table 5 and 6) do results diverge from each other. It seems that using conditional variance or conditional standard error does not alter the results significantly.

[13] When the number of regressors are the same, then one can use likelihood values, as in Sala-i-Martin (1997). Since the number of regressors is not constant in the estimated equations, we decided to use the Schwarz' Bayesian Criterion to construct the weights This criterion is computed as, $S(\theta_{ij})=-2*\log L+k_{ij}*\log(n_{ij})$, where n is the number of observations, k is the number of regressors and logL is the log likelihood value. Instead of minimizing this criterion, we maximized the negative of it to assign higher value to the regressions with better fit. Since the

$$w_{ij} = S(\theta_{ij}) / \sum_{j=1}^{N} S(\theta_{ij})$$

In addition, the average variance for θ_i can be computed using the same weights.

$$\sigma_i^2 = \sum_{j=1}^{N} w_{ij} \sigma_{ij}^2$$

The weighted means, standard errors, and 0.25th, 0.50th, 0.75th, and 0.90th percentile values are presented in Table 9. In addition, the CDF(0)[14] values using the normal distribution with the known weighted mean and standard error are computed for each measure and country, and are reported in Table 9. For US exports to France, there is no clear support in favor of a relationship between exchange rate volatility and real exports. In the case of US exports to Germany, most of the weighted θ_i's are negative. In addition, with the exceptions of ac, rvar, and npar measures, the values are negative at least for the 0.75th percentile. We obtained this same result in Table 7. The results are somewhat different in the case of US exports to Japan. Except in the case of ac, ar(6) and dvol measures, at least 75 percent of the density function for the estimates of θ lies to the left of zero. For US exports to the UK, there does not seem to be a systematic correlation between volatility measures and real exports. Furthermore, the probabilities computed under the assumption of a normal distribution are consistent with the results obtained by looking at the coefficient values at different percentiles. Therefore, the implication we obtain is similar to the implication we obtained from Table 7: results are mixed for different measures.

By looking at the density function of the coefficient estimates, we try to answer the question of whether the extreme-bounds test is too strong to pass. For our data and analysis, the answer is no since both extreme bounds and the above analysis provide similar result.

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values were negative, we added max(abs($S(\theta_{ij})$))+1 to each $S(\theta_{ij})$ values. This gave the worst fitting regression a value of one for the modified $S(\theta_{ij})$.

[14] That is, we compute the $P_{\Phi}(\hat{\beta}_W < 0)$ where Φ is the normal distribution.

The lack of significance for many of the volatility measures can be attributed to problems associated with statistical modeling. Gagnon (1993) discusses this possibility and provides some evidence with a simulation analysis that it is statistically difficult to detect volatility effects on trade volumes.

5. Concluding Remarks

This paper examined the short run impact of currency risk on real exports using US exports to five major trading partners over the flexible exchange rate period. Our objective was to convince as wide an audience as possible that this relationship is robust or fragile by applying Extreme Bound Analysis. Various measures of volatility are used in order to investigate whether the results depend upon the measure chosen.

The main conclusion is that the relationship between currency risk and real exports is not robust. Although it is possible to find a robust relationship for some measures, not all of them lead to the same conclusion for all countries. Furthermore, the results indicate that there is a relationship between the country investigated and the robustness and/or direction of the effect. This implies that country specific factors should be taken into account. Given these findings, it is wrong to generalize the hypothesis of adverse currency risk to all countries without reservations. In addition, the sign and the robustness of the coefficient are very sensitive to the measure used and even for the same data one can get different results with different measures.

Given the mixed results found across different measures of volatility, the validity of the assumption that risk and volatility move together has to be questioned. Hence, one possible avenue for future research is to investigate how closely related the volatility movements to movements in risk. Furthermore, the availability of hedging strategies and costs of hedging has to be incorporated into future work.

Table 1: A Selective Comparison of Empirical Literature on Exchange Rate Risk and Export Volume

NAME	TIME PERIOD	SAMPLE	MEASURE OF RISK	REAL OR NOMINAL	EFFECTS
Ascheim et al (1993)	1975:1-1990:2 Quarterly	US, Fr, Gr, It, Jap, UK, Can	V1=Absolute value of the percentage change in the exchange rate. V2=Moving standard deviation of the exchange rate.	Real	Mixed
Assery & Peel (1991)	1972-1987 Quarterly	Aus, Jap, UK, US, Gr	V6=Squared residual from the ARIMA process fitted to the logarithm of real exchange rate.	Real	Mixed
Bailey et al (1987)	(a)1962:2-1974:4 (b)1975:1-1985:3 Quarterly	Can, fr, Gr, It, Jap, UK, US	V1=Absolute value of the percentage change in the exchange rate. V2=Moving standard deviation of the exchange rate.	Both	Mixed
Bailey et al (1986)	1973:1-1984:3 Quarterly	Can, Fr, Gr, It, Jap, UK, US	V1=Absolute value of the percentage change in the exchange rate.	Nominal	No statistically significant results.
Chowdhurry (1993)	1973:1-1990:4 Quarterly	US, UK, Can, Fr, Gr, It, Jap	V15=Moving sample standard deviation of the growth rate of the real exchange rate.	Real	Negative
Cushman (1986)	(a) 1965-77 (b) 1973-83 Quarterly	US to: UK, Net, Fr, Gr, Can, Jap	V11=Four-quarter standard deviation of real exchange rate.	Real	Mixed
De Grauwe (1988)	(a) 1960-69 (b) 1973-84 Annual-CS	Bel, Can, Fr, Gr, It, Jap, Net, Swit, UK, US	V10=Variability of the yearly percentage changes of the bilateral exchange rate between country i and j around the mean observed during subperiod k, k=a,b.	Both	Negative for (b) when real exchange rate is used
Hooper & Kohlhagen (1978)	1965:1-75:4 Quarterly		V12=Variance of the spot rate for the 13 weekly observations during each quarter. V13=Variance of the forward rate for the 13 weekly observations during each quarter. V14=Average absolute difference between the previous forward rate and the current spot rate.		Mixed
Kroner & Lastrapes (1993)	1973:1-1990:12 - 1990:11 - 1989:4 Monthly	US, UK, Gr, Jap, Fr	V4=A function of conditional variance from a GARCH or ARCH process.	Nominal	Mixed
Peree &	1960-85	UK, Bel,	V7=	Nominal	Mixed

Steinherr (1989)	Annual	Gr, Jap	$\frac{\max S^{t}_{t\text{-}k} - \min S^{t}_{t\text{-}k}}{\min S^{t}_{t\text{-}k}} + \left(1 + \frac{(X_t - X^{p}_{t})}{X^{p}_{t}}\right)^2$ where X is nominal exchange rate, X^p is the equilibrium exchange rate, and max and min are over a given time interval of size k up to time t. V8= $\left(\sum_{i=t\text{-}10}^{t} \frac{\lvert X_i - X_i^* \rvert}{X_i^*}\right)\left(1 + \sum_{i=t\text{-}k}^{t} \frac{\lvert X_i - X_i^* \rvert}{X_i^*}\right)$ where X* is the equilibrium or PPP exchange rate, and k<10.		
Pozo (1992)	1900-1940 Annual	UK-US	V3=Standard deviation of monthly real exchange rate for a period of one year. V4=A function of conditional variance from a GARCH or ARCH process.	Real	Negative
Qian & Varangis (1994)	1973:1-1990:12 Monthly	Can, Aus, Jap, UK, Net, Swe	V4=A function of conditional variance from a GARCH or ARCH process.	Nominal	Mixed
Savvides (1992)	1973-86 Cross-Section	Includes developed and LDCs	V9=Exchange rate variability is explained by openness, terms of trade disturbances, real productivity shocks, domestic monetary disturbances, and domestic inflation disturbances.	Both	Negative
Thursby & Thursby (1987)	1974-82 Annual	Sample of 17 countries	V5=Variance of the monthly spot exchange rate around its predicted trend where trend is estimated as $\log s_t = a_0 + a_1 t + a_2 t^2 + e_t$ The mean of these measures over a year is used as the relevant risk measure.	Nominal	Mixed

Table 2

Cross-Correlations (1974:01-1996:05)

A: Real and Nominal Exchange Rate Changes

lag (lead)	-2	-1	0	1	2
Japan	-0.016	0.314	0.940	0.286	-0.032
France	0.082	0.284	0.991	0.279	0.086
Germany	0.049	0.279	0.980	0.287	0.080
Canada	-0.007	0.197	0.939	0.195	-0.039
UK	0.001	0.382	0.974	0.345	-0.007

B: Relative Price and Nominal Exchange Rate Changes

lag (lead)	-2	-1	0	1	2
Japan	-0.040	-0.041	-0.043	-0.053	-0.047
France	-0.086	-0.090	-0.095	-0.077	-0.084
Germany	-0.028	-0.026	-0.030	-0.054	-0.041
Canada	-0.071	-0.072	-0.076	-0.076	-0.087
UK	-0.037	-0.038	-0.042	-0.027	-0.031

US dollar is used as the base currency.

Table 3

Measures of Exchange Rate Risk

Formula	Acronym	Measure
(1) $h_t = \lvert \text{ change in } \Delta s_t \rvert$	apc	Absolute change in the differences
(2) $h_t = \left\{ [\sum_{j=t-3}^{t} (\Delta s_j - \mu^a)^2]/3 \right\}^{0.5}$	ms(4)	Moving standard deviation with 3 lags
(3) $h_t = \left\{ [\sum_{j=t-7}^{t} (\Delta s_j - \mu^b)^2]/7 \right\}^{0.5}$	ms(8)	Moving standard deviation with 7 lags
(4) $h_t = \mu + \sum_{i=1}^{6} \alpha_i e_{t-i}^2$	ar(6)	Autoregressive model in squared errors
(5) $h_t = \mu + \alpha e_{t-1}^2 + \beta h_{t-1}$	g(1,1)	GARCH(1,1)-MA(1)
(6) $h_t = (\sum_{j=1}^{t} w_{jt} \hat{e}_j^2) / (t-1)$	rvar	recursive variance estimate with w_t=1, ∀t
(7) $h_t = \sum_{j=1}^{T} w_{jt} \hat{e}_j^2$	npar	nonparametric estimate of conditional variance
(8) $h_t = \left\{ [\sum_{t=1}^{n_t} (\Delta s_{j,t} - \mu_t)^2]/n_t \right\}^{0.5}$	dvol	Monthly standard deviation of daily data

Table 4

Exchange Rates and Time-Varying Conditional Variance (1974:1-1997:12)

	a_0	a_1	b_0	b_1	b_2
S_{fr}	-0.015	0.302	0.001	0.107	0.876
	(.148)	(.000)	(.148)	(.001)	(.000)
S_{jp}	-0.007	0.362	0.000	0.052	0.940
	(.046)	(.000)	(.345)	(.000)	(.000)
S_{gm}	-0.006	0.317	0.000	0.073	0.891
	(.136)	(.000)	(.189)	(.010)	(.000)
S_{uk}	0.000	0.437	0.000	0.120	0.723
	(.571)	(.000)	(.039)	(.000)	(.000)

S_k is the price of US dollar in terms of country k's currency.
Estimated model for bilateral exchange rates is given as;
$S_k = a_0 + a_1 \varepsilon_{t-1} + \varepsilon_t$; $\sigma^2_t = b_0 + b_1 \varepsilon^2_{t-1} + b_2 \sigma^2_{t-1}$.
P-values are given in parenthesis.

Table 5

Correlation Matrix for the Volatility Measures

FRANCE/US

	apc	ms(4)	ms(8)	ar(6)	g(1,1)	sg(1,1)	rvar	npar	dvol
apc	1.00								
ms(4)	0.67	1.00							
ms(8)	0.57	0.79	1.00						
ar(6)	0.27	0.44	0.65	1.00					
g(1,1)	0.42	0.66	0.81	0.69	1.00				
sg(1,1)	0.43	0.68	0.85	0.68	0.98	1.00			
rvar	0.17	0.27	0.35	0.21	0.31	0.37	1.00		
npar	0.55	0.52	0.49	0.39	0.34	0.34	0.14	1.00	
dvol	0.52	0.59	0.60	0.42	0.58	0.58	0.19	0.42	1.00

GERMANY/US

	apc	ms(4)	ms(8)	ar(6)	g(1,1)	sg(1,1)	rvar	npar	dvol
apc	1.00								
ms(4)	0.60	1.00							
ms(8)	0.46	0.71	1.00						
ar(6)	0.21	0.40	0.62	1.00					
g(1,1)	0.33	0.58	0.72	0.71	1.00				
sg(1,1)	0.33	0.59	0.74	0.71	0.99	1.00			
rvar	0.10	0.24	0.47	0.20	0.40	0.42	1.00		
npar	0.04	0.41	0.36	0.26	0.31	0.29	0.19	1.00	
dvol	0.42	0.49	0.57	0.38	0.52	0.52	0.14	0.27	1.00

JAPAN/US

	apc	ms(4)	ms(8)	ar(6)	g(1,1)	sg(1,1)	rvar	npar	dvol
apc	1.00								
ms(4)	0.58	1.00							
ms(8)	0.48	0.78	1.00						
ar(6)	0.22	0.32	0.61	1.00					
g(1,1)	0.34	0.63	0.80	0.52	1.00				
sg(1,1)	0.34	0.61	0.79	0.50	0.99	1.00			
rvar	0.30	0.45	0.59	0.35	0.80	0.82	1.00		
npar	0.18	0.42	0.32	0.19	0.13	0.13	0.12	1.00	
dvol	0.41	0.43	0.41	0.24	0.35	0.35	0.27	0.21	1.00

UK/US

	apc	ms(4)	ms(8)	ar(6)	g(1,1)	sg(1,1)	rvar	npar	dvol
apc	1.00								
ms(4)	0.66	1.00							
ms(8)	0.56	0.81	1.00						
ar(6)	0.45	0.68	0.77	1.00					
g(1,1)	0.51	0.76	0.87	0.82	1.00				
sg(1,1)	0.51	0.79	0.88	0.80	0.98	1.00			
rvar	0.23	0.30	0.36	0.23	0.29	0.33	1.00		
npar	-0.01	0.55	0.46	0.36	0.30	0.31	0.08	1.00	
dvol	0.49	0.62	0.59	0.46	0.62	0.62	0.19	0.43	1.00

CANADA/US

	apc	ms(4)	ms(8)	ar(6)	g(1,1)	sg(1,1)	rvar	npar	dvol
apc	1.00								
ms(4)	0.62	1.00							
ms(8)	0.43	0.73	1.00						
ar(6)	0.33	0.47	0.30	1.00					
g(1,1)	0.00	0.00	0.00	0.00	0.00				
sg(1,1)	0.00	0.00	0.00	0.00	0.00	0.00			
rvar	0.16	0.29	0.42	0.11	0.00	0.00	1.00		
npar	0.22	0.32	0.25	0.06	0.00	0.00	0.07	1.00	
dvol	0.29	0.34	0.35	0.16	0.00	0.00	0.35	0.34	1.00

Table 6

Standard Efficiency Tests

GERMANY/US

	apc	ms(4)	ms(8)	ar(6)	g(1,1)	rvar	npar	dvol
Constant	-0.002	-0.003	-0.003	0.000	0.000	-0.002	-0.107	0.001
	(-3.13)	(-3.08)	(-3.16)	(0.01)	(0.14)	(-0.76)	(-7.57)	(2.34)
slope	0.087	0.121	0.118	0.999	0.986	1.110	34.59	10.87
	(7.38)	(5.46)	(5.23)	(2.53)	(2.86)	(2.15)	(7.74)	(3.81)
R^2-adj	0.51	0.31	0.23	0.10	0.06	0.02	0.46	0.18
Q(8)	48.20*	17.87*	6.99	5.29	8.72	44.64*	28.23*	26.79*
H_0	0.000	0.000	0.000	0999	0.939	0.001	0.000	0.000

FRANCE/US

	apc	ms(4)	ms(8)	ar(6)	g(1,1)	rvar	npar	dvol
Constant	-0.015	-0.023	-0.027	0.000	0.005	0.009	-1.577	0.006
	(-2.66)	(-2.71)	(-2.82)	(0.01)	(0.88)	(1.29)	(-16.16)	(1.30)
slope	0.269	0.373	0.377	1.000	0.778	0.792	73.92	12.48
	(5.56)	(4.56)	(4.42)	(2.59)	(2.89)	(2.08)	(16.29)	(3.35)
R^2-adj	0.48	0.30	0.23	0.13	0.07	0.01	0.88	0.21
Q(8)	71.84*	23.37*	16.44*	4.73	20.92*	55.14*	7.22	40.71*
H_0	0.000	0.000	0.000	0.999	0.681	0.119	0.000	0.000

JAPAN/US

	apc	ms(4)	ms(8)	ar(6)	g(1,1)	rvar	npar	dvol
Constant	-0.002	-0.002	-0.002	0.000	0.001	-0.007	-0.051	0.001
	(-2.80)	(-1.99)	(-2.13)	(0.01)	(1.45)	(-2.68)	(-6.03)	(2.10)
slope	0.091	0.106	0.104	1.000	0.770	2.859	21.73	14.72
	(5.54)	(3.76)	(3.70)	(2.40)	(3.54)	(3.34)	(6.27)	(4.41)
R^2-adj	0.47	0.23	0.16	0.06	0.03	0.05	0.48	0.19
Q(8)	35.25*	33.54*	9.24	1.66	10.11	16.24*	16.73*	19.45*
H_0	0.000	0.000	0.000	0.999	0.343	0.000	0.000	0.000

UK/US

	apc	ms(4)	ms(8)	ar(6)	g(1,1)	rvar	npar	dvol
Constant	-0.000	-0.000	-0.000	0.000	0.000	0.000	-0.009	0.000
	(-2.09)	(-2.40)	(-2.15)	(0.01)	(0.37)	(2.71)	(-22.59)	(0.94)
slope	0.024	0.038	0.035	1.000	0.921	1.003	45.66	11.85
	(5.12)	(4.03)	(3.56)	(3.39)	(2.95)	(3.44)	(22.81)	(2.60)
R^2-adj	0.40	0.40	0.27	0.16	0.11	0.02	0.83	0.23
Q(8)	57.82*	26.33*	19.68*	0.64	21.46*	77.61*	12.80	50.08*
H_0	0.000	0.000	0.000	0.999	0.899	0.000	0.000	0.000

CANADA/US

	apc	ms(4)	ms(8)	ar(6)	g(1,1)	rvar	npar	dvol
Constant	0.000	-0.000	-0.000	-0.000	---	0.000	-0.006	0.000
	(0.15)	(-3.27)	(-2.52)	(-0.05)	---	(1.99)	(-10.97)	(4.12)
slope	0.012	0.021	0.020	1.021	---	0.913	47.69	7.709
	(7.99)	(7.84)	(6.26)	(2.89)	---	(3.23)	(11.21)	(3.38)
R^2-adj	0.33	0.27	0.14	0.02	---	0.02	0.44	0.11
Q(8)	11.54	31.58*	20.76**	8.26	---	12.86	5.08	13.64*
H_0	0.000	0.000	0.000	0.933	---	0.000	0.000	0.000

$\hat{e}_t^2 = a + b\hat{h}_t + u_t$ is the estimated regression equation.

T-values are in paranthesis.

H_0: $b_0=0, b_1=1$ vs H_a: $b_0 \neq 0$, $b_1 \neq 1$ (p-values are presented in the table for this joint hypothesis).
Q is the Ljung-Box Q statistic. * and ** means statistical significance at 5% and 10%, respectively.

Table 7

Extreme Bounds

FRANCE/US

	ac	ms(4)	ms(8)	ar(6)	g(1,1)	sg(1,1)	rvar	npar	dvol
Base	-0.0006	-0.0019	-0.0183	0.0110	0.0015	-0.0115	-0.0221	-0.5457	-0.0204
LB(A)	-0.0021	-0.0606	-0.1979	-0.0290	-0.4533	-0.8779	-0.1991	-2.3625	-0.0393
UB(A)	0.0003	0.0595	-0.0074	0.1270	0.8831	0.4523	0.2414	1.9476	-0.0097
	fragile	fragile	robust	fragile	fragile	fragile	fragile	fragile	robust
LB(B)	na	na	na	na	na	na	na	na	na
UB(B)	na	na	na	na	na	na	na	na	na
	fragile	fragile	fragile	fragile	fragile	fragile	fragile	fragile	fragile

GERMANY/US

	ac	ms(4)	ms(8)	ar(6)	g(1,1)	sg(1,1)	rvar	npar	dvol
Base	0.0081	-0.0293	-0.2697	-0.1490	-0.0331	-0.1133	0.2396	1.5083	-0.0679
LB(A)	-0.0265	-0.0943*	-1.2374*	-0.5622*	-3.1635*	-5.6726*	-1.1032	0.6678	-0.1636
UB(A)	0.0649	0.0636	-0.0212	-0.0605	0.7827	1.4044	0.9514	6.3588	0.1090
	fragile	fragile	robust	robust	fragile	fragile	fragile	robust	fragile
LB(B)	na	-0.0943	-1.2374	-0.5622	-3.1635	-5.5626	na	na	na
UB(B)	na	-0.0815	-0.6241	-0.3668	-1.4142	-1.9314	na	na	na
	fragile	robust	robust	robust	robust	robust	fragile	fragile	fragile

JAPAN/US

	ac	ms(4)	ms(8)	ar(6)	g(1,1)	sg(1,1)	rvar	npar	dvol
Base	-0.0051	-0.0411	-0.2827	0.1225	-0.3748	-0.6316	-1.7417	-4.2750	0.0510
LB(A)	-0.0288	-0.0755	-0.9797	-0.3315	-1.8100	-3.1153	-11.099*	-8.8071*	-0.0268
UB(A)	0.0550	0.0180	0.4974	0.6799	0.4140	0.2379	-0.9300	0.1022	0.1639
	fragile	fragile	fragile	fragile	fragile	fragile	robust	fragile	fragile
LB(B)	na	na	na	na	na	-2.8261	-11.099	-8.8071	na
UB(B)	na	na	na	na	na	-2.8261	-5.6765	-8.4950	na
	fragile	fragile	fragile	fragile	fragile	robust	robust	robust	fragile

UK/US

	ac	ms(4)	ms(8)	ar(6)	g(1,1)	sg(1,1)	rvar	npar	dvol
Base	0.0132	0.0001	0.0099	0.0264	-0.0392	-0.1493	0.0390	-0.8660	-0.0719
LB(A)	-0.0121	-0.0194	-0.0229	-0.0025	-0.2544	-0.2982	0.0125	-1.6974	-0.2409
UB(A)	0.0643	0.0580	0.1444	0.4087*	0.0376	0.2562	0.1173	0.7835	-0.0272
	fragile	fragile	fragile	fragile	fragile	fragile	robust	fragile	robust
LB(B)	na	na	na	0.1830	na	na	na	na	na
UB(B)	na	na	na	0.4087	na	na	na	na	na
	fragile	fragile	fragile	robust	fragile	fragile	fragile	fragile	fragile

CANADA/US

	apc	ms(4)	ms(8)	ar(6)	g(1,1)	sg(1,1)	rvar	npar	dvol
Base	-0.0162	-0.1547	-0.1723	0.7240	--	--	0.0458	-6.4949	0.0150
LB(A)	-0.5097*	-0.6159*	-0.5150	-1.2666	--	--	-0.3411	-116.12*	-0.0570
UB(A)	0.0554	0.1116	0.0767	3.0081	--	--	10.789	50.305	0.0292
	fragile	fragile	fragile	fragile	--	--	fragile	fragile	fragile
LB(B)	-0.5097	-0.6159	na	na	--	--	na	-116.12	na
UB(B)	-0.3099	-0.5181	na	na	--	--	na	-86.479	na
	robust	robust	fragile	fragile	--	--	fragile	robust	fragile

LB: Lower bound ; UB: Upper bound
A: gives the lower and upper bound with no constraint on the statstical significance.
B: gives the lower and upper bounds when the coefficient on focus variable is significant at α=0.10.
* means significance at 0.10 level.
na means we couldn’t find a significant coefficient.

Table 8

Lagged Volatility and Robustness

FRANCE/US

Lag	apc	ms(4)	ms(8)	ar(6)	g(1,1)	sg(1,1)	rvar	npar	dvol
1	robust(+)	fragile	fragile	robust(-)	fragile	fragile	fragile	robust(+)	fragile
2	fragile	robust(-)	fragile	robust(-)	fragile	fragile	fragile	robust(-)	fragile
3	fragile	fragile	fragile	robust(+)	fragile	fragile	fragile	fragile	fragile
4	robust(-)	fragile	fragile	fragile	fragile	fragile	fragile	fragile	fragile
5	fragile	fragile	fragile	fragile	robust(+)	fragile	fragile	robust(-)	fragile
6	fragile	fragile	fragile	robust(+)	fragile	fragile	fragile	robust(+)	robust(-)

GERMANY/US

Lag	apc	ms(4)	ms(8)	ar(6)	g(1,1)	sg(1,1)	rvar	npar	dvol
1	fragile	fragile	fragile	fragile	robust(-)	robust(-)	fragile	fragile	fragile
2	fragile	fragile	robust(-)	robust(-)	fragile	fragile	fragile	robust(-)	fragile
3	fragile	fragile	fragile	fragile	fragile	fragile	fragile	robust(+)	fragile
4	fragile	robust(-)	fragile	fragile	robust(-)	robust(-)	fragile	fragile	fragile
5	fragile	robust(-)	fragile	fragile	fragile	fragile	fragile	robust(-)	fragile
6	fragile	fragile	fragile	fragile	fragile	fragile	fragile	robust(+)	fragile

JAPAN/US

Lag	apc	ms(4)	ms(8)	ar(6)	g(1,1)	sg(1,1)	rvar	npar	dvol
1	fragile	robust(-)	robust(+)	robust(-)	fragile	fragile	fragile	fragile	fragile
2	robust(-)	fragile	fragile	robust(+)	fragile	fragile	fragile	robust(-)	fragile
3	fragile	fragile	fragile	robust(-)	fragile	fragile	fragile	robust(+)	fragile
4	robust(+)	fragile	fragile	robust(+)	robust(-)	robust(-)	fragile	robust(+)	robust(+)
5	robust(-)	robust(+)	fragile	robust(-)	fragile	fragile	robust(-)	robust(-)	robust(-)
6	fragile	fragile	fragile	fragile	fragile	fragile	fragile	fragile	fragile

UK/US

Lag	apc	ms(4)	ms(8)	ar(6)	g(1,1)	sg(1,1)	rvar	npar	dvol
1	fragile	fragile	fragile	robust(-)	fragile	fragile	fragile	robust(+)	fragile
2	fragile	fragile	fragile	fragile	fragile	fragile	fragile	robust(-)	fragile
3	fragile	fragile	fragile	fragile	fragile	fragile	fragile	robust(+)	fragile
4	robust(-)	fragile	fragile	fragile	fragile	fragile	fragile	fragile	fragile
5	fragile	fragile	fragile	fragile	fragile	fragile	fragile	fragile	fragile
6	robust(+)	fragile	fragile	fragile	fragile	fragile	fragile	fragile	robust(+)

CANADA/US

Lag	apc	ms(4)	ms(8)	ar(6)	g(1,1)	sg(1,1)	rvar	npar	dvol
1	robust(+)	fragile	fragile	robust(-)	--	--	robust(-)	robust(+)	robust(-)
2	robust(-)	robust(-)	robust(-)	fragile	--	--	robust(-)	robust(-)	fragile
3	fragile	fragile	fragile	fragile	--	--	robust(-)	robust(-)	robust(-)
4	fragile	fragile	fragile	fragile	--	--	fragile	robust(+)	robust(+)
5	robust(-)	fragile	fragile	fragile	--	--	robust(-)	robust(-)	fragile
6	robust(+)	fragile	fragile	robust(-)	--	--	fragile	fragile	fragile

Lags shows the which lagged variable included as the focus variable.
Robust(-) and robust(+) means that coefficient estimate is robust negative and robust positive, respectively.

Table 9

An Alternative Interpretation of EBA Results

Ctr	**Vars**	**apc**	**ms(4)**	**ms(8)**	**ar(6)**	**g(1,1)**	**sg(1,1)**	**rvar**	**npar**	**dvol**
FR	$\hat{\theta}_W$	-0.0007	-0.0044	-0.0628	0.0259	0.0119	-0.1444	-0.0185	0.0620	-0.0263
	$\hat{\sigma}_W$	0.0018	0.0691	0.1362	0.0913	0.3049	0.5514	0.2044	2.9500	0.0282
	$\Phi_{0.25}$	-0.0018	-0.0456	-0.1944	-0.0338	-0.1209	-0.6131	-0.1289	-1.7180	-0.0400
	$\Phi_{0.50}$	.0.0004	-0.0171	-0.0072	-0.0044	-0.0364	0.0930	-0.0239	-0.0034	-0.0240
	$\Phi_{0.75}$	0.0006	0.0203	0.0599	0.0638	-0.0204	0.1525	0.0966	1.7839	-0.0068
	$\Phi_{0.90}$	0.0013	0.1037	0.0780	0.1789	0.5106	0.3843	0.2411	3.9525	0.0045
	CDF(0)	0.6481	0.5253	0.6777	0.3882	0.4845	0.6033	0.5360	0.4916	0.8242
GER	$\hat{\theta}_W$	0.0146	-0.0293	-0.4356	-0.2267	-0.3816	-0.7744	-0.0842	2.3299	-0.0539
	$\hat{\sigma}_W$	0.0491	0.0466	0.3484	0.2041	0.5553	1.0123	0.9630	4.2268	0.0965
	$\Phi_{0.25}$	-0.0119	-0.0476	-0.6736	-0.3621	-0.6938	-1.4129	-0.6672	-1.0833	-0.1039
	$\Phi_{0.50}$	0.0074	-0.0376	-0.3490	-0.1637	-0.0962	-0.2503	-0.1310	1.1854	-0.0740
	$\Phi_{0.75}$	0.0353	-0.0236	-0.1744	-0.0663	-0.0514	-0.1664	0.5716	4.8966	-0.0304
	$\Phi_{0.90}$		0.0843	0.0452	-0.1340	-0.0251	-0.0289	-0.1180	1.0449	8.6007
		0.0898								
	CDF(0)	0.3833	0.7349	0.8944	0.8666	0.7540	0.7779	0.5349	0.2907	0.7119
JAP	$\hat{\theta}_W$	0.0062	-0.0478	-0.3287	0.2284	-0.7070	-1.2506	-3.5678	-4.1652	0.0360
	$\hat{\sigma}_W$	0.0514	0.0540	0.5112	0.4611	0.8378	1.3848	2.9999	4.9185	0.1597
	$\Phi_{0.25}$	-0.0313	-0.0826	-0.5994	0.0262	-1.3846	-2.4042	-5.7558	-7.0010	-0.0796
	$\Phi_{0.50}$	-0.0038	-0.0517	-0.3614	0.2349	-0.3005	-0.5092	-2.3755	-3.4429	0.0129
	$\Phi_{0.75}$	0.0400	-0.0247	-0.0848	0.4788	-0.1135	-0.1950	-1.1816	-1.2203	0.1385
	$\Phi_{0.90}$	0.0793	0.0240	0.2677	0.7218	0.0313	0.0252	-0.6355	1.1144	0.2587
	CDF(0)	0.4520	0.8121	0.7399	0.3102	0.8006	0.8168	0.8828	0.8015	0.4109
UK	$\hat{\theta}_W$	0.0298	0.0139	0.0437	0.0804	-0.0424	-0.0662	0.0568	-0.6426	-0.0037
	$\hat{\sigma}_W$	0.0584	0.0618	0.1088	0.1054	0.1292	0.4528	0.0885	2.6621	0.0175
	$\Phi_{0.25}$	-0.0119	-0.0341	-0.0497	-0.0095	-0.0589	-0.3709	-0.0143	-2.7581	-0.0136
	$\Phi_{0.50}$	0.0222	-0.0019	-0.0031	0.0488	-0.0093	-0.2074	0.0618	-0.7275	-0.0024
	$\Phi_{0.75}$	0.0745	0.0623	0.1500	0.1465	0.0202	0.2282	0.1152	0.9385	0.0086
	$\Phi_{0.90}$	0.1150	0.1026	0.1973	0.2348	0.0734	0.5796	0.1682	3.1836	0.0182
	CDF(0)	0.3050	0.4110	0.3439	0.2230	0.6287	0.5581	0.2605	0.5954	0.5829
CAN	$\hat{\theta}_W$	-0.0901	-0.1096	-0.0724	1.3406	--	--	-0.5739	-29.8544	-0.0028
	$\hat{\sigma}_W$	0.1844	0.2756	0.3278	1.3360	--	--	6.8035	22.8081	0.0521
	$\Phi_{0.25}$	-0.1652	-0.2000	-0.2680	0.7036	--	--	-4.8727	-50.6944	-0.0288
	$\Phi_{0.50}$	-0.0251	-0.0179	0.0607	1.6068	--	--	1.6925	-18.6549	0.0099
	$\Phi_{0.75}$	0.0533	0.0716	0.1557	1.9324	--	--	2.0849	-15.1246	0.0346
	$\Phi_{0.90}$	0.0813	0.1018	0.2132	2.3285	--	--	4.8899	-9.9326	0.0555
	CDF(0)	0.6875	0.6545	0.5874	0.1578			0.5336	0.9047	0.5217

$\hat{\beta}_W$ and $\hat{\sigma}_W$ are the weighted coefficient estimate and standard error on volatility measure. $\Phi_{0.k}$ is the kth percentile values of the empirical distribution function. CDF(0) gives the P($\hat{\beta}_W$ <0) when the coefficient estimate is assumed to be normally distributed with mean equal to weighted coefficient estimate and standard error equal to weighted standard error estimate.

Data Appendix

Exports: Millions of US dollars, not seasonally adjusted, reported on F.A.S. value. *Source: Citibase Databank.*

Foreign Income : Industrial production index, seasonally adjusted.
Source : IMF's International Financial Statistics CD-Rom.

Price of Exports : Unit price index for exports.
Source : IMF's International Financial Statistics CD-Rom.

Relative Prices : Calculated by Consumer price index.
Source: Citibase Databank.

Monthly Exchange Rates : Monthly averages of nominal exchange rates.
Source : St. Louis Federal Reserve Web site (FRED)

Daily Exchange Rates: Noon buying rates in New York City certified by the Federal reserve Bank of New York.
Source: Federal Reserve Bank of New York

Unit costs: Hourly earnings, manufacturing for US; Average Earnings for UK; Labor costs for France; Wages and Salaries per man hour for Germany; Wages : monthly earnings for Japan; Wages: hourly earnings for Canada..
Source : IMF's International Financial Statistics CD-Rom.

Interest rates: Japan yield on 60 day short term government securities (end period); Treasury bill discount – 3 month (auction) for France; 3-month treasury bill rate (end period) for Germany, UK, Canada, and US.

Source: Datastream International

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