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Estimating the Effects of Exchange Rate Volatility on Export Volumes

Kai-Li Wang and Christopher B. Barrett

This paper takes a new empirical look at the long-standing question of the effect of exchange rate volatility on international trade flows by studying the case of Taiwan's exports to the United States from 1989–1998. In particular, we employ sectoral-level, monthly data and an innovative multivariate GARCH-M estimator with corrections for leptokurtic errors. This estimator allows for the possibility that traders' forward-looking contracting behavior might condition the way in which exchange rate movement and associated risk affect trade volumes. Change in importing country industrial production and change in the expected exchange rate are found to jointly drive the trade volumes. More strikingly, monthly exchange rate volatility affects agricultural trade flows, but not trade in other sectors. These results differ significantly from those obtained using more conventional and restrictive modeling assumptions.

Key words: agricultural trade, exchange rate, expectations, GARCH

Introduction

One of the leading conundrums in international economics concerns the relationship between exchange rate risk and international trade volumes. The widespread popular perception that greater exchange rate risk reduces trade has helped motivate monetary unification in Europe (European Union Commission, 1990) and is strongly related to currency market intervention by central banks (Bayoumi and Eichengreen, 1998). Most current microstructural theoretical models of exporter behavior predict a negative relation between exchange rate risk, reflected in the conditional variance of the exchange rate, and export volumes [see Barkoulas, Baum, and Calgayan (2002) for one good, recent example].

Yet a vast economic literature yields highly inconsistent empirical results on this issue. One common argument is that exporters can easily ensure against short-run exchange rate fluctuations through financial markets, while it is much more difficult and expensive to hedge against long-term risk. Cho, Sheldon, and McCorriston (2002), DeGrauwe and de Bellefroid (1986), Obstfeld (1995), and Peree and Steinherr (1989), for example, demonstrate that longer-run changes in exchange rates seem to have more significant impacts on trade volumes than do short-run exchange rate fluctuations that can be hedged at low cost.

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On the other hand, Vianne and de Vries (1992) show that even if hedging instruments are available, short-run exchange rate volatility still affects trade because it increases the risk premium in the forward exchange rate. Doroodian (1999), Krugman (1989), Mundell (2000), and Wei (1999) argue that hedging is both imperfect and costly as a basis to avoid exchange rate risk, particularly in developing countries and for smaller firms more likely to face liquidity constraints. This leads to the conventional argument that exchange rate volatility causes revenue uncertainty which will dampen trade due to risk aversion, irreversible investment in productive capital, or both (Ethier, 1973; Demers, 1991; Sercu, 1992). DeGrauwe (1988) nicely illustrates how the relationship between exchange rate volatility, whether long run or short run, and trade flows is analytically indeterminate when one allows for sufficient flexibility in assumptions. This suggests the effects of exchange rate volatility on trade volumes remain a fundamentally empirical issue.[1]

The empirical literature on this topic is mixed. Several authors have found that exchange rate uncertainty may induce marginal producers and traders to shift from trade to nontraded goods, thereby dampening trade volumes (Arize, Osang, and Slottje, 2000, 2004; Broda and Romalis, 2004; Chowdhury, 1993; Pozo, 1992). In contrast, other studies have found exchange rate volatility may stimulate trade (Dellas and Zillberfarb, 1993; Frankel, 1992; Sercu and Vanhulle, 1992). Finally, many empirical studies have failed to establish any significant link between measured exchange rate variability and the volume of international trade (Aristotelous, 2001; Assery and Peel, 1991; Gagnon, 1993; Tenreyro, 2004). The empirical evidence on this relationship is therefore equally ambiguous to the theoretical evidence.

One possible reason for such mixed results is the aggregation problem. The effects of exchange rate volatility on export volumes may vary across sectors (Bini-Smaghi, 1991; Klein, 1990; Maskus, 1986; McKenzie, 1999). This might occur because the level of competition, the nature of contracting—and thus the price-setting mechanism—the currency of contracting, the use of hedging instruments, the economic scale of production units, openness to international trade, and the degree of homogeneity and storability of goods vary among sectors. To date, most studies have focused on industrial countries and on manufactured exports. Intersectoral differences in exporters' access to financial instruments, currency of contracting, production scale, storability, etc., may be particularly pronounced in developing countries, perhaps especially compared to agriculture based largely on traditional production methods practiced by many small-scale, private producers and larger-scale, higher-technology manufactured goods sectors that typically enjoy state support. This contrast is only accentuated by the fact that agriculture is typically a notably competitive sector with flexible pricing on relatively short-term contracts more likely to be denominated in U.S. dollars, irrespective of the exporter's home country. Further, agricultural commodities are relatively homogeneous and typically less storable than is true of merchandise exports in other sectors (Frankel, 1986; Kim and Koo, 2002; Schuh, 1974). Bordo (1980) and Maskus (1986) therefore argue that agricultural trade volumes may be far more responsive to exchange rate changes than is trade in manufactured goods. This may also translate into greater trade volume sensitivity to exchange rate risk in agriculture compared to other sectors of the economy (Anderson and Garcia, 1989; Maskus, 1986).

[1] McKenzie (1999) offers a more detailed and comprehensive review of this literature.

The empirical evidence on this point remains thin and somewhat inconclusive, especially as regards agricultural exports from developing countries. For example, Klein (1990) comprehensively tests the impact of exchange rate uncertainty on U.S. monthly bilateral sectoral exports to six major industrial countries, and finds that exchange rate volatility negatively affects agricultural exports, far more than trade volumes from other sectors. Pick (1990) indicates exchange rates adversely affected U.S. agricultural exports to developing countries, underscoring the importance of exchange rate risk in trading behavior of developing countries.

Recently, Cho, Sheldon, and McCorriston (2002) found the negative impact of uncertainty on agricultural trade has been more significant compared to other sectors for a sample of bilateral trade flows across 10 developed countries. Using monthly data disaggregated by markets of destination and sectors, de Vita and Abbott (2004) reported that UK exports to the EU14, in aggregate and across sectors, are largely unaffected by short-term exchange rate volatility. In contrast, Langley et al. (2000) found exchange rate volatility had a positive impact on Thailand's poultry exports, but no statistically significant effect on aggregate exports. To date, we know of no study that compares the impact of exchange rate volatility on agricultural exports versus trade volumes from other sectors from a developing country to the United States. That is the topical innovation of this paper.

This topic is of particular salience to contemporary economic policy in middle-income economies heavily dependent on international trade and in the midst of what Timmer (1988) terms the "agricultural transformation." Foreign trade has been the engine of Taiwan's rapid growth over the past half century. Agriculture played a very important role in the country's accelerating economic growth in the 1960s and 70s, but beginning in the early 1980s, Taiwan turned from being a net agricultural exporter into a net agricultural importing nation with an annually expanding agricultural trade deficit. In recent years, faced with pressures due to trade liberalization and globalization, the challenge of how to promote agricultural sector growth, especially in exports, has become a high-level policy issue in Taiwan. The United States is Taiwan's largest export market overall and is the main source of Taiwan's agricultural imports.[2]

Exports to the United States during the 1989–1998 study period were mainly electronics and consumer goods, while Taiwan's major agricultural exports to the United States included frozen fish, aquaculture and sea products, canned and frozen vegetables, and grain products. Our hypothesis is that sectoral and temporal disaggregation of the trade and exchange rate data might bring the contrast between the agricultural and nonagricultural sectors in developing countries into sharper focus as it concerns the issue of the effects of exchange rate volatility on trade flows.

One of the main contributions of this study, however, is methodological. Tenreyro (2004) argues that the methods conventionally used to examine the impact of exchange rate volatility on trade are plagued by a variety of estimation problems. McKenzie's (1999) excellent survey of the literature emphasizes a few key points in charting the empirical road ahead. These include (*a*) the need for care in specifying the technique by which exchange rate volatility is measured, ideally with increased attention paid to traders' forward-looking contracting behavior; (*b*) necessary correction for prospective

[2] Taiwan is the United States' eighth largest trading partner overall, behind only Canada, Mexico, Japan, P.R. China, Germany, the United Kingdom, and Korea, and its fifth largest market for agricultural exports, behind Japan, Canada, Mexico, and Korea [Ministry of Foreign Affairs of the Republic of China, 2001 (online at http://www.mofa.gov.tw)].

problems of serial correlation, nonstationarity and nonnormality in time-series data; and (*c*) the importance of using data disaggregated by sector, market, and time period.

In this paper, we offer a new look at the exchange rate volatility-trade relationship which, for the first time to the best of our knowledge, addresses each of these three issues simultaneously. Specifically, we rely not on measures of realized exchange rate volatility, as is commonplace in this literature,[3] but instead on forward-looking conditional variance estimates that exporters could have generated using a generalized autoregressive, conditional heteroskedasticity (GARCH) model (Bollerslev, 1986; Engle, 1982) to proxy for exchange rate risk, as has become reasonably standard in the empirical finance literature over the past decade or so. This specification is consistent with the assumption that exporters incorporate all available information into their estimates of future exchange rate volatility (Taylor and Spriggs, 1989). We offer what we believe to be the first attempt to incorporate traders' forward-looking expectations of the level and volatility of exchange rates into a model explaining trade volume patterns, especially disaggregated by sector. Toward this end, we develop and apply a novel multivariate generalized autoregressive conditional heteroskedasticity-in-mean model (MGARCH-M), which accommodates nonnormality in regression residuals and attends to each of the three problems McKenzie (1999) identified in this literature.

The remainder of the paper is structured as follows. The next section briefly motivates our approach to specifying exchange rate volatility. Model specification and related econometric questions are then presented, followed by a discussion of our estimation results. Concluding remarks are given in the final section.

Estimating Exchange Rate Volatility

We start with the maintained hypothesis that agents are concerned about the real exchange rate, not nominal rates.[4] As several studies have demonstrated, this assumption makes little difference in practice; nominal and real exchange rate series generate nearly identical empirical results (McKenzie and Brooks, 1997; McKenzie, 1999; Qian and Varangis, 1994). The level and returns[5] of the NT$/US$ exchange rate series we use in estimation are plotted in figures 1 and 2, respectively.

A few crucial issues underpin many of the empirical inconsistencies in the existing literature. The first is how a trader conceptualizes exchange rate risk and incorporates it into trade contracting decisions. We assume traders are forward-looking because they may make contractual commitments to trade volumes before they know the exchange rate that will prevail at time of delivery. Precisely because there exists considerable inter-sectoral variation in the extent to which firms forward contract internationally or must pre-commit assets (e.g., cultivable land) to a particular product, this forward-looking formulation of exchange rate levels and volatility may matter in some sectors where forward contracting and short-run quasi-fixity are important, as in agriculture,

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[3] The most common measure of exchange rate volatility used in this literature has been the moving average standard deviation of the change in the exchange rate (Arize, Osang, and Slottje, 2000; Cho, Sheldon, and McCorriston, 2002; Chowdhury, 1993; de Vita and Abbott, 2004; Kenen and Rodrik, 1986; Kim and Koo, 2002; Koray and Lastrapes, 1989). A range of recent authors have noted this systematically underestimates the effect of exchange rate risk and typically involves inherently ad hoc selection of the order of the moving average process.

[4] The real exchange rate (RX) is defined as $E * (P_{foreign}/P_{home})$, where E is the nominal NT$/US$ exchange rate and $P_{foreign}$ and P_{home} represent the U.S. and Taiwan wholesale price indices, respectively.

[5] Returns are defined as the rate of change, estimated as the first difference of the natural logarithm of the exchange rate.

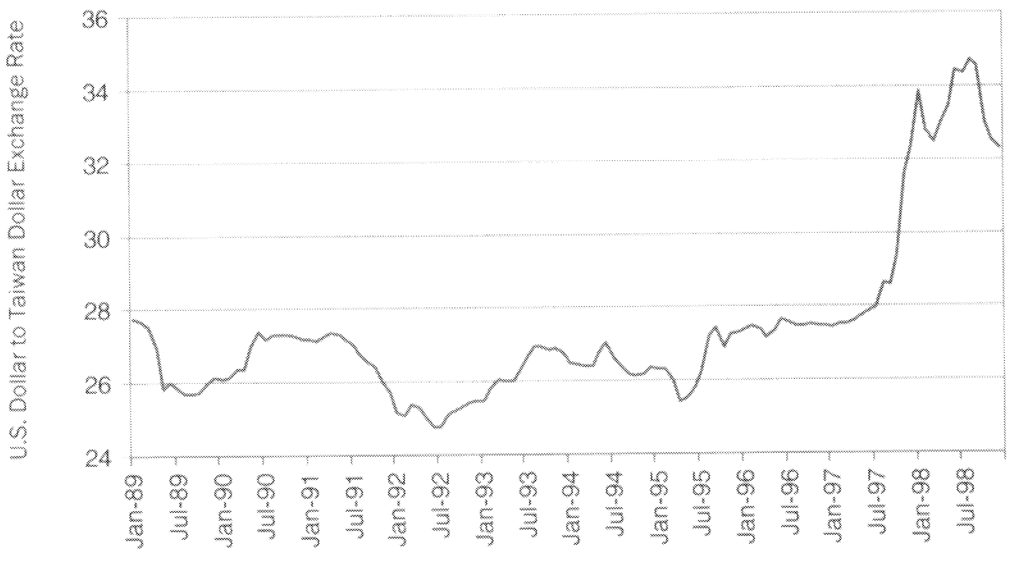


Figure 1. Exchange rate series

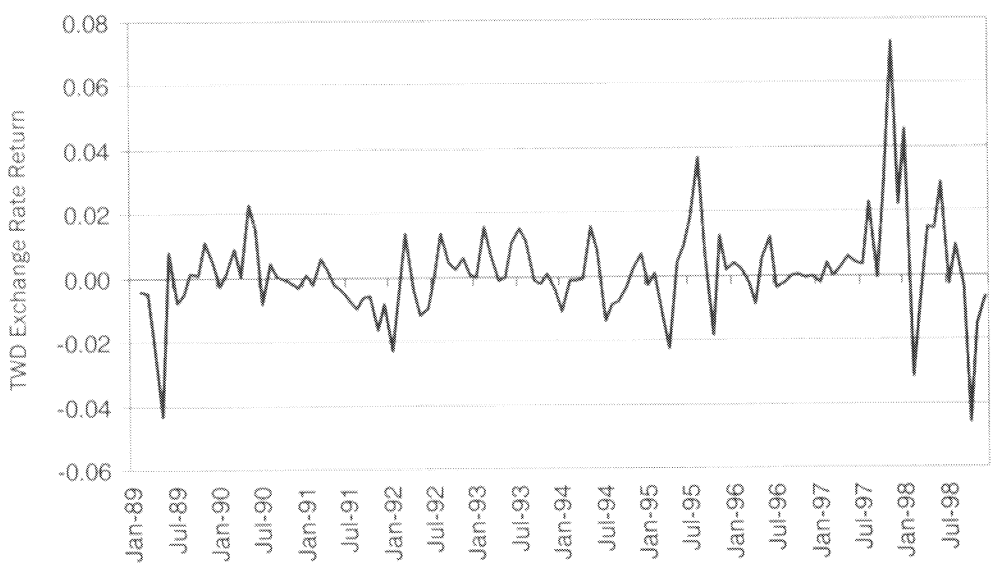


Figure 2. Exchange rate return

but not in other sectors. By incorporating multiple lags in expected exchange rates, our approach allows for the possibility that traders form forward-looking expectations of the moments of the conditional exchange rate distribution perhaps many months ahead, based only on data available at the time of the decision. This allows for contracting decisions at time $t + s$ $(s > 0)$ based on forecasts made in period t of the conditional mean and variance of the exchange rate s periods ahead. Allowing for multiple lags permits intersectoral and intertemporal variation in the impacts of expected exchange rate movements on trade volumes.

The second feature differentiating our econometric strategy is that most of the extant empirical literature uses realized, rather than expected, exchange rate volatility, as proxied by measures such as the absolute percentage changes in the exchange rate, lagged standard deviations, or moving average variance around trend. These measures either impose an assumption of adaptive expectations, wherein economic agents use only past exchange rates to predict future exchange rate distributions, or impose an assumption of fulfilled expectations—i.e., agents accurately predict the time path of exchange rates up to the delivery period—and thereby suffer endogeneity, as when centered moving averages are used in spite of the fact that future exchange rate movements are almost surely affected in part by current trading behaviors. All measures that use realized values of exchange rate volatility suffer both conceptual and statistical problems of various sorts (Lanyi and Suss, 1982). As we report later, for the sample data studied in this paper, models based on estimates of agents' rational expectations of conditional mean and variance far outperform those based on realized level and volatility statistics.

The period over which agents form expectations likewise matters. The literature generally assumes contemporaneous or one-period lagged relationships between exchange rates and trade volumes. In part, this is due to widespread use of quarterly or annual data, and it would seem reasonable to expect that contracts typically lock in nominal prices only out to a six-month horizon or so. But when one uses higher frequency data, as the literature increasingly acknowledges is preferable, it then becomes less clear what lead/lag structure one ought to employ. Our approach is to let the data speak for themselves. We use established statistical methods to test for appropriate lag structures. Furthermore, the econometric literature generally supports the use of autoregressive moving average (ARMA) specifications as a convenient, reduced-form method of capturing rational expectations processes of uncertain lag structure (Feige and Pearce, 1976; Nerlove, Grether, and Carvalho, 1979; Wallis, 1980). We follow that tradition.

The final major issue to be considered is how the econometrician proxies for the exchange rate uncertainty perceived by economic agents. Even if researchers agree on how agents conceptualize uncertainty and form expectations over exchange rate distributions, there is no generally accepted method for quantifying this risk (McKenzie, 1999). Here we follow a burgeoning recent literature that relies on Bollerslev's (1986) generalized autoregressive conditional heterskedasticity (GARCH) model to allow for time-varying conditional variance (i.e., volatility clustering) in exchange rate series (Caporale and Doroodian, 1994; Kroner and Lastrapes, 1993; McKenzie and Brooks, 1997; Pozo, 1992; Qian and Varangis, 1994). Unlike most of this literature, however [with the notable exceptions of Caporale and Doroodian (1994) and Kroner and Lastrapes (1993)], we estimate the exchange rate process simultaneously with the trade volume equation using a multivariate GARCH-in-mean estimator,[6] thereby avoiding the generated regressors problem which bedevils the rest of the literature that uses GARCH modeling in a two-step process to identify the conditional variance of the (real) exchange rate series (McKenzie, 1999; Pagan, 1984).

Model Specification

In specifying our econometric model, we take four further issues into consideration: (*a*) potential intersectoral or temporal aggregation bias, (*b*) appropriate lag specification for both the ARMA and distributed lag terms in the model, (*c*) prospective time-varying correlation in the trade volume and exchange rate equations' regression errors, and (*d*) potential nonnormality in the regression errors. We address these in turn in introducing our estimation framework.

Most previous studies use data on trade flows aggregated across sectors and overseas markets and on exchange rates averaged over time. This necessarily imposes the strong, undesirable assumption that the impact of exchange rate volatility is uniform across sectors and destination markets, and introduces index number problems into the determination of the relevant exchange rate for contracts written in any of several currencies. Bini-Smaghi (1991), Klein (1990), and McKenzie (1999) argue strongly for sectorally disaggregated estimation of the trade-risk relationship and demonstrate that disaggregation uncovers significant intersectoral variation in the effect of exchange rate volatility on trade flows. As already discussed, there is strong reason to believe that agriculture may be far more sensitive to exchange rate risk than are other sectors (Maskus, 1986; Pick, 1990).

A related aggregation issue concerns the frequency of the data used in estimation. Due largely to data limitations, most studies employ lower frequency quarterly or annual series to examine the trade and risk relationship (McKenzie, 1999). However, temporal aggregation necessarily dampens exchange rate variability, which may make identifying any true trade-risk relationship more difficult (Wang, Fawson, and Barrett, 2002). Furthermore, since trade contracts in many sectors include agreement for delivery in less than 90 days, even quarterly frequency data may be aggregating trade flows excessively to identify short-term fluctuations in response to predicted changes in exchange rate levels or volatility. This is true for many of the relevant agricultural exports from Taiwan, such as fish and other highly perishable seafood products. Temporal disaggregation may thereby complement sectoral disaggregation in permitting inter-sectoral differences to reveal themselves more plainly.

Finally, rather than analyzing national-level exports irrespective of destination—and thus the relevant exchange rate—we use monthly export data over 10 years (1989–1998) from Taiwan to its largest trading partner, the United States, for eight different productive sectors: (*a*) animal and vegetable products and prepared foods; (*b*) textiles and textile articles; (*c*) wood, paper, pulp, and articles; (*d*) chemicals, plastics, rubber, and articles; (*e*) primary metals and articles; (*f*) optical and precision instruments; (*g*) electronic machinery; and (*h*) transportation. These sectoral categories correspond to the Standard Classification of Commodities (SCC) codes of the Republic of China. We constructed export volume series for each sector as the ratio of export values reported

[6] This builds on the seminal paper on ARCH-M estimation by Engle, Lilien, and Robins (1987).

in the *Monthly Statistics of Exports and Imports, Republic of China* tape to the export price reported in the serial *Commodity Price Statistics Monthly in Taiwan Area of the Republic of China*. Panels A–H of figure 3 display these trade volume series. Some industries (e.g., wood, paper, and pulp) exhibit clear export decline over time, while other industries (e.g., electronics) show clear growth in trade volumes from January 1989 to December 1998. As shown by figure 3, panel A, Taiwan's agricultural exports to the United States declined during the first half of this period, but recovered in the second half, with no clear trend overall.

The literature pays relatively little attention to the dynamic specification of the trade-risk relationship. Most studies consider only the contemporaneous or lagged one-period effect of the independent variables on the trade decisions without further investigating the possibility of any longer lead in agents' forecast of exchange rates or exchange rate volatility. This seems an especially important issue when using higher frequency and sectorally disaggregated data, since one-month leads may be suitable for some sectors where spot market transactions and rapid payment settlements are common, while longer leads may be more appropriate in other sectors characterized by significant forward contracting, payment delays, or both. If one wishes to reduce aggregation bias in estimation by using more temporally and sectorally disaggregated data, it seems all the more important to take care in specifying appropriate lead specifications. We therefore develop a model with a quite general lead structure, then painstakingly search for the optimal specification following established methods before estimating the resulting system of equations.

We assume exporters form expectations of the real exchange rate series following an ARMA(m, n) process, with conditional variance specified as a GARCH(p, q) process, following equations (1)–(4):

$$\phi_m(L)DLRX_t = \gamma_0 + \varphi_n(L)\varepsilon_{1,t}, \tag{1}$$

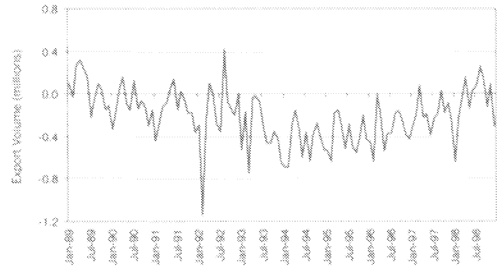
$$\varepsilon_{1,t} = z_t\sqrt{h_t}, \tag{2}$$

$$z_t \sim N(0, 1), \tag{3}$$

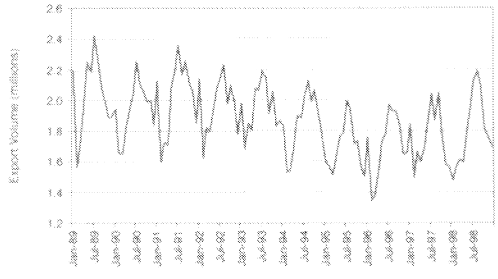
$$h_t = w_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{1,t-j}^2 + \sum_{k=1}^{p} \beta_k h_{t-k}, \tag{4.1}$$

$$h_t = w_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{1,t-j}^2 + \sum_{k=1}^{p} \beta_k h_{t-k} + \eta S_{t-1}\varepsilon_{1,t-1}^2. \tag{4.2}$$

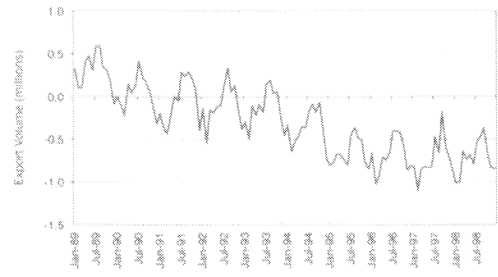
$DLRX_t$ is the first difference in the natural logarithm of the real exchange rate with respect to the previous period, representing monthly percentage change in the real exchange rate. It is essential in time-series analysis of these relationships to test for stationarity since if trade flows are nonstationary, as is typically the case, yet exchange rate volatility is stationary, as is likewise common, then currency risk necessarily cannot determine trade volumes. We therefore test for stationarity using the augmented Dickey-Fuller (ADF) test (results are available from the authors on request). The logarithm of the real exchange rate series was found to be integrated of order one, hence the first-differencing used here. L represents a polynomial lag operator used to capture the ARMA properties of the conditional mean equation.



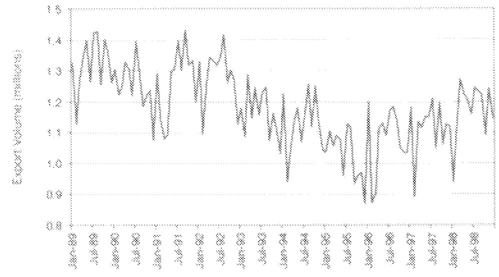
A. Agriculture (animal & vegetable products and prepared foods)



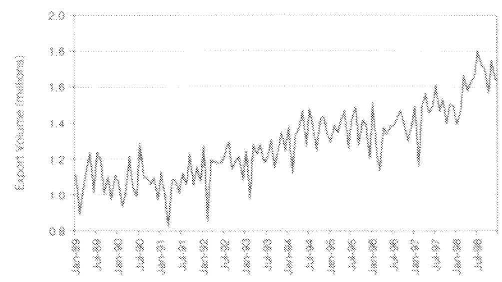
B. Textiles & Textile Articles



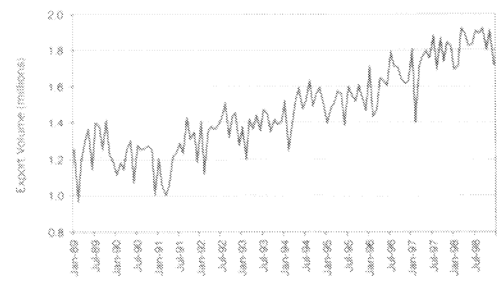
C. Wood, Paper, Pulp & Articles



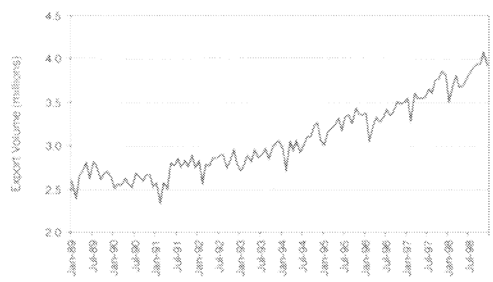
D. Chemicals, Plastics, Rubber & Articles



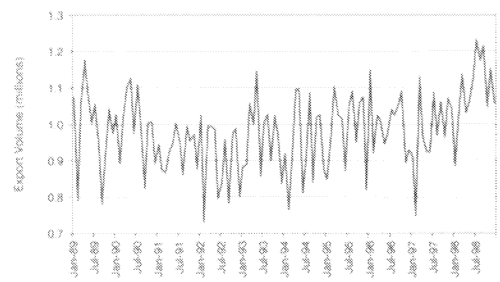
E. Primary Metals & Articles



F. Optical & Precision Instruments



G. Electronic Machinery



H. Transportation

Figure 3. Export trade volume series, by sector (1989–1998)

The residuals from equation (1), $\varepsilon_{1,t}$, are a function of the independent and identically standard normal distributed z_t, and the conditional variance h_t. In order to examine the time-varying conditional exchange rate volatility, a GARCH specification was adopted [equation (4.1)] that allows h_t to vary over time as a function of the lagged squared residuals $(\varepsilon^i_{1,t-j})^2$ and lagged conditional variance (h^i_{t-k}). Glosten, Jagannathan, and Runkle (1993; henceforth GJR) suggested a GJR-GARCH(p,q) conditional variance specification [equation (4.2)] to maintain the tractability of conventional GARCH models while accommodating a leverage effect by adding a term to permit asymmetry in the GARCH model. The leverage effect variable S_{t-1} takes on the value of 1 if $\varepsilon_{1,t-1} < 0$, and $S_{t-1} = 0$ otherwise. The leverage effect is captured by the parameter η; if $\eta = 0$, the GJR model reduces to the conventional GARCH specification. GJR-GARCH thus nests the conventional GARCH; hence a likelihood-ratio (LR) test can test performance of the GJR-GARCH versus the standard GARCH model. We impose restrictions $w_0 > 0$; $\beta_k \geq 0\ \forall\ k$; $\alpha_j \geq 0\ \forall\ j$; and $\eta \geq 0$ on parameter estimates to ensure strictly positive conditional variance. The sum of the parameters (α_j, β_k, and η) in the conditional variance can be interpreted as a measure of persistence in variance. That value must be less than one in order to satisfy the necessary and sufficient condition for covariance stationarity.

The estimated AR(1)-GARCH(1,1) process for the first difference in the natural logarithm of the real exchange rate ($DLRX_t$), per equation (1), is then used to generate $k2$-period-ahead expectations of real exchange rate changes ($DLRX^e_{t-k2}$) and $k3$-period-ahead expected conditional variance estimates for exchange rate risk ($h^e_{i,t-k3}$):

$$(5) \qquad DLRX^e_t = \gamma_0 \sum_{i=0}^{k-1} \phi^i_1 + \phi^k_1 DLRX_{t-k},$$

$$(6) \qquad h^e_t = w_0 \sum_{i=0}^{k-1} \beta^i_1 + \alpha_1 \beta^{k-1}_1 \varepsilon^2_{1,t-k} + \beta^k_1 h_{t-k}.$$

The $DLRX^e_t$ series is then integrated (undifferenced) back to the exchange rate level ($RX^e_{i,t-k2}$). $RX^e_{i,t-k2}$ and $h^e_{i,t-k3}$ thus reflect expectations of the level and volatility of exchange rates, respectively. These expected values become regressors in the export equation (7). We accept the general consensus in the literature that there is a long-run relationship among exports, the level of economic activity, real exchange rate, and a measure of exchange rate risk (DeGrauwe, 1988; Kenen and Rodrik, 1986; McKenzie, 1999; Pozo, 1992).[7] Assuming a linear first-order approximation to the true underlying relationship, we specify a reduced-form model as:

$$(7) \qquad \mathrm{Ln}(Q_{i,t}) = \delta_0 + \sum_{k1=1}^{6} \delta_{1,k1} \ln(IP_{t-k1}) + \sum_{k2=1}^{6} \delta_{2,k2} \ln(RX^e_{i,t-k2}) + \sum_{k3=1}^{6} \delta_{3,k3} \ln(h^e_{i,t-k3})$$
$$+ \sum_{k4=1}^{3} \delta_{4,k4} D_{k4,t} + \sum_{k5=1}^{6} \delta_{5,k5} \ln(Q_{i,t-k5}) + \varepsilon_{2i,t},$$

[7] There is considerable variation in the literature as to the control variables used in the export equation. As McKenzie's (1999) survey points out, however, the variables we include appear to suffice as there is rarely any appreciable difference between the parameter estimates obtained using such a parsimonious specification and those arising from models that include a wider range of explanatory variables. Moreover, the higher frequency data we use render many other candidate series unavailable as regressors.

where $Q_{i,t}$ is Taiwan's export volume for industry i to the United States during period t. Industrial production, IP_{t-k1}, is used as the monthly proxy for the exogenous component of income in the U.S. in period $t-k1$. We use IP because more conventional proxies for economic activity, such as income, are only available at quarterly frequency. $RX^{e}_{i,t-k2}$ is the $k2$-month-ahead expected exchange rate predicted for time t by traders standing at time $t-k2$ ($k2 = 1, \ldots, 6$), generated from the estimates of equation (5). Equation (6) generates analogous estimates for $h^{e}_{i,t-k3}$, the expected exchange rate volatility predicted in month t as $k3$ months ahead by traders ($k3 = 1, \ldots, 6$). Optimal lags and leads, $k1$, $k2$, and $k3$, are identified using Hendry's now-standard method, described below. In contrast with most of the extant literature, which concentrates on the relationship between *realized* exchange rates and trade, we offer what we believe to be the first attempt to incorporate traders' forward-looking expectations of expected exchange rates ($RX^{e}_{i,t-k2}$) and associated conditional volatility ($h^{e}_{i,t-k3}$). This approach is more consistent with traders' contracting decision processes.

We also control for the seasonality readily apparent in the export plots (figure 3) using quarterly dummy variables, $D_{k4,t}$. Quarterly dummies are adopted because preliminary analyses found this more parsimonious specification consistently outperformed one based on monthly dummy variables, per both the Akaike information criterion (AIC) and the Schwarz Bayesian criterion (SBC). Finally, lagged export volume ($Q_{i,t-k5}$) was included in the specification to allow for the possibility of autoregressive persistence in export volumes, with an estimable lag length of $k5$. The regression residual, $\varepsilon_{2i,t}$, has the usual Gauss-Markov properties. All the variables except $D_{k4,t}$ are in natural logarithm form, implying a constant elasticity structure.[8]

While the estimated conditional mean and variance of real exchange rate could be substituted into the export equation in a two-step estimation procedure, as several previous authors have done, this can lead to a generated regressors problem of biased estimates of the parameters' standard errors and potentially inconsistent parameter estimates (McKenzie, 1999; Murphy and Topel, 1985; Pagan, 1984; Pagan and Ullah, 1988). We resolve this problem by estimating the parameters of the conditional mean and conditional variance real exchange rate equations simultaneously with the export volume equation by using full information maximum likelihood (FIML), which ensures both consistency and efficiency conditional on distributional assumptions. When we estimated the model sequentially instead, it affected the parameter estimates and their standard errors and yielded statistically inferior results overall, corroborating our preference for the FIML estimator.

Specification of the FIML covariance matrix then becomes important. Although we allow for time-varying conditional variance for the real exchange rate series, we do impose the assumption of time-invariant conditional variance on the export volume series because statistical analysis revealed that the variances of each sector's export volume series in our sample are time invariant. This finding is consistent with those reported by other studies (Kroner and Lastrapes, 1993).

Real exchange rates and international trade move together in general equilibrium. We therefore allow for time-varying covariance among the two regressions' error terms, obviating the potential inefficiency that comes from ignoring the time-varying covariance

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[8] The industrial production, nominal exchange rate, and wholesale price index series come from the International Monetary Fund Economic Information System (IMFEIS) and Taiwan AREMOS system.

terms (Holt and Aradhyula, 1998). Although the variance of export volume does not vary across periods, the covariance between export volume and the real exchange rate likely does vary since the conditional variance of the latter series is clearly time-varying. We therefore specify a covariance matrix for the FIML model that includes a constant variance for export volume, σ_{22}, but allows for time-varying conditional variance of the real exchange rate returns following the GARCH process, and hence time-varying covariance ($\sigma_{12} = \sigma_{21}$) between export volumes and the real exchange rate. To conserve degrees of freedom, we follow Bollerslev's (1990) constant correlation coefficient (CCC) approach, which assumes the conditional correlation between the two variances, $\rho \in [-1, 1]$, is constant through time.[9] The time-varying covariance is proportional to the square root of the product of the two conditional variances, h_t and σ_{22}. Under standard regularity conditions, the error terms $\varepsilon_{1i,t}$ and $\varepsilon_{2i,t}$ are distributed multivariate normal with zero mean and the time-varying variance-covariance matrix H_t. The system could be expressed as:

$$\hat{\varepsilon}_t = \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}, \tag{8}$$

$$\hat{\varepsilon}_t \sim N(0, H_t), \tag{9}$$

$$H_t = \begin{bmatrix} h_t & \sigma_{12,t} \\ \sigma_{21,t} & \sigma_{22} \end{bmatrix}, \tag{10}$$

$$\sigma_{12,t} = \sigma_{21,t} = \rho\sqrt{(h_t \sigma_{22})}. \tag{11}$$

Our model thus involves simultaneous nonlinear estimation of equations (1)–(11). We used the Berndt, Hall, Hall, and Hausman (BHHH) algorithm in the Gauss Constrained Maximum Likelihood (CML) module. Let θ denote the unknown parameters in $\hat{\varepsilon}_t$ and H_t. The log-likelihood function of the k-variate under general heteroskedasticity with a multivariate normal distribution and n observations then becomes:

$$\mathrm{L}(\theta) = -\frac{nk}{2}\ln(2\pi) - \tfrac{1}{2}\sum_{t=1}^{n}\left(\ln|H_t| + \hat{\varepsilon}_t' H_t^{-1}\hat{\varepsilon}_t\right). \tag{12}$$

Conventional estimation methods in this literature often understate the effects of exchange rate variability on trade volumes because they fail to take into account the nonnormal properties of exchange rate changes (Arize, 1997).[10] Pagan and Sabau (1987) demonstrate that both efficiency and, in the case of maximum-likelihood estimation, consistency of parameter estimates require correct specification of that conditional distribution. We therefore test explicitly for nonnormality and, where appropriate, relax the usual multivariate normal distribution assumption to accommodate greater leptokurtosis using a multivariate Student-t distribution. With this assumption, the marginal

[9] The constant conditional correlation assumption simplifies computation and inference. Moreover, it has been proved reasonable in many previous applications (Baillie and Bollerslev, 1990; Kanas, 1998; Lien and Tse, 1998; Park and Switzer, 1995; Theodossiou and Lee, 1993; Tse and Tsui, 2002).

[10] Exchange rate change distributions typically exhibit leptokurtosis (heavy tails), as shown by Baillie and Bollerslev (1990), Baillie and DeGennaro (1990), Engle and Bollerslev (1986), Hsieh (1989), Milhϕj (1987), Wang et al. (2001), and Westerfield (1977).

distribution of each term is univariate Student-t, including the Cauchy and normal distribution as special cases. The degree of freedom parameter ($\nu > 2$) provides a measure of leptokurtosis. This attractive feature has induced several authors to apply the conditional-t distribution to model financial time-series data (Brooks, 1997; Mittnik and Paolella, 2000; Wang et al., 2001). We find that the substitution of a conditional heavy-tailed multivariate Student-t distribution for the conditional multivariate normal distribution helps improve the estimation performance when the data exhibit leptokurtosis. The likelihood function of the k-variate Student-t distribution with unknown ν degrees of freedom and n observations is given by:

$$(13) \qquad L(\theta) = \ln\left(\Gamma\left(\frac{\nu + k}{2}\right)\right) - \ln\left(\Gamma\left(\frac{\nu}{2}\right)\right) - \tfrac{1}{2}\ln((\nu - 2)\pi)$$
$$-\tfrac{1}{2}\sum_{t=1}^{n}\left(\ln|H_t| + (\nu + k)\ln\left(1 + \frac{\hat{\varepsilon}_t' H_t^{-1}\hat{\varepsilon}_t}{\nu - 2}\right)\right),$$

where Γ denotes the gamma function.

Estimation Results

We began estimation by identifying and estimating a common ARMA(m, n) process for the *DLRX* series following a three-step procedure proposed by Wang et al. (2001). First, Box-Jenkins iterative techniques are used to reduce the set of prospective ARMA specifications. Next, we further screen among the resulting candidate ARMA specifications to eliminate those having a p-value for the Ljung-Box portmanteau $Q(12)$ statistic less than 0.3, a significance level clearly supporting the assumption of white noise. Finally, from among the candidate models having passed the Box-Jenkins and $Q(12)$ screens, we chose the optimal conditional mean specification based on the Schwarz Bayesian criterion (SBC).

This procedure established that an AR(1) model best represents the conditional mean of the *DLRX* series in equation (1). Table 1 reports the estimated parameters and diagnostic checking of exchange rate equations. The Ljung-Box Q-statistic of residuals from the AR(1) process proved insignificant [$Q(12) = 7.33$, p-value $= 0.84$], signaling the absence of residual serial correlation. The squared residuals from the AR(1) process were then found to exhibit serial correlation ($Q = 29.14$, p-value $= 0.004$), indicating a need to accommodate time-varying conditional variance.

We then tested a variety of symmetric GARCH and asymmetric GJR-GARCH specifications. The diagnostic statistics for both the GARCH(1,1) and GJR-GARCH(1,1)[11] models (models 2 and 3) indicate no violation of the normality assumption (the p-values of the Jarque-Bera statistics were 0.81 and 0.77, respectively), and also show that models 2 and 3 successfully account for both first- and second-order serial dependence [the p-values of the $Q(12)$ statistics were 0.85 and 0.84, respectively, and the p-values of the $Q^2(12)$ statistics were 0.70 and 0.71, respectively]. Although both models fit the exchange rates process adequately, we opted for the more parsimonious GARCH(1,1)

[11] Other higher-order GARCH model processes such as GARCH(1, 2) or GARCH(2, 1) were examined and GARCH(1, 1) was found to be generally better on the model fit and parameter significance.

Table 1. Estimated Results and Diagnostic Checking of Exchange Rate Models

Description	Model 1[a]	Model 2[b]	Model 3[c]
Conditional Mean Equation:			
$\gamma_0 * 10^2$	0.100	0.100	0.100
	(0.100)	(0.100)	(0.100)
γ_1	0.41***	0.42***	0.41***
	(0.08)	(0.09)	(0.09)
Conditional Variance Equation:			
$w_0 * 10^4$		0.20**	0.19**
		(0.09)	(0.08)
α_1		0.15***	0.18**
		(0.07)	(0.09)
β_1		0.58***	0.60***
		(0.12)	(0.12)
η			0.08
			(0.09)
Model Diagnostic Checking:			
$Q(12)$	7.33	7.10	7.22
	[0.84]	[0.85]	[0.84]
$Q^2(12)$	29.14	9.10	8.91
	[0.004]	[0.70]	[0.71]
Skewness	0.09	0.03	0.05
	(0.24)	(0.24)	(0.24)
Kurtosis	2.82	2.71	2.67
	(0.47)	(0.47)	(0.47)
J-B	0.31	0.43	0.53
	[0.85]	[0.81]	[0.77]
LLH	−152.45	−149.27	−149.02
LR			0.50

Notes: Single, double, and triple asterisks (*) denote significance of a two-tailed test at the 0.10, 0.05, and 0.01 significance levels, respectively. Q and Q^2 represent the Ljung-Box test statistics up to 12th-order serial correlation for each series; p-values are reported in brackets. Skewness = coefficient of skewness; kurtosis = coefficient of kurtosis; the asymptotic standard errors of skewness and kurtosis are reported in parentheses and computed as $(6/\text{Obs})^{0.5}$ and $(24/\text{Obs})^{0.5}$, respectively, where Obs represents the number of observations. J-B = Jarque-Bera normality test statistic; LLH denotes the log-likelihood value; LR indicates the likelihood-ratio test for the null hypothesis of GJR-GARCH(1,1) vs. GARCH(1,1) specification.

[a] Model 1, AR(1): $DLRX_t = \gamma_0 + \gamma_1 DLRX_{t-1} + \varepsilon_{1,t}$.

[b] Model 2, AR(1)-GARCH(1,1): $DLRX_t = \gamma_0 + \gamma_1 DLRX_{t-1} + \varepsilon_{1,t}$; $h_t = w_0 + \alpha_1 \varepsilon^2_{1,t-1} + \beta_1 h_{t-1}$.

[c] Model 3, AR(1)-GJR-GARCH(1,1): $DLRX_t = \gamma_0 + \phi_1 DLRX_{t-1} + \varepsilon_{1,t}$;

$$h_t = w_0 + \alpha_1 \varepsilon^2_{1,t-1} + \beta_1 h_{t-1} + \eta S_{t-1} \varepsilon^2_{1,t-1},$$

where $S_t = 1$ if the exchange rate exhibits negative shock, and zero otherwise.

model because the estimated asymmetry parameter (η) of the GJR-GARCH model was not statistically significantly different from zero and, relatedly, a likelihood-ratio test indicated no statistically significant difference between the GJR-GARCH and the symmetric GARCH model.

Having thus determined the optimal specification of equations (1)–(4) in these data, we next determined the optimal lead structure for equations (5)–(7). The predicted exchange rates and exchange rate volatility generated from equations (5) and (6) were allowed to range from one to six months ahead for each industry. The expected exchange rate and exchange rate risk were jointly estimated with sector-specific export equations sequentially for different predicted leads based on the rational expectations multivariate GARCH-M model.[12] To accommodate the possibility of complex expectations formation based on multiple observations over time, we adopt an autoregressive distributed lead model. The multiple leads model allows a great deal of flexibility to consider explicitly the behavior of variables over time, which is critical to better describe the dynamic relationship and to improve the forecasting ability of relevant variables.

In order to conserve degrees of freedom and minimize inference problems associated with multicollinearity, we follow the general-to-simple (Hendry, 1995) selection procedure in which the significantly influential variables are chosen based on the AIC and SBC optimal criteria. Specifically, the selection procedure initially allowed up to six months' lag for U.S. industrial production variables and six-months-ahead prediction of both the exchange rate and its conditional variance. The approach ends with a parsimonious specification that retains as many variables as are necessary to satisfy all diagnostic regression tests such as Ljung-Box Q, Breusch-Godfrey (B-G) serial correlation, ARCH conditional heteroskedasticity, Jarque-Bera (J-B) normality, and Chow tests. In some cases insignificant variables are left in the model, such as the exchange rate risk variables, if the apparent lack of relationship is itself of our interest. We report White robust standard errors.

With the ARMA, GARCH, and lead/lag structures for equations (1)–(7) established, we then compared model performance. Table 2 reports the log-likelihood values, and AIC and SBC statistics of both models. The rational expectations-based, multivariate GARCH-M model can be compared with the traditional multivariate GARCH-M model based instead on *realized* exchange rates. This comparison validates the potential of using forward-looking exchange rate predictions to better proxy exporters' actual (but unobservable) expectations. The results clearly indicate the superiority of our MGARCH-M model in all except the textile and transportation sectors, for which the AIC, SBC, and log-likelihood results are statistically indistinguishable. This merely corroborates that agents are unable to observe realized exchange rates months in advance and that they act instead on expectations of exchange rates, if exchange rates really matter at all.

Accordingly, we now turn our attention to the results of the rational expectations-based MGARCH-M estimation. As one might expect, the parameter estimates show

[12] For each sector, the export volume, industrial production, estimated expected real exchange rate, and estimated conditional variance of the real exchange rate were all tested for stationarity and found to be integrated of order 1. We therefore used Johansen's multivariate cointegration method to check the number of cointegrating vectors for the nonstationary time series. Detailed results are omitted for the sake of brevity, but we found at least one cointegrating vector for each sectoral export volume-exchange rate system, clearly suggesting the existence of long-run equilibrium relationships among the export volume, foreign income, real exchange rate, and exchange rate volatility. Thus, the spurious regression problem associated with nonstationary data does not affect our estimation.

Table 2. Log-Likelihood Value Comparison of Multivariate GARCH-M Models Based on Realized and Forward-Looking Exchange Rates

	SECTOR							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Description	Agriculture	Textiles	Wood, Paper & Pulp	Chemicals	Metals	Optical & Precision Instruments	Electronic Machinery	Transportation
Rational Expectations-Based Multivariate GARCH-M (forward-looking exchange rate):								
LLH	−635.97	−600.01	−586.95	−538.40	−532.23	−529.24	−558.03	−557.38
AIC	−1,305.95	−1,234.03	−1,209.91	−1,112.81	−1,100.46	−1,096.48	−1,148.07	−1,144.77
SBC	−1,306.92	−1,235.13	−1,210.92	−1,113.83	−1,101.48	−1,097.56	−1,149.10	−1,185.94
Multivariate GARCH-M (realized exchange rate):								
LLH	−647.65	−600.63	−595.35	−541.51	−534.83	−531.81	−561.57	−556.17
AIC	−1,325.32	−1,233.27	−1,224.71	−1,117.03	−1,105.66	−1,101.62	−1,155.15	−1,142.36
SBC	−1,326.17	−1,234.30	−1,225.68	−1,118.00	−1,106.69	−1,102.70	−1,156.13	−1,143.27

Notes: LLH = log-likelihood, AIC = Akaike information criterion, and SBC = Schwarz Bayesian criterion.

considerable variability across sectors (table 3). Exports are significantly increasing in the conditional mean of the expected exchange rate (RX^e_{t-k2}) for all sectors except transportation. In most sectors, including agriculture, the one-period-ahead expected exchange rate has a positive and significant effect on exports. The positive exchange rate level effect has a longer lead for optical and precision instruments (three months) and electronic machinery (four months). Simply put, expected local currency depreciation (appreciation) stimulates expansion (contraction) in export volumes, consistent with the belief that traders contract based on expectations of the exchange rates that condition prices.

While the relevant horizon for exchange rate expectations varies across sectors, in these data, that horizon is three months or less for all sectors except electronic machinery. This is highly consistent with routine use of 90-day-ahead contracting or contract settlement terms in most sectors. The two- or three-month-ahead significant estimated negative impact of local currency depreciation and the one-month-ahead significant estimated positive impact on export volumes together suggest a whipsawing effect of exchange rate expectations on trade volumes. Since the changes of exchange rates not only affect the price of exports but are also an influential factor on cost of imported intermediate goods, the inconsistent exchange rate levels' impact might relate to the hypothesis that the effect of devaluation on trade depends on the elasticity of exports and imports (Marshall, 1923; Lerner, 1944). Note in particular that the estimated expected exchange rate effects are strongest in traditional, commodity-based sectors such as agriculture, with estimated coefficients on expected real exchange rates several times larger—at least twice and commonly five times larger—than coefficients estimated for other sectors and consistently significant at the 1% level. This underscores the relative elasticity of agricultural exports with respect to expected exchange rates, consistent with Bordo (1980) and Frankel (1992), who argue that agricultural prices and trade flows react with greater magnitude and speed to exchange rate changes than do manufactured goods sectors.

By way of contrast, we also estimated the traditional multivariate GARCH-M method using realized exchange rates instead of expected exchange rates and making the standard assumption that the contemporaneous conditional variance suffices to represent all

Table 3. FIML Estimates of Sector-Specific Rational Expectations-Based Multivariate GARCH-M Model

	SECTOR				
		[1]	[2]	[3]	[4]
Variables/Leads	Agriculture*	Agriculture	Textiles	Wood, Paper & Pulp	Chemicals
Export Equation Parameters:					
δ_0	3.5053**	3.3053**	3.4244***	13.6271***	3.0668***
	(1.5451)	(1.4195)	(0.9708)	(1.8590)	(0.7878)
$\delta_{1,1}(IP_{t-1})$	2.6991***	2.5029***		3.3993***	
	(0.8981)	(0.8663)		(0.7021)	
$\delta_{1,2}(IP_{t-2})$					1.2504***
					(0.4486)
$\delta_{1,3}(IP_{t-3})$			−2.1018***	−2.3267***	
			(0.5149)	(0.5905)	
$\delta_{1,4}(IP_{t-4})$	−2.6333**	−2.2755*	1.6925***		
	(1.1659)	(1.1917)	(0.5623)		
$\delta_{1,5}(IP_{t-5})$					
$\delta_{1,6}(IP_{t-6})$				−2.6345***	−1.1862***
				(0.5132)	(0.4056)
$\delta_{2,1}(RX^e_{t-1})$	9.1698***	10.0611***	1.9806***	4.2264***	1.6658***
	(3.3266)	(3.9568)	(0.6653)	(0.6348)	(0.6415)
$\delta_{2,2}(RX^e_{t-2})$				−6.2244***	
				(1.4009)	
$\delta_{2,3}(RX^e_{t-3})$	−13.5961***	−12.4315***	−2.1515***		−2.5038***
	(4.9343)	(4.4232)	(0.8457)		(0.8635)
$\delta_{2,4}(RX^e_{t-4})$					
$\delta_{2,5}(RX^e_{t-5})$					
$\delta_{2,6}(RX^e_{t-6})$					
$\delta_{3,1}(h^e_{t-1})$	−1.0538***	−2.2044**			
	(0.1075)	(1.1003)			
$\delta_{3,2}(h^e_{t-2})$				0.2029	
				(0.6896)	
$\delta_{3,3}(h^e_{t-3})$			−0.0724		0.0182
			(0.1019)		(0.0867)
$\delta_{3,4}(h^e_{t-4})$					
$\delta_{3,5}(h^e_{t-5})$					
$\delta_{3,6}(h^e_{t-6})$					
$\delta_{4,1}(D_{1,t})$	−0.0257	−0.0477	−0.1040**	−0.1290***	0.0765**
	(0.0600)	(0.0588)	(0.0431)	(0.0432)	(0.0310)
$\delta_{4,2}(D_{2,t})$	0.1408***	0.1388***	0.0174***	0.0521*	0.1201***
	(0.0551)	(0.0541)	(0.0438)	(0.0302)	(0.0199)
$\delta_{4,3}(D_{3,t})$	0.0691**	0.0815	0.0251***	0.3294***	0.0118***
	(0.0339)	(0.0576)	(0.0284)	(0.0368)	(0.0178)

(continued . . .)

Table 3. Extended

	SECTOR			
	[5]	[6]	[7]	[8]
Variables/Leads	Metals	Optical & Precision Instruments	Electronic Machinery	Transportation
Export Equation Parameters:				
δ_0	−5.0530*** (0.8464)	−7.4254*** (1.2987)	−12.3762*** (1.7438)	−1.1717** (0.5478)
$\delta_{1,1}(IP_{t-1})$		1.1980*** (0.3418)		
$\delta_{1,2}(IP_{t-2})$	2.0603*** (0.3742)	1.6414*** (0.4325)	2.3772*** (0.4726)	1.5843*** (0.4358)
$\delta_{1,3}(IP_{t-3})$				−1.3955*** (0.3743)
$\delta_{1,4}(IP_{t-4})$			−1.0798* (0.4617)	
$\delta_{1,5}(IP_{t-5})$				
$\delta_{1,6}(IP_{t-6})$	−1.7796*** (0.4121)	−1.9247*** (0.3989)		
$\delta_{2,1}(RX^e_{t-1})$	1.2936*** (0.3234)			3.8366 (3.9282)
$\delta_{2,2}(RX^e_{t-2})$				
$\delta_{2,3}(RX^e_{t-3})$		1.2656* (0.6772)		
$\delta_{2,4}(RX^e_{t-4})$			2.5243*** (0.6052)	
$\delta_{2,5}(RX^e_{t-5})$				
$\delta_{2,6}(RX^e_{t-6})$				
$\delta_{3,1}(h^e_{t-1})$	0.0025 (0.0468)			
$\delta_{3,2}(h^e_{t-2})$		0.0030 (0.1097)		0.0367 (0.0493)
$\delta_{3,3}(h^e_{t-3})$				
$\delta_{3,4}(h^e_{t-4})$			0.1568 (0.0965)	
$\delta_{3,5}(h^e_{t-5})$				
$\delta_{3,6}(h^e_{t-6})$				
$\delta_{4,1}(D_{1,t})$	−0.0805*** (0.0285)	0.0398 (0.0310)	−0.0651** (0.0306)	−0.0842*** (0.0283)
$\delta_{4,2}(D_{2,t})$	0.0171*** (0.0249)	0.1157*** (0.0237)	−0.0109 (0.0207)	0.0053 (0.0208)
$\delta_{4,3}(D_{3,t})$	0.0138*** (0.0216)	0.0110*** (0.0204)	0.0234 (0.0213)	0.0040 (0.0193)

(continued . . .)

Table 3. Continued

		SECTOR			
		[1]	[2]	[3]	[4]
Variables/Leads	Agriculture*	Agriculture	Textiles	Wood, Paper & Pulp	Chemicals
Export Equation Parameters (cont'd):					
$\delta_{5,1}(Q_{t-1})$					
$\delta_{5,2}(Q_{t-2})$			0.4118***		0.2121***
			(0.0921)		(0.0822)
$\delta_{5,3}(Q_{t-3})$					0.2322***
					(0.0916)
$\delta_{5,4}(Q_{t-4})$			0.1997***		
			(0.0674)		
$\delta_{5,5}(Q_{t-5})$					
$\delta_{5,6}(Q_{t-6})$					
Exchange Rate Equation Parameters:					
Conditional Mean:					
$\gamma_0 * 10^2$	0.1152	0.1200	0.1300*	0.1269*	0.1194
	(0.0781)	(0.0763)	(0.0754)	(0.0760)	(0.0763)
ϕ_1	0.3987***	0.4041***	0.3832***	0.3925***	0.4103***
	(0.0965)	(0.0937)	(0.0894)	(0.0918)	(0.0935)
Conditional Variance:					
$w_0 * 10^4$	0.1745**	0.1870**	0.1881**	0.1898**	0.1911**
	(0.0870)	(0.0827)	(0.0857)	(0.0817)	(0.0832)
α	0.1586**	0.1508**	0.1474**	0.1467**	0.1514**
	(0.0801)	(0.0730)	(0.0734)	(0.0721)	(0.0734)
β	0.6221***	0.5943***	0.5933***	0.5929***	0.5879***
	(0.1266)	(0.1220)	(0.1268)	(0.1143)	(0.1217)
Variance-Covariance Parameters:					
σ_{22}	324.8317***	339.4875***	149.8393***	151.4887***	61.2676***
	(123.3400)	(115.6720)	(18.8867)	(27.7986)	(9.6061)
ρ	0.1630**	0.1676*	0.0213	0.2288**	−0.0177
	(0.0806)	(0.0935)	(0.0874)	(0.1024)	(0.0946)
Shape Parameter:					
ν	10.0484**				
	(4.5356)				

Notes: Single, double, and triple asterisks (*) denote significance of a two-tailed test at the 0.10, 0.05, and 0.01 significance levels, respectively. The sector denoted "Agriculture*" reflects estimates from the rational expected multivariate GARCH-M model based on a multivariate Student-*t* distribution, while sectors [1]–[8] use a multivariate normal distribution.

The GARCH-M Model:

$$\mathrm{Ln}(Q_{i,t}) = \delta_0 + \sum_{k1=1}^{6} \delta_{1,k1} \ln(IP_{t-k1}) + \sum_{k2=1}^{6} \delta_{2,k2} \ln(RX^e_{i,t-k2}) + \sum_{k3=1}^{6} \delta_{3,k3} \ln(h^e_{i,t-k3}) + \sum_{k4=1}^{3} \delta_{4,k4} D_{k4,t} + \sum_{k5=1}^{6} \delta_{5,k5} \ln(Q_{i,t-k5}) + \varepsilon_{2i,t};$$

$$DLRX_t = \gamma_0 + \phi_1 DLRX_{t-1} + \varepsilon_{1,t}; \qquad h_t = w_0 + \alpha_1 \varepsilon^2_{1,t-1} + \beta_1 h_{t-1};$$

$$DLRX^e_t = \gamma_0 \sum_{i=0}^{k2-1} \phi_1^i + \phi_1^k DLRX_{t-k}; \qquad h^e_t = w_0 \sum_{i=0}^{k2-1} \beta_1^i + \alpha_1 \beta_1^{k-1} \varepsilon^2_{1,t-k2} + \beta_1^k h_{t-k}.$$

Table 3. Extended / Continued

	SECTOR			
	[5]	[6]	[7]	[8]
Variables/Leads	Metals	Optical & Precision Instruments	Electronic Machinery	Transportation
Export Equation Parameters (cont'd):				
$\delta_{5,1}(Q_{t-1})$	−0.3583***	−0.2466***		
	(0.0805)	(0.0771)		
$\delta_{5,2}(Q_{t-2})$		0.1576**	0.3010***	
		(0.0754)	(0.1011)	
$\delta_{5,3}(Q_{t-3})$	0.1787***	0.2456***		
	(0.0686)	(0.0781)		
$\delta_{5,4}(Q_{t-4})$	0.1690***			
	(0.0614)			
$\delta_{5,5}(Q_{t-5})$				
$\delta_{5,6}(Q_{t-6})$				
Exchange Rate Equation Parameters:				
Conditional Mean:				
$\gamma_0 \cdot 10^2$	0.1250	0.1201	0.1300*	0.1189
	(0.0769)	(0.0763)	(0.0754)	(0.0754)
ϕ_1	0.3827***	0.4098***	0.3812***	0.4037***
	(0.0945)	(0.0925)	(0.0887)	(0.0917)
Conditional Variance:				
$w_0 \cdot 10^4$	0.1696**	0.1905**	0.1895**	0.1860**
	(0.0836)	(0.0834)	(0.0865)	(0.0814)
α	0.1520**	0.1516**	0.1459**	0.1504**
	(0.0701)	(0.0733)	(0.0733)	(0.0708)
β	0.6186***	0.5886***	0.5927***	0.5937***
	(0.1288)	(0.1217)	(0.1277)	(0.1177)
Variance-Covariance Parameters:				
σ_{22}	57.7661***	52.2243***	76.1810***	78.8798***
	(7.3245)	(8.2761)	(10.6029)	(10.0920)
ρ	−0.2223***	−0.0366	−0.0393	0.0357
	(0.0906)	(0.0883)	(0.0968)	(0.1139)

the lags/leads of exchange rate risk. This model is statistically inferior to the specification reported in table 3, but except for the exchange rate regressors, generates coefficient estimates statistically quite similar to those in table 3. The estimated impacts of exchange rates and exchange rate risk on trade are sharply different under this approach, however. As shown in appendix table A1, the more traditional approach finds at most one statistically significant lead for all sectors, suggesting less high-frequency volatility than our approach does.[13] The traditional approach using realized exchange

[13] In order to identify the source of the differences between the estimation results reported in text table 3 and appendix table A1, we reestimated the model imposing exactly the same specification, so that the only difference was due to the use of realized rather than predicted exchange rates data. As one might expect, the results then appear much closer to those reported in table 3, although they remain statistically significantly different. Thus the differences between the two tables appear attributable primarily to the changed specification induced by following Hendry's method of model reduction to determine the optimal lag specifications for both $RX^e_{i,t-k2}$ and $h^e_{i,t-k3}$. We thank an anonymous reviewer for encouraging us to explore this difference more carefully.

rates data also estimates substantially weaker trade volume responses to exchange rates in most sectors. This is especially true for agriculture, which no longer appears most responsive. This finding underscores the importance of the choice as to how to represent exchange rates and exchange rate risk and how specification choice implies a process by which traders form expectations. The standard approach using fulfilled expectations based on realized exchange rates and only contemporaneous exchange rate risk is not only conceptually implausible, but it dampens the intersectoral differences, especially the responsiveness of Taiwanese agricultural exports to exchange rate fluctuations. With the exception of anomalous negative and statistically significant estimates for textiles and wood, paper, and pulp,[14] the sum of the coefficients of industrial production is positive for all sectors. This implies export volumes respond positively and significantly to increases in the United States' industrial production. Specifically, although the impact of U.S. income on Taiwan's agricultural exports is statistically significant for one- and four-month lags, the sum of the coefficients is relatively lower, implying less income elasticity in agricultural sectors. The sum of estimated income elasticity of export volumes is highest in the electronics sector, at 1.2974, an order of magnitude larger than that of agricultural exports at 0.1274. This confirms one's intuition about relative income elasticities of demand in the United States for electronics versus agricultural products. Comparing the statistically significant lead/lag structures across variables, traders appear to respond more quickly to changes in expected exchange rates than to changes in U.S. incomes, as proxied by industrial production.

The individual coefficient estimates on particular lagged values of U.S. industrial production or the real exchange rate capture only short-term movements. In long-run equilibrium, if the coefficients of the various lags sum to zero, then change rather than levels matters. We therefore investigate the overall responsiveness of exports with respect to expected exchange rates and industrial production for each sector by testing the null hypothesis that the sum of coefficients equals zero.[15] Table 4 reports the likelihood-ratio test statistics (and associated p-values) for the null hypotheses that the sum of coefficients of expected exchange rates and of industrial production equals zero. The likelihood-ratio test rejects that null with respect to the conditional mean of the expected exchange rate for all sectors except textiles and transportation, and with respect to industrial production for all sectors except agriculture, textiles, and transportation. These findings generally confirm that export volumes tend to respond significantly to increases in the expected real exchange rate and to U.S. industrial production. But the opposing signs of many of the parameter estimates signal that the short-run effect of changes is far greater than the longer-run effect of levels.

Of primary interest to us, the estimated effects of expected exchange rate volatility on trade prove statistically small and insignificantly different from zero in seven of eight sectors. Our result is consistent with Tenreyro's (2004) recent findings that, after taking account of potential estimation problems, exchange rate fluctuations do not seem to affect most trade significantly. There are several likely reasons why exchange rate risk

[14] As panels B and C of figure 3 show, export volumes consistently declined in the two anomalous sectors over the sample period as increasing labor costs, rising land prices, and stricter environmental protection laws forced many Taiwanese textile and wood, paper, and pulp firms to shut down or relocate abroad, primarily to mainland China and Southeast Asia. The negative estimated coefficient on U.S. industrial production therefore most likely reflects induced structural change for which the current specification does not control satisfactorily.

[15] In comparison to the individual t-tests on each parameter estimate, one added benefit of the joint significance test is to simultaneously make allowance for correlation among parameter estimates.

Table 4. Likelihood-Ratio Test Statistics for the Restriction that the Sum of Coefficients Equals Zero

	SECTOR							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Description	Agriculture	Textiles	Wood, Paper & Pulp	Chemicals	Metals	Optical & Precision Instruments	Electronic Machinery	Transportation
LLH_U	−635.97	−600.01	−586.95	−538.40	−532.23	−529.24	−558.03	−557.38
LLH_R^{RX}	−657.76	−600.05	−606.38	−539.82	−538.98	−532.47	−569.59	−557.87
LLH_R^{IP}	−635.98	−600.57	−605.11	−542.92	−550.50	−533.48	−563.92	−557.71
LR^{RX}	43.58	0.08	38.86	2.84	13.50	6.46	23.12	0.98
	[0.00]	[0.77]	[0.00]	[0.09]	[0.00]	[0.01]	[0.00]	[0.32]
LR^{IP}	0.02	1.12	36.32	9.04	36.54	8.48	11.78	0.66
	[0.88]	[0.29]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.42]

Notes: LLH_U represents the log-likelihood values for each unrestricted regression, as reported in table 3; LLH_R^{RX} and LLH_R^{IP} report the log-likelihood values for the restricted regression imposing the sum of coefficients of expected exchange rates and of industrial production equal zero, respectively; LR^{RX} and LR^{IP} report the likelihood-ratio test statistics (and associated p-values in brackets) for the null hypotheses that the sum of coefficients of expected exchange rates and of industrial production equal zero, respectively.

seems to have little effect on Taiwanese exports. First, long-standing business relations between many American and Taiwanese trading partners include arrangements to help eliminate exchange rate risk, such as open account agreements, especially for intra-firm trade between divisions of multinational firms, a widespread phenomenon in Taiwan, particularly in the transportation and high technology sectors (e.g., electronics and optical and precision instruments).

Second, Taiwan's Central Bank holds unusually large foreign exchange reserves—the second largest in the world on average over the sample period, behind only Japan—and it routinely uses its reserves to stabilize the exchange rate. Taiwanese exporters therefore likely expect the Central Bank to be able and willing to intervene in currency markets if fluctuations become excessive, effectively providing exporters with insurance and perhaps making it somewhat easier for firms to predict exchange rate movements. The state and the banking sector have also long had close relations with large, capital-intensive firms in the nonagricultural sectors, and are reasonably likely to help provide information and financial services necessary for those firms to manage exchange rate risk inexpensively and reliably.

However, Taiwan's agricultural exports appear to respond quite negatively and statistically significantly to expected exchange rate volatility. This is consistent with both an extant literature which argues that the agricultural sector is most susceptible to exchange rate uncertainty (Anderson and Garcia, 1989; Cho, Sheldon, and McCorriston, 2002; Maskus, 1986; Pick, 1990) and with empirical evidence that Pacific Basin agricultural markets of importance to Taiwan are highly competitive in terms of price (Barrett, Li, and Bailey, 1999; Barrett and Li, 2002). Agriculture differs from the other sectors.[16]

[16] An anonymous reviewer suggested a robustness test, given that FIML can perform poorly in misspecified models. Toward that end, we reestimated the model from agricultural trade, this time using a two-step estimator—first estimating the AR(1)-GARCH(1,1) exchange rate process, then estimating the trade equation—because the two-step estimator is consistent and more robust to misspecification, albeit less efficient than FIML when the latter is properly specified. The two-step OLS estimation results are quite consistent with the FIML estimates we report here: agricultural exports appear to respond negatively and statistically significantly to expected exchange rate volatility. (Detailed results of the two-step estimation are available from the authors by request.)

There are at least two likely explanations for Taiwanese agriculture's sensitivity to exchange rate volatility. First, Taiwan's agricultural exports are relatively import intensive, depending on considerable imports of farm inputs such as fertilizer, pesticides, and animal feeds (for both aquaculture and livestock) from the United States, which account for more than 30% of Taiwan's agricultural import demand. Given heavy reliance on imported intermediate inputs in those agricultural subsectors that account for most of Taiwan's exports to the United States (Liu, 2001), exchange rate instability thus discourages agricultural production and trade by causing volatility in both the cost of inputs and in expected export revenues.

Second, Taiwan's agriculture relies heavily on small-scale farming and agribusinesses, with average farm size around one hectare and relatively little capital, as compared to its trading partners, and intensely competitive, with low average profit margins (Liu, 2001). These firms operate in a low-margin, highly competitive environment and are likely more reluctant than large industrial firms to manage exchange rate risk through hedging instruments in the futures or forward markets, both because of the high cost associated with these transactions and specific requirements on farm credit, as well as availability of skilled human capital for such sophisticated management. In addition, although forward/futures markets exist in Taiwan's currency markets, periodic exchange rate interventions by the Central Bank of Taiwan also limit the ability of farmers to cover the foreign exchange position (Pick, 1990; Anderson and Garcia, 1989). Moreover, the Taiwanese dollar is not actively traded in either the forward or futures markets, and it has been argued that hedging exchange rate risk via futures/forward markets in less developed countries is costly and relatively ineffective (Arize, Osang, and Slottje, 2000; Doroodian, 1999). Taiwan's farmers and agribusinesses appear to have limited ability to absorb temporary losses associated with low passthrough of exchange rate changes to the export markets, and thus export volumes are dampened by exchange rate volatility.

Our estimation results strongly support the hypothesis that agricultural trade volumes exhibit an unusually high degree of sensitivity to exchange rate uncertainty, far more than in other sectors; indeed, this effect emerges only in agriculture in the Taiwan-U.S. trade flow data we study. This suggests a possible role for policy mechanisms to help farmers and agricultural commodity exporters hedge currency risk in the marketing system (Adubi and Okunmadewa, 1999). Our results reinforce the existing literature implying that policy to stabilize agricultural markets must pay attention not only to agricultural sectoral policy, but also to macroeconomic policies that affect real exchange rate levels and volatility.

Returning to the parameter estimates reported in table 3, there are strong seasonality effects evident in each sector's $D_{1,t}$ –$D_{3,t}$ parameter estimates. Several sectors—but not agriculture—likewise exhibit significant autoregression. The exchange rate series indeed exhibit significant ARCH and GARCH effects, as reflected in the coefficient estimates for α and β in the conditional variance equation. The estimated variance (σ_{22}) of exports in agriculture, textiles, and wood, paper, and pulp were substantially higher than those of the other five sectors, with the estimated variance of exports from the latter two sectors roughly double those of the other sectors, and the variance of agricultural exports more than four times that of the higher technology manufactured goods and services sectors. Most of the estimated cross-equation correlation parameters (ρ) were statistically insignificantly different from zero, with the exception, again, of agriculture, along with wood, paper, and pulp, and metals.

Table 5. Diagnostic Test Statistics on Sector-Specific Export Volume Equations

	SECTOR							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Description	Agriculture	Textiles	Wood, Paper & Pulp	Chemicals	Metals	Optical & Precision Instruments	Electronic Machinery	Transportation
Mean	0.0016	0.0021	0.0022	0.0038	0.0041	0.0040	0.0031	0.0047
Std. Dev.	0.0976	0.0778	0.1053	0.0936	0.1117	0.0939	0.0782	0.0840
Skewness	0.1617	0.0722	0.0704	0.1106	0.1140	0.1198	0.1037	0.0983
Kurtosis	5.0079	2.8433	2.9571	2.9363	2.9694	2.9368	2.8446	2.8729
$Q(12)$	7.7121	9.1629	7.7547	7.7066	7.8236	7.7066	9.1638	8.8362
	[0.8070]	[0.6890]	[0.8040]	[0.8080]	[0.7990]	[0.8080]	[0.6890]	[0.7170]
$Q^2(12)$	9.3332	9.9458	9.4646	9.2617	9.5704	9.2671	9.9550	9.5317
	[0.6740]	[0.6210]	[0.6630]	[0.6800]	[0.6540]	[0.6800]	[0.6200]	[0.6570]
B-G	1.0154	0.9801	1.0219	1.0144	1.0456	1.0215	0.9803	0.9461
	[0.4192]	[0.4422]	[0.4150]	[0.4199]	[0.3549]	[0.3633]	[0.4421]	[0.4654]
ARCH	0.1906	0.1319	0.1884	0.1963	0.1835	0.1961	0.1337	0.1667
	[0.6632]	[0.7170]	[0.6642]	[0.6576]	[0.6683]	[0.6578]	[0.7145]	[0.6829]
J-B	19.649	0.2318	0.2197	0.1857	0.2418	0.1865	0.2309	0.2110
	[0.0001]	[0.8905]	[0.8959]	[0.9112]	[0.8860]	[0.9109]	[0.8909]	[0.8998]
Chow	0.4203	0.3249	0.4340	0.4132	0.5900	0.5380	0.4783	0.2413
	[0.5180]	[0.5697]	[0.5113]	[0.5216]	[0.4440]	[0.4647]	[0.4905]	[0.6242]

Notes: Numbers in brackets are p-values; Q and Q^2 indicate the Ljung-Box portmanteau test statistics on the residuals and square residuals; B-G is the Breusch-Godfrey serial correlation test statistic; ARCH is the White test statistic for autoregressive conditional heteroskedasticity; J-B is the Jarque-Bera normality test statistic for skewness and excess kurtosis; and Chow is the Chow stability test statistic.

Table 5 reports a battery of diagnostic test statistics from these regressions. The results generally confirm the satisfactory specification of each sectoral multivariate GARCH-in-mean model, as reflected in goodness of fit, and various tests for serial correlation (Ljung-Box Q and B-G) in the residuals and squared residuals, for residual heteroskedasticity or ARCH effects, and for normality and structural stability.[17]

The only significant failure of the multivariate normal GARCH-in-mean model seems to be the evident nonnormality of the residuals in the model for the agricultural sector, where the risk-trade effect was most pronounced. Since nonnormality corrupts inference with respect to this parameter estimate of primary interest, we reestimated the model using the multivariate Student-t distribution for the error term. Table 5 indicates that excess kurtosis was the main source of nonnormality, and the Student-t distribution directly accommodates leptokurtosis. The parameter estimates under the multivariate Student-t GARCH-M model for the agriculture sector are presented in the leftmost column of table 3, as "Agriculture*". Where the multivariate normal model estimates an elasticity of agricultural exports with respect to expected exchange rate volatility of −2.2044, controlling for apparent leptokurtosis drops that point estimate to −1.0538. Exchange rate volatility still seems to exert a considerable, statistically significantly negative effect on agricultural exports—and not on exports from any other sectors in

[17] Although the Chow test indicates that the estimated parameters of the metals sector model are not constant over the full range of the data (we used a breakpoint in the middle of the sample), subsample-specific parameter estimates yielded qualitatively identical estimates, in particular that exchange rate risk has no significant effect on metals exports.

Taiwan's economy—but the effects are plainly exaggerated by misspecification of the multivariate error term distribution. The superiority of the multivariate Student-t distribution in capturing leptokurtosis is evident in both the lower estimated degrees-of-freedom parameter ($v = 10.0484$) and in the likelihood-ratio test statistics for "Agriculture*". The likelihood-ratio test statistic for the multivariate Student-t distribution against multivariate normal distribution is $4.08(= (-633.93 - 635.97) * 2)$, suggesting the accommodation of leptokurtosis indeed yields modest but statistically significant gains in model performance. We remind readers that the exchange rate data used here do not exhibit leptokurtosis, so these effects are almost surely dampened in this sample. Since leptokurtosis has been commonly observed in exchange rate data, the multivariate Student-t GARCH-M model could offer significant improvements in other samples.

Conclusions

This paper explored the impact of the conditional mean and conditional variance of real exchange rates on Taiwan's exports by estimating an innovative rational expectations-based multivariate GARCH-M model using sector- and destination-specific monthly data. By using more disaggregated data and attending to a variety of econometric issues that bedevil much of the extant literature on this high-profile issue, we offer a new look at this long-standing question.

Our approach and results underscore the importance of the choices of how to represent exchange rate risk, of the data frequency one employs in analysis, and of specification choice to correspond with the process by which one hypothesizes traders form expectations about variables that remain uncertain at the moment of contract execution. We find considerable variation among sectors. Our estimates consistently indicate the change in expected exchange rate as well as change in industrial production jointly drive trade volumes. Further, while exchange rate and industrial production levels matter to trade volumes in long-run equilibrium, high-frequency changes in those variables have the strongest short-term effects and traders appear to respond more quickly to changes in expected exchange rates than to changes in U.S. industrial production.

Our most striking finding is that agricultural trade flows are quite significantly negatively affected by high frequency exchange rate volatility that does not seem to impact other sectors significantly. Agriculture appears far more responsive to both expected exchange rates and to expected volatility in the exchange rate, and less responsive to importer incomes, than do other sectors in Taiwan's economy. Even in the agricultural sector, however, our results show that failure to attend to issues of nonnormality in the regression residuals seems to lead to substantial overstatement of the negative effect of exchange rate risk on trade flows and that the effects of expected exchange rate levels on export volumes are a complex mix of negative and positive effects over months.

These results highlight the importance of both continued further disaggregated exploration of this long-standing question and of the need for more careful theoretical and empirical work on the processes by which farmers and agribusinesses form expectations over the profitability of production and trade decisions, the timing of such decisions, and what these processes mean for the design and implementation of policies to help stimulate international agricultural trade. As we point out, agriculture differs in fundamental ways from other export sectors in Taiwan; it is based on very small firms that depend heavily on imported intermediate inputs and that frequently suffer liquidity constraints in a highly competitive, low-margin industry which receives relatively little support from government. Intuitively, these features of Taiwan's agricultural economy may account for the anomalous (relative to other sectors) effect of exchange rate volatility on agricultural export volumes.

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Table A1. The Estimated Parameters of the Multivariate GARCH-M Model Based on the Realized Exchange Rate

	SECTOR							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Variables/Leads	Agriculture	Textiles	Wood, Paper & Pulp	Chemicals	Metals	Optical & Precis. Instruments	Electronic Machinery	Transportation
Export Equation Parameters:								
δ_0	-1.9967**	2.6449***	8.3141***	1.3108**	-3.9528***	-5.7746***	-9.2011***	-1.1175***
	(0.9926)	(0.7403)	(0.8981)	(0.5342)	(0.7974)	(0.9764)	(1.3575)	(0.4549)
$\delta_{1,1}(IP_{t-1})$			3.0151***			1.5398***		
			(0.7023)			(0.3220)		
$\delta_{1,2}(IP_{t-2})$					2.3633***	1.8147***	3.1682***	1.5658***
					(0.3753)	(0.4155)	(0.4739)	(0.4195)
$\delta_{1,3}(IP_{t-3})$	-3.2241***	-2.2842***	-2.9125***					-1.3430***
	(0.6718)	(0.4871)	(0.5598)					(0.3664)
$\delta_{1,4}(IP_{t-4})$		1.4384***					-1.1729**	
		(0.5047)					(0.4678)	
$\delta_{1,5}(IP_{t-5})$								
$\delta_{1,6}(IP_{t-6})$			-2.8759***	-1.1767***	-1.7308***	-2.0518***		
			(0.5456)	(0.4003)	(0.3989)	(0.3818)		
$\delta_{2,1}(RX_{t-1})$	1.5319***				4.6364***			
	(0.3683)				(1.6093)			
$\delta_{2,2}(RX_{t-2})$		0.6852***	1.2760***	0.4837**				0.3104*
		(0.2607)	(0.2772)	(0.2139)				(0.1748)
$\delta_{2,3}(RX_{t-3})$						0.1976		
						(0.1374)		
$\delta_{2,4}(RX_{t-4})$								
$\delta_{2,5}(RX_{t-5})$							0.4699***	
							(0.1697)	
$\delta_{2,6}(RX_{t-6})$								
$\delta_3(h_t)$	-1.5365**	0.0563	0.1072	0.4834	0.0511	-0.2244	-0.2576	0.2942
	(0.6757)	(0.5158)	(0.1096)	(0.5411)	(0.5182)	(0.4995)	(0.5802)	(0.3710)

(continued . . .)

Table A1. Continued

	SECTOR							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Variables/Leads	Agriculture	Textiles	Wood, Paper & Pulp	Chemicals	Metals	Optical & Precis. Instruments	Electronic Machinery	Transportation
Export Equation Parameters (cont'd.):								
$\delta_{4,1}(D_{1,t})$	−0.0556	−0.0109**	−0.1955***	0.0629**	−0.0833***	0.0455	−0.0670**	−0.0834**
	(0.0426)	(0.0435)	(0.0438)	(0.0312)	(0.0206)	(0.0318)	(0.0337)	(0.0287)
$\delta_{4,2}(D_{2,t})$	0.1886***	0.1647***	0.0418	0.1022***	0.0401***	0.1403***	0.0313	0.0069
	(0.0593)	(0.0444)	(0.0360)	(0.0225)	(0.0069)	(0.0222)	(0.0218)	(0.0205)
$\delta_{4,3}(D_{3,t})$	0.0601	0.2413***	0.3496***	0.0993***	0.0381***	0.1209***	0.0245	0.0054
	(0.0523)	(0.0263)	(0.0393)	(0.0184)	(0.0075)	(0.0204)	(0.0203)	(0.0190)
$\delta_{5,1}(Q_{t-1})$					−0.0942***	−0.2117***		
					(0.0295)	(0.0756)		
$\delta_{5,2}(Q_{t-2})$		0.4278*		0.2534***		0.1821**	0.4282***	
		(0.0936)		(0.0803)		(0.0726)	(0.0895)	
$\delta_{5,3}(Q_{t-3})$				0.3204***	0.1844***	0.2719***		
				(0.0887)	(0.0254)	(0.0764)		
$\delta_{5,4}(Q_{t-4})$					0.1462***			
					(0.0228)			
$\delta_{5,5}(Q_{t-5})$			0.1725***					
			(0.0619)					
$\delta_{5,6}(Q_{t-6})$								
Exchange Rate Equation Parameters:								
Conditional Mean:								
$\gamma_0 * 10^2$	0.1200	0.1300*	0.1027	0.1177	0.1293	0.1206	0.1113	0.1157
	(0.0782)	(0.0757)	(0.0796)	(0.0737)	(0.0867)	(0.0780)	(0.0778)	(0.0739)
ϕ_1	0.4135***	0.3815***	0.3839***	0.4352***	0.3770***	0.4075***	0.4127***	0.3933***
	(0.0919)	(0.0892)	(0.1061)	(0.1013)	(0.0969)	(0.0942)	(0.1021)	(0.0942)

(continued . . .)

Table A1. Continued

	SECTOR							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Variables/Leads	Agriculture	Textiles	Wood, Paper & Pulp	Chemicals	Metals	Optical & Precis. Instruments	Electronic Machinery	Transportation
Conditional Variance:								
$w_0 * 10^4$	0.2017*	0.1871*	0.1754**	0.1947**	0.1620**	0.1871**	0.1846**	0.1932*
	(0.1169)	(0.0848)	(0.0845)	(0.0809)	(0.0822)	(0.0839)	(0.0776)	(0.1058)
α	0.1563**	0.1475**	0.1376**	0.1502**	0.1512**	0.1509**	0.1451**	0.1543**
	(0.0773)	(0.0746)	(0.0613)	(0.0697)	(0.0727)	(0.0747)	(0.0669)	(0.0783)
β	0.5692***	0.5942***	0.6092***	0.5788***	0.6304***	0.5942***	0.6003***	0.5796***
	(0.1734)	(0.1259)	(0.2156)	(0.2153)	(0.1835)	(0.1626)	(0.1079)	(0.1676)
Variance-Covariance Parameters:								
σ_{22}	416.5798***	151.5159***	178.1996***	64.6474***	61.3033***	54.7595***	85.0582***	77.2556***
	(73.1124)	(19.1780)	(27.2987)	(7.7167)	(7.7456)	(8.2467)	(11.9020)	(10.0577)
ρ	0.1501*	0.0295	0.2618***	0.0009	-0.2509***	-0.0605	-0.0623	0.0412
	(0.0886)	(0.0879)	(0.1002)	(0.0863)	(0.0880)	(0.0888)	(0.1004)	(0.1155)

Note: Single, double, and triple asterisks (*) denote significance of a two-tailed test at the 0.10, 0.05, and 0.01 significance levels, respectively.

The GARCH-M Model:

$$\mathrm{Ln}(Q_{i,t}) = \delta_0 + \sum_{k1=1}^{6} \delta_{1,k1} \ln(IP_{i,t-k1}) + \sum_{k2=1}^{6} \delta_{2,k2} \ln(RX_{i,t-k2}) + \delta_3 \ln(h_{i,t}) + \sum_{k4=1}^{3} \delta_{4,k4} D_{k4,t} + \sum_{k5=1}^{6} \delta_{5,k5} \ln(Q_{i,t-k5}) + \varepsilon_{2i,t};$$

$$DLRX_t = \gamma_0 + \phi_1 DLRX_{t-1} + \varepsilon_{1,t};$$

$$h_t = w_0 + \alpha_1 \varepsilon^2_{1,t-1} + \beta_1 h_{t-1} + \eta S_{t-1} \varepsilon^2_{1,t-1}.$$