Exchange rate exposure of stock returns at firm level

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Abstract

The use of conventional augmented CAPM specification in estimating the exchange rate exposure may result in less reliable estimates for, at least, two reasons. First, it does not take into account a few important stylized facts associated with financial time series. Second, one cannot estimate the total impact of the exchange rate changes on stock returns as a single coefficient with it and for this reason it does not help us analyze the reinforcing or offsetting interactions between direct and indirect exchange rate exposure effects. In this paper, we suggest an orthogonalized GJR-GARCH-*t* version of augmented CAPM that simultaneously addresses the above issues. Our findings have important implications for hedging and investment decision making.

*JEL Classifications***:** F3, F23, F31, G15

*Key Words***:** Exchange rate exposure, GARCH, *t* distribution, Asymmetric volatility

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1. Introduction

A firm's exchange rate exposure refers to "the sensitivity of [its] economic value, or stock price, to exchange rate changes" (Heckman, 1983) or its "economic exposure to exchange rate risk" (Adler and Dumas, 1984). Thus, exchange rate exposure of stock returns indicates an important component of total risk. A number of previous studies report statistically and economically significant exchange rate exposure of various firms and industries (He and Ng, 1998; Koutmos and Martin, 2003a and 2003b; Patro et al., 2002; Williamson, 2001). Another set of studies show evidence that exchange rate risk is actually priced in stock markets (Choi et al., 1998; De Santise and Gerard, 1998; Dumas and Solnik, 1995). What all these evidence imply is that exchange rate exposure of stock returns is too important to be ignored in hedging and investment decisions and that the parties involved (portfolio managers, investors etc.) have to use more reliable estimates of exchange rate exposure in their decision making. In this regard, estimates of exchange rate exposure of individual firms' stocks are more useful than that of aggregate indexes of industries, sectors or countries. The objective of this paper is to suggest a more reliable means to estimate exposure coefficients of firms that are extremely useful in hedging and investment decision making.

Adler and Dumas (1984), the study that is considered to be the pioneering attempt towards measuring exchange rate exposure in terms of firm value, suggests the following simple model:

$$r_{i,t} = \beta_{0,i} + \beta_{1,i} r_{x,t} + \varepsilon_{i,t} \qquad i = 1,2,...n \qquad (1)$$

$$\varepsilon_{i,t} \sim N\left(0, \sigma^2\right)$$

where $r_{i,t}$ is return on firm i's stock at time t; $r_{x,t}$ is percentage change in exchange rate at time t; $\beta_{1,i}$ is firm i's exchange rate exposure coefficient (also known as exposure beta or exposure coefficient) which measures the sensitivity of a firm's returns to the exchange rate movements; and $\varepsilon_{i,t}$ is the residual that is unexplained by the regression. When exchange rate is expressed as the foreign currency price of home currency, there exists a negative relationship between the exchange rate changes and the firm value of an exporter. For instance, a depreciation of home currency (a negative value of $r_{x,t}$) may increase the firm's profitability which implies an increase in $r_{i,t}$. For an importer the opposite is the case.

In spite of its simplicity, this model has a number of drawbacks. For instance, $\beta_{1,i}$ in equation (1) may also contain the impact of macroeconomic factors which are spuriously correlated with both exchange rate changes and firm's stock returns during the estimation period (Bodnar and Wong, 2003). There may also be an omitted variable bias. In order to overcome these limitations of the model, some authors suggest the following augmented capital asset pricing model (augmented CAPM) which includes the return on market portfolio ($r_{m,t}$) as an additional regressor:

$$r_{i,t} = \beta_{0,i} + \beta_{1,i} r_{x,t} + \beta_{2,i} r_{m,t} + \varepsilon_{i,t} \qquad i = 1,2,...n \qquad (2)$$

$$\varepsilon_{i,t} \sim N\left(0, \sigma^2\right)$$

In this version, as in the market model, $\beta_{2,i}$ or market beta measures the firm's exposure to the changes in the return on market portfolio (proxied by overall stock market index). Then $\beta_{1,i}$ measures the firm's exposure to exchange rate changes that are independent of the overall market's exposure to exchange rate changes (Bodnar and Gentry, 1993). Inclusion of the return on market portfolio implicitly controls for the macroeconomic factors that happen to be correlated with exchange rate changes and firm's stock returns over the estimation period. Since the market return is assumed to explain a substantial amount of a firm's stock returns, inclusion of the return on market portfolio also reduces the residual variance of regression and thereby improves the precision of $\beta_{1,i}$ [1] (Bodnar and Wong, 2003).

This paper is organized as follows. Section 2 attempts to answer the question why we have to look for an alternate means to estimate exposure coefficients. Suggested model is elaborated in section 3 which also includes a detailed discussion of the reinforcing and offsetting behaviour of direct and indirect exposure effects as well. Data and methodology used are described in section 4. Results and major findings are reported in section 5. Section 6 includes concluding remarks.

2. Why look for an alternate method to estimate exchange rate exposure?

In exchange rate exposure literature, most popular means of estimating exposure coefficients is the augmented CAPM version represented by (2). And the majority of studies based on augmented CAPM employ OLS method to estimate exposure coefficients. However, sometimes it is highlighted that this conventional augmented CAPM specification neglects a few stylized facts of financial time series. This negligence tends to result in biased and inconsistent exposure estimates. More specifically, there are three important stylized facts that have not been taken into account by the conventional augmented CAPM version.

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[1] For an explanation of the difference between $\beta_{1,i}$ in equation (2) and $\beta_{1,i}$ in equation (1), see Bodnar and Wong (2003).

First, time-varying volatility and volatility persistence is clearly visible with many financial time series. Since exchange rate exposure process includes three financial time series (namely, return on the stocks of individual firms, return on the market portfolio and percentage change in exchange rates) time-varying volatility argument is applicable to the regressions used to estimate exposure coefficients as well. We have tested daily, weekly and monthly simple regressions related to all firms in our sample for ARCH effect. Our results strongly support the notion of existence of volatility persistence. 95% of the total number of cases in daily and weekly data regressions shows the presence of ARCH effect at 1% level of significance. The negligence of this effect in estimating exposure coefficients may surely lead to biased estimates. Koutmos and Martin (2003a) partly attribute the difficulty in detecting exchange rate exposure in earlier studies to the negligence of this time-varying volatility feature.

Second, as many authors showed in financial economics literature, due to leverage and volatility feedback effects, volatility of stock returns is asymmetric. This means that the volatility changes that come into being in response to good and bad news are not the same in magnitude. One can argue that there may also be an asymmetry in the volatility of stock returns associated with exchange rate changes[2]. For instance, for a holder of stocks of an exporting firm, depreciation of local currency is a good news and the appreciation of it is a bad news which may lead to higher volatility than the volatility generated by a good news. Since these asymmetric volatility changes are an

[2] Here we refer to the asymmetry in volatility of stock returns associated with exchange rate changes, but not to the asymmetry in exchange rate exposure itself. The former refers to the asymmetry in variance while the latter refers to the asymmetry in mean. Actually, there are a number of attempts to capture the asymmetric nature of exchange rate exposure. See De Iorio and Faff (1999); Kanas, 1997; Koutmos and Martin (2003a); and Priestley and Odegaard (2002).

integral part of decision making in stock markets the negligence of it may result in less reliable estimates.

Third, stock return time series are well known for leptokurtosis. For instance, return series of all firms contained in our sample show thick tails: kurtosis of all daily return series are greater than 5 while it is greater than 4 for all weekly return series. For both daily and weekly data, Jarque-Bera statistic for non-normality is highly significant in all cases. However, this feature is not captured by early studies in exposure literature. Even the usual GARCH models that are based on the assumption of conditional normality do not address the issue of thick tails. One may argue that even though the error term is conditionally normal, unconditional distribution of a GARCH process is non-normal with heavy tails than the normal distribution. However, it is argued that the implied unconditional distributions of estimated models are usually not sufficiently leptokurtic to represent actual data. As Bauwens et al. (2003) put it "the increase in kurtosis coefficient brought by the dynamics of the conditional variance is not usually sufficient to match the unconditional kurtosis of the data". The distribution that is assigned to the error term must do justice to the investment decision making and hedging activities in the sense that the selected distribution must be able to properly represent the underlying stochastic process of the asset returns. Analyses of returns based on unsuitable error term distributions may lead to inconsistent estimates which may bring about awful results in hedging and investment decision making.

In addition to the negligence of these three stylized facts, there exists another drawback of the conventional augmented CAPM version. One cannot estimate the total impact of the exchange rate changes on stock returns as a single coefficient with this specification. Since exchange rate changes and market returns are correlated, in addition to its direct effect on individual stocks, exchange rate changes do have an indirect effect on individual stocks through market returns. Since β_1 in equation (2) measures only the direct exposure effect and the indirect effect is contained in β_2, β_1 alone would under/overestimate a firm's true exposure to exchange rate changes[3]. More importantly, these two effects may reinforce or offset each other depending on their sign and the magnitude.

Fortunately, one can observe that there are a number of earlier attempts to address these issues, some of which enriched the literature with really fruitful outcomes. Various authors seem to have isolated one or two of those issues and then made important attempts to solve them. For instance, Entorf and Jamin (2003), among others, use an auxiliary regression between market returns and exchange rate changes in order to avoid possible multicolinearity between market returns and exchange rate changes[4].

$$r_{m,t} = \delta_0 + \delta_1 r_{x,t} + r_{m,t}^R \tag{3}$$

Since orthogonalized market returns ($r_{m,t}^R$) in (3) represent the component of market returns that is uncorrelated with exchange rate changes, market returns ($r_{m,t}$) in (2) is replaced with $r_{m,t}^R$. Substituting (3) into (2) and rearranging one can obtain

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[3]Henceforward we drop the subscript i attached to β_1 and β_2 for convenience when it comes to discussions. However, it will remain attached to β_1 and β_2 when they appear in equations.

[4] Among others who use this method to address the issue in question are Jorian (1991), Pritamani et al. (2001), Choi and Prasad (1995) Priestley and Odegaard (2002). However, Jorian (1991), Pritamani et al. (2001)and Choi and Prasad (1995) use exchange rate changes as the dependent variable and substitute orthogonalized exchange rate changes obtained from auxiliary regression into the augmented CAPM equation. For a discussion about the invalidity of this method, see Entorf and Jamin (2003). Priestley and Odegaard (2002) orthogonalize both market returns and exchange rate changes and use a number of macroeconomic factors in the auxiliary regressions.

$$r_{i,t} = \beta^*_{0,i} + \beta^*_{1,i}\ r_{x,t} + \beta_{2,i} r^R_{m,t}\ + \varepsilon_{i,t} \qquad i = 1,2,...n \qquad (4)$$

where $\beta^*_{1,i} = \delta_1 \beta_{2,i} + \beta_{1,i}$

$$\beta^*_{0,i} = \beta_{0,i} + \beta_{2,i}\delta_0$$

Entorf and Jamin (2003) argue that the lack of evidence for exchange rate exposure in previous studies may be due to the colinearity between market returns and exchange rate changes that would prevent significant results. With this new version of augmented CAPM they are also able to estimate the total exchange rate exposure as a single coefficient (β^*_1). However, Entorf and Jamin (2003), whose main objective was to price exchange rate risk with the help of a multifactor Arbitrage Pricing Model, do not carry out a detailed analysis of total exchange rate exposure effect in terms of the reinforcing and offsetting behaviour of direct and indirect exposure effects.

Some studies (Bodart and Reding, 2001; Koutmos and Martin, 2003a and 2003b; Patro et al., 2002, for instance) tried to address the negligence of time-varying volatility and volatility clustering by employing GARCH family models to estimate exposure coefficients. Error term of equation (2) is assumed to follow conditionally normal distribution with time-varying conditional variance.

Initial studies that use GARCH-type models in estimating exchange rate exposure implicitly assume that the volatility movements of stock returns associated with exchange rate changes are symmetric (Bodart and Reding, 2001; Patro et al., 2002, for instance). Recently, Kanas (2000), Yang (2003) and Giurda and Tzavalis (2004) employ asymmetric GARCH models to analyse the asymmetric volatility at country level. More specifically, with the help of multivariate GARCH models and taking country as the unit of analysis, they examine the asymmetric volatility spillovers between stock and exchange rate markets. These studies are not interested in inquiring about firm-level asymmetric volatility of stock returns generated by exchange rate movements.

Apparently, no proper attempt has been made in the exposure literature to address the feature of leptokurtic distribution of stock returns. At the most, some authors seem to have used GARCH models with the assumption of conditional normality to estimate exposure coefficients. However, for the reasons mentioned above, mere use of GARCH models is not enough to address the feature of leptokurtic distribution of stock returns, especially when daily or weekly data is used.

In summary, in exposure literature, there is no firm-level study which simultaneously captures stylized facts such as time-varying volatility, asymmetric volatility and thick tails of error term distribution together with both direct and indirect exposure effects. Employing an appropriate model that is able to capture all these features simultaneously, this study shows that the estimates given by the models that neglect those stylized facts and indirect exposure effect are misleading and less reliable in the sense that they seriously under/overestimate the exchange rate risk of firms.

3. The model

To address the above issues simultaneously, we combine a few improvements with the existing exchange rate exposure estimating apparatus. First, to capture time-varying volatility, like some previous authors (Patro et al., 2002; Bodart and Reding

(2001), to name a few), we also use GARCH family models. Second, following Bollerslev (1987) who argues that "a 'fat tailed' conditional distribution might be superior to the conditional normal [distribution]" in handling leptokurtosis of stock returns and exchange rate changes, we suggest a GARCH(1,1) model whose error term is assumed to be *t*-distributed conditionally. Third, to analyse the reinforcing and offsetting interactions between direct and indirect exchange rate exposure effects, we employ an auxiliary regression between market returns and exchange rate changes and use the orthogonalized market returns in place of market returns in the main equation. Fourth, to capture asymmetry in volatility of stock returns associated with exchange rate changes, we prefer to use GJR-GARCH(1,1) specification. More specifically, we employ an orthogonalized GJR-GARCH(1,1)-t model[5].

$$r_{i,t} = \beta^*_{0,i} + \beta^*_{1,i} r_{x,t} + \beta_{2,i} r^R_{m,t} + \varepsilon_{i,t} \qquad i = 1,2,...n \qquad (5)$$

$$\varepsilon_t | \psi_{t-1} \sim f_\nu(\varepsilon_t | \psi_{t-1})$$

$$r_{m,t} = \delta_0 + \delta_1 r_{x,t} + r^R_{m,t} \qquad (6)$$

$$h_{i,t} = c_{0,i} + a_i \varepsilon^2_{t-1} + \gamma_i \varepsilon^2_{t-1} d_{t-1} + b_i h_{i,t-1} \qquad (7)$$

where $\beta^*_{1,i} = \delta_1 \beta_{2,i} + \beta_{1,i}$; $\beta^*_{0,i} = \beta_{0,i} + \beta_{2,i}\delta_0$; $h_{i,t}$ is conditional variance of the error term from (5); ψ_{t-1} is information available at time t-1; d_{t-1} is equal to 1 if ε_t is negative and 0 otherwise; and ν is degrees of freedom of *t* distribution, an additional parameter that explains the leptokurtosis of the distribution. The lower the ν the thicker the tails represented by it. The variance and kurtosis of *t*-distribution are

[5] Throughout the paper, we use GARCH(1,1) and GARCH(1,1)-*t* to denote GARCH(1,1) model whose error term is conditionally normally distributed and GARCH(1,1) model whose error term is conditionally *t*-distributed respectively.

$\sigma^2 = \nu/(\nu-2)$ and $k = 6/(\nu-4)+3$ respectively. Second and fourth moments exist only if $\nu > 2$ and $\nu > 4$ respectively. Underlying distribution is leptokurtic within the range $4 < \nu < 25$ (Verhoeven and McAleer, 2003). Usual non-negativity constraints like $c > 0$, $a > 0$, $b > 0$, $a + \gamma > 0$ apply. For the conditional variance to be stationary, $(1/2)\gamma + a + b < 1$ must hold. If γ is statistically significant, that implies the existence of asymmetric volatility. To claim that the β_1^* is statistically different from β_1, in addition to β_1, β_2 and δ_1 must also be statistically different from zero. Usually, market beta of a firm is significantly different from zero. However, the correlation between market returns and exchange rate changes may or may not be statistically significant.

β_1^* in (5) is expected to show the total impact of exchange rate changes on individual stock returns. The resultant orthogonalization improves the exposure estimates in the sense that the new total exposure coefficient (β_1^*) contains the indirect effect of exchange rate changes on individual stocks via market returns ($\delta_1\beta_2$) as well as the direct effect (β_1). One cannot neglect the indirect effect raising the argument that what is important is the firm-specific component of exposure effect. Apparently, indirect exposure effect is also firm-specific in the sense that market beta (β_2) varies across firms according to the nature of a firm's relationship with the market portfolio.

A firm's market beta (β_2) and exposure beta (β_1) can be negative or positive. If we assume a positive relationship between exchange rate changes and market returns, a case in which δ_1 in (6) is positive[6], there may be four different scenarios. If both these coefficients are positive, then β_1^* is always positive and $\beta_1^* > \beta_1$. The significance of exposure coefficient seems to improve with orthogonalization in this case. If both coefficients are negative, still $|\beta_1^*| > |\beta_1|$ and the significance of exposure coefficient also improves with orthogonalization. In both these cases, direct exchange exposure effect is reinforced by the indirect exposure effect, meaning that absolute value of the total exposure coefficient is greater than the absolute value of direct exposure coefficient.

If $\beta_1 < 0$ and $\beta_2 > 0$, then there may be two possibilities: $|\delta_1\beta_2| > |\beta_1|$ and $|\delta_1\beta_2| < |\beta_1|$. The former will produce positive β_1^* and may lead to either of the following outcomes. If $|\beta_1^*| > |\beta_1|$, then the significance of exposure coefficient improves with orthogonalization. On the other hand, if $|\beta_1^*| < |\beta_1|$, the significance of exposure coefficient erodes with orthogonalization. However, if $|\delta_1\beta_2| < |\beta_1|$, then β_1^* is negative and $|\beta_1^*| < |\beta_1|$. The significance of exposure coefficients seems to erode with orthogonalization. If $\beta_1 > 0$ and $\beta_2 < 0$, again there may be two possibilities depending on whether the absolute value of indirect exposure coefficient is greater/less than the absolute value of the direct exposure coefficient. If $|\delta_1\beta_2| > |\beta_1|$, β_1^* is negative and one of the following two things can happen. If $|\beta_1^*| > |\beta_1|$, then significance of exposure coefficient improves with orthogonalization. Conversely, if $|\beta_1^*| < |\beta_1|$, still the significance of exposure coefficient erodes with orthogonalization.

[6] This assumption is just for convenience. One can consider a negative relationship and the resulting large number of different scenarios.

If $|\delta_1\beta_2| < |\beta_1|$, then β_1^* is positive, but $|\beta_1^*| < |\beta_1|$ and the significance of exposure coefficient tends to erode.

In summary, when β_1 and β_2 have the same sign, direct exchange exposure effect is reinforced by the indirect exposure effect, meaning that absolute value of the total exposure coefficient is greater than the absolute value of the direct exposure coefficient and the significance of the total exposure coefficient improves with orthogonalization. On the other hand, when β_1 and β_2 have opposite signs, direct exposure effect is totally or partly offset by the indirect exposure effect and, as a result, the magnitude and the sign (direction) of the total exposure coefficient is inconclusive. Change in the significance is also inconclusive and dependent on the magnitudes of the total and direct exposure coefficients. This has some direct insights for hedging. Since the magnitude, significance and even the sign (direction) of the total exposure effect may be different from the direct exposure coefficient (conventionally known as exposure beta or in our terminology β_1), hedging decisions based only on the direct exposure coefficient may be misleading.

4. Data and the methodology

All data is from DataStream. We focussed on electronics and electrical goods sector. The reason for selection of firms in this sector is their high international involvement as exporters or import competitors. 40 large firms have been selected from Japan and U.S. Market portfolio is assumed to be represented by the overall stock indexes of the country in question. Accordingly, we selected Nikkei 225 for Japan and Dow Jones Industrial Average (DJIA) for U.S. All stock returns and market returns are expressed in local currency.

Trade-weighted exchange rates are used to measure the exchange rate changes in the case of both countries. Exchange rates are expressed as the foreign currency price of local currency: i.e. an increase in the index shows appreciation of local currency. Changes in nominal exchange rates have been used. Justification of using nominal exchange rates are based on a few valid arguments: (a) "using the real exchange rates would assume that financial markets instantaneously observe the inflation rates that are necessary for calculating the real exchange rate" (Bodnar and Gentry, 1993); (b) it is a well established observation that there exists a high correlation between the changes in nominal and real exchange rates (Bodnar and Gentry, 1993; Khoo, 1994).

Exchange rate exposure is measured for three time horizons: daily, weekly and monthly. Some authors argue that exchange rate exposure is not well reflected in daily returns as infrequent trading, bid-ask spread, and asynchronous pricing may influence exposure coefficient estimates (see Patro et al. 2002, for instance). However, we decided to discuss all possible scenarios including daily data as GARCH-family models are good at capturing volatility associated with high frequency data. We also noticed that there are some previous studies in exposure literature, that use daily data (see Chamberlin et al. 1997; Kanas, 1997; Koutmos and Martin 2003b). In the case of weekly data, prices/rates on every Wednesday are taken into consideration. For both countries, sample period for all time horizons extends from June 1989 through May 2004. Total number of observations for daily, weekly, and monthly data are 3910, 782 and 180 respectively. Exchange rate exposure coefficients were estimated using maximum likelihood procedure with the help of GAUSS.

The firm was selected as the unit of analysis for a few important reasons. First, even the firms within the same industry are not homogenous and may have different exposure coefficients (i.e. within the same industry various firms may be exposed in opposite ways). Thus, although the industry-wide exposure is really high, individual exposure effects may be averaged out with the aggregation of the firms' returns (Dominguez and Tesar, 2001). Second, since an industry may nest both importers and exporters, asymmetry of the second moment of stock returns associated with exchange rate changes may also be averaged out at industry level. So, the asymmetry, if at all, can best be captured at the firm level. Finally, our objective is to suggest a means to find more realistic and reliable estimates that are useful in risk management/hedging decisions of firms, an area where the key institution in question is the firm.

We experimented with different model specifications in estimating exchange rate exposure coefficients, namely unorthogonalized OLS, GARCH(1,1), GARCH(1,1)-*t*, GJR-GARCH(1,1), GJR-GARCH(1,1)-*t* and orthogonalized OLS, GARCH(1,1), GARCH(1,1)-*t*, GJR-GARCH(1,1), GJR-GARCH(1,1)-*t*. Then the resulting exposure coefficients and their *t* values, degrees of freedom values of *t*-distribution-based models and their *t* values, maximum likelihood values of each specification etc have been compared. This analysis, results of which are recorded in the following section, seems to shed new light on the matter.

Since we simultaneously add a few remedial modifications to the conventional augmented CAPM specification, a mere comparison between the exposure coefficients from the conventional augmented CAPM and orthogonalized GJR-GARCH(1,1)-*t* models do not help us isolate the improvements brought about by each remedy. For this reason, we consider one factor (or two) at a time when comparisons are made. Details are indicated in Table 1.

Table 1
Summary of model comparisons

Feature/s to be addressed	Remedy	How to isolate impact of the remedy	More specifically, comparisons are made between	Relevant Table/s
Leptokurtosis	Use of *t* distribution based GARCH models	Only unorthogonalized specifications are compared	GARCH(1,1)-*t* Vs GARCH(1,1) GJR-GARCH(1,1)-*t* Vs GJR-GARCH(1,1)	02, 03 and 04
Asymmetric volatility	Use of GJR specification	Only unorthogonalized specifications are compared	GJR-GARCH(1,1)-*t* Vs GARCH(1,1)-*t* GJR-GARCH(1,1) Vs GARCH(1,1)	05 and 06
Taking both Direct and Indirect exposure effects into account	Orthogonalization	Only Normal distribution based specifications are compared	Orthogonalized GARCH(1,1) Vs Unorthogonalized GARCH(1,1) Orthogonalised GJR-GARCH(1,1) Vs Unorthogonalized GJR-GARCH(1,1)	07 and 08
All features At the same Time	Use of orthogonalized GJR-GARCH(1,1)-*t* Model	Not applicable	Unorthogonalized OLS Vs Orthogonalized GJR-GARCH(1,1)-*t* Unorthogonalized GARCH(1,1) Vs Orthogonalized GJR-GARCH(1,1)-*t*	09 and 10

5. Results and major findings

5.1. Estimation of exposure coefficients in the presence of leptokurtosis

In order to isolate the impact on exchange rate exposure coefficients arising from capturing leptokurtosis, we make comparisons between unorthogonalized GARCH(1,1) and GARCH(1,1)-*t* models and between unorthogonalized GJR-

GARCH(1,1) and GJR-GARCH(1,1)-*t* models. We use two measures to check whether the argument that the leptokurtic distribution of error terms is too important to be ignored in estimating exposure coefficients holds: (a) validity of GARCH-t specifications against GARCH specifications; (b) the magnitude of the degrees of freedom values.

In terms of maximum log-likelihood value, GARCH(1,1)-*t* and GJR-GARCH(1,1)-*t* specifications are superior to their counterparts with conditional normality assumption. LR test statistics of *t*-distribution-based models against their normal distribution-based counterparts are significant at 1% level in almost all the cases for daily and weekly data (see Table 2). However, the results for monthly data are somewhat mixed. As expected, the degrees of freedom values (ν) are very low (ranging from 3.94 to 5.82 for daily data for Japanese firms, for instance). In majority of cases, this value seems to increase as the time horizon expands, meaning that the tails of distributions tend to become thinner when it turns to longer time horizons (see Table 3). Degrees of freedom values are statistically significant in almost all the cases in daily and weekly scenarios.

Our results also reveal that taking the leptokurtosis into account will lead to a different set of β_1 values and there exists a considerable difference between β_1 values estimated by *t*-distribution based models and normal distribution based models. For instance, in the case of daily data for Japanese firms, expressed as a percentage of β_1 obtained from GARCH(1,1) specification, the difference between the absolute values of β_1 estimated with GARCH(1,1) and GARCH(1,1)-*t* varies within the range

4.4 % - 144.71 % with the average value of 37.58% across the sample[7]. Measured in the same way, the average difference (after neglecting one outlier) between β_1 values obtained from GARCH(1,1) and GARCH(1,1)-*t* for US daily regressions is 53.84%. (see Table 4 for more details). More importantly, in some cases, even the sign of the exposure coefficient changes with the use of *t* distribution based models.

Table 2

Validity of GARCH(1,1)-*t* and GJR-GARCH(1,1)-*t* models against their normal distribution-based counterparts (number of firms out of 20)

Country	Time Horizon	Model specifications involved	Significance of LR statistic at 1%
Japan	Daily	GARCH(1,1)-*t* against GARCH(1,1)	20
		GJR-GARCH(1,1)-*t* against GJR-GARCH(1,1)	20
	Weekly	GARCH(1,1)-*t* against GARCH(1,1)	20
		GJR-GARCH(1,1)-*t* against GJR-GARCH(1,1)	20
	Monthly	GARCH(1,1)-*t* against GARCH(1,1)	12
		GJR-GARCH(1,1)-*t* against GJR-GARCH(1,1)	10
US	Daily	GARCH(1,1)-*t* against GARCH(1,1)	20
		GJR-GARCH(1,1)-*t* against GJR-GARCH(1,1)	20
	Weekly	GARCH(1,1)-*t* against GARCH(1,1)	19
		GJR-GARCH(1,1)-*t* against GJR-GARCH(1,1)	19
	Monthly	GARCH(1,1)-*t* against GARCH(1,1)	07
		GJR-GARCH(1,1)-*t* against GJR-GARCH(1,1)	06

In order to isolate the impact arising from the introduction of *t*-distribution based models on exchange rate exposure coefficients, only unorthogonalized version of the relevant models are compared here

[7] Absolute values are used for the comparison of magnitudes as exposure coefficients are similar to elasticities. Average values are computed taking the absolute value of the changes.

Table 3

Degrees of freedom values (ν) of GARCH(1,1)-*t* and GJR-GARCH(1,1)-*t* models

Panel A: Japanese firms

Firm	GARCH(1,1)-*t*		GJR GARCH(1,1)-*t*	
	Daily	Weekly	Daily	Weekly
Alps	5.82 (10.66)	8.21 (4.11)	5.86 (10.61)	8.38 (4.05)
Brother	4.24 (12.63)	5.59 (5.10)	4.32 (12.46)	5.60 (5.07)
Canon	5.72 (10.12)	6.44 (4.664)	5.79 (10.03)	6.55 (4.53)
Canon S	4.15 (12.96)	3.90 (7.15)	4.15 (12.97)	4.09 (6.87)
Fuji	4.63 (12.84)	4.65 (5.65)	4.70 (12.60)	4.83 (5.52)
Fujikura	5.10 (11.81)	4.93 (5.69)	5.16 (11.70)	4.92 (5.60)
Furukawa	4.87 (11.77)	3.87 (7.26)	4.93 (11.58)	4.04 (6.77)
Hitachi	4.07 (13.04)	6.18 (5.12)	4.06 (13.08)	6.15 (5.17)
Hitachi C	4.99 (10.76)	4.82 (6.27)	5.02 (10.62)	5.10 (5.99)
Hitachi K	3.99 (13.43)	3.76 (7.93)	4.04 (13.24)	3.87 (7.70)
Matsushita	5.51 (10.32)	5.73 (4.55)	5.59 (10.11)	5.73 (4.58)
Mitsubishi	4.36 (11.49)	4.51 (5.70)	4.45 (11.42)	4.72 (5.80)
Mitsumi	4.45 (12.74)	3.83 (7.59)	4.46 (12.72)	3.82 (7.53)
NEC	5.00 (11.65)	6.05 (5.04)	5.04 (11.30)	6.17 (4.90)
Olympus	5.57 (10.84)	4.51 (3.98)	5.58 (10.86)	4.62 (4.51)
Ricoh	4.36 (13.30)	5.04 (4.87)	4.38 (13.22)	5.19 (4.74)
Sanyo	4.51 (12.40)	6.15 (4.50)	4.61 (11.47)	6.62 (4.90)
Sharp	5.20 (11.32)	5.41 (5.30)	5.22 (11.20)	5.49 (5.25)
TDK	4.66 (12.52)	6.10 (4.17)	4.68 (12.57)	6.44 (3.94)
Toshiba	3.94 (13.95)	4.34 (5.67)	3.95 (13.89)	4.40 (5.72)

Panel B: US firms

Firm	GARCH(1,1)-*t*		GJR GARCH(1,1)-*t*	
	Daily	Weekly	Daily	Weekly
Anixter	4.13 (13.78)	6.94 (4.67)	4.22 (13.61)	7.51 (4.26)
Audiovox	3.79 (14.14)	4.26 (6.29)	3.81 (14.16)	4.25 (6.24)
Avnet	4.72 (11.58)	5.18 (5.16)	4.78 (11.42)	5.23 (5.31)
Cooper	4.09 (12.30)	3.76 (6.76)	4.08 (12.33)	3.68 (6.82)
Emerson	7.12 (7.00)	7.80 (4.09)	7.12 (7.64)	8.32 (3.88)
Fastenal	3.53 (15.38)	5.15 (5.43)	3.56 (15.37)	-
Grainger	4.26 (13.42)	4.44 (6.51)	4.26 (13.40)	4.47 (6.51)
Molex	4.80 (13.00)	6.72 (5.11)	4.86 (12.80)	6.90 (4.97)
Pitney	5.66 (8.91)	7.23 (4.26)	5.67 (8.89)	7.16 (4.35)
Plexus	5.03 (10.93)	7.25 (3.88)	5.04 (10.98)	7.43 (3.59)
Rockwell	4.45 (12.87)	4.60 (5.97)	4.47 (12.79)	4.79 (5.66)
Smith	3.21 (16.30)	3.86 (6.87)	3.20 (16.32)	-
Sparton	2.58 (14.41)	3.19 (8.05)	2.61 (14.44)	3.14 (7.97)
SPX	3.88 (14.20)	3.57 (7.38)	3.89 (14.19)	3.62 (7.29)
STD Micro	4.19 (13.62)	6.05 (4.31)	4.21 (13.57)	6.17 (4.28)
Technitrol	2.83 (17.43)	3.6 (7.22)	2.82 (17.35)	3.60 (7.19)
Teradyne	5.46 (11.22)	7.18 (3.92)	5.47 (11.21)	7.54 (3.77)
Thomas B	4.40 (11.39)	4.36 (6.14)	4.41 (11.42)	4.38 (6.13)
Thomas I	4.55 (12.68)	4.79 (6.19)	4.68 (12.26)	4.73 (6.28)
Vishay	4.34 (13.69)	9.66 (3.30)	4.41 (13.58)	9.77 (3.29)

Notes: In order to isolate the impact arising from the introduction of *t*-distribution based models on exchange rate exposure coefficients, only unorthogonalized version of the relevant models are compared here; *t* values are indicated within parenthesis; - denotes the absence of estimates due to convergence problems; unlike in other Tables, asterisk marks are not used to show the level of significance as all ν values indicated in panels A and B are statistically different from zero at 1% level of significance.

Table 4

The difference between exchange rate exposure coefficients (β_1) estimated by GARCH(1,1) and GARCH(1,1)-*t* models

Panel A: Daily data

Japan				US			
Firm	GARCH (1,1)	GARCH (1,1)-*t*	Difference	Firm	GARCH (1,1)	GARCH (1,1)-*t*	Difference
Alps	-0.0404 (-0.64)	-0.0226 (-0.41)	-44.06	Anixter	0.1008 (1.32)	0.0526 (0.85)	-47.82
Brother	-0.0428 (-0.69)	-0.0655 (-1.15)	53.04	Audiovox	-0.0903 (-0.58)	-0.0445 (-0.33)	-50.72
Canon	-0.2325*** (-3.93)	-0.1878*** (-4.48)	-19.23	Avnet	0.0067 (0.10)	0.0059 (0.09)	-11.94
Canon S	-0.0450 (-1.01)	-0.0792** (-2.02)	76.00	Cooper	0.0150 (0.23)	0.0337 (0.67)	124.67
Fuji	-0.0289 (-0.63)	-0.0360 (-0.88)	24.57	Emerson	0.1245*** (2.80)	0.1186*** (2.61)	-4.74
Fujikura	0.0410 (0.856)	0.0341 (0.846)	-16.83	Fastenal	0.1106 (1.28)	0.0753 (1.17)	31.92
Furukawa	0.0991* (1.77)	0.0903* (1.86)	-8.88	Grainger	0.0036 (0.07)	-0.0065 (-0.15)	80.55
Hitachi	0.0132 (0.215)	0.0218 (0.45)	65.15	Molex	-0.0151 (-0.22)	0.0006 (0.01)	-96.03
Hitachi C	0.0800 (1.54)	0.0857* (1.94)	7.13	Pitney	-0.0335 (-0.58)	-0.0253 (-0.52)	-24.48
Hitachi K	-0.0170 (-0.35)	-0.0416 (-1.00)	144.71	Plexus	0.1863 (1.29)	0.0764 (0.60)	-58.99
Matsushita	-0.0290 (-0.73)	-0.0306 (-0.86)	5.52	Rockwell	0.0905 (1.56)	0.1611*** (3.11)	78.01
Mitsubishi	0.1951*** (3.01)	0.1347*** (2.72)	-30.96	Smith	0.0968 (1.34)	0.0559 (1.04)	-42.25
Mitsumi	-0.1292* (-1.84)	-0.1097** (-2.11)	-15.09	Sparton	-0.0077 (-0.08)	-0.1006 (-1.58)	1206.49
NEC	-0.0303 (-0.48)	-0.0194 (-0.34)	-35.97	SPX	0.0287 (0.29)	0.0456 (0.67)	58.89
Olympus	-0.1357*** (-2.59)	-0.1062** (-2.31)	-21.74	STD Micro	0.0687 (0.49)	0.0754 (0.62)	9.75
Ricoh	-0.1542*** (-3.12)	-0.1328*** (-3.26)	-13.88	Technitol	0.0401 (0.374)	-0.0029 (-0.05)	-92.77
Sanyo	-0.0179 (-0.39)	-0.3780 (-0.96)	111.17	Teradyne	0.1416 (1.09)	0.1854* (1.67)	30.93
Sharp	-0.0625 (-1.53)	-0.0553 (1.45)	-11.52	Thomas B	0.0515 (0.83)	0.0401 (0.83)	-22.14
TDK	-0.1385** (-2.45)	-0.1324*** (-2.72)	-4.40	Thomas I	-0.0825 (-1.16)	-0.0177 (-0.29)	-78.55
Toshiba	-0.0684 (-0.98)	-0.0969* (-1.83)	41.67	Vishay	0.0063 (0.04)	-0.0112 (-0.11)	77.77

Panel B: Weekly data

Japan				US			
Firm	GARCH (1,1)	GARCH (1,1)-*t*	Difference	Firm	GARCH (1,1)	GARCH (1,1)-*t*	Difference
Alps	-0.1833 (-1.46)	-0.1964 (-1.58)	7.15	Anixter	-0.0417 (-0.26)	-0.0157 (-0.09)	-62.35
Brother	-0.1013 (-0.85)	-0.1353 (-1.24)	33.56	Audiovox	-0.1078 (-0.38)	-0.0408 (-0.14)	-62.15
Canon	-0.6439*** (-5.75)	-0.5610*** (-5.25)	-12.87	Avnet	0.1502 (0.91)	0.0823 (0.57)	-45.21
Canon S	-0.0832 (-0.72)	-0.1421 (-1.63)	70.79	Cooper	-0.0936 (-0.77)	-0.0697 (-0.61)	25.53
Fuji	-0.0704 (-0.78)	-0.0178 (-0.22)	-74.72	Emerson	0.1017 (1.34)	0.1016 (1.29)	-0.10
Fujikura	0.0941 (0.73)	0.1007 (1.10)	7.01	Fastenal	0.2921** (1.97)	0.3463** (2.40)	18.56
Furukawa	0.1353 (1.17)	0.1178 (1.13)	-12.93	Grainger	0.0052 (0.04)	0.0102 (0.09)	96.15
Hitachi	-0.0769 (-0.66)	-0.0680 (-0.59)	-11.57	Molex	-0.0796 (-0.50)	-0.0325 (-0.23)	-59.17
Hitachi C	0.1741 (1.37)	0.2019** (1.99)	15.97	Pitney	-0.0418 (-0.41)	0.0057 (0.06)	-86.36
Hitachi K	-0.0581 (-0.45)	0.0801 (0.84)	37.87	Plexus	-0.0301 (-0.10)	-0.1957 (-0.75)	550.17
Matsushita	-0.2054** (-2.13)	-0.2203** (-2.58)	7.25	Rockwell	-0.0657 (-0.55)	-0.0152 (-0.15)	-76.41
Mitsubishi	0.3184** (2.44)	0.2425** (2.33)	-23.84	Smith	0.1914 (1.00)	0.1240 (0.85)	35.12
Mitsumi	-0.1561 (-1.04)	-0.2064 (-1.56)	32.22	Sparton	-0.0235 (-0.10)	-0.1328 (-0.83)	465.11
NEC	-0.2529* (-1.75)	-0.1733 (-1.22)	-31.47	SPX	0.1039 (0.57)	0.1626 (1.06)	56.50
Olympus	-0.5680*** (-4.45)	-0.3622*** (-2.64)	-36.23	STD Micro	0.6538** (1.97)	0.3842 (1.51)	-41.24
Ricoh	-0.4109*** (-3.97)	-0.4374*** (-4.93)	6.45	Technitol	0.0170 (0.11)	-0.0094 (-0.10)	-44.71
Sanyo	-0.1727** (-2.21)	-0.1661** (-2.17)	-3.82	Teradyne	0.3484 (1.04)	0.2641 (0.85)	-24.20
Sharp	-0.1496* (-1.64)	-0.1534* (-1.93)	2.54	Thomas B	0.0542 (0.43)	-03430 (-0.42)	-36.72
TDK	-0.4749*** (-3.51)	-0.3995*** (-3.07)	-15.88	Thomas I	0.0005 (0.00)	0.1207 (0.99)	24040
Toshiba	-0.0125 (-0.11)	0.0294 (0.27)	135.2	Vishay	-0.0806 (-0.36)	0.0442 ((0.19)	-45.16

In order to isolate the impact arising from the introduction of *t*-distribution based models on exchange rate exposure coefficients, only unorthogonalized version of the relevant models are compared here; *t* values are indicated within parenthesis; *** indicates significance at 1% level. ** and * indicate the same at 5% and 10% levels respectively

5.2. Asymmetry in volatility of stock returns associated with exchange rate changes

In order to isolate the impact on exchange rate exposure coefficients arising from taking asymmetric volatility into account, we make comparisons between unorthogonalized GJR-GARCH(1,1) and GARCH(1,1) models and between unorthogonalized GJR-GARCH(1,1)-*t* and GARCH(1,1)-*t* models. We use two measures to check whether the volatility of stock returns actually behave asymmetrically in response to the changes in exchange rates: (a) the validity of GJR-GARCH specifications that accommodate asymmetric volatility against symmetric GARCH specifications; (b) statistical significance of the coefficient of the GJR term or γ in equation (7).

Our results show that, for regressions based on daily and weekly data, both normal- and *t*-distribution-based GJR-GARCH specifications are superior to their counterpart symmetric GARCH specifications in estimating exposure coefficients at least in the case of 65% of the total number of firms in the Japanese sample. The same argument is true for at least 50 % of the total number of firms in the US sample (see Table 5). For regressions based on daily and weekly data, coefficient of GJR term (γ) is statistically different from zero at 5% level of significance at least in the case of 35% of the total number of firms in the Japanese sample. γ is statistically significant at least in the case of 15% of the total number of firms in the US sample (see Table 6). However, we hardly found evidence to conclude that asymmetric volatility exists with monthly data. As Tables 5 and 6 indicate, when it comes to monthly time horizon, the argument of existence of asymmetric volatility is not empirically supported at all. We observed that the feature of volatility asymmetry of stock returns associated with exchange rate changes tends to disappear with the expansion of time horizon.

As in the case of previous subsection, we also checked whether there is a remarkable difference between β_1 values estimated with GJR-GARCH specifications and their symmetric GARCH counterparts. Although there exists a difference, it is not that remarkable and for the same reason those differences are not reported here.

Given the less promising results from monthly data regressions in this and the previous sections, one may argue that the best model specification for monthly time horizon is symmetric GARCH with the conditional normality assumption. However, we suggest that such situations be handled with extreme cautious as asymmetric GARCH models with conditional *t*-distribution seem to be appropriate in estimating exposure coefficients at least in the case of some monthly regressions (see Tables 2, 5 and 6).

Table 5

Validity of GJR-GARCH(1,1) and GJR-GARCH(1,1)-*t* specifications against their symmetric counterparts

Country	Time Horizon	Model specifications involved	Significance of LR statistic at 5%
Japan	Daily	GJR-GARCH(1,1) against GARCH(1,1)	17
		GJR-GARCH(1,1)-*t* against GARCH(1,1)-*t*	17
	Weekly	GJR-GARCH(1,1) against GARCH(1,1)	13
		GJR-GARCH(1,1)-*t* against GARCH(1,1)-*t*	14
	Monthly	GJR-GARCH(1,1) against GARCH(1,1)	03
		GJR-GARCH(1,1)-*t* against GARCH(1,1)-*t*	05
US	Daily	GJR-GARCH(1,1) against GARCH(1,1)	16
		GJR-GARCH(1,1)-*t* against GARCH(1,1)-*t*	12
	Weekly	GJR-GARCH(1,1) against GARCH(1,1)	15
		GJR-GARCH(1,1)-*t* against GARCH(1,1)-*t*	10
	Monthly	GJR-GARCH(1,1) against GARCH(1,1)	05
		GJR-GARCH(1,1)-*t* against GARCH(1,1)-*t*	02

In order to isolate the impact on exchange rate exposure coefficients arising from taking the asymmetric volatility into account, only unorthogonalized version of the relevant models are compared

Table 6

Significance of the coefficient of the GJR term (γ)

Country	Time Horizon	Model	Significant cases out of 20 at 5%	at 10%
Japan	Daily	GJR-GARCH(1,1)	10	13
		GJR-GARCH(1,1)-*t*	14	16
	Weekly	GJR-GARCH(1,1)	07	10
		GJR-GARCH(1,1)-*t*	08	12
	Monthly	GJR-GARCH(1,1)	00	01
		GJR-GARCH(1,1)-*t*	00	02
US	Daily	GJR-GARCH(1,1)	04	06
		GJR-GARCH(1,1)-*t*	11	13
	Weekly	GJR-GARCH(1,1)	03	05
		GJR-GARCH(1,1)-*t*	03	06
	Monthly	GJR-GARCH(1,1)	01	01
		GJR-GARCH(1,1)-*t*	00	00

In order to isolate the impact on exchange rate exposure coefficients arising from taking the asymmetric volatility into account, only unorthogonalized version of the relevant models are used here

5.3. Interaction between direct and indirect exchange rate exposure effects

Some previous studies on exchange rate exposure argue that the magnitude of exposure increases with the expansion of the time horizon (see Bartov and Bodnar, 1994; Bodnar and Wong, 2003; Dominguez and Tesar, 2001, for instance). The underlying explanation is that exchange rate changes are more reflected in longer time horizons than in shorter time horizons because there exists a time lag between observing the changes in exchange rates and the relevant decision making in stock markets. We have an interesting finding here. As long as the direct exchange rate exposure coefficient (β_1**)** is taken into account, our results are consistent with the findings of those previous studies and the magnitude of exposure seems to increase with the time horizon. For instance, in terms of unorthogonalized GARCH(1,1) specification, 19/20 Japanese firms and 14/20 US firms show an increase in their exposure coefficients when we move from daily scenario to weekly scenario. Put differently, the direct impact of exchange rate changes on stock returns becomes more relevant with the expansion of the time horizon. However, when indirect exposure effect is also taken into account, this pattern disappears and β_1^* may either increase or decrease with the expansion of the time horizon. This means that the indirect exposure effect of exchange rate changes does not show a similar pattern (see Tables 9 and 10 for details).

Our results are also consistent with the early studies that report that US firms are adversely affected by depreciation of the US dollar as opposed to the theoretical arguments of the positive impact of depreciation on profits of large firms (see Jorion, 1990; Bodnar and Gentry, 1993; Bodnar and Wong, 2003). One potential explanation of this is that international trade is simply less important for US firms (Dominguez and Tesar, 2001). In all time horizons, in terms of β_1 obtained from unorthogonalized GARCH(1,1) specification**,** returns of a considerable percentage of US firms seem to be positively related with foreign currency price of local currency and always this percentage is greater than the relevant percentage of Japanese firms. Interestingly, when indirect exchange exposure impact is also taken into account, in terms of β_1^* obtained from orthogonalized GARCH(1,1), this percentage increases further (see Table 7).

Table 7

Percentage of firms that are adversely affected by the depreciation of local currency

Time horizon	In terms of β_1 in unorthogonalized GARCH(1,1)		In terms of β_1^* in orthogonalized GARCH(1,1)	
	Japan	US	Japan	US
Daily	25%	75%	80%	95%
Weekly	20%	55%	30%	100%

Monthly Scenario is not included here because exposure coefficients could not be estimated with monthly data in some cases due to convergence problems.

Splitting out the total exchange rate exposure effect into direct and indirect sub effects is extremely important in hedging and investing decisions. For instance, a certain firm's returns may be slightly negatively related to exchange rate changes (i.e. firm returns increase with a depreciation of local currency). However, if its returns are positively correlated with the market returns and market returns and exchange rate changes also show a positive correlation, then the direct exposure effect may be totally offset by the indirect exposure effect and the firm's total exchange rate coefficient may become slightly positive[8].

As indicated in Table 8, orthogonalization has a great impact on the significance of exchange rate exposure coefficient. Significance of exchange rate exposure coefficients of most of the firms in Japanese and US samples seem to improve with orthogonalization. Put differently, the estimated total exchange rate exposure

[8] This may sometimes go to extreme situations as one of the firms in our US sample demonstrates. In weekly data regressions, although Audiovox's direct exposure effect is remarkably negative (-0.1078), the strong positive correlations between the market returns and the firm returns (represented by β_2 = 1.0143) and the market returns and the exchange rate changes (represented by δ_1 = 0.206) result in a remarkably positive total exposure effect of 0.1011.

coefficients are more reliable than the estimated direct exchange rate exposure coefficients. Although both U.S. and Japanese firms show similar pattern in this regard, more interestingly, the underlying reasons for this common pattern are different in two cases[9]. In terms of the direct exposure effect, nearly three-fourth of Japanese firms chosen is negatively exposed to exchange rate changes. However, the weak negative direct exposure effect is totally offset by the strong positive indirect exposure effect as $|\delta_1 \beta_2| > |\beta_1|$. As a result, total exposure coefficient becomes positive and absolute value of it is greater than the absolute value of direct exposure coefficient. According to the explanation in section 3, we know that when $|\beta_1^*| > |\beta_1|$, which happens to be the case here, significance of exposure tends to improve. Conversely, in terms of the direct exposure effect, nearly three-fourth of US firms chosen is positively exposed to exchange rate changes. This means that positive indirect exchange rate exposure effect reinforces the positive direct exposure effect and as a result $|\beta_1^*| > |\beta_1|$, a situation which tends to improve the significance of total exposure effect.

The result that a relatively larger percentage of Japanese firms show statistically significant exchange rate exposure is also in accordance with previous studies like Doidge et al. (2002), Griffin and Stulz (2001) and Williamson (2001) who found similar results for Japanese firms. For instance, in the case of daily data, exchange rate exposure of 25% firms are statistically significant at 5% level according to the β_1 values obtained from unorthogonalised GARCH(1,1). However, we noticed that this figure increased to 45% with orthogonalization.

[9] We are not tempted to make generalisations on this behaviour of Japanese and US firms as we know that our small sample of firms is not adequate to do so. However, we believe that there is no harm in using these features of chosen US and Japanese firms as concrete examples in elaborating on the offsetting and reinforcing behaviour of direct and indirect exchange rate effects.

Table 8

Significance of exposure coefficients in orthogonalized and unorthogonalized versions of GARCH(1,1) and GJR-GARCH(1,1) models (daily data scenario)

Japan					US				
Firm	GARCH(1,1)		GJR-GARCH(1,1)		Firm	GARCH(1,1)		GJR-GARCH(1,1)	
	UO	O	UO	O		UO	O	UO	O
Alps	-	-	-	-	Anixter	-	xxx	-	xxx
Brother	-	-	-	-	Audiovox	-	-	-	-
Canon	xxx	xx	xxx	xx	Avnet	-	-	-	-
Canon S	-	-	-	-	Cooper	-	xx	-	-
Fuji	-	xxx	-	xxx	Emerson	xxx	xxx	xxx	xxx
Fujikura	-	xxx	-	xxx	Fastenal	-	xxx	-	xx
Furukawa	x	xxx	x	xxx	Grainger	-	x	-	x
Hitachi	-	xx	-	xx	Molex	-	x	-	x
Hitachi C	-	xxx	x	xxx	Pitney	-	-	-	-
Hitachi K	-	-	-	-	Plexus	-	xx	-	xx
Matsushita	-	xx	-	xx	Rockwell	-	xxx	-	xxx
Mitsubishi	xxx	xxx	xxx	xxx	Smith	-	xx	-	xx
Mitsumi	x	-	xx	-	Sparton	-	-	-	-
NEC	-	x	-	x	SPX	-	-	-	-
Olympus	xxx	-	xx	-	STD Micro	-	-	-	-
Ricoh	xxx	-	xxx	-	Technitrol	-	-	-	-
Sanyo	-	xxx	-	xxx	Teradyne	-	xx	-	xx
Sharp	-	x	-	xx	Thomas B	-	xxx	-	xxx
TDK	xx	-	xx	-	Thomas I	-	-	-	-
Toshiba	-	-	-	-	Vishay	-	-	-	-

Notes: We use only GARCH(1,1) and GJR-GARCH(1,1) specifications in order to isolate the effect of orthogonalization. Although to a lesser degree, this pattern remains almost the same with weekly data as well. However, regressions based on monthly data do not show such a pattern; xxx indicates significance at 1% level. xx and x indicate the same at 5% and 10% levels respectively; O and UO represent orthogonalized and unorthogonalized versions of the relevant model.

5. 4. Implications of the findings for hedging and investment decision making

Although they are not widely used for a number of reasons, exchange rate exposure coefficients can be used as an important piece of information in decision making in stock investment activities and firms' hedging against exchange rate exposure. To this end, estimates of exposure coefficients must be a reliable measure of a firm's actual exposure to currency risk. One remarkable way of achieving this reliability is to take the stylized facts underlying the exchange rate exposure process into account in estimating exposure coefficients. In this paper, we suggest a model that is able to capture a number of such stylised facts. Our results reveal that there exists a remarkable difference between the exposure coefficients estimated by the suggested model and other conventional models.

Tables 9 and 10 indicate the exposure coefficients estimated with the help of a few different model specifications, namely unorthogonalized conventional CAPM model, unorthogonalized GARCH(1,1) model and orthogonalized GJR-GARCH(1,1)-*t* model. Respectively, they represent the conventional direct exposure coefficient of a firm, a direct exposure coefficient when time-varying volatility is taken into account and the total exposure coefficient which is assumed to capture time-varying volatility, leptokurtosis, asymmetric volatility and both direct and indirect exposure effects. Contents in Tables 9 and 10 reveal that when we switch from unorthogonalised conventional CAPM or GARCH(1,1) models to orthogonalized GJR-GARCH(1,1)-*t* model, the magnitude, the significance and even the sign (direction) of a exchange rate exposure coefficient may vary. This means that conventional exchange rate exposure estimates are misleading in the sense that they may seriously under/overestimate the exchange rate risk. More importantly, this over/underestimation is sometimes associated with wrong direction as well. These findings have direct and important implications for the use of exchange rate exposure coefficients in hedging and investment decisions.

Table 9

The difference between exchange rate exposure coefficients estimated with different model specifications using daily data[1]

Panel A: Japanese firms

Firm	OLS[2]	GARCH (1,1) [3]	GJR GARCH (1,1)-t[4]	5	6	7	8
Alps	-0.0694 (-1.10)	-0.0404 (-0.64)	0.1091** (1.99)	57.20	x	170.05	x
Brother	-0.0574 (-0.87)	-0.0428 (-0.69)	0.0580 (1.03)	1.04	x	35.51	x
Canon	-0.2484*** (-3.66)	-0.2325*** (-3.93)	-0.0791* (1.90)	-68.16	-	-65.98	-
Canon S	-0.0034 (-0.02)	-0.0450 (-1.01)	-0.0087 (-22)	155.88	-	-80.67	-
Fuji	-0.0773 (-1.52)	-0.0289 (-0.63)	0.1167*** (2.85)	50.97	x	303.81	x
Fujikura	0.0343 (0.60)	0.0410 (0.86)	0.1802*** (4.40)	425.36	-	339.51	-
Furukawa	0.0070 (0.30)	0.0991* (1.77)	0.2790*** (5.80)	3885.71	-	181.53	-
Hitachi	-0.0047 (-0.06)	0.0132 (0.22)	0.1208** (2.48)	2470.21	x	815.15	-
Hitachi C	0.0594 (1.01)	0.0800 (1.54)	0.2100*** (4.78)	253.53	-	162.5	-
Hitachi K	-0.0627 (-0.06)	-0.0170 (-0.35)	0.0409 (0.98)	-34.77	x	140.59	x
Matsushita	-0.0568 (-1.38)	-0.0290 (-0.73)	0.0825** (2.33)	45.25	x	184.48	x
Mitsubishi	0.1942** (2.44)	0.1951*** (3.01)	0.2691*** (5.53)	38.57	-	37.93	-
Mitsumi	-0.1234* (-1.87)	-0.1292* (-1.84)	0.0284 (0.05)	-76.99	x	-78.02	x
NEC	-0.0276 (-0.41)	-0.0303 (-0.48)	0.1206** (2.12)	336.96	x	298.02	x
Olympus	-0.1987*** (-3.42)	-0.1357*** (-2.58)	-0.0045 (-0.10)	-97.74	-	-96.68	-
Ricoh	-0.2076*** (-4.27)	-0.1542*** (-3.12)	-0.0065 (-0.16)	-96.78	-	-95.78	-
Sanyo	-0.0118 (-0.53)	-0.0179 (-0.39)	0.1282*** (3.21)	986.44	x	616.20	x
Sharp	-0.0660 (-1.43)	-0.0625 (-1.53)	0.0824** (2.15)	24.87	x	31.84	x
TDK	-0.1026* (-1.728)	-0.1385** (-2.45)	-0.0037 (-0.06)	-96.39	-	-97.33	-
Toshiba	-0.0812 (-1.163)	-0.0684 (-0.98)	0.0204 (0.39)	-74.88	x	-74.88	x

Panel B: US firms

Firm	OLS[2]	GARCH (1,1)[3]	GJR GARCH (1,1)-t[4]	5	6	7	8
Anixter	0.0693	0.1008	0.1702***	145.59	-	68.85	-
	(0.77)	(1.32)	(2.73)				
Audiovox	0.0254	-0.0903	0.0568	123.62	-	-37.10	x
	(0.27)	(-0.58)	(0.43)				
Avnet	0.0632	0.0067	0.1113*	76.11	-	1561.19	-
	(0.80)	(0.10)	(1.73)				
Cooper	0.0419	0.0150	0.1466***	249.88	-	877.33	-
	(0.57)	(0.23)	(2.91)				
Emerson	0.1034**	0.1245***	0.2436***	135.59	-	95.22	-
	(2.07)	(2.80)	(5.40)				
Fastenal	0.0705	0.1106	0.1735***	146.10	-	56.87	-
	(0.717)	(1.28)	(2.68)				
Grainger	0.0130	0.0036	0.0845*	550.00	-	2247.22	-
	(0.373)	(0.07)	(1.94)				
Molex	-0.0312	-0.0151	0.1235*	295.83	x	717.88	x
	(-0.28)	(-0.02)	(1.94)				
Pitney	-0.0464	-0.0335	0.0794	71.12	x	137.01	x
	(-0.61)	(-0.58)	(1.63)				
Plexus	0.1487	0.1863	0.2289*	53.93	-	22.87	-
	(0.94)	(1.29)	(1.80)				
Rockwell	0.0325	0.0905	0.2802***	762.15	-	209.61	-
	(0.41)	(1.56)	(5.47)				
Smith	0.1006	0.0968	0.1050*	4.37	-	8.47	-
	(1.38)	(1.34)	(1.93)				
Sparton	0.0925	-0.0077	-0.0860	-7.03	x	1016.88	-
	(0.77)	(-0.08)	(-1.36)				
SPX	0.1115	0.0287	0.1392**	24.84	-	385.02	-
	(1.27)	(0.29)	(2.05)				
STD Micro	0.1129	0.0687	0.1799	59.34	-	161.86	-
	(0.79)	(0.49)	(1.49)				
Technitrol	0.1673*	0.0401	0.0382	-77.17	-	-4.74	-
	(1.68)	(0.37)	(0.66)				
Teradyne	0.2777**	0.1416	0.3607***	29.89	-	154.73	-
	(2.10)	(1.09)	(3.25)				
Thomas B	0.0079	0.0515	0.1352***	1611.3	-	162.52	-
	(-0.79)	(0.83)	(2.80)				
Thomas I	0.0624	-0.0825	0.0300	-51.92	-	-63.64	x
	(-0.78)	(-1.16)	(0.50)				
Vishay	0.0524	0.0063	0.1098	109.54	-	1642.86	-
	(0.44)	(0.04)	(1.27)				

Table 10

The difference between exchange rate exposure coefficients estimated with different model specifications using weekly data[1]

Panel A: Japanese firms

Firm	OLS[2]	GARCH (1,1) [3]	GJR GARCH (1,1)-t[4]	5	6	7	8
Alps	-0.1324 (-0.87)	-0.1833 (-1.46)	-0.1128 (-0.91)	-14.80	-	-38.46	-
Brother	-0.0721 (-0.60)	-0.1013 (-0.84)	-0.0541 (-0.49)	-24.97	-	-46.59	-
Canon	-0.7546*** (-7.13)	-0.6439*** (-5.75)	-0.4996*** (-4.71)	-33.79	-	-22.41	-
Canon S	-0.0973 (-0.85)	-0.0832 (-0.72)	-0.1010 (-1.16)	3.80	-	21.39	-
Fuji	0.0051 (0.02)	-0.0704 (-0.78)	0.0533 (0.66)	945.10	-	-24.29	x
Fujikura	0.0681 (0.63)	0.0941 (0.73)	0.1670* (1.91)	145.23	-	77.47	-
Furukawa	0.1514 (1.16)	0.1353 (1.17)	0.2083** (2.02)	37.58	-	53.95	-
Hitachi	-0.0658 (-0.53)	-0.0769 (-0.66)	-0.0119 (-0.11)	-81.89	-	-84.52	-
Hitachi C	0.1899 (1.16)	0.1741 (1.37)	0.2590*** (2.66)	36.39	-	48.77	-
Hitachi K	-0.1273 (-1.09)	-0.0581 (-0.45)	0.1562* (1.77)	22.70	x	168.85	x
Matsushita	-0.2180** (-2.30)	-0.2054** (-2.13)	-0.1587* (-1.91)	-27.20	-	-22.74	-
Mitsubishi	0.3842** (2.27)	0.3184** (2.44)	0.3081*** (3.17)	-19.77	-	-3.23	-
Mitsumi	-0.1658 (-1.08)	-0.1561 (-1.04)	-0.1257 (-0.93)	-24.19	-	-19.47	-
NEC	-0.2826* (-1.95)	-0.2529* (-1.74)	-0.0862 (-0.62)	-69.5	-	-65.92	-
Olympus	-0.6170*** (-4.65)	-0.5680*** (-4.45)	-0.3167** (-2.38)	-48.67	-	-44.24	-
Ricoh	-0.5821*** (-5.39)	-0.4109*** (-3.97)	-0.3667*** (-4.20)	-37.00	-	-10.76	-
Sanyo	-0.0875 (-0.92)	-0.1727** (-2.21)	-0.0849 (-1.12)	-2.97	-	-50.84	-
Sharp	-0.1214 (-1.23)	-0.1496 (-1.641)	-0.0830 (-1.04)	-31.63	-	-44.52	-
TDK	-0.3757** (-2.56)	-0.4749*** (-3.51)	-0.3304*** (-2.60)	-12.06	-	-30.42	-
Toshiba	0.0524 (0.39)	-0.0125 (-0.11)	0.1077 (1.01)	105.53	-	761.60	x

Panel B: US firms

Firm	OLS[2]	GARCH (1,1) [3]	GJR GARCH (1,1)-t[4]	5	6	7	8
Anixter	0.0525 (0.30)	-0.0417 (-0.26)	0.2296 (1.51)	337.33	-	450.6	x
Audiovox	0.0006 (0.01)	-0.1078 (-0.38)	0.1722 (0.59)	28600.00	-	59.74	x
Avnet	0.0438 (0.22)	0.1502 (0.91)	0.3258** (2.27)	643.84	-	116.91	-
Cooper	-0.0824 (-0.61)	-0.0936 (-0.77)	0.1389 (1.24)	68.57	x	48.40	x
Emerson	-0.0224 (-0.22)	0.1017 (1.34)	0.2942*** (3.84)	1213.39	x	139.21	-
Fastenal	0.4680** (2.23)	0.2921** (1.97)	-	-	-	-	-
Grainger	-0.0158 (-0.096)	0.0052 (0.039)	0.1845* (1.69)	1067.72	x	3448.08	-
Molex	-0.1148 (-0.72)	-0.0796 (-0.50)	0.1904 (1.32)	65.86	x	139.20	x
Piney	-0.1328 (-1.18)	-0.0418 (-0.41)	0.1937** (1.96)	45.86	x	363.4	x
Plexus	-0.2190 (-0.78)	-0.0301 (-0.10)	0.0422 (0.16)	-80.73	x	40.20	x
Rockwell	-0.1269 (-0.88)	-0.0657 (-0.55)	0.1596 (1.58)	25.77	x	142.92	x
Smith	0.1803 (0.83)	0.1914 (1.00)	-	-	-	-	-
Sparton	-0.0442 (-0.17)	-0.0235 (-0.10)	-0.0924 (-0.59)	109.05	-	293.19	-
SPX	0.0678 (0.35)	0.1039 (0.57)	0.3687** (2.45)	443.81	-	254.86	-
STD Micro	0.6330* (1.87)	0.6538** (1.97)	0.5784** (2.37)	-8.63	-	-11.53	-
Technitrol	-0.0672 (-0.34)	0.0170 (0.11)	0.1518 (1.51)	125.89	x	792.94	-
Teradyne	0.3123 (1.10)	0.3484 (1.04)	0.6061** (1.97)	94.08	-	73.97	-
Thomas B	-0.1589 (-1.24)	0.0542 (0.43)	0.1307 (1.59)	-17.75	x	141.14	-
Thomas I	0.0443 (0.28)	0.0005 (0.00)	0.2640** (1.97)	495.94	-	52700.00	-
Vishay	0.1304 (0.62)	-0.0806 (-0.36)	0.3228 (1.49)	147.55	-	300.50	x

Notes to Tables 9 and 10:
1 – Although the results of only three model specification are compared here, we actually estimated the exposure coefficients with ten different model specifications. These include orthogonalized and unorthogonalized OLS, GARCH(1,1), GARCH(1,1)-*t*, GJR-GARCH(1,1), GJR-GARCH(1,1)-*t*.
2 - Exchange rate exposure coefficient (β_1) from unorthogonalized OLS regression
3 – Exchange rate exposure coefficient (β_1) from unorthogonalized GARCH(1,1) model
4 - Exchange rate exposure coefficient (β_1^*) from orthogonalised GJR-GARCH(1,1)-*t* model
5 - The difference between absolute values of 2 and 4 as a percentage of 2
6 - x indicates whether there is a sign change when we switch from unorthogonalized OLS to orthogonalized GJR-GARCH(1,1)-*t*
7 - The difference between absolute values of 3 and 4 as a percentage of 3
8- x indicates whether there is a sign change when we switch from unorthogonaliszed GARCH(1,1) to orthogonalized GJR-GARCH(1,1)-*t*
t values are indicated within parenthesis
*** indicates significance at 1% level. ** and * indicate the same at 5% and 10% levels respectively

6. Concluding remarks

In estimating more reliable and realistic exposure coefficients of firms, suggested orthogonalized GARCH(1,1)-*t* and GJR-GARCH(1,1)-*t* models seem to be superior to unorthogonalized conventional augmented CAPM models and GARCH(1,1) models with conditionally normally distributed error term. This conclusion is based on three important observations. First, in terms of LR tests and degrees of freedom values, validity of *t*-distribution-based specifications is higher than their normal distribution-based counterparts in capturing leptokurtosis. Second, in terms of LR test results and the significance of the coefficient of GJR term, GJR version of the suggested model is more suitable than symmetric GARCH specifications in estimating the exposure coefficients of the firms whose returns respond asymmetrically to exchange rate changes. Third, the orthogonalization employed here helps us capture indirect exposure effect, which is too important to be ignored, and explain the reinforcing and offsetting interactions between direct and indirect exposure effects.

We believe that the suggested specification is more applicable to daily data setting of exchange rate exposure. It may also be applicable, although to a lesser degree, to weekly data as well. However, its applicability to monthly data is doubtful for, at least, two reasons. First there may be no GARCH effect when it comes to monthly data. Secondly, as time horizon expands, tail thickness may decrease and the non-normality associated with daily, and to a lesser extent weekly, data may disappear. This argument is supported by empirical facts as well. In our sample, nine out of twenty US firms and six out of twenty Japanese firms fail either ARCH-LM test or Jarque-Bera test or both when it turns to monthly data. However, one should not be tempted to jump to the generalization that conventional augmented specification based on OLS method normal GARCH models are the best way to estimate exposure coefficients in monthly data scenario. This is because the suggested specification appears to fit into the return series of some firms even in the case of monthly data.

Our results reveal that, in majority of the cases in both Japanese and US samples, the exposure coefficients estimated with the suggested model are remarkably different in magnitude, significance and even sign (direction) from the coefficients estimated by unorthogonalised conventional CAPM or GARCH(1,1) models. This gives rise to the argument that the exposure coefficients estimated by the models that do not capture the stylized facts of financial time series and the indirect exposure effect may seriously under/overestimate the exchange rate risk. The problem becomes worse when the over/underestimation is associated with the wrong sign. In this study, we suggest a model that is able to capture a number of stylised facts of financial time series and indirect exposure effect simultaneously. The findings have direct and important implications for the use of exchange rate exposure coefficients in hedging and investment decisions.

Acknowledgements

We would like to thank the participants in the inaugural Singapore Econometric Study Group (SESG) meeting and the academic session A12 (Stock Markets for Pacific Basin Countries) in the 12th Annual Conference of Pacific Basin Finance, Economics, Accounting and Business (PBFEAB) for their helpful comments. Second author would like to appreciate the financial assistance from the Department of Economics at National University of Singapore under ARF research grant WBS No: R-122-000-051-112.

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