Exchange rate exposure: A nonparametric approach

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Abstract

The typical conclusion reached when researchers examine exchange rate exposure using a linear model is that only a few firms are exposed. This finding is puzzling since institutional knowledge and basic finance theory points to a larger effect. In this paper, we compare results obtained using a linear approach with those from nonlinear, partially parametric and nonparametric models. Our data consist of nonfinancial firms in five emerging market countries and the US. Among firms that were not found to have a linear exposure, we find that a considerable proportion of these are exposed when nonlinear, partially parametric or nonparametric models are used. The increase in exposure is most striking when a nonparametric model is used. We also find evidence that firms' hedging activities decrease linear exposure but do not affect nonparametric exposure.

1. Introduction

In the aftermath of the emerging market currency crises, linked mainly to speculative attacks on fixed exchange rate regimes, countries have announced limited commitments, if at all, to pegging their exchange rates. Even so, substantial evidence shows that these countries intervene heavily in foreign exchange markets to limit the volatility of exchange rates. Balance sheet effects have been argued as one of the main reasons for this intervention. More specifically, the large amounts of unmatched foreign currency denominated liabilities firms carry have been a source of concern for emerging market central banks. Therefore, it is important to understand the effects of exchange rate risk on firms' balance sheets and value, and develop methods to measure firms' exposures to such risks.

While it is well established that exchange rate fluctuations are an important source of risk for a firm, the literature does not agree on a benchmark methodology to be used in measuring exposure.

One branch of the literature quantifies the idiosyncratic effects of exchange rate fluctuations on a firm's stock return by using various extensions of the Adler-Dumas (1984) model. The main conclusion of this line of work (c.f. Jorion, 1990; Griffin and Stulz, 2001) is that exchange rate exposure, measured by the proportion of firms with significant exposure, is trivial. This finding contrasts with the predictions of finance theory and substantial anecdotal evidence suggesting a considerable vulnerability to exchange rate movements. Indeed, Bartram and Bodnar (2007) define the inability to find exposure -- even for firms that have extensive operations abroad -- as the exchange rate exposure puzzle.

Empirical studies using various estimation techniques, sample selection, and different exchange rates report limited success in capturing exchange rate exposure. Most of this literature

agrees that the linear relationship between exchange rates and stock returns assumed under the Adler-Dumas (1984) model may understate the level of exposure. This is especially agreed to be true if exchange rates have nonlinear effects on a firm's cash flow or firms' operational decisions. Indeed, some studies (Allayannis, 1997; Allayannis and Ihrig, 2001; Bartram, 2004; Bodnar et al., 2002; Bodnar and Wong 2003; Broll, 2001; Doidge et al., 2000; Griffin and Stulz, 2001; Priestly and Odegaard, 2007, Taylor and Peel, 2000; Taylor et al., 2001) show that using various functional forms such as quadratic and cubic can more effectively capture, for some firms, the degree of exposure when a linear model can not. Nevertheless, the use of different functional forms does not change the conclusions considerably and does not solve the exchange rate exposure puzzle. It is important to point out further that, these studies do not agree on a specific functional form to use in estimating exchange rate exposures.

In the literature, we identified three important reasons why conventional models may not capture exchange rate exposure accurately or why there may be a lack of exposure.

First, using the same functional form for each firm can be restrictive and could generate low levels of exchange rate exposure. This is especially true if firms differ in the way they are affected by exchange rate movements. Indeed, it is agreed that the degree of exposure depends on firm and industry characteristics such as size, monopoly power, external orientation, degree of import penetration and the substitutability between domestically produced and imported inputs. More importantly, the theoretical studies mentioned above suggest that these characteristics not only determine the degree of exposure but also have implications for the functional relationship between exchange rate movements and firms' value.

Second, there are a large number of studies (c.f. Allayannis and Ihrig, 2001; Jorion, 1990, Koutmos and Knif, 2002; Brunner et al., 2000; Williamson, 2001) arguing or finding that

exchange rate-stock return relationship does not follow a time invariant functional form. Exchange rate exposures in these studies vary over time as firm and market characteristics such as markup and market shares change. Therefore, the time invariant functional form assumption of the Adler-Dumas model can falsely predict that exposure is insignificant.

Third, some studies (c.f. Allayannis and Ofek, 2001; Bartram and Bodnar, 2007) argue that firms use foreign currency derivatives effectively to protect themselves against unanticipated exchange rate fluctuations. Therefore, it is possible that the lack of exposure does not reflect the inadequacy of the methodology, but may be due to the hedging behavior of firms.

In this paper, we offer a different approach and estimate exchange rate exposure nonparametrically. In so doing, we are able to account for two of the main shortcomings of the conventional methods mentioned above. Specifically, a nonparametric (NP) approach allows us to estimate a different functional form for each firm and allows this functional form to change over time. We choose to use the local linear regression method developed by Stone (1977) as our NP estimation strategy due to its high asymptotic efficiency compared to alternative NP methods. Although we are not the first to use this approach to study exchange rate exposure[1], our paper makes a first attempt at comparing the results from NP models with those from parametric and partially parametric (PP) models.

Using stock return data from firms in 5 emerging market countries and the U.S., we provide a comparison of the number of firms with exchange rate exposure where we have computed exposure using linear, nonlinear (NL), PP and NP models.[2] Including U.S. firms is

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[1] Guo and Wu (1998) study the effect of financial liberalization on the exchange rate exposure of Taiwanese industries using a nonparametric model.

[2] Few papers in the literature analyze the exchange rate exposure of firms in emerging market economies, partially due to insufficient data (c.f. Chue and Cook, 2008; Dominguez and Tesar, 2001; Kho and Stulz , 2000; Parsley and Popper, 2008). The conclusions of these papers are mixed at best. However, there is some evidence for a larger degree of exposure in these economies. Therefore, we also include firms from these economies in our sample.

advantageous for two reasons. First, it allows us to compare our results to those from the large body of work on exchange rate exposure of U.S firms. More importantly, the data that is available for these firms (and not available for other firms) is convenient for measuring the effects of hedging and testing the soundness of our NP methodology.

Our results show that when NL and PP models are used, the number of firms classified as exposed is considerable. More strikingly, when we use a NP methodology, we find that the number of firms exposed and the economic significance of exposure increases substantially in each country. This result clearly shows that utilizing only a linear model to measure exchange rate exposure significantly underestimates the degree of exposure.

Next, we investigate the role that foreign exchange hedging plays using the notional amounts of foreign currency derivatives held by S&P 500 firms (disclosed in the notes to their annual reports). Although we would have liked to examine the effects of hedging in emerging markets, data on derivatives is not publically available to the best of our knowledge. Our findings reveal that while firms reduce their linear exposure using foreign currency derivatives, this does not carry over to the NP case. These results are robust to altering the choice of exchange rate and return horizons. Additionally, using several tests we find no evidence that the high level of exposure is artificially generated by the NP methodology.

The rest of the paper is organized as follows. Section 2 presents the linear, NL, PP and the NP models used to measure exchange rate exposure and discusses the methodology followed to measure the effects of hedging on exchange rate exposure. Section 3 discusses the data. Section 4 presents the results. Section 5 reports the results from some robustness checks and Section 6 concludes.

2. Methodology

In this section, we describe the models used to approximate firm level exchange rate exposures. We start with the commonly used linear model. Next we discuss NL and then PP models. Then we detail our preferred NP model. Finally, we discuss the effects of hedging within the context of these models.

Linear Model

Initially we follow the standard practice in the literature, and use the following extension of the Adler-Dumas (1984) model to measure exchange rate exposure:

$$R_{it} = \beta_{1i}R_{mt} + \beta_{2i}\Delta e_t + \gamma_{it} \tag{1}$$

where R_{it} and R_{mt} are the returns on firm i's stock and a value weighted stock market index respectively, and Δe_t is the percent change in the foreign exchange rate.

The regression model measures the idiosyncratic effects of exchange rate volatility on a firm's stock return. The market index is included to account for economy wide shocks faced by every firm. This includes for example an expansionary monetary policy that would inflate stock prices and depreciate the currency concurrently. One reason behind the widespread use of this equation is the low likelihood of encountering endogeneity problems since exchange rates can be assumed to be exogenous for an individual firm.[3]

We estimate this model for every firm in our sample using OLS as an empirical strategy, and classify a firm as exposed to exchange rates if its β_{2i} coefficient is significant.[4] In so doing, we orthogonolize the market return and replace this variable with the residuals obtained from the estimation of the following regression:

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[3] Notice that it is more probable for an individual firm to affect exchange rate fluctuations in developing countries characterized by shallow financial markets. Nevertheless, we did not think it was unreasonable to follow the widely used model, especially for the U.S. and for the large emerging market economies considered in our analysis.

[4] In the Appendix of Adler Dumas (1984), it is shown how the coefficient of the exchange rate variable in (1) would represent the economic exposure of a firm to exchange rates fluctuations.

$$R_{mt} = \alpha_1 \Delta e_t + \kappa_t \qquad\qquad\qquad\qquad\qquad (2)$$

This approach has been followed by Allayannis (1996), Griffin and Stulz (2001), Jorion (1991), Priestley and Odegaard (2007) and addresses the possibility of a lack of significance due to the high collinearity between market returns and exchange rates.[5] Specifically, when the estimation of equation (1) yields an insignificant $\hat{\beta}_{2i}$, this does not imply that the firm i is not exposed to exchange rate fluctuations but rather that the exposure of the firm is greater than the market portfolio. Therefore, by orthogonalizing the market return, we are able to measure absolute rather than relative exchange rate exposures of firms. We follow the same approach in all the other models described below.

Nonlinear (NL) Model

Finance theory provides several reasons why there may be a nonlinear relationship between exchange rates and stock returns. Among these are, the nonlinear effects of exchange rates on cash flows (Stulz, 2003), shifting of production activities to different locations in response to exchange rate movements (Kogut and Kulatilaka, 1994; Ware and Winter, 1988), the absence of nonlinear hedging strategies (Bodnar and Gebhart, 1999; Bodnar, Hayt and Marston, 1998), default risk (Stulz, 2003), and pricing to market (Knetter, 1994). Therefore, the literature identifies nonlinear effects and decisions of firms as a possible source of exchange rate exposure and highlights the importance of measuring these exposures.

To gauge the significance of these nonlinear exposures, researchers (c.f. Bartram, 2004; Priestly and Odegaard, 2007) use various nonlinear functions of the exchange rate and estimate the following:

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[5] We also experimented with the standard model (without orthogonolization) and found similar results. However, for all the models we used the proportion of firms that were exposed was significantly higher when we orthogonalized market returns.

$$R_{it} = \beta_{1i} R_{mt} + \beta_{2i} f(\Delta e_t) + \iota_{it} \tag{2}$$

where $f(e_t)$ has taken generic functional forms such as quadratic (Priestly and Odegaard, 2007) and cubic (Bartram, 2004). The latter functional forms have been argued to do a better job of evaluating asymmetric effects of depreciations and appreciations.[6] These studies use other functional forms such as the cubical function, the sinus hyperbolicus, the cubical root function, and the inverse sinus hyperbolicus. The main difference between these functional forms is the ability to capture convex and concave exposures. Theory does not, however, identify a benchmark functional form to use for each firm and for every pattern of exchange rate movements.[7] To be clear, we do not attempt to offer a different method for measuring nonlinear exposures. We estimate nonlinear exposure in order to provide a basis of comparison to our NP results. We follow several approaches to measure nonlinear exposures. Specifically, we estimate the above equation using the quadratic, cubical, sinus hyperbolicus, the cubical root, and the inverse sinus hyperbolicus functional forms.

Partially Parametric (PP) Model

One common observation in the literature is the positive relationship between the magnitude and the significance of the exchange rate exposure coefficients and the size of the exchange rate shock (c.f. Bartram, 2004; Doidge, Griffin and Williamson, 2000; Odegaard and Priestly, 2007). This is partially explained by the inability to identify the effects that small exchange rate shocks have on stock returns when other price relevant information are the main determinants of stock returns. However, when exchange rate shocks are large the effects on stock

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[6] See for example: Bartram (2004), Carter et al. (2005), Di Iorio and Faff (2000), Koutmos and Martin (2003a,b), Choi and Prasad (1995), Tai (2005).

[7] For example it is argued that some functional forms such as the cubic root do a better job of capturing vulnerability to large movements but unreasonably predict high vulnerability to smaller movements.

returns are observed more clearly. Therefore, it is important to measure the effects of these large disturbances separately.

To measure the effect of these large exchange rate movements on stock returns, we estimate the following model:

$$R_{it} = \gamma_{1i}R_{mt} + \gamma_{2i}\Delta e_t + \gamma_{3i}D_{1t}\Delta e_t + \gamma_{4i}D_{1t} + \gamma_{5i}D_{2t}\Delta e_t + \gamma_{6i}D_{2t} + v_{it} \tag{3}$$

$$D_{1i} = \begin{cases} 1 & if \quad -0.5s_{e_t} < \Delta e_{it} < 0.5s_{e_t} \\ 0 & otherwise \end{cases}$$

$$D_{2i} = \begin{cases} 1 & if \quad 0.5s_{e_t} < \Delta e_{it} \\ 0 & otherwise \end{cases}$$

where D_{1t} and D_{2t} are the dummy variables that are used to differentiate exchange rate movements based on size and sign respectively, and s_{e_t} is the standard deviation of the exchange rate variable in the sample period. This formulation allows us to capture the effects of small, large, positive and negative exchange rate movements separately.[8] To decide whether a firm has significant exposure, we will use the null hypothesis that all the exchange rate coefficients are equal to zero (rejection of this hypothesis will indicate significant exposure).

Nonparametric (NP) Model

All three of the estimation strategies used above impose a functional form and also assume that this functional form does not change during the sample period. Furthermore, these methodologies rule out the possibility of different functional forms for different firms. In this section, we address these issues by estimating the relationship between exchange rate fluctuations and stock returns without adhering to a functional form. Therefore, we are able to

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[8] Some studies (c.f. Bartram, 2004; Dominguez and Tesar, 2001, 2006) use sign and size bias tests to check whether the sign and the size of exchange rate shocks have different effects on stock returns. Following the methodology in Bartram (2004), we found evidence for both sign and size bias. This evidence points to the separate effects that large, small, positive and negative exchange rate shocks have on stock returns, and further highlights the misspecification of the linear model in equation (1).

avoid specification problems that parametric approaches are subject to. We use the local linear regression method developed by Stone (1977) as our NP strategy. We chose this method since it is characterized by higher asymptotic efficiency and has faster convergence at boundary points compared to other NP methods.[9] Using this strategy, we estimate the following for each firm:

$$\hat{R}_{it}^{e} = f(\Delta e_{t}) + \varepsilon_{it} \tag{4}$$

where $\hat{R}_{it}^{e} = R_{it} - \hat{\beta}_{i} R_{mt}$ is the excess return on firm i's stock. R_{mt} is orthogonalized as in equation (2), and β_{i} is estimated using the following linear regression:

$$R_{it} = \beta_{i} R_{mt} + v_{it} \tag{5}$$

Although the exact form for $f(\Delta e_{t})$ is not known, the local linear estimation methodology approximates the relationship between Δe_{t} and R_{it}^{e} by making use of the Taylor's series expansion around each observation of exchange rates such that,

$$f(\Delta e_{t}) \approx f(\Delta e_{j}) + f'(\Delta e_{j})(\Delta e_{t} - \Delta e_{j}) = a_{j} + b_{j}(\Delta e_{t} - \Delta e_{j}) \qquad \text{for each} \quad j \tag{6}$$

Next, it fits a line for each observation of Δe_{j} by minimizing the following:

$$\sum_{t=1}^{N}\left(R_{ijt}^{e} - \left[a_{j} + b_{j}(\Delta e_{t} - \Delta e_{j})\right]\right)^{2} K_{j} \tag{7}$$

where $K_{j} = K(\Delta e_{t} - \Delta e_{j})/h$ and h are the normal kernel and the regression smoother bandwidth respectively. Following the standard practice, we set h equal to σ_{e}/N^{5}, where σ_{e} is the standard deviation of the exchange rate. Notice that only observations close to Δe_{j} are included in the minimization problem so that the coefficients a and b are functions of Δe_{j}.

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[9] See Fan and Gijbels (1992) and Pagan and Ullah (1999) for a discussion of these properties.

After estimating b_j for every point in the sample, we calculate $\overline{\hat{b}}_i = \sum_{j=1}^{N} \hat{b}_j / N$ to quantify

the relationship between the exchange rate and a firm's excess stock return. Similarly we

measure the variance of $\hat{b}_i$'s as $\mathrm{var}(\hat{b}_i) = \sum_{j=1}^{N}\left(\hat{b}_j - \overline{\hat{b}}\right)^2 /(N-1)$. Rilstone (1991) shows that this

estimator is consistent and asymptotically normal. Furthermore, this estimator is widely used

since (as shown in Rilstone, 1991) the standard errors of this estimator are comparable to

standard errors obtained from parametric estimation. Therefore, comparing the t-ratios obtained

using these coefficient estimates to t-ratios obtained from parametric approaches is not

unreasonable.

Effects of Hedging

The exposure levels found using the models described above can be low, if firms are

successful in hedging their exchange rate exposures. Therefore, it is interesting to investigate

how the exposure levels found in these models are related to the derivative usage, and to observe

how results differ across models. We test the effect of firms' foreign currency derivative usage

on their exchange rate exposure using the two stage regression process of Cragg (1971).

Specifically, we estimate the following model.

$$\hat{\beta}_i^k = \lambda_1 + \lambda_2 \left(DER/TA\right)_i + \lambda_3 \left(FS/TS\right)_i + \lambda_4 \left(Size/TSize\right)_i + \varepsilon_i \qquad k = \{L, NL, PP, NP\} \qquad (8)$$

where $\hat{\beta}_i^L$, $\hat{\beta}_i^{NL}$, $\hat{\beta}_i^{PP}$, $\hat{\beta}_i^{NP}$ represent the coefficients of the exchange rate variable estimated

using a linear, NL, PP and a NP model respectively. The right-hand side variables $\left(DER/TA\right)_i$,

$\left(FS/TS\right)_i$ and $\left(Size/TSize\right)_i$ denote firm i's foreign currency derivatives to total assets, foreign

sales to total sales ratios and its total assets as a fraction of the sum of the total assets of every

firm in the country (and in our sample) respectively. It is widely observed (c.f. Jorion, 1990; Kho

and Stulz, 2000; Nance et al., 1993; Parsley and Popper, 2008) that exposure is positively related to openness and negatively related to the size of the firm. The latter observation is generally attributed to the higher likelihood of larger firms to be multinational companies that therefore, have natural hedges inherent in their operations. Given this substantial evidence, these variables are included in equation (8). It is important to point out that this second stage regression is not a contribution of our paper. Indeed, studies such as Allayannis and Ofek (2001), Hagelin and Pramborg (2004), Muller and Verschoor (2006) Pantzalis, Simkins and Laux (2001) have used a similar methodology to study the determinants of exchange rate exposure. We add to this work by also considering exposures as measured by NP, as well as NL, PP and linear models.

The literature offers several options for measuring the extent of derivative usage. In contrast to a majority of the literature that uses binary or survey data to indicate whether firms use derivatives or not, Allayannis and Ofek (2001) were to first to use a continuous variable (notional derivative usage). This approach has become the benchmark recently as it is more convenient for controlling firm characteristics (such as size and openness) when measuring the effects of derivative usage on exposure. Therefore, we use notional figures in our estimation since we have no reason to use binary data and this data was not available.

There are two other noteworthy issues in the estimation of equation (8). First is related to the choice of the dependent variable. A number of studies use only the significant coefficients from the first stage, others use all. Furthermore, some studies use the absolute value of these coefficients. Second is related to the choice of an estimation strategy. Although, a majority of the literature uses OLS, there are some studies that use Weighted Least Squares (WLS) and Probit models (those that include only the significant coefficients).[10] To check for robustness, we

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[10] Weights in the WLS regression are generally the standard deviation of the exposure coefficients (c.f. Allayannis and Ofek, 2001).

used all of these approaches. The reader should rest assured that there were no noteworthy differences when comparing the results of regressions obtained by using each of the $\hat{\beta}_i^k$ as dependent variables.[11,12] Therefore, we only report the OLS estimation results and use absolute values but do not omit the insignificant coefficients. The main reason for following this convention was to be compatible with a majority of the studies that use a similar approach.[13]

3. Data

In our data set, we include nonfinancial firms from the U.S. and 5 relatively large emerging market economies.[14] The contents of the data set are displayed in Table 1. We used Datastream International to gather data for the firms in emerging market economies and used CRISP to obtain stock prices and total assets for the U.S firms listed in the S&P 500. Our choice of emerging market countries was determined by data availability. We included U.S. firms since data on derivatives markets participation was only available for these firms.

The dataset includes daily observations for stock returns, exchange rates, return on market indices for the 1995-2006 period. In our simulations, we use value weighted market indices and the standard monthly return horizon.[15] We check the sensitivity of exposure to return horizons, however in our robustness section. We follow the standard practice in the exposure

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[11] We found that the coefficient of the derivative variable was considerably larger and more significant in every model when only the significant coefficients were included and a Probit model was used as an estimation strategy..

[12] When using the absolute values of the coefficients, we corrected for the resulting truncation bias by using the methodology in Dominguez and Tesar (2001)

[13] Note that since the number of significant coefficients will be different for each model we use, by not excluding the insignificant coefficients we are able to avoid any effects that the different degrees of freedom may have on the comparison of the results across models. Nevertheless, including insignificant coefficients could understate any effect that hedging may have on exposure coefficients. As mentioned above, however, the two methods did not generate any noticeable differences when comparing across models.

[14] The emerging market economies are: Brazil, Chile, Korea, Mexico and Turkey.

[15] Bodnar and Wong, 2003 demonstrate that value weighted index can introduce a bias by giving more weight to firms that are large and trade more and thus, suggest that an equally weighted market index maybe a better option. Therefore, we also considered equally weighted indices. However, the effects were immaterial to our conclusions.

literature and exclude financial firms from our data set. These firms are generally excluded due to their market making property in both foreign exchange and derivatives markets.

Notional amounts of foreign exchange hedging contracts used by the S&P 500 firms were collected from the footnotes in the annual reports of these firms.[16] Out of the 367 nonfinancial firms in our sample, 268 reported a notional amount for foreign currency derivative in their annual reports. We gathered this information from the Mergent database for the 2004-2006 period. In general, firms that report the notional amounts of foreign currency derivatives, also report the foreign sales/total sales ratios. Furthermore, some of these firms also reveal the currency to which they are most exposed. We utilize this information in the estimation of the model in equation (8). To measure the right hand side variables in equation (8), we take the simple and weighted (using total assets as weights) averages of these variables over the 2004-2006 period for each firm. Since there was no considerable difference between using simple and weighted averages, we only report the results from simulations that use simple averages. For consistency, we also measure the dependent variable (exchange rate exposure) for the 2004-2006 period using weekly returns.[17]

At this point we should point out a potential caveat to our analysis. In particular, the utilization of notional amount of derivatives reported can also introduce a bias since most firms do not report whether they have short or long positions in the underlying currency. However, this should not be a major concern as firms appear to be netting foreign currency positions when

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[16] A majority of these firms used forward contracts to manage foreign exchange risk. However, our sample also includes foreign currency derivatives such as options and futures contracts. Swap contracts were not included since they are mainly used to translate foreign debt to domestic liabilities.

[17] We do not have any reason for expecting asymmetric effects of using a shorter sample period on the exposures found using different functional forms. Nevertheless, we increased the number of observations and measured exchange rate exposures using daily and weekly overlapping observations for monthly return horizons. Simulations revealed similar results and are available upon request.

aggregating them. [18] Furthermore, since we are studying the relationship between absolute exposure and the absolute value of derivative usage, whether a firm has a long or a short position should not present a systematic bias in our results.

Choice of Exchange Rates

To date, there is no consensus in the literature on the choice of exchange rates when measuring exposure. Previous studies have used major currencies, trade weighted exchange rates, broad exchange rate indices, or have included exchange rates simultaneously in equation (1). In choosing the exchange rate we consider several options. First, we include exchange rates measured as local currency per major currencies such as the US Dollar, Euro, Japanese Yen, British pound and the trade weighted exchange rates individually. Second, using the output of the regressions with individual currencies, we identify, for each firm the exchange rate that generates the maximum significance of exposure (denoted as ERMAX in the rest of the paper) and report the results obtained using this methodology. This methodology, different from previous work, allows the data to predict the exchange rate instead of restricting the analysis by measuring exposure of every firm to a single currency or a basket of currencies. Third, for U.S. firms we measure firms' exposure to the currencies they identify in their footnotes in addition to their exposures to the major currencies mentioned above (denoted as ERStated in the rest of the paper).

4. Results

Proportion of Firms exposed to exchange rate shocks

Table 2 shows the percentages of firms with significant (at the 5% level using robust standard errors) exposures. Columns correspond to the different models used to measure exchange rate exposure and the last row represents the number of regressions for which we find evidence for first and/or second order serial correlation in the residuals. For convenience, we

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[18] When firms reported both short and long positions we netted these positions for each currency.

report the results obtained using the local currency/US Dollar exchange rate for emerging markets and the US Dollar/Euro exchange rate for the U.S. As mentioned in the previous section, we report the sensitivity of some of our results to alternative exchange rate measures. We only report the results from the nonlinear model with a quadratic functional form since the other generic nonlinear forms resulted in considerably lower proportions of exposure. The latter convention is followed in the rest of the paper.

Figures reported in the first column of Table 2 are within the range of values found in studies that use linear models and show that only a few firms are exposed to exchange rate movements.[19] Notice also that our models appear to be reasonably specified as we failed to find substantial evidence of first and/or second order serial correlation in the residuals. More importantly, we find that exchange rate exposures in each country are substantially underestimated if NL, PP, and NP models are not considered. This can be seen clearly in columns 2 to 4 which show the proportion of firms that did not have linear exposure but had significant NL, PP, or a NP exposure to exchange rate movements. Indeed, the number of firms with linear or NL, and linear or PP exposure is significantly higher (100 percent higher in a majority of the cases) than the number of firms with linear exposure only.

More strikingly, we find that NP estimation produces proportions that are significantly higher for each country. These results, however, are qualitatively similar to the results from the linear model. For example, we find that Korea has the highest percentage of firms that are exposed and Brazil and Mexico have the lowest percentages when using either model. These figures are not too unreasonable if we consider that Korea and Brazil have the most open and

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[19] Most of the studies use U.S. data and find frequency of exposure less than 15%. We can not do justice to the vast amount of research. Albeit, here are some of the exposure proportions we found: Jorion (1990), 5.2%; Walsh (1994), 5.6%; Prasad and Rajan (1995), 15.0%; Dukas, Fatemi and Tavakkol (1996), 5%-8.3%. For other countries: Prasad and Rajan (1995), 4% (JPN), 5.9% (GBR), 16.7 % (DEU); Doidge, Griffin and Williamson (2006), 8.2% (18 countries).

closed economies in the sample, respectively.[20] Furthermore, NP results show that in general proportions of exposure in emerging markets are higher than the U.S.[21] This is in contrast to some studies (c.f. Dominguez and Tesar, 2001; Kho and Stulz , 2000) that do not find material evidence for this difference. This contrast can partially be explained by the different exchange rates and return horizons we employ. However, the main difference in this paper is the orthogonalization of the market return variable. Using this method, we capture the absolute effects of exchange rate movements on a firm's stock return rather than only measuring the relative exposure of firms. Therefore, our results demonstrate that absolute exposure to exchange rates is more frequent in emerging markets.[22]

Next we consider the economic significance of exposure. The average coefficient values that represent this magnitude of exposure are displayed in Table 3. In contrast to the results in Table 2, we do not find a uniform increase or decrease in the size (economic significance) of exposure when we compare the results from the linear and NP models. Averages are computed using the absolute values of the exchange rate coefficients and equal weights.[23] Therefore, the NP model only predicts higher frequency of exposure and not a larger size of exposure. The results also show, compared to studies using advanced economies that the size of linear

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[20]The average values for the (Exports+Imports)/GDP ratios between 1998 and 2008 for Korea and Brazil were 77.3 and 24.9 percent respectively.

[21] Note however that we do not measure relative exposure (relative to the market index) as in Dominguez and Tesar (2001) and Kho and Stulz (2000) and use orthogonalized market returns in our experiments.

[22] Using an alternative strategy to measure absolute exposure Chue and Cook (2008) find results similar to this paper. Although it is not our immediate concern, we ran simulations using the methodology in Chue and Cook (2008). Specifically, we replaced domestic stock market index with the world stock market index and used instrumental variables for the exchange rate variable. The results revealed slightly higher levels of exposure. However, the conclusions drawn from the comparison of the results from the different models did not change.

[23] We also used weighted averages (with total assets as weights) and obtained similar results.

exposures is higher in emerging market economies and that exposure of US firms are within the range of values found in the literature.[24]

The Effects of Hedging

The results of our second stage regression described in equation (8) are presented in Table 4. When generating the dependent variable for each firm, we use ERMAX as the exchange rate variable. We use this method since we assume that firms use foreign currency hedging instruments to limit their vulnerabilities to the fluctuations of the currencies to which they are most exposed.

Our main finding is that hedging has a negative and significant (at the 5% level using robust standard errors) effect on exposures estimated using linear and PP models but does not have a significant effect on exposure when NL and NP models are used. The signs of the size and openness coefficients, as expected imply that small and open firms are more exposed.

Alternatively, we use the exchange rates that firms state as the main currencies they are exposed to in their annual reports. Results are displayed in Table 5. We find that the size and the significance of the derivative usage variable increases. Furthermore, we find that firms were able to reduce their nonlinear exposures to the currencies their most vulnerable to by hedging. However, we find that NP exposures remain unaffected by the level of derivative usage.

Financial options provide nonlinear payoff schedules, which would be convenient for reducing nonlinear exposures. However, our results indicate that either nonlinear exposures are not identified clearly or that these financial instruments are not being used effectively by firms.

4. Testing the soundness of the NP methodology

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[24] For example for U.S., Jorion (1990) estimates a maximum exposure of 0.56 over the period, 1971-1989. Dominguez and Tesar (2006) similarly estimate a maximum exposure of 0.17-0.56 over the period 1980-1999 in 6 non-US advanced economies. Hagelin and Pramborg (2002) estimate it to be 0.52 over the period 1997-2001 in Sweden.

In this section we use several experiments to test the soundness of the results from the NP model. In so doing, we attempt to determine whether the substantial differences in results obtained using a NP model versus alternative models are due to the NP estimation methodology itself. We use the S&P 500 firms in this section. This sample set was chosen mainly for brevity and consistency. The data required to conduct the first two tests were only available for U.S. firms and we could not find evidence pointing to different conclusions when we used data from emerging markets in the last three tests.

Firms that declare no exposure

Sixty-nine of the S&P 500 firms explicitly declare that they do not have significant exposure to foreign currency fluctuations and therefore do not carry any foreign currency derivatives. Conveniently, this information allows us to scrutinize the results obtained from the NP model. Specifically, by comparing exposure coefficients obtained using NP and other methods for these firms, we are able to investigate whether the higher frequency of exposure found with a NP estimation is artificially generated by this methodology. Results are displayed in Panel A of Table 6. Consistent with firms' declarations, we see that the proportion of firms with estimated exposure (among firms who state no exposure) is low regardless of the different models used in estimation. Furthermore, the results also suggest that the relatively high proportion of exposure found using a NP approach is unlikely due to the approach itself (to the extent that the information provided by these firms are accurate).

Profile of firms that have a nonparametric exposure

In this section, we analyze the characteristics of firms that are classified as exposed when a NP approach is used, but are not classified as exposed if parametric models are used. Specifically, we estimate the following model to determine the effects of derivative usage,

foreign sales and size on the likelihood of finding exposure in a NP model but not in the other models. In so doing, we use data for U.S. firms that have NP exposure.

$$D_i^{NP,j} = \psi_{0i} + \psi_{1i}(DER/TA)_i + \psi_{2i}(FS/TS)_i + \psi_{3i}(Size/TSize)_i + v_i \quad j = L, NL, PP \qquad (9)$$

$$D_i^{NP,j} = 1 \quad if \ \hat{\beta}_i^{NP} \ is \ significant \ and \ \hat{\beta}_i^{j} \ is \ not$$

$$D_i^{NP,j} = 0 \quad if \ \hat{\beta}_i^{NP} \ and \ \hat{\beta}_i^{j} \ are \ both \ significant$$

We estimate this model using 3 different dependent variables. The dependent variable, $D_i^{NP,j}$ is set equal to 1 if there is NP exposure but no linear, NL or PP exposure, respectively.

In Section 3 we found, consistent with the literature, that firms smaller in size and/or firms with higher foreign sales are relatively more exposed to exchange rate fluctuations. Accordingly, we would expect to observe these characteristics in firms that have NP exposure but are classified as not exposed when parametric specifications are used. Conversely, if we observe that the NP approach is -- inaccurately -- finding a significant exposure for firms that have no operations abroad nor any economic exposure, this would point to methodology related shortcomings.

The results obtained from a probit estimation strategy are displayed in Panel B of Table 6. We find that firms classified as exposed under a NP approach but not exposed using the other methods (L, NL, PP) have relatively high foreign sales and are smaller in size. This is consistent with our findings described in the previous section. Also consistent with our main results, we find that derivative usage does not affect the likelihood of finding exposure when using a NP model.

Specification Tests

As mentioned above, we identify the usage of the same parametric form for each firm as a possible determinant of our results. To test whether this constraint is a determinant of the low

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exposure found using parametric models, we follow the methodology of Li and Whang (1998). The authors propose a method for testing for specific functional forms against alternative functional forms. This method is especially convenient for our purposes since the alternative functional forms do not have to be specified. The construction of the author's test statistic and its properties is summarized in Appendix A.

Panel C of Table 6 displays the results of our specification tests using US data. Columns correspond to the functional forms that were tested under the null hypothesis. To be concise, we only report the proportion of firms for which the functional form listed in the corresponding column was rejected at the 5% level. The results suggest that a linear model provides a better overall fit compared with the other parametric models. However, for a majority of the firms in our sample, the parametric forms were rejected.[25]

Return horizons and the choice of exchange rates

In this section, we replicate our simulations using different exchange rates and return horizons and measure the proportion of S&P 500 firms exposed under these scenarios.

We focus on the weekly, monthly, quarterly and semiannual horizons when measuring the change in exchange rates, stock prices and returns to market in equation (1). Note that comparing exposure across different return horizons in this way would be questionable due to the large differences in the degrees of freedom associated with each return horizon. To overcome the lack of power and make significance more comparable across different frequencies, we use overlapping observations similar to Dominguez and Tesar (2006) and Bodnar and Wong (2003). In so doing, we use daily overlapping observations for weekly return horizons, and weekly

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[25] When we used the same test for emerging market firms in our sample we found that the functional forms were rejected for a larger proportion of firms compared to the US. These results are available upon request. We also experimented with other nonlinear functional forms and found proportions that were larger than under the linear specification.

overlapping observations for monthly, quarterly and semiannual horizons. We correct for serial correlation stemming from the usage of overlapping observations by employing the Newey and West (1987) method. The results from the estimation of equation (1) (using the US Dollar/Euro exchange rate) are displayed in Panel D of Table 6. Consistent with a majority of the research (c.f., Allayannis, 1997; Bartov and Bodnar, 1994; Bodnar and Wong, 2003; Chow and Chen, 1998; Chow, Lee and Solt, 1997; Dominguez and Tesar, 2001, 2006; Jongen, Muller and Verschoor, 2007), we find, in general, that the proportion of firms with significant exposure increases with the return horizon. Notice, however that the conclusions drawn from our benchmark model remain the same. Specifically, we observe that NL, PP, and NP models capture the exposure of a noticeable number of firms and that these numbers are considerably higher for the NP model.

We reach a similar conclusion when we use different exchange rates. Results (using monthly return horizons) displayed in Panel E of Table 6 demonstrate that the number of firms with exposure according to the NP model is higher for every exchange rate we use. We also find that exchange rate exposure is not as frequent when a trade weighted exchange rate is used, and that the proportions are the highest for ERStated and -- by definition -- for ERMAX.

Subsamples and the lagged effects of exchange rate fluctuations

There is evidence in the literature that suggests a lagged effect of exchange rate movements on stock prices. Partially indicating delayed processing of information by investors when evaluating firms' exchange rate risk. Furthermore, some studies (c.f. Domniguez and Tesar, 2006) argue that measuring exchange rate exposures using a long sample period may understate the level of exposure. This especially true for firms in countries where significant exchange rates

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fluctuations are limited to short periods of time.[26] Our simulations including the lagged effects of exchange rates and limiting the sample to periods with high exchange rate volatility generally yielded larger exchange rate coefficients. However, simulation results from the linear, NL, PP and NP models were qualitatively similar.[27]

5. Conclusion

Our results demonstrate that when exchange rate exposure is measured using only a linear model, the proportion of firms with exposures are understated in both emerging markets and an advanced economy such as the US. We show that if NL, PP and NP models are used as an estimation strategy the frequency of exposure increases. Among these models, however we find that only NP results display the high frequencies of exposure that are parallel to anecdotal evidence, finance theory and institutional knowledge. Consistent with these results, our second stage regression results implied that firms are able to lower their linear exposures but not the NP (and nonlinear in some cases) exposures by using foreign currency derivatives.

Although the NP approach used in this paper has several advantages for every country, this approach would be most useful for countries that have a high degree of variety among their firms (in terms of openness and economic exposure) and/or are experiencing structural breaks (for example those that are in the process of integrating with global capital markets). Indeed, by estimating the nature (or the functional form) of the relationship between stock prices and exchange rates uniquely for each firm and by more effectively accounting for the dynamics of this relationship before and after structural breaks, a NP approach can be more advantageous over parametric approaches. The latter characteristic would be especially useful when using long sample periods.

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[26] Although our partially nonparametric approach accounts for these large fluctuations, limiting the sample to specific periods marked by high volatility can do a better job of capturing the dynamics governing these periods.
[27] These results are available upon request.

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Table 1. Data

Data source			
	Emerging Market Economies	Datastream Int.	
	US-stock prices, size, and openness	CRISP	
	US-derivatives, stated exchange rates	Mergent	notional figures reported in the footnotes to annual reports
Number listed nonfinancial firms			
	Brazil	708	Sao Paulo Stock Ex.(BOVESPA)
	Chile	183	Santiago Stock Ex. (SSE)
	Korea	849	Korea Stock Exchange (KSE)
	Mexico	249	Bolsa Mexicana de Valores (BMV)
	Turkey	226	Istanbul Stock Ex. (ISE)
	US	369	S&P 500
Sample period	Stock prices	1995-2006, daily	
	Derivatives	2004-2006, annual	

Table 2. Different Methods for Measuring Exchange Rate Exposure -- % of Firms Exposed

	Proportion of Firms with Significant Exposure (%)			
	Linear	Nonlinear	Partially parametric	Nonparametric
Brazil	2.0	2.7	3.3	16.9
Chile	5.1	2.1	3.8	28.5
Korea	10.8	11.2	15.4	53.1
Mexico	6.1	3.5	8.1	18.7
Turkey	5.9	4.0	12.1	44.3
United States	5.4	7.9	10.5	16.2
Firms with serial correlation	12/2584	15/2584	8/2584	17/2584

Note: This table reports the percentage of firms exposed to exchange rate fluctuations. In Column 2, a firm is classified as exposed if the β_{2i} in equation (1) is significant (using robust standard errors) at the 5% level. OLS is used to estimate equation (1). Columns 3 to 5 report the percentages of firms that did not have significant exposure according to the linear model but were significantly exposed according to the nonlinear, partially parametric and nonparametric estimation results. The US Dollar/Euro exchange rate is used for U.S. and the local currency/US Dollar is used for emerging market countries. Quadratic functional form is used in the nonlinear model. Returns are measured monthly. Last row shows the proportion of regressions that had either a first or second order serial correlation in the error term.

Table 3. Different Methods for Measuring Exchange Rate Exposure -- Economic Significance

	Average Exposure Coefficients			
	Linear	Nonlinear	Partially parametric	Nonparametric
Brazil	0.56	0.15	0.50	1.04
Chile	0.65	0.16	0.51	0.55
Korea	1.57	0.43	1.18	0.56
Mexico	0.93	0.30	0.72	1.19
Turkey	0.80	0.14	0.67	1.03
United States	0.42	0.13	0.42	0.33

Note: This table reports the simple average of the $\hat{\beta}_{2i}$ coefficients (measured in absolute terms) for each country. $\hat{\beta}_{2i}$ denotes the exchange rate exposure coefficient estimated by the linear, nonlinear, partially parametric and nonparametric models. The US Dollar/Euro exchange rate is used for U.S. and the local currency/US Dollar is used for emerging market countries. Quadratic functional form is used in the nonlinear model. Returns are measured monthly.

Table 4. The Effect of Hedging on Exposure -- ERMAX

	Dependent Variables			
	$\hat{\beta}^L$	$\hat{\beta}^{NL}$	$\hat{\beta}^{PP}$	$\hat{\beta}^{NP}$
Constant	1.61	0.38	0.84	0.56
	(0.69)**	(0.07)***	(0.28)***	(0.08)***
Hedging	-0.49	-0.08	-0.34	-0.14
	(0.27)*	(0.07)	(0.14)**	(0.67)
Openness	1.11	0.17	0.21	0.33
	(0.52)**	(0.08)**	(0.10)**	(0.14)**
Size	-0.18	-0.05	-0.11	-0.30
	(0.09)*	(0.02)**	(0.06)*	(0.15)*
R2	0.03	0.01	0.04	0.01
Observations	268	268	268	206

Note: This table reports the results form the OLS estimation of equation (8) using data from S&P 500 firms. $\hat{\beta}^L$, $\hat{\beta}^{NL}$, $\hat{\beta}^{PP}$ and $\hat{\beta}^{NP}$ denote the dependent variables (measured in absolute terms) that are generated using a linear, nonlinear, partially parametric and nonparametric model respectively. The ERMAX is used as the exchange rate. Quadratic functional form is used in the nonlinear model. Hedging, openness and size denote the $(DER/TA)_i$, $(FS/TS)_i$ and $(Size/TSize)_i$ variables respectively. Robust standard errors are in parentheses. Returns are measured monthly.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5. The Effect of Hedging on Exposure -- ER Stated

	Dependent Variables			
	$\hat{\beta}^{L}$	$\hat{\beta}^{NL}$	$\hat{\beta}^{PP}$	$\hat{\beta}^{NP}$
Constant	0.85	0.45	0.66	0.52
	(0.12)***	(0.08)***	(0.10)***	(0.08)***
Hedging	-0.29	-0.18	-0.28	0.70
	(0.06)***	(0.09)*	(0.06)***	(0.86)
Openness	0.27	0.29	0.38	0.30
	(0.14)*	(0.14)**	(0.17)**	(0.12)**
Size	-0.11	-0.04	-0.09	-0.44
	(0.04)***	(0.02)**	(0.03)***	(0.19)**
R2	0.01	0.02	0.01	0.01
Observations	210	210	210	206

Note: This table reports the results form the OLS estimation of equation (8) using data from S&P 500 firms. $\hat{\beta}^{L}$, $\hat{\beta}^{NL}$, $\hat{\beta}^{PP}$ and $\hat{\beta}^{NP}$ denote the dependent variables (measured in absolute terms) that are generated using a linear, nonlinear, partially parametric and nonparametric model respectively. The ERStated is used as the exchange rate. Quadratic functional form is used in the nonlinear model. Hedging, openness and size denote the $(DER/TA)_i$, $(FS/TS)_i$ and $(Size/TSize)_i$ variables respectively. Robust standard errors are in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6: Robustness

Panel A: Firms declaring that exposure is insignificant

	Linear	Nonlinear	Partially parametric	Nonparametric
Firms with significant exposure	2/69	3/69	5/69	4/69

Panel B: Profile of firms with nonparametric exposure

Dependent Variables	$D_i^{NP,L}$	$D_i^{NP,NL}$	$D_i^{NP,PP}$	
Hedging	0.0024	-0.0018	-0.0007	
	(0.074)	(0.074)	(0.076)	
Size	-1.8339	-1.7765	-1.8087	
	(0.055)***	(0.053)***	(0.055)***	
Openness	6.7263	6.5539	6.7446	
	(2.194)***	(2.212)***	(2.241)***	
Number of Observations	262	265	268	

Panel C: Specification Tests

	linear	quadratic	cubic
% of parametric forms rejected	0.67	0.75	0.85

Panel D: Different Return Horizons

	Linear	Nonlinear	Partially parametric	Nonparametric
Weekly	3.6	7.1	8.3	20.6
Monthly	7.3	9.1	13.1	28.3
Quarterly	8.6	9.5	12.1	29.2
Semiannual	9.2	11.0	15.9	30.2

Panel E: Different Exchange Rates

	Linear	Nonlinear	Partially parametric	Nonparametric
Euro	5.4	7.9	10.5	16.2
Yen	4.8	10.1	12.3	13.9
GBP	7.0	7.9	8.7	10.9
Trade Weighted	4.5	3.4	3.2	10.0
ERStated	9.1	9.3	12.6	21.9
ERMAX	12.9	13.5	13.3	25.8

Note: These results are for the S&P 500 firms. Monthly return horizons and the Euro/US Dollar exchange rate are used in all of the simulations except for those studying different return horizons and exchange rates respectively. Panel A reports the proportion of firms that explicitly state their lack of exposure to any currency but are classified as exposed according to the models in the paper. Panel B reports the estimation results of equation (8) using only the exposure coefficients that were significant according to the nonparametric model using firms. Panel C displays the proportion of firms for which the linear functional form was rejected by the Li-Whang test. Panel D reports the proportions of firms with exposure when different return horizons were considered. We use daily overlapping observations for weekly return horizons, and weekly overlapping observations for the monthly, quarterly and semiannual return horizons. Panel E compares the proportion of firms with exposure across different currencies. ERStated denotes the currency identified by S&P 500 firms in their annual reports (as the main the currency they have the most exposure to). ERMAX is the exchange rate for which a maximum significance of exposure was found in the regressions.

Appendix A: Functional Form Testing

Suppose we observe a sample of n random variables: $\{(Y_i, X_i): i = 1...n\}$ where $Y_i \in R$ and $X_i \in R^k$. Given this sample we can define our null and alternative hypothesis by equations (A.1) and (A.2) below,

$$E(Y \mid X) = g(X, \beta) \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (A.1)$$

$$E(Y \mid X) = h(X, \beta) \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (A.2)$$

where β denotes a vector of parameters, $g(X, \beta)$ is a known function that is to be tested and $h(X, \beta)$ is a function that is different from $g(X, \beta)$.

Using additive error terms the models under the null and alternative hypothesis can be expressed as :

$$Y_i = g(X_i, \beta) + e_i \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (A.3)$$

$$Y_i = h(X_i, \beta) + v_i \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (A.4)$$

where $E(e \mid X) = 0$ only if the null hypothesis is true. Given this setup Li and Whang (1998) measure $E(e \mid X)$ using a nonparametric kernel estimation method and generate a test statistic given by,

$$J_n = \frac{\sum\limits_{i=1}^{n} \sum\limits_{j \neq i}^{n} \hat{e}_i \hat{e}_j K_{ij}}{(n-1)\lambda^{\frac{p}{2}} \sqrt{\dfrac{2}{n(n-1)\lambda^p} \sum\limits_{i=1}^{n} \sum\limits_{j \neq i}^{n} \hat{e}_i^{\,2} \hat{e}_j^{\,2} K_{ij}^2}} \qquad\qquad\qquad\qquad (A.5)$$

where $\hat{e}_i$ and $\hat{e}_j$ are the least square residuals from the linear regression under the null hypothesis, λ is the smoothing (bandwidth) parameter, q is the number of independent variables and the kernel function K_{ij} is given by $K_{ij} = (X_i - Y_i)/\lambda$. Li and Whang also show that this statistic has an asymptotic standard normal distribution under the null hypothesis.