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ORIGINAL RESEARCH

Measuring currency exposure with quantile regression

Ding Du · Pin Ng · Xiaobing Zhao

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Abstract In this paper, we explore an alternative explanation of the exposure puzzle, the missing variable bias in previous studies. We propose to correct the bias with the quantile regression technique invented by Koenker and Bassett (Econometrica 46:33–51, 1978). Empirically, as soon as we take into account the missing variable bias as well as time variation in currency exposure, we find that 26 out of 30 or 87 % of the US industry portfolios exhibit significant currency exposure to the Major Currencies Index, and 23 out of 30 or 77 % show significant exposure to the Other Important Trading Partners Index. Our results have important theoretical and practical implications. In terms of theoretical significance, our results strengthen the findings in Francis et al. (J Financ Econ 90:169–196, 2008), and suggest that methodological weakness, not hedging, may explain the insignificance of currency risk in previous studies. In terms of practical significance, our results suggest a simple yet efficient approach for managers to estimate currency exposure of their firms.

Keywords Currency exposure · Missing variable bias · Exposure puzzle · Quantile regression

JEL Classification G15 · F31

D. Du (✉) · P. Ng · X. Zhao
The W. A. Franke College of Business, Northern Arizona University, PO Box 15066, Flagstaff, AZ 86011, USA
e-mail: ding.du@nau.edu

P. Ng
e-mail: Pin.Ng@nau.edu

X. Zhao
e-mail: Xiaobing.Zhao@nau.edu

1 Introduction

There is substantial evidence suggesting that purchasing power parity does not hold after the breakdown of the Bretton Wood system in 1973,[1] which implies that in theory firms are exposed to currency risk. Adler and Dumas (1984) forcefully state that "US corporations, including those with no foreign operations and no foreign currency assets, liabilities, or transactions, are generally exposed to foreign currency risk." (p. 41) Such theoretical implication is consistent with evidence from practitioners. For instance, Francis et al. (2008) cite a Philadelphia Fed survey which finds that "over 45 % of US firms reported that they are affected by currency movements" (p. 177); Nucci and Pozzolo (2010) "document a statistically significant effect of exchange rate variations on employment, hours worked and wages in a representative panel of Italian manufacturing firms." (p.121).

Despite the support from the theory and the evidence from practitioners, empirical academic studies usually find that only a small proportion of US firms have significant currency exposure. For instance, Jorion (1990) finds that only 5.2 % of individual firms and 20 % of portfolios have significant currency exposure.[2] This anomaly is called the exposure puzzle in the exchange rate literature.

What can possibly explain the exposure puzzle is still controversial. Bodnar and Bartram (2007), Bartram (2008) and Bartram et al. (2010) argue that firms use financial and operating hedges to greatly reduce currency exposure. However, their argument does not seem to be consistent with the evidence in the Philadelphia Fed survey (Francis et al. 2008). On the other hand, Francis et al. (2008) (denoted hereafter as FHH) suggest that methodological weakness, not hedging, may explain the insignificance of currency exposure in previous studies. Specifically, by allowing time variation in currency exposure (as well as currency risk premium), FHH find more significant currency exposure in US industry portfolios.

In this paper, we explore an alternative explanation of the exposure puzzle. Our argument is motivated by the mounting empirical evidence which suggests that currency exposure may depend on a large number of factors (i.e. Wei and Starks 2005; Aggarwal and Harper 2010). If currency exposure is conditional on many firm-specific and non-firm-specific factors, the standard approach (which is to regress asset returns on foreign exchange rate changes as well as market returns with ordinary least-squares regression) may lead to not only inefficient estimates due to heteroskedasticity but also biased estimates. To correct this problem, we take a reduced-form approach in this paper. Specifically, we utilize the quantile regression technique invented by Koenker and Bassett (1978) to estimate currency exposure. We discuss the details of our motivation and the advantages of our approach in the next section.

Empirically, we find that only 20 % (17 %) of US industry portfolios have significant exposure to the currencies of the industrialized economies (the currencies of the developing economies), if we use the standard approach. This is consistent with the findings in previous studies (e.g. Jorion 1990). However, if we use the quantile regression technique and allow for time variation in currency exposure, we find that 87 % (77 %) of US industry portfolios exhibit significant exposure to the currencies of the developed economies (the currencies of the developing economies).

Our results have important theoretical and practical implications. In terms of theoretical significance, our results extend FHH, suggesting that methodological weakness not

[1] See Taylor and Taylor (2004) for a review.

[2] See also Khoo (1994), Bartov and Bodnar (1994), Cheung et al. (1995), Allayannis (1997), Chow et al. (1997), Chiao and Hung (2000), Bodnar and Wong (2003), Bartram (2004), (2007), Bartram and Bodnar (2005), Elyasiani and Mansur (2005), and Du and Hu (2012a, 2012b).

hedging may explain the insignificance of currency exposure in previous studies. Put differently, while FHH show that a major methodological weakness in previous studies is the assumption of constant currency exposure (as well as currency risk premium), we demonstrate that another methodological weakness is the missing variable bias. If both weaknesses are taken into account, significantly more firms demonstrate significant exposure to currency movements.

In terms of practical significance, besides suggesting a simple yet efficient approach for managers to estimate currency exposure of their firms, our results (that substantially more firms have significant currency exposure) also imply that corporate managers of all firms including domestic firms may need to take into account currency exposure. This echoes the insight of Adler and Dumas (1984). Consequently, current accounting policy ought to be modified to allow for a more favorable treatment of foreign currency hedges. For instance, present accounting policy that requires mark-to-market for foreign exchange derivative positions should probably be amended to allow for identifiable expected offsetting foreign currency flows.

The remainder of the paper is organized as follows: Section 2 discusses the motivation of the paper. Section 3 presents data and empirical results. Section 4 concludes the paper with a brief summary.

2 Motivation

The standard approach in the currency exposure literature is to regress monthly stock returns on the market return and the percentage change in the foreign exchange rate index with ordinary least-squares regression (e.g. Adler and Dumas 1983; Bartram 2007):

$$r_{it} = \alpha_i + \beta_{i,M} M_t + \beta_{i,FX} FX_t + \varepsilon_{it} \quad for\, i = 1, \cdots, N \tag{1}$$

where r_{it} is the excess return on asset i in period t, M_t is the excess return of the market factor, FX_t is the percentage change in the foreign exchange rate index, and N is the number of assets. The β's are the associated loadings and assumed to be time invariant, and ε_{it} is the disturbance.

However, there is growing empirical evidence suggesting that currency exposure may depend on a large number of firm-specific and non firm-specific factors (i.e. Patro et al. 2002; Wei and Starks 2005; Aggarwal and Harper 2010). In a recent study, Aggarwal and Harper (2010) show that debt level, financial risk, gross margin, asset turnover, asset tangibility, R&D investment, firm size, the market to book ratio (growth opportunities), industry competition, and the industry within which a firm operates can all affect currency exposure of a firm. Such evidence suggests that there should be interaction terms in Eq. (1) to capture the effects of these factors:

$$r_{it} = \alpha_i + \beta_{i,M} M_t + \beta_{i,FX} FX_t + \sum_j \beta_{i,F_j} F_{jt} FX_t + \sum_k \beta_{i,NF_k} NF_{kt} FX_t + u_{it} \tag{2}$$

where F_{jt}'s represent firm-specific factors such as leverage and size, and NF_{kt}'s represent non firm-specific factors such as industry competition. Comparing Eqs. (1) and (2), it is easy to see that the error term ε_{it} in Eq. (1) is.

$$\varepsilon_{it} = \sum_j \beta_{i,F_j} F_{jt} FX_t + \sum_k \beta_{i,NF_k} NF_{kt} FX_t + u_{it}$$

As a result, the standard model of Eq. (1) is misspecified in the sense that it omits relevant variables, which may lead to not only heteroskedasticity but also biased estimates when ordinary least-squares regression is used.

There may be two possible approaches to correct for the misspecification problem. One is a structural approach, which is to explicitly include all relevant variables in the model. For practical managerial decision making, however, the major challenge of this structural approach is its complexity. As Aggarwal and Harper (2010) suggest, there may be a very large number of relevant factors that can affect currency exposure of a firm. Some may be firm-specific, and others may be non firm-specific. Furthermore, their impacts on currency exposure may be more complicated than what the above simple linear model depicts. Therefore, this structural approach is difficult for managers to use in practical decision making.

A second alternative is a reduced-form approach, which is to utilize the quantile regression technique invented by Koenker and Bassett (1978) to capture the effects of missing variables in the standard model of Eq. (1). Applications of quantile regression have seen a rapid rise in the last decade in various disciplines: labor and health economics, finance, genetics, population biology, medicine, environmental pollution studies, political science, education, demography, ecology and internet traffic.[3] Cade and Noon (2003) attribute the need and success of using quantile regression in ecology to the complexity of the interactions between different independent variables leading to unequal variation (heteroskedasticity) of the dependent variable over different ranges of the conditioning independent variables, which is exactly the implication of Aggarwal and Harper (2010) as well as Wei and Starks (2005).

We present a simulation example in the Appendix to illustrate how the quantile regression coefficients can pick up the effects of missing variables. In a nutshell, if there is not any missing variable and the model "perfectly" describes the underlying relationship between the excess return and all the relevant factors, there will not be any quantile effect or any error/disturbance term needed in a regression analysis. However, this is an unrealistic assumption. As a result, the traditional regression specification utilizes the disturbance term to capture all other factors that influence the dependent variable. When there is no interaction between the missing and included variables, the standard least-squares regression provides unbiased and consistent estimates of the conditional mean coefficients under the standard assumptions. In the presence of interaction between the missing and included variables, however, the least-squares estimates will be biased and the quantile effect can only be estimated using quantile regression analysis.

The quantile regression model of Eq. (1) can be specified as

$$r_{it} = \alpha_i^\tau + \beta_{i,M}^\tau M_t + \beta_{i,FX}^\tau FX_t + e_{it} \tag{3}$$

where α_i^τ, $\beta_{i,M}^\tau$ and $\beta_{i,FX}^\tau$ are the τ-th quantile regression coefficients that minimize the following objective function:

$$\sum_{i:e_t > 0} (\tau)\left(r_{it} - \alpha_i^\tau - \beta_{i,M}^\tau M_t - \beta_{i,FX} FX_t\right) + \sum_{t:e_t \le 0} (\tau - 1)\left(r_{it} - \alpha_i^\tau - \beta_{i,M}^\tau M_t - \beta_{i,FX} FX_t\right) \tag{4}$$

for any $0 < \tau < 1$ while the error term ε_{it} has a probability distribution with the τ-th quantile being 0. Positive residuals in Eq. (4) are assigned a weight of τ while negative residuals receive a weight of $(\tau - 1)$. Hence the τ-th quantile regression plane dissects the

[3] A few of the good primers for quantile regression are Koenker and Hallock (2001), Cade and Noon (2003), Yu et al. (2003), and Koenker (2005).

data points in the excess returns direction into two portions conditioned on the independent variables with 100 τ % of them falling above and 100 $(1 - \tau)$ % of them below the plane such that the weighted absolute residuals has the smallest sum in Eq. (4). The special case of $\tau = 0.5$ corresponds to the median regression plane which divides the data points into two equal halves, one falling above and the other below the plane, that yields the least-absolute deviation regression estimates (See Portnoy and Koenker 1997, for an interesting historical account of the least-absolute deviation regression). The quantile regression coefficients $\beta^{\tau}_{i,FX}$ that correspond to the higher values of τ provide estimates of currency exposure near the upper tail of the asset's excess return distribution, while the coefficients that correspond to the lower values of τ estimates currency exposure in the lower end of the excess return distribution.

This reduced-form approach via the quantile regression does not require managers to include all relevant factors and understand how they affect currency exposure, but it still is able to capture the impacts of omitted variables on currency exposure in a simple yet efficient way. Therefore, it is more useful for practical managerial decision making. Another advantage of the quantile regression is its robustness to outliers, which is important given well-known fat-tail feature of financial data (Rachev and Mitnik 2000; Rachev et al. 2005).

3 Data and empirical results

3.1 Data

Following FHH, we focus on two trade-weighted currency indexes from the Federal Reserve Bank in St. Louis. The first is the Federal Reserve's Major Currencies Index (*MCI*), which is a weighted average of the foreign exchange value of the dollar against currencies of major industrial countries.[4] The second is the Other Important Trading Partners Index (*OITP*), which is a weighted average of the foreign exchange value of the US dollar against currencies of major developing countries.[5] As FHH remark, there are two reasons to take the *OITP* index into account. First, trade with the developing economies has become increasingly important, growing from 31 % of total trade in 1980 to about 42 % in 1999 and 48 % in 2006. Second, studying the exposure to the *OITP* index can shed light on whether hedging can explain the low exposure found in previous studies. As FHH argue, it is more difficult for US firms to hedge the exchange rate risk of the currencies of developing countries as compared to the industrialized countries. Therefore, if hedging could explain the exposure puzzle, we would expect that the exposure to the *OITP* index should be stronger than that to the *MCI* index.

We focus on 30 industry portfolios as our exposure test assets. Wei and Starks (2005) point out that industry portfolio may be better test assets when a trade-weighted currency index is used since a firm is not exposed to all currencies in the basket. Moreover, it is well known that using portfolios instead of individual stocks in empirical asset pricing tests can result in more precise parameter estimates (see Fama and MacBeth 1973; Chen et al.

[4] Major currency index includes the Euro Area, Canada, Japan, United Kingdom, Switzerland, Australia, and Sweden.

[5] Countries whose currencies are included in the other important trading partners index are Mexico, China, Taiwan, Korea, Singapore, Hong Kong, Malaysia, Brazil, Thailand, Philippines, Indonesia, India, Israel, Saudi Arabia, Russia, Argentina, Venezuela, Chile and Colombia.

Table 1 Summary statistics for industry excess returns (1980:1-2009:12)

Industry	Mean	Variance	CAPM β
Food	1.29	19.96	0.61
Beer	1.43	28.96	0.66
Smoke	1.57	47.58	0.63
Games	1.12	49.97	1.25
Books	0.96	33.92	1.03
Hshld	1.09	22.13	0.73
Clths	1.11	42.18	1.05
Hlth	1.16	23.24	0.76
Chems	1.05	32.79	1.02
Txtls	1.04	62.25	1.12
Cnstr	0.97	38.10	1.14
Steel	0.89	65.85	1.40
FabPr	0.94	42.75	1.23
ElcEq	1.35	42.19	1.21
Autos	0.94	55.84	1.17
Carry	1.15	41.08	1.04
Mines	0.86	69.29	0.91
Coal	1.40	110.66	1.12
Oil	1.14	32.36	0.74
Util	1.00	16.54	0.45
Telcm	0.97	26.89	0.83
Servs	1.22	47.04	1.31
BusEq	1.01	58.91	1.38
Paper	1.02	28.69	0.92
Trans	1.05	33.38	0.99
Whlsl	0.99	28.38	0.98
Rtail	1.25	31.73	0.96
Meals	1.11	29.26	0.87
Fin	1.08	30.71	1.01
Other	0.69	34.39	1.03

Table 1 shows the summary statistics of our 30 industry portfolios

1986). The industry portfolio returns (as well as market returns and risk-free rate) are obtained from Kenneth French's website.[6] In empirical tests, we focus on a similar sample period as FHH, the post-1980 period. More precisely, our sample covers the period from January 1980 to December 2009. Table 1 shows the summary statistics for our 30 industry portfolios.

To help understand currency exposure, we follow Wei and Starks (2005) and compile the international trade data for the 21 US manufacturing industries.[7] We first retrieve monthly commodity imports and exports data at the four-digit SIC level from the US International Trade Commission. The imports data are US general imports based upon general custom values, and the exports are the total exports data based upon FAS values. Since we focus on two

[6] The data are available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[7] For service industries, we do not have relevant data from the US International Trade Commission to compute their trade balances.

trade-weighted currency indexes in this paper, we extract the total imports/exports from/to each group of countries (i.e. *MCI* countries or *OITP* countries) for each four-digit SIC commodity group for the period from 1989 to 2001 (the trade data based on the SIC codes are only available for this period). Then, we match the imports and exports data with the stock returns data based on the SIC codes. Finally, we compute the trade balance for each industry as the difference between total exports and general imports. It is important to note that the trade data may only be viewed as a rough estimate of international transactions of firms because the match is based on the SIC codes not the actual firm-level imports and exports data. For instance, household furniture and appliances are classified as Consumer Goods. However, such consumer goods are not only imported or exported by the US Consumer Goods industry (Hshld) but also maybe by the US wholesale industry. Nevertheless, the trade data may still help us gain valuable understanding of currency exposure.

3.2 Empirical results

3.2.1 *Time-invariant currency exposure based on least-squares regression*

Since we examine two trade-weighted currency indexes as in FHH, our benchmark model in this paper is:

$$r_{it} = \alpha_i + \beta_{i,M} M_t + \beta_{i,MCI} MCI_t + \beta_{i,OITP} OITP_t + \varepsilon_{it} \quad (5)$$

where MCI_t and $OITP_t$ are the percentage changes in the *MCI* and the *OITP*. Table 2 shows the least-squares regression results for the 30 industry portfolios over our entire sample period from 1980 to 2009. The *t*-ratios are based on Newey-West HAC standard errors with the lag parameter set to 12.[8] We focus on the exposure to the currency indexes; the factor loadings that are significant at the 5 % level for the two-sided test are highlighted in bold. We also report the average trade balances for the 21 manufacturing industries.

As we can see, only 6 out of 30 or 20 % of the industry portfolios have statistically significant exposure to the *MCI*. Books (Printing and Publishing), Clths (Apparel), Txtls (Textiles), Trans (Transportation), and Rtail (Retail) have significant positive exposure, while Mines (Precious Metals, Non-Metallic, and Industrial Metal Mining) has significant negative exposure. The exposure signs for the manufacturing industries are generally consistent with the trade pattern: three out of four industries have the expected signs. Mines has a negative exposure because with a positive trade balance it is an exporting industry and suffers from an appreciation of the dollar. Apparel and Textiles have positive exposure because they are importing industries and benefit from an appreciation of the dollar. This is consistent with the findings in Jorion (1990).

Similarly, only 5 out of 30 or 17 % of the industry portfolios have statistically significant exposure to the *OITP*. Two out of four manufacturing industries have the expected signs that are consistent with the trade pattern. Since the trade data are not based on the firm-level imports and exports, and currency exposure can be due to non-trade related reasons, it is not surprising to see a relatively weak connection between currency exposure and trade balance.

The important point to note here is that our estimates produce similar results of low exposure (low percentage of industries that exhibit significant currency exposure) as in

[8] We also experimented with the lag parameter set to 4, 8, 16 and the results are qualitatively similar.

Table 2 Least-squares estimates of fixed foreign exchange exposure (1980:1-2009:12)

Industry	β_{M}	β_{MCI}	β_{OITP}	t_{M}	t_{MCI}	t_{OITP}	Trade balance with MCI ($1,000)	Trade balance with OITP ($1,000)
Food	**0.61**	−0.10	0.17	7.90	−0.93	1.54	1,052,476	322,915
Beer	**0.65**	−0.16	0.09	7.22	−1.33	0.59	−285,133	−39,573
Smoke	**0.63**	−0.04	0.08	6.14	−0.19	0.48	223,945	73,821
Games	**1.25**	0.18	−0.16	15.47	1.14	−0.72	−173,999	−1,619,881
Books	**1.04**	**0.21**	−0.10	12.64	2.29	−0.52	125,306	−17,945
Hshld	**0.74**	0.07	0.04	10.19	0.84	0.31	−859,461	−1,533,359
Clths	**1.06**	**0.33**	−0.21	12.55	2.74	−1.33	−275,878	−2,762,729
Hlth	**0.77**	−0.06	**0.24**	11.13	−0.78	2.13	−43,720	29,768
Chems	**1.01**	−0.03	−0.15	14.28	−0.36	−1.09	239,503	995,073
Txtls	**1.11**	**0.31**	**−0.54**	6.37	2.02	−1.98	−21,893	−179,577
Cnstr	**1.13**	−0.05	−0.11	14.98	−0.77	−0.88	−518,432	−482,290
Steel	**1.37**	−0.20	−0.34	17.07	−1.32	−1.87	−553,546	−290,017
FabPr	**1.20**	−0.10	**−0.41**	27.92	−0.98	−2.86	−500,448	1,197,132
ElcEq	**1.21**	0.03	0.01	29.69	0.43	0.05	−105,764	−17,1135
Autos	**1.17**	0.11	−0.11	11.92	0.83	−0.40	−4,977,314	−78,8119
Carry	**1.04**	0.18	−0.11	13.59	1.23	−0.68	833,093	1,119,816
Mines	**0.85**	**−0.68**	−0.38	8.01	−3.22	−1.40	67,645	−19,674
Coal	**1.04**	−0.33	**−1.25**	9.00	−1.64	−3.90	196,824	31,866
Oil	**0.72**	−0.18	−0.26	10.25	−1.29	−1.68	−1,397,252	−2,201,703
Util	**0.44**	−0.14	0.00	6.68	−1.26	0.00	–	–
Telcm	**0.85**	0.05	**0.33**	12.27	0.50	2.71	–	–
Servs	**1.32**	0.10	0.09	17.80	1.11	0.74	–	–
BusEq	**1.38**	0.07	−0.18	12.79	0.60	−1.10	509,524	−1,863,198
Paper	**0.91**	−0.04	−0.05	13.70	−0.49	−0.34	−506,882	214,245
Trans	**1.00**	**0.18**	0.09	14.55	2.10	1.03	–	–
Whlsl	**0.98**	0.08	−0.02	16.68	0.81	−0.17	–	–
Rtail	**0.99**	**0.45**	0.12	15.59	4.37	1.07	–	–
Meals	**0.88**	0.19	−0.03	11.61	1.74	−0.23	–	–
Fin	**1.02**	0.19	−0.05	14.60	1.89	−0.34	–	–
Other	**1.04**	0.03	0.09	18.44	0.27	0.91	–	–

Table 2 shows the least-squares results for the 30 industry portfolios over our entire sample period from 1980 to 2009. The *t*-ratios are based on Newey-West HAC standard errors with the lag parameter set to 12. The factor loadings that are significant at the 5 % level for the two-sided test are highlighted in bold. We also report the average trade balances for the 21 manufacturing industries

previous studies (e.g. Jorion 1990) if we estimate currency exposure with least-squares regression and do not allow for time variation in currency exposure.

3.2.2 Time-variant currency exposure based on least-squares regression

FHH and Ferson and Harvey (1993) among others emphasize the importance of time variation in currency exposure. In the same spirit of FHH, we take into account the time variation in currency exposure with a two-step procedure. The first step is to run time-series regressions to obtain the currency exposure of each industry in each month by estimating Eq. (5) in a rolling regression fashion. More specifically, currency exposure of an industry in a month is estimated with its recent 5 years of data to obtain meaningful estimates. Consequently, the test period starts in 1985:1. We update estimates monthly by dropping the earliest observation and adding the latest observation. Our rolling regressions thus yield a time-series of currency exposure for each industry for the period from 1985:1 to 2009:12.

The second step is to test for the significance of the mean exposure as in FHH. Essentially, we regress the time-series of currency exposure of each industry from step 1 on a constant, and test its significance. Since we use rolling overlapping samples in the first step, we artificially introduce strong autocorrelation in the error term. We, therefore, use the *t*-ratios based on Newey-West HAC standard errors with the lag parameter set to 12 for statistical inference. In this study, we first apply the traditional least-squares regression, then the quantile regression technique in our two-step approach. The idea is to separate the effects of time dependence from those of missing variables.

The results based on the least-squares regression are reported in Table 3. That is, we first use least-squares regression to estimate currency exposure in a rolling regression fashion. Then, we test for the significance of the mean exposure as in FHH. We focus on the exposure to the currency indexes; the significant factor loadings (at the 5 % level for the two-sided test) are in bold. We also report the average trade balances for the 21 manufacturing industries. As we can see, if we allow for time variation in currency exposure, 17 out of 30 or 57 % of industry portfolios have significant exposure to the *MCI*, and 12 out of 30 or 40 % of industry portfolios have significant exposure to the *OITP*. The exposure to the *MCI* is more consistent with the trade pattern. Seven out of 12 manufacturing industries have the expected exposure to the *MCI,*[9] where only 2 out of 8 manufacturing industries have the expected exposure to the *OITP*.[10] As mentioned before, since the trade data are not based on the firm-level imports and exports and currency exposure can be due to non-trade related reasons, the relatively weak connection between currency exposure and trade is to be expected. Nevertheless, the real reasons of this weak connection are not the focus of this study.

3.2.3 Time-variant currency exposure based on quantile regression

We next take into account the effects of missing variables. That is, we first use the quantile regression technique to estimate currency exposure in a rolling regression fashion. All the results are computed using the quantreg package (Koenker 2012) for R (R Core Team 2012) based on the interior-point algorithm of Koenker and Ng (2005) that utilizes the linear algebra for sparse matrices implemented in Koenker and Ng (2003). Then, we test for the significance of the mean exposure as in the least-squares regression setting. The results are reported in Tables 4 and 5. We present the currency exposure with the significant factor loadings (at the 5 % level for two-sided tests) highlighted in bold face. Again, we also report the average trade balances for the 21 manufacturing industries.

Strikingly, as soon as we take into account the effects of missing variables, we find that most industries exhibit significant foreign exchange exposure in at least one of the nine quantiles signified by τ in discrete steps of 0.1 from 0.1 to 0.9. Table 4 shows that 26 out of 30 or 87 % of

[9] They are Games (Recreation), Hshld (Consumer Goods), Clths (Apparel), Txtls (Textile), Autos (Automobiles and Trucks), Mines (Precious Metals, Non-Metallic, and Industrial Metal Mining), and Bus Eq (Business Equipment).

[10] They are Smoke (Tobacco Products) and Steel (Steel Works Etc).

Table 3 Two-step least-squares estimates of time-varying foreign exchange exposure (1985:1-2009:12)

Industry	β_{M}	β_{MCI}	β_{OITP}	t_{M}	t_{MCI}	t_{OITP}	Trade balance with MCI ($1,000)	Trade balance with OITP ($1,000)
Food	**0.67**	−0.07	−0.06	10.99	−1.89	−1.10	1,052,476	322,915
Beer	**0.71**	**−0.13**	**−0.29**	10.68	−2.61	−4.06	−285,133	−39,573
Smoke	**0.68**	0.01	**−0.51**	9.83	0.05	−2.41	223,945	73,821
Games	**1.21**	**0.21**	−0.06	34.89	3.82	−0.58	−173,999	−1,619,881
Books	**0.96**	**0.24**	**−0.24**	21.02	5.81	−4.17	125,306	−17,945
Hshld	**0.77**	**0.05**	**−0.10**	13.29	2.40	−2.62	−859,461	−1,533,359
Clths	**1.10**	**0.28**	−0.04	22.89	8.16	−0.39	−275,878	−2,762,729
Hlth	**0.84**	**−0.11**	0.01	14.49	−2.51	0.07	−43,720	29,768
Chems	**0.97**	0.06	−0.20	24.18	0.82	−1.69	239,503	995,073
Txtls	**0.96**	**0.50**	**−0.76**	16.01	7.63	−9.20	−21,893	−179,577
Cnstr	**1.11**	0.01	**−0.24**	22.88	0.27	−2.73	−518,432	−482,290
Steel	**1.33**	−0.09	**0.21**	19.06	−1.40	2.09	−553,546	−290,017
FabPr	**1.19**	−0.07	−0.04	47.05	−1.38	−0.29	−500,448	1,197,132
ElcEq	**1.20**	0.01	0.09	71.34	0.29	1.41	−105,764	−171,135
Autos	**1.09**	**0.18**	−0.09	23.37	2.78	−0.70	−4,977,314	−788,119
Carry	**0.98**	**0.20**	−0.08	25.95	2.60	−0.39	833,093	1,119,816
Mines	**0.73**	**−0.47**	−0.16	10.18	−6.89	−1.53	67,645	−19,674
Coal	0.98	−0.21	−0.24	16.50	−1.65	−1.15	196,824	31,866
Oil	**0.67**	**−0.16**	**−0.25**	22.10	−2.05	−3.31	−1,397,252	−2,201,703
Util	**0.41**	−0.07	−0.34	11.97	−1.30	−1.51	–	–
Telcm	**0.90**	−0.03	**0.37**	26.08	−0.46	3.55	–	–
Servs	**1.37**	0.01	0.25	33.18	0.34	1.64	–	–
BusEq	**1.45**	**−0.10**	0.17	18.38	−2.42	1.45	509,524	−1,863,198
Paper	**0.88**	−0.05	−0.03	21.76	−1.53	−0.24	−506,882	214,245
Trans	**1.00**	**0.17**	**0.22**	25.82	4.98	2.61	–	–
Whlsl	**0.96**	**0.11**	**−0.16**	20.93	2.83	−2.24	–	–
Rtail	**1.05**	**0.40**	0.08	30.19	13.16	0.78	–	–
Meals	**0.91**	**0.19**	**−0.43**	15.82	3.96	−2.50	–	–
Fin	**1.02**	**0.26**	−0.13	28.40	8.24	−1.55	–	–
Other	**1.00**	0.09	−0.27	20.47	1.60	−1.64	–	–

Table 2 shows the least-squares results for the 30 industry portfolios over our entire sample period from 1980 to 2009. The *t*-ratios are based on Newey-West HAC standard errors with the lag parameter set to 12. The factor loadings that are significant at the 5 % level for the two-sided test are highlighted in bold. We also report the average trade balances for the 21 manufacturing industries

industry portfolios have significant exposure to the *MCI* in at least one of the quantiles, where Table 5 demonstrates that 23 out of 30 or 77 % of the industry portfolios have significant exposure to the *OITP* in at least one of the quantiles. Again, the currency exposure is weakly consistent with the trade pattern. Nine out of 18 manufacturing industries have the expected exposure to the *MCI*,[11] where 8 out of 16 manufacturing industries have the expected exposure

[11] They are Food (Food Products), Games (Recreation), Hshld (Consumer Goods), Clths (Apparel), Txtls (Textile), EleEq (Electrical Equipment), Autos (Automobiles and Trucks), Mines (Precious Metals, Non-Metallic, and Industrial Metal Mining), and BusEq (Business Equipment).

to the OITP.[12] Again, since the trade data are not based on the firm-level imports and exports, and currency exposure can be due to non-trade related reasons, the relatively weak connection between currency exposure and trade is not surprising.[13]

It is, therefore, evident that taking into account time variation in exposure and the effects of missing variables enables us to discover more significant currency exposure. We focus on the Food (Food Products) industry as an example. This industry does not have significant currency exposure if we estimate currency exposure with least-squares (recall Tables 2 and 3). However, the Food industry, based on our trade data, is a top exporting industry in the US (with the highest exports to developed countries and the fourth highest exports to developing countries). It is also impossible for such an industry to completely hedge away currency risk. Therefore, it would be an anomaly if the Food industry had no currency exposure. As we have shown, as soon as we take into account time variation in exposure and the effects of missing variables, this industry is found to have significant negative exposure to both the *MCI* and the *OITP* in some return quantiles. For instance, the exposures to the *MCI* and *OITP* when $\tau = 0.5$ are -0.13 and -0.24, respectively, and are both significant at the 5 % level. The sharp difference in results, therefore, highlights the importance of taking into account the effects of missing variables when studying currency exposure.

As we can see, US industries are sensitive to both the *MCI* index and the *OITP* index, which suggests that hedging may not be a convincing explanation for the exposure puzzle. If hedging were important, we would expect that US industries be more sensitive to the *OITP* than to the *MCI* (because as FHH point out, it is more difficult for US firms to hedge against the exchange rate risk of the developing countries currencies). However, the results in Tables 4 and 5 are clearly inconsistent with this conjecture; recall that 87 % of industry portfolios have significant exposure to the *MCI* in at least one of the quantiles, while only 77 % of the industry portfolios have significant exposure to the *OITP* in at least one of the quantiles. Therefore, in terms of theoretical significance, our results extend FHH, and suggest that the methodological weakness, not hedging, explains the insignificance of currency risk in previous studies.

Our results also have important implications for practical decision making. Our findings suggest that corporate managers can use the quantile regression technique to estimate the currency exposure of their firms. If a firm has significant currency exposure across most quantiles, the firm should unambiguously hedge currency movements. However, if a firm only has significant exposure in some quantiles, especially lower or higher quantiles, hedging may still be necessary,[14] because it is these extreme outcomes in the tails of the

[12] They are Food (Food Products), Smoke (Tobacco Products), Chems (Chemicals), Steel (Steel Works Etc), FebPr (Fabricated Products and Machinery), EleEq (Electrical Equipment), Autos (Automobiles and Trucks), and Coal (Coal).

[13] An alternative explanation for our findings is that quantile regression may capture the long-horizon exposure suggested by Chow et al. (1997), Bodnar and Wong (2003) and Bartram (2007). As Bartram (2007) point out: "Estimating exposures over longer horizons may be useful since it is possible that they can be estimated more accurately given the complexities of the factors determining exposure and the noise in high-frequency exchange rates relative to the persistence of movements with low frequency" (p. 987). If monthly exchange rate changes are noisy proxy for persistent exchange rate changes, additional instrument variables may be necessary to estimate persistent exchange rate movements (for instance, FHH use imports, exports, and the federal funds rate to forecast future exchange rate changes). As a result, the standard specification of Eqn. (1) may again suffer missing variable biases, since additional instrument variables that help predict persistent movements in exchange rates are not included. Consequently, quantile regression may help take into account the effects of missing variables and capture the long-horizon exposure.

[14] Hedging costs should also be taken into account.

Table 4 Two-step quantile regression foreign exchange exposure estimates using MCI (1985:1-2009:12)

Industry	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	Trade balance
Food	−0.08	**−0.16**	**−0.19**	**−0.17**	**−0.13**	−0.06	−0.10	−0.10	0.14	1,052,476
Beer	−0.16	−0.07	−0.09	−0.04	−0.08	−0.02	−0.02	−0.09	−0.11	−285,133
Smoke	**0.55**	0.14	0.07	0.04	−0.05	**−0.20**	**−0.30**	**−0.30**	−0.04	223,945
Games	0.14	0.13	**0.16**	**0.15**	**0.15**	**0.23**	**0.27**	**0.37**	0.52	−173,999
Books	**0.27**	**0.21**	**0.11**	**0.14**	**0.21**	**0.25**	**0.28**	**0.23**	0.23	125,306
Hshld	0.10	**0.25**	**0.21**	**0.13**	**0.12**	**0.11**	**0.07**	0.03	−0.02	−859,461
Clths	**0.28**	**0.26**	**0.30**	**0.31**	**0.33**	**0.38**	**0.43**	**0.37**	0.11	−275,878
Hlth	**−0.22**	**−0.20**	−0.10	−0.09	−0.07	−0.04	−0.03	−0.07	**−0.18**	−43,720
Chems	0.16	0.18	0.15	0.12	0.11	0.06	−0.01	−0.03	0.08	239,503
Txtls	**0.48**	**0.47**	**0.45**	**0.46**	**0.41**	**0.39**	**0.42**	**0.44**	**0.34**	−21,893
Cnstr	**0.12**	0.07	**0.08**	0.07	0.09	0.02	−0.04	**−0.19**	**−0.22**	−518,432
Steel	0.02	**−0.25**	**−0.25**	**−0.25**	−0.12	−0.08	−0.12	**−0.19**	−0.11	−553,546
FabPr	−0.03	0.03	0.02	−0.08	**−0.17**	**−0.21**	**−0.20**	**−0.22**	−0.15	−500,448
ElcEq	−0.15	−0.07	−0.05	−0.04	−0.02	**0.11**	0.07	0.07	0.02	−105,764
Autos	0.07	**0.12**	**0.22**	**0.19**	**0.23**	**0.18**	0.14	0.12	0.09	−4,977,314
Carry	**0.32**	**0.25**	0.14	**0.17**	**0.25**	**0.26**	**0.16**	0.02	0.00	833,093
Mines	−0.10	**−0.19**	−0.19	−0.15	**−0.27**	**−0.52**	**−0.77**	**−0.90**	**−0.93**	67,645
Coal	−0.10	−0.17	−0.23	−0.17	−0.05	−0.02	−0.18	−0.13	−0.26	196,824
Oil	**−0.24**	−0.16	**−0.20**	−0.17	−0.12	−0.08	−0.10	−0.11	−0.03	−1,397,252
Util	−0.05	−0.03	−0.07	−0.07	−0.06	−0.14	**−0.17**	**−0.19**	−0.09	–
Telcm	0.08	0.07	−0.02	−0.04	−0.08	−0.04	−0.03	−0.13	−0.14	–
Servs	**0.21**	0.04	−0.02	−0.03	−0.09	−0.07	−0.07	**−0.12**	−0.03	–
BusEq	**−0.31**	**−0.27**	**−0.14**	**−0.12**	**−0.13**	−0.09	−0.09	−0.08	−0.11	509,524
Paper	−0.03	−0.08	−0.02	0.00	**−0.08**	−0.08	**−0.11**	**−0.18**	−0.06	−506,882
Trans	0.04	**0.15**	**0.18**	**0.22**	**0.17**	**0.17**	**0.21**	**0.35**	**0.44**	–
Whlsl	**0.12**	**0.16**	**0.15**	**0.19**	**0.19**	**0.18**	**0.20**	**0.17**	−0.04	–
Rtail	**0.53**	**0.49**	**0.48**	**0.43**	**0.42**	**0.39**	**0.37**	**0.36**	**0.35**	–
Meals	**0.17**	**0.21**	**0.22**	**0.22**	**0.16**	**0.18**	**0.18**	**0.18**	**0.25**	–
Fin	**0.17**	**0.29**	**0.35**	**0.33**	**0.29**	**0.28**	**0.27**	**0.28**	**0.36**	–
Other	0.13	0.05	−0.01	0.03	0.06	**0.07**	**0.17**	**0.18**	0.13	–

We use the *t*-ratios based on Newey-West HAC standard errors with the lag parameter set to 12 for statistical inference. We present the currency exposure with the significant factor loadings (at the 5 % level for two-sided tests) highlighted in bold face. We also report the average trade balances for the 21 manufacturing industries

return distribution that should be most concerned by investors or corporate managers from a risk management perspective. We discuss such a case in the next section.

3.2.4 Firm-level evidence

To explore the robustness of extending our portfolio-level results to firm-level data, we also use US individual stocks as test assets. The stock return data are from CRSP. To achieve a clean comparison between the OLS and quantile regression results, we focus on the 2005–2009 period and 3,109 individual stocks that do not have missing values on

Table 5 Two-step quantile regression foreign exchange exposure estimates using OITP 1985:1-2009:12

Industry	τ									Trade balance
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	
Food	0.10	0.03	−0.06	−0.17	**−0.24**	**−0.26**	**−0.23**	−0.06	−0.03	322,915
Beer	−0.16	−0.23	**−0.21**	**−0.28**	**−0.43**	**−0.51**	**−0.49**	**−0.40**	**−0.54**	−39,573
Smoke	−1.02	−0.66	−0.07	−0.12	−0.09	−0.08	−0.09	−0.28	**−0.63**	73,821
Games	−0.30	−0.19	−0.05	0.06	−0.02	−0.13	−0.02	0.00	−0.10	−1,619,881
Books	**−0.38**	**−0.41**	**−0.21**	**−0.24**	**−0.22**	**−0.20**	−0.15	**−0.24**	**−0.28**	−17,945
Hshld	0.15	−0.01	−0.10	−0.10	−0.09	**−0.13**	**−0.14**	**−0.13**	**−0.21**	−1,533,359
Clths	0.03	0.05	−0.03	0.02	0.12	0.06	−0.14	−0.06	0.07	−2,762,729
Hlth	0.10	0.09	0.01	0.00	0.01	0.05	0.07	0.01	0.00	29,768
Chems	−0.08	−0.09	−0.11	−0.11	−0.21	−0.24	**−0.32**	**−0.33**	−0.18	995,073
Txtls	−0.39	**−0.98**	**−0.87**	**−0.83**	**−0.80**	**−0.76**	**−0.73**	**−0.81**	**−1.07**	−179,577
Cnstr	−0.11	−0.21	−0.18	−0.19	−0.21	−0.14	**−0.26**	**−0.40**	**−0.26**	−482,290
Steel	0.28	**0.53**	**0.68**	**0.67**	**0.58**	**0.33**	0.08	−0.02	−0.25	−290,017
FabPr	0.19	0.11	−0.09	−0.01	0.09	0.14	0.02	−0.09	**−0.60**	1,197,132
ElcEq	0.27	**0.22**	0.00	0.04	0.14	0.08	0.08	0.05	**0.35**	−171,135
Autos	−0.44	0.13	**0.23**	**0.32**	**0.45**	**0.43**	**0.40**	0.25	−0.04	−788,119
Carry	−0.51	−0.48	−0.33	−0.16	−0.13	−0.11	0.28	**0.57**	**0.57**	1,119,816
Mines	**−0.68**	**−0.50**	−0.05	0.20	−0.02	−0.03	−0.08	−0.18	0.02	−19,674
Coal	**0.87**	0.60	**0.66**	0.25	−0.27	**−0.78**	**−0.68**	**−0.88**	**−1.04**	318,66
Oil	0.27	0.17	0.09	−0.07	**−0.33**	**−0.42**	**−0.55**	**−0.52**	**−0.63**	−2,201,703
Util	−0.52	−0.38	−0.42	−0.42	−0.36	−0.30	−0.20	−0.16	−0.23	–
Telcm	**−0.40**	0.06	0.13	**0.23**	**0.31**	**0.31**	**0.41**	**0.47**	**0.91**	–
Servs	**−0.27**	−0.03	0.18	0.15	0.19	0.25	0.21	0.39	**0.53**	–
BusEq	0.28	0.28	0.12	0.18	0.24	0.23	0.20	0.32	0.30	−1,863,198
Paper	−0.02	0.09	−0.04	−0.10	−0.04	0.06	−0.09	−0.07	0.24	214,245
Trans	**0.71**	**0.53**	**0.26**	0.15	0.15	0.13	0.14	0.07	−0.04	–
Whlsl	0.16	−0.12	−0.13	−0.19	**−0.24**	**−0.24**	**−0.30**	**−0.38**	**−0.38**	–
Rtail	**0.26**	0.07	−0.04	−0.05	−0.05	−0.02	0.09	0.20	0.25	–
Meals	−0.24	−0.36	**−0.52**	**−0.57**	**−0.53**	**−0.49**	**−0.48**	**−0.41**	−0.34	–
Fin	−0.07	−0.13	−0.21	−0.19	−0.11	−0.10	−0.09	−0.12	−0.07	–
Other	**−0.28**	−0.28	−0.37	**−0.40**	−0.35	−0.31	−0.13	−0.12	–	–

We use the *t*-ratios based on Newey-West HAC standard errors with the lag parameter set to 12 for statistical inference. We present the currency exposure with the significant factor loadings (at the 5 % level for two-sided tests) highlighted in bold face. We also report the average trade balances for the 21 manufacturing industries

returns. Empirically, we estimate Eq. (5) for each stock by OLS and then by quantile regression. To get a more detailed picture, we use a jump of 0.05 for quantile regressions.

The results are summarized in Panel A of Table 6. Consistent with the portfolio-level results, the quantile regression, by taking into account the missing variables problem, detects much stronger currency exposure among US firms. Specifically, we find that only 4.7 % (2.4 %) of US firms have significant exposure to the currencies of the developed economies (the currencies of the developing economies) if we use the standard OLS approach. This is generally consistent with Jorion (1990). However, if we use the quantile

Table 6 Firm level evidence

Panel A: All firms

	MCI		OCI	
	OLS	QR	OLS	QR
% of firms with significant exposure	4.7	27.7	2.4	25.1

Panel B: Cardinal health, Inc. (PERMNO = 21,371)

		MCI		OCI	
		Coefficient	t-statistics	Coefficient	t-statistics
OLS		0.43	0.81	−1.38	−1.41
	τ	Coefficient	t-statistics	Coefficient	t-statistics
	0.05	**2.31**	3.91	**−4.05**	−2.76
	0.10	**2.00**	2.44	**−3.82**	−2.17
	0.15	**2.42**	2.41	**−4.52**	−2.48
	0.20	2.09	1.76	−3.83	−1.74
	0.25	1.48	1.33	−1.88	−0.96
	0.30	0.88	0.81	−1.37	−0.73
	0.35	0.47	0.47	−1.02	−0.51
	0.40	0.02	0.02	−0.99	−0.56
	0.45	0.23	0.37	−0.92	−0.55
QR	0.50	−0.33	−0.50	−0.46	−0.28
	0.55	−0.40	−0.62	0.25	0.16
	0.60	−0.30	−0.49	−0.45	−0.32
	0.65	−0.28	−0.45	−0.52	−0.35
	0.70	−0.63	−1.06	−1.06	−0.78
	0.75	−1.02	−1.69	−0.97	−0.81
	0.80	−0.43	−0.64	−0.95	−0.79
	0.85	−0.78	−0.88	0.08	0.06
	0.90	0.65	0.61	−1.08	−0.67
	0.95	0.57	0.48	−0.36	−0.16

To achieve a clean comparison between the OLS and quantile regression results, we focus on the 2005–2009 period and 3,109 individual stocks that do not have missing values on returns. Empirically, we estimate Eq. (5) for each stock by OLS and then followed by the quantile regression. To get a more detailed picture, we use a jump of 0.05 for quantile regressions. The results are summarized in Panel A of Table 6. Again, we use an example to highlight the usefulness of the quantile regression. Our example is Cardinal Health, Inc. We present its exposure estimates based on OLS and the quantile regression in Panel B of Table 6 with the factor loadings that are significant at the 5 % level for the two-sided test highlighted in bold

regression technique, we find that 27.7 % (25.1 %) of US firms exhibit significant exposure to the currencies of the major industrial economies (the currencies of the developing economies).

Again, we use an example to highlight the usefulness of the quantile regression. Our example is Cardinal Health Inc. As of December 2009, its market capitalization is about

$12 billion. Its company description from Campus Research—Hoover's Company Records (Westlaw) states:

> The company is a top distributor of pharmaceuticals and other medical supplies and equipment in the US. Its pharmaceutical division provides supply chain services including branded and generic prescription and OTC drug distribution. It also franchises Medicine Shoppe retail pharmacies. Its medical division parcels out medical, laboratory, and surgical supplies and provides logistics, consulting, and data management. Customers include retail pharmacies, hospitals, nursing homes, doctor's offices, and other health care businesses.

Hoover's Company Records also shows that Cardinal Health, Inc. has very little foreign sale (about 2 %). However, currency movements can affect a firm through many channels. Therefore, even a domestic firm can have significant currency exposure (e.g. Adler and Dumas 1984; Aggarwal and Harper 2010).

We present the exposure estimates based on OLS and the quantile regression in Panel B of Table 6 with the factor loadings that are significant at the 5 % level for the two-sided test highlighted in bold. As we can see, if we use standard OLS to estimate the currency exposure, we find that this firm has no significant exposure to either MCI or OITP. The OLS coefficient on the percentage change in MCI is 0.43 with a t-ratio of 0.81, while that on the percentage change in OITP is −1.38 with a t-ratio of −1.41. Thus, the OLS regression suggests that this firm is not exposed to currency movements and does not need to hedge currency fluctuations.

The standard OLS regression, however, may produce biased estimates due to missing variables. We, therefore, also use the quantile regression to estimate the currency exposure of Cardinal Health. Interestingly, the company has significant exposure to both MCI and OITP in lower quantiles ($\tau = 0.05$, 0.10 and 0.15). Our finding that Cardinal Health (a domestic firm) has significant currency exposure supports Adler and Dumas (1984) and Aggarwal and Harper (2010), and has important practical implications. Specifically, if these extreme outcomes in the lower tail are most concerned by its investors and managers from a risk management perspective, our finding suggests that Cardinal Health, Inc. should engage in hedging.

Again, it is important to point out that our use of quantile regression is well motivated by both empirical evidence and econometric theory. Empirically, Patro et al. (2002), Wei and Starks (2005), and Aggarwal and Harper (2010) among others suggest that currency exposure depends on a large number of factors, which implies that the standard specification of Eq. (1) suffers from missing variable biases. Theoretically, as Cade and Noon (2003) point out, quantile regression is proposed to precisely deal with the heteroskedasticity caused by missing variables. Therefore, our methodology is justified, and, consequently, our results are not likely to be spurious.

4 Conclusions

Although it is widely believed that most US corporations are exposed to foreign currency risk, previous empirical studies usually find that only a small proportion of US firms have significant foreign exchange exposure. Bodnar and Bartram (2007), Bartram (2008), and Bartram et al. (2010) explain the exposure puzzle by arguing that firms use hedges to greatly reduce currency exposures. FHH, however, suggest that methodological weakness, not hedging, may explain the insignificance of currency risk in previous studies.

In this paper, we explore an alternative explanation of the exposure puzzle, the possibility of missing variable bias in previous studies. We attempt to absorb the bias with the quantile regression technique invented by Koenker and Bassett (1978). Empirically, we find that if we use the standard approach, only 6 out of 30 or 20 % of the US industry portfolios have significant foreign exchange exposure to the Major Currencies Index, and only 5 out of 30 or 17 % have significant exposure to the Other Important Trading Partners Index. This is consistent with the findings in previous studies (i.e. Jorion 1990). However, as soon as we take into account the time variation in exposure and the missing variables bias with the quantile regression technique, we find that 26 out of 30 or 87 % of the US industry portfolios exhibit significant foreign exchange exposure (in at least one quantile) to the Major Currencies Index, and 23 out of 30 or 77 % show significant exposure (in at least one quantile) to the Other Important Trading Partners Index.

Our findings that most industries have significant currency exposure support Adler and Dumas (1984) and Aggarwal and Harper (2010), and have important theoretical as well as practical implications. In terms of theoretical significance, our results strengthen the findings in Francis et al. (2008), and suggest that methodological weakness, not hedging, may explain the insignificance of currency risk in previous studies. In terms of practical significance, our results suggest a simple yet efficient approach for managers to estimate currency exposure of their firms.

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Appendix

The quantile regression coefficients can pick up the effects of missing variables. To illustrate the idea, consider a simple case in which only leverage affects currency exposure and takes value of one when leverage is high and zero otherwise. Then we can express the true model in Eq. (2) as.

$$r_{it} = \alpha_i + \beta_{i,M} M_t + \beta_{i,FX} FX_t + u_{it}, \text{ when leverage is low} \tag{6a}$$

$$r_{it} = \alpha_i + \beta_{i,M} M_t + \beta_{i,FX} FX_t + \beta_{i,leverage} FX_t + u_{it}, \text{ when leverage is high} \tag{6b}$$

When leverage is high, the conditional mean of r_{it} on FX_t given a specific value of M in Eq. (6b) will be higher or lower than the conditional mean of r_{it} on FX_t in Eq. (6a) when leverage is low depending on the signs of FX and $\beta_{i,\text{leverage}}$. When the least-squares regression is applied to the misspecified model in Eq. (1), however, the regression attempts to estimate the conditional mean of the misspecified model, which will obviously yield biased estimate for either of the two true conditional mean relationships depicted in either Eqs. (6a) or Eq. (6b). However, if Eq. (1) is estimated with the quantile regression instead, the effects of leverage will be captured by the quantile regression coefficients $\beta^{\tau}_{i,FX}$ near the tails.

Figure 1 is a simple simulation of a scenario depicted above where M_t in the true model specified by Eqs. (6a) and (6b) is generated as a normal random variable with a mean of 0 and a standard deviation of 5, FX_t is a uniform random variable between 0 and 5, u_{it} is a standardized normal, the leverage dummy variable is generated as a binomial random variable with a 0.5 probability of being in either state, $\alpha = \beta_{i,FX} = 1$, $\beta_{i,M} = 0$, $\beta_{i,leverage} = 3$ and the sample size is 1,000. In the figure, the solid dark line is the conditional mean of r_{it} on FX_t when the leverage is low, while the dash-dot dark line depicts the

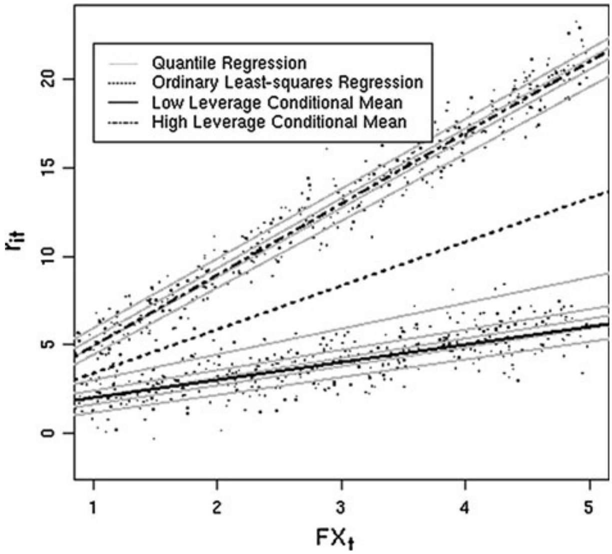

Fig. 1 A Simulation of the least-squares regression bias caused by missing variables The two conditional means of the true model specified in Eqs. (6a) and (6b) are represented by the solid dark line for low leverage and the *dash-dot dark line* for high leverage. The *dark dotted line* is the least-squares regression based on the misspecified model in Eq. (1). The least-squares regression applied to the model with missing variable yields a biased estimate of both conditional mean relationships. The *grey solid* lines are the quantile regressions for the misspecified model in Eq. (1) for $\tau \in [0.1, 0.9]$ in increments of 0.1. The nine quantile regression lines for the misspecified model in Eq. (1) capture the heteroskedastic effect caused by the omitted interaction effect between the leverage dummy and FX_t. The different *slopes*, $\beta^{\tau}_{i,FX}$, of the quantile regression lines also reveal the effect of the omitted variable

conditional mean of r_{it} on FX_t when the leverage is high. The dark dotted line is the least-squares regression applied to the misspecified model in Eq. (1). It is obvious in the figure that the least-squares regression line results in a biased estimate of both conditional mean relationships. The grey solid lines are the quantile regressions for the misspecified model in Eq. (1) for $\tau \in [0.1, 0.9]$ in increments of 0.1. The nine quantile regression lines manage to capture the heteroskedastic effect caused by the missing interaction effect between the leverage dummy and FX_t when the misspecified model in Eq. (1) is used. The different slopes, $\beta^{\tau}_{i,FX}$, of the quantile regression lines also reveal the effect of the omitted variable.

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