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RESEARCH ARTICLE

Imports, Exports, Dollar Exposures, and Stock Returns

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Abstract Economic theory suggests that the magnitude and direction of a firm's currency risk exposure depends crucially on its fundamental involvement in international trade. For U.S. industries, we find that the stock performance of import-oriented companies moves positively with the performance of the dollar, but the stock performance of export-oriented companies tends to move against the dollar. Based on this finding, we use the imports and exports information to enhance the identification of the dollar risk exposure for different industries, and analyze how each industry's expected stock return varies with its dollar risk exposure. We identify a strongly negative risk premium for bearing positive exposures to the dollar. On average, import-oriented companies generate lower expected stock returns.

Keywords Dollar risk exposure · Imports · Exports · Currency risk premium · Stock returns

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1 Introduction

Exchange rate policy and exchange rate movements have profound impacts on the domestic economy while also having spillover effects on other economies linked through international trade. Currency wars between trading partners are a perennial topic for policy debates and often flare up during structural changes of the economy. To appreciate the implications of the exchange rate movements on the fundamental economy, one must go deep into the microeconomic level and understand how exchange rate fluctuation impacts different types of companies with different import/export orientations.

In this paper, we address these fundamental questions with a focus on U.S. industries. First, we quantify the cross-sectional variation of the exchange rate exposure of different industries. We regress the stock returns for each industry against the returns on a broadly defined dollar index, while controlling the stock return's exposure on common stock-market risk factors. An industry has a positive dollar exposure if its stock return increases with the appreciation of the dollar while other common risk factors are held fixed. Our estimation shows that the dollar exposure estimates vary widely across different industries in both magnitude and direction. The variation is witnessed even within the same broad sector classification.

Second, we trace the large cross-sectional variation in dollar exposure among U.S. industries to their international trading activities. Similar to many existing studies (e.g., Jorion 1990; Amihud 1994; He and Ng 1998; Griffin and Stulz 2001; Dominguez and Tesar 2001, 2006), we believe that international trade lies at the heart of the exchange rate exposure. A firm with no direct or indirect international trading activity shall have little exposure to exchange rate fluctuations. However, deviating from these studies, we argue that it is not the aggregate international trade activity that determines the currency risk exposure. It is the *imbalance* of the trade that generates currency exposure. A firm can undergo large quantities of international trade while maintaining little currency exposure if the firm balances its imports with its exports. Simply put, import- and export-oriented companies should have quite different currency exposures. When left unhedged, these different exposures can show up in stock returns. To test this hypothesis, we regress cross-sectionally the dollar exposure estimates of each industry against the logarithm of the industry's imports volume and the exports volume, each normalized by the market capitalization of the industry. The regression identifies a significantly positive relation with imports, but a significantly negative relation with exports. On average, dollar appreciation helps the stock performance of import-oriented companies, but hurts the stock performance of export-oriented companies.

Our findings make economic sense. Dollar appreciation renders U.S. exports more expensive and hurts the demand for exports. Reduced demand hurts the sales and thus profitability of the exporting firms. On the other hand, dollar appreciation reduces the cost of imports (Campa and Goldberg 2005) and therefore increases the profitability of an import-oriented firm. When left unhedged, these differential impacts on profitability can affect stock returns and generate the negative exposure estimates for exporting firms and positive exposure estimates for importing firms.

The return-regression based dollar risk exposure estimates tend to have large standard errors, making the estimates for many industries insignificant. The literature regards this lack of significance as a puzzle and has proposed many explanations (e.g., Bartov and Bodnar 1994; He and Ng 1998; Guay 1999; Allayannis and Ihrig 2001; Allayannis and Ofek 2001; Hentschel and Kothari 2001; Williamson 2001; Bodnar et al. 2002; Bodnar and Wong 2003; Dominguez and Tesar 2006; Bartram 2008; Bartram et al. 2010). While all explanations likely play some role, this paper focuses on a very simple reason. Stock returns are noisy and relations estimated from stock returns often show large errors.[1] When statistical regression generates noisy estimates, we can often reduce the noise by incorporating our knowledge of structural relations between the risk exposures and fundamental variables. In this paper, we explore whether we can sharpen the dollar risk exposure estimates by incorporating the structural link that we have identified between the dollar risk exposure and the import–export activities. We propose to use a weighted average of imports, exports, and the dollar exposure estimates from the return regression to define an enhanced dollar exposure estimate, and we use this enhanced dollar exposure to predict excess returns on the industry stock portfolios based on cross-sectional regressions, while controlling exposures to other common stock market risk factors. The weighting coefficients for the enhanced dollar exposure are estimated by maximizing the likelihood of predicting errors. Analogous to the methodology proposed by Fama and MacBeth (1973), the time series average of the cross-sectional regression slopes on the enhanced dollar exposure reveals the average expected excess return, or risk premium, for each unit of dollar exposure. We find that incorporating the information in imports and exports helps us predict a more significant risk premium estimate on the dollar exposure. The risk premium estimate is statistically insignificant when we only use the return-regression generated dollar risk exposure, but becomes significantly negative when we incorporate the information in imports and exports to sharpen the dollar exposure identification. The negative risk premium on the dollar risk exposure suggests that on average, import-oriented companies generate lower returns than export-oriented companies.

Our paper contributes to the literature in two important dimensions. First, we link the cross-sectional variation of the dollar risk exposure across different industries to variations in imports and exports. The linkages are identified as a result of our focus on cross-sectional variation instead of time-series variation and our stress on trade imbalance instead of total trades. Second, we show that once a cross-sectional linkage is established between a risk exposure estimate and firm/industry characteristics, we can exploit this linkage to sharpen the identification of the risk exposure. Standard risk exposure estimates based on return regressions tend to be very noisy.

[1] It is well-known that the beta estimates from regressing stock returns on the market portfolio return are very noisy. Many corporate finance textbooks explicitly recognize the noisy feature of the beta estimates and propose various methods to reduce the noise, such as by averaging within peers, bottom-up analysis, and leverage analysis.

The errors-in-variables issue dictates that risk premium estimates based on these noisy risk exposures are biased toward zero and thus may become insignificant even if the underlying risk is highly priced. Our analysis shows that with the sharpened risk exposure estimate, it is possible to obtain more significant risk premium estimates.

The rest of the paper is organized as follows. The next section reviews the literature that forms the background of our study. Section 3 describes the data. Section 4 estimates the dollar risk exposure, and Section 5 links the dollar exposure estimates to imports and exports activities. Section 6 enhances the identification of the dollar exposure using the imports and exports information, and estimates the risk premium on the enhanced dollar risk exposure. Section 7 concludes.

2 Background

Identifying currency exposures of different firms, industries, or economies has been a perennial topic of interest in the academic literature. Jorion (1990) examines 287 U.S. multinationals during 1981–1987 and finds 15 % of the firms to have significant exposures. Bodnar and Gentry (1993) examine industries from the U.S., Canada, and Japan during 1979-1988 and find that 20 % to 35 % of the industries have significant currency risk exposures. Amihud (1994) examines 32 large U.S. exporting firms during 1982–1988 but finds no significant currency exposure. Allayannis (1997) analyzes the time variation of the exchange rate exposure of U.S. manufacturing industries from 1978 to 1986. He finds that the level of industry aggregation at which the exposure is examined matters. Significant exposure at the four-digit SIC level is often masked at the more aggregated two-digit level. He and Ng (1998) find that high exchange rate exposure is related to high exports for Japanese multinationals. Allayannis and Ihrig (2001) analyze the exchange rate exposure of U.S. manufacturing industries and find that 4 of 18 industry groups are significantly exposed to exchange rate movements. They find that on average, a 1 % appreciation of the dollar decreases the return of the average industry by 0.13 %. Griffin and Stulz (2001) examine the hypothesis that industry competitiveness across countries is an important explanation for exchange rate exposure, but they do not find supporting evidence among U.S. industries. Dominguez and Tesar (2001, 2006) examine a set of non-U.S. industrialized countries over the period 1980–1999 and find large cross-country differences. They find that a large fraction of Japanese firms have exposures to weekly movements in exchange rates, but Chilean firms show very weak exposures. Bartram and Karolyi (2006) examine how the introduction of euro affects the currency exposure of nonfinancial firms in Europe, the United States, and Japan. Bartram et al. (2011) and Bartram (2015) examine the effect of derivatives use on the exchange rate exposure.

It is understandable that different firms, industries, or economies have different currency exposures. In the U.S., we find that the dollar exposure estimates vary greatly across different industries while the average dollar exposure across all industries is close to zero. Interestingly, earlier studies often try to select a more homogeneous sample, e.g., firms with large international business exposures and large exports, in the hope of obtaining more uniform currency exposure estimates. In this paper, we do not shun away from the cross-sectional heterogeneity in currency exposure. Instead, we regard it as a natural outcome of the heterogeneity in business operations and, more importantly, a key information source for identifying the market price of currency risk.

When investigating the fundamental sources of currency exposures, many studies direct their attention to the "openness" of a firm, an industry, or an economy. Jorion (1990) uses the share of foreign sales in total sales as a measure for openness. Dominguez and Tesar (2006) use the aggregate bilateral trade flows with the U.S. as a measure of openness for the non-U.S. industrialized countries. In this paper, we argue that it is not the aggregate openness that matters for currency risk exposure. It is the direction or *imbalance* of openness that generates currency exposure. A firm can be very open in terms of international trade, but can still show minimal currency exposure by balancing its imports with its exports. Furthermore, an import-driven firm and an export-driven firm may both have strong currency exposures, but their exposures are unlikely to be in the same direction. Our empirical findings confirm our conjecture and show that import-oriented U.S. firms tend to react positively to dollar appreciation whereas export-oriented companies tend to react negatively. In related works, Allayannis (1997) finds that the time variation of the dollar exposure in an industry is related positively to the variation of the industry's share of imports but negatively to the variation of the industry's exports share. Campa and Goldberg (1999) show that investment responsiveness to exchange rate varies positively with respect to sectoral reliance on exports and negatively with respect to sectoral reliance on imports. Pritamani et al. (2004) find that on average import-firms tend to have positive dollar exposures whereas export firms tend to have negative dollar exposures. Dominguez and Tesar (2006) use imports and exports separately to study the linkage between trade and exposure, but instead of including both quantities in the regression, they use imports and exports in separate regressions as alternative measures of trade intensity. Recently, several studies look into the question of exchange rate pass-through in the context of price indices. An and Wang (2012) find that the greatest exchange rate pass-through occurs in import prices and it is smallest for the overall consumer price index. This evidence is further supported by Boug et al. (2013), who apply a co-integrated VAR model to study the impact of pass-through in the Norwegian economy. Kashiwagi (2013) studies the political economics behind exchange rate pass-through and finds that if two similar countries cooperate, they can compensate for the insufficient changes in terms of trade when exchange rate pass-through is more moderate.

Given the identified linkage between dollar exposures and international trades, we further explore whether we can exploit the information embedded in the linkage to improve our prediction of future expected excess returns on equity portfolios. We obtain positive results on the enhanced prediction and find that firms with positive dollar exposures generate lower expected excess returns. By linking currency exposures to economic fundamentals and analyzing the currency risk premium, our research is related to classic theoretical and empirical studies on the fundamental determination of exchange rates, e.g., Aizenman and Riera-Crichton (2008), Betts and Kehoe (2001, 2006), Dumas (1992), Engel et al. (2007), Engel and West (2005), Evans and Lyons (2002), Lothian and Taylor (1996), Mark (1995), Sercu and Uppal (2000).

When regressing stock returns on the dollar index return, we find, as in several other studies, that the dollar exposure estimates can show large standard errors, making the estimates for many industries statistically insignificant. Several studies regard this finding as a puzzle and strive to explain the phenomenon via mispricing (Bartov and Bodnar 1994), long-horizon effects (Bodnar and Wong 2003), alternative samples (He and Ng 1998; Dominguez and Tesar 2006), currency risk hedging (Guay 1999; Allayannis and Ofek 2001; Hentschel and Kothari 2001; Bartram 2008; Bartram et al. 2010), and time-variation and product-market competition (Bodnar et al. 2002; Allayannis and Ihrig 2001; Williamson 2001). While all these explanations can indeed contribute to the lack of significance, we focus on a much simpler reason. Stock returns are noisy and relations estimated from stock returns often show large errors. In this case, the statistical noise in the exposure estimates makes the fundamental links that we have identified between the exposure and the imports/exports activities all the more important. The identified structural linkage can serve two purposes. First, it shows that even though the return-regression-based exposure estimates are very noisy for each industry, the cross-sectional variations of these estimates show significant and meaningful structural link with economic fundamentals. Thus, by focusing on the cross-sectional difference across different industries instead of the time-series variation for one particular industry, we can still identify structural information from the noisy estimates. Second, the identified structural linkage can be used to reduce the noise of the return-regression-based estimates. We show the latter point via the application on the dollar risk premium estimation. When using the noisy return-regression-based exposure estimates, we cannot identify a significant risk premium on the dollar exposure. On the other hand, when we sharpen the dollar risk exposure estimates through the fundamental linkages to imports and exposures, we are able to obtain significantly negative risk premium estimates on the dollar risk exposure.

Our work is also related to the large stream of empirical studies that strive to identify the market pricing of the exchange rate risk. For example, Jorion (1991) uses a sample of U.S. firms to show that currency risk exposures vary systematically across different industries, but he does not find any significant pricing for the currency risk exposure. Dumas and Solnik (1995) and De Santis and Gerard (1998) study the currency pricing in the framework of an international asset pricing model, where country portfolio returns are related to the return on a world portfolio and returns on several foreign currencies. In a similar framework, Carrieri et al. (2006) study whether currency risks in emerging markets are priced and whether they have spillover effects on the developed markets. A key feature of these studies is their reliance on the *intertemporal* variation in the expected returns of the country portfolios and the conditional covariances between these portfolio returns and the risk factors. In this paper, we argue that the currency exposures vary much more *cross-sectionally* than intertemporally. Different types of industries have different business operations that lead to different risk exposures. By contrast, as the industry classification largely stays the same over time, the risk exposure of an industry cannot vary too much over time. Therefore, it is much more efficient to identify the market pricing of risk factors based on cross-sectional variations instead of intertemporal variations. By combing this cross-sectional variation with the information in international trades, we are able to identify significant risk premiums for currency risk exposures.

3 Data

Our analysis involves four broad data types. To study the dollar risk exposure of U.S. firms, we build an aggregate dollar index, and we relate the dollar index return to returns on U.S. stocks. To explore the sources of the exposure, we obtain imports and exports data on different industries. We also control our risk exposure analysis by incorporating standard market risk factors. Our analysis is based on data from January 1973 to December 2007. Since then, the U.S. has experienced the 2008 financial meltdown and the ensuing economic depression that has brought out drastic structural changes around the world, including the quantitative easing monetary policy, the restructuring of the banking industry, and potential long-run impacts on the real economy (Didier et al. 2012; Papell and Prodan 2011). By constraining our analysis before these structural changes, we generate results that are largely comparable to that in the literature. Nevertheless, for future research, it will be interesting to re-examine the exchange rate effects under the new economic landscape.

3.1 The Dollar Index and Stock Market Risk Factors

The dollar index is a weighted average of foreign exchange values of the U.S. dollar against the currencies of a large group of major U.S. trading partners. The index weights vary over time and are derived from U.S. export shares and U.S. and foreign import shares. Monthly data for the dollar index are available from the Federal Reserve Bank of Atlanta Statistical Release. Each exchange rate reveals the relative strength of two currencies. By forming a broad dollar index, we focus on the strength of dollar against a basket of other currencies. The dollar index has been used to study international stock returns in, for example, Ferson and Harvey (1993, 1994), Harvey (1995a, b).

When we measure the dollar risk exposure of U.S. stocks, we control for systematic risk factors identified from the stock market, including the excess return on the market portfolio over the Treasury bill rate (ER^{mkt}), as well as the size (SMB) and book to market (HML) risk factors identified by Fama and French (1993). Time series on these risk factors and the Treasury bill rates are available on Kenneth French's data library. In a series of papers, Fama and French (1993, 1995, 1996) document the importance of these factors in explaining the stock market returns.

Table 1 reports the summary statistics of the monthly returns on the dollar index and the stock market risk factors. The dollar index return (R^{fx}) has an annualized mean estimate of 3.173 %, and an annualized standard deviation estimate of 4.426 %. The monthly return series show a first-order autocorrelation of 0.37. The skewness and excess kurtosis estimates are both small. In the column under ER^{fx}, we also

Table 1 Summary statistics of monthly returns on the dollar index and market risk factors

	R^{fx}	ER^{fx}	ER^{mkt}	SML	HML	R_f
Mean	3.173	–2.721	5.878	2.474	5.609	5.893
Std	4.426	4.311	15.668	11.290	10.594	0.836
Minimum	–4.089	–4.499	–23.140	–16.790	–12.400	0.060
Maximum	4.335	3.442	16.050	21.960	13.850	1.350
Skewness	0.027	–0.073	–0.525	0.588	0.035	0.846
Kurtosis	0.503	0.582	2.297	6.767	2.455	1.237
Autocorrelation	0.370	0.336	0.046	0.007	0.126	0.952

Entries report the summary statistics of monthly returns on the dollar index (R^{fx}), excess monthly returns over Treasury bill rate on the dollar index (ER^{fx}), excess monthly returns on the market portfolio (R^{mkt}), returns on the size (SML) and book-to-market (HML) risk portfolios, and the Treasury bill rate (R_f). Data are monthly from February 1973 to December 2007. The mean and standard deviations (Std) are in annualized percentages, the minimum and maximum are in monthly percentages. We also report the skewness, excess kurtosis, and monthly autocorrelation for each time series

report the summary statistics of the excess return on the dollar index over the Treasury bill rate. The excess return has an annualized mean of -2.721 % and an annualized standard deviation of 4.311 %.

The market portfolio has an annualized excess return of 5.878 % over the Treasury rate. The size and book-to-market portfolios both generate positive mean excess returns at 2.474 % and 5.609 %, respectively. The Treasury rate has a sample average of 5.893 % during our sample period. The excess return on the market portfolio has an annualized standard deviation of 15.668 %, close to four times larger than that on the dollar index excess return. The standard deviation estimates on SML and HML are smaller at 11.29 % and 10.594 %, respectively. The autocorrelation estimates for returns on the stock market risk factors are all much smaller than the estimate on the dollar index returns.

3.2 Industry-Level International Trades and Stock Returns

We obtain the annual U.S. import and export data by four-digit SIC coded industries. The data from 1972 to 1988 are compiled by Robert Feenstra and are made publicly available at the Center for International Data at University of California, Davis. Trade data from 1989 to 2007 are available at the United States International Trade Commission (USITC). The USITC ceased publishing the trade data for 4-digit SIC coded industries after 2001. We compile the data from 2002 to 2007 by mapping the 6-digit NAICS code to the 4-digit SIC code using the industry concordance definitions available at the website of the U.S. Census Bureau. See Feenstra (1996, 1997), Feenstra et al. (2002) for a detailed documentation of the data. To control for the size difference for different industries in our analysis, we scale the imports (IM) and exports (EX) by the aggregate market capitalization (ME) for each industry, and we take natural logarithm on the scaled quantity to obtain better distributional behaviors.

Corresponding to imports and exports, we compute the monthly stock returns for each industry. Stock returns data are available from CRSP. We assign each stock to a four-digit SIC industry. At each year t, we use the four-digit Compustat SIC code of the stock for the fiscal year ending in calendar year $t - 1$. Whenever the Compustat SIC code is not available, we use the CRSP SIC code for June of year t. Then, we construct equal-weighted industry portfolios at the beginning of July of year t and rebalance the portfolios on an annual basis. We choose equal weighting instead of value weighting in constructing the industry portfolio because larger companies tend to span more than one industry and thus can weaken the industry distinction across different portfolios. To be included in an industry portfolio in year t, a stock must have return data for July of year t and market capitalization for December of year $t - 1$. Once we have formed the industry portfolio, we compute the monthly excess return on each portfolio, defined as the portfolio return minus the Treasury bill rate of the corresponding month.

There are 491 unique SIC codes in the original trade data set. To be included in the study, each industry must have at least three observations on the import and export measures and at least 24 monthly industry portfolio returns. We lose 87 industries because of the restrictions. Applying this filter leaves us with 404 industries.

Table 2 reports the summary statistics of the scaled imports (ln(IM/ME)), exports (ln(EX/ME)), and the stock portfolio excess returns (ER). Since the observation is on an unbalanced panel of 404 industries over 36 years, we summarize the behavior of the data from two angles. In panel A, we first take the time-series average on each series and then report the cross-sectional statistics of the time-series averages. Thus, the statistics in panel A measure the cross-sectional variation of the average trade quantities across different industries. In the panel B, we first measure the time-series statistics of each series and then report the cross-sectional average of these time-series statistics. Thus, the numbers reflect the time-series statistics of a typical industry.

Panel A shows that the average imports and exports vary greatly from one industry to another. The log import-market capitalization ratio has a mean of −0.683, but has a standard deviation three times as large in absolute magnitude at 2.174. The standard deviation on log export-market capitalization at 1.859 is also more than twice as large in absolute value as the mean of −0.909. In contrast to the large cross-sectional variation, panel B shows that the average time-series standard deviation for each industry is much smaller, at 0.913 for log import-market capitalization ratio and 0.909 for log export-market capitalization ratio. The different magnitudes of variation along the two dimensions suggest that different industries can differ dramatically from one another in their respective international trading activities, but that the international trading activities for a fixed industry and for the U.S. economy as a whole vary only slowly over time.

Different from the trade data, the industry portfolio excess returns show large cross-sectional variation but even larger time-series variation. The standard deviation estimate in panel A at 0.786 reflects the standard deviation of the mean excess return across different industry portfolios. By contract, the standard deviation estimate in panel B at 10.602 reflects the large intertemporal variation of the industry portfolio

Table 2 Summary statistics on imports, exports, and stock returns

	ln(IM/ME)	ln(EX/ME)	ER
A. Cross-sectional statistics of time-series averages			
Mean	–0.683	–0.909	1.098
Median	–0.674	–0.881	1.092
Std	2.174	1.859	0.786
Minimum	–7.075	–6.725	–2.447
Maximum	4.318	4.382	8.178
Skewness	–0.329	–0.083	1.651
Kurtosis	0.149	0.311	18.044
B. Cross-sectional averages of time-series statistics			
Mean	–0.683	–0.909	1.098
Median	–0.757	–0.977	0.264
Std	0.913	0.909	10.602
Minimum	–2.182	–2.416	–32.211
Maximum	0.947	0.672	49.946
Skewness	0.153	0.115	0.744
Kurtosis	0.674	0.345	4.568

Entries report the summary statistics on the natural logarithms of the ratio of imports and exports to the market capitalization of the corresponding industry (ln(IM/ME), ln(EX/ME)), as well as the monthly percentage excess returns on industry portfolios (ER). Panel A takes time-series averages on the quantities and report the cross-sectional summary statistics of the time-series averages. Panel B computes the time-series statistics for each industry and reports the cross-sectional average of the statistics. The cross-sectional statistics are over 404 industry observations. The time-series statistics are over 36 annual observations for the trade data (from 1972 to 2007) and 414 monthly observations for the industry portfolio excess returns (from July 1973 to December 2007)

excess returns. Taken together, the much larger intertemporal standard deviation estimates on the portfolio excess returns suggest that the large randomness in return realization can overwhelm the cross-sectional differences in risk premiums. This feature suggests that it is inherently difficult to accurately estimate risk premiums on different risk exposures.

4 Measuring the Dollar Exposure of U.S. Industries

To gauge how stock returns from different industries vary with the dollar index, we perform the following time-series regression on each industry portfolio i,

$$ER_t^i = \beta_{i0} + \beta_i^{fx} ER_t^{fx} + \beta_i^{mkt} ER_t^{mkt} + \beta_i^{smb} SMB_t + \beta_i^{hml} HML_t + e_t^i, \quad (1)$$

where ER_t^i denotes the time-t monthly percentage excess return on the i-th industry portfolio, ER_t^{fx} denotes the time-t monthly percentage excess return on the dollar index, ER_t^{mkt} denotes the time-t monthly percentage excess return on the market portfolio, and SMB_t and HML_t denote the monthly return series on the size and book-to-market portfolios, respectively. Thus, the slope coefficient β_i^{fx} measures the dollar risk exposure of the i-th industry portfolio while controlling for variations in the three stock market risk factors. If the common stock market risk factors (market, SMB, and HML) have non-zero dollar exposure, the slope coefficient β_i^{fx} would capture the excess dollar exposure in addition to those captured by the common risk factors. By controlling for the common risk factors, we reduce the cross-sectional correlation between the regression errors e_t^i across different industries, thus making the statistics in the second-stage estimation more interpretable (Jorion 1990).

We repeat this estimation for each of the 404 industries over the whole sample period from February 1973 to December 2007.[2] Table 3 reports the cross-sectional statistics of the full-sample estimates and Newey and West (1987) t-statistics on the slope coefficients in panel A. The last column reports the statistics on the R-squares of the regressions. The most interesting estimate to us is the estimate on β^{fx}, which measures the dollar exposure of different industry portfolio returns while controlling for variations in the three stock market risk factors. The cross-sectional average of the estimates on β^{fx} is very small, so is the average t-statistics. The small average estimate is consistent with the often insignificant findings in the literature when one regresses the market aggregate returns on the dollar index returns. Nevertheless, the dollar exposure estimates show large cross-sectional variation, ranging from −3.557 to 3.095. The Newey-West t-statistics range from −3.672 to 3.780. The cross-sectional standard deviation of the dollar exposure estimates is 0.667. Out of the 404 industries, 186 of them have negative dollar exposure estimates with 8 of them significant at at least the 5 % level, and 218 of them have positive dollar exposure estimates, with 22 significant at at least the 5 % level.

When we look into the descriptions of the different industries and their dollar exposure estimates, we find that industries under the title of “steel investment foundaries,” “space vehicle equipment,” and “boot and shoe cut stocking,” generate highly negative dollar exposure estimates, but industries under “men’s and boy’s underwear,” “electronic resistors,” and “household refrigerator and freezer” generate highly positive dollar exposure estimates. The dollar exposure estimates can vary greatly even within the same broad sector classification. For example, while “space vehicle equipment” under the defense sector generates highly negative exposure estimates, the “ordnance and necessary accessories” industry under the same defense sector generates highly positive exposure estimates.

For other controlling risk factors, the market beta estimates (β^{mkt}) average around one as expected. The cross-sectional standard deviation of the estimates is small at 0.277. The average exposure estimates on the SMB and HML risk factors are also

[2] For balanced panels with correlated regression errors, the literature often uses seemingly unrelated regressions to improve the identification of the coefficients. In our case, the panel is not balanced. We reduce the correlations in the errors by controlling the common stock market risk factors. As a robustness check, we have repeated the analysis by controlling additional risk factors from other markets, such as default spreads, term spreads, and log dividend-price ratio. Adding these additional control factors does not alter the main conclusions of the analysis.

Table 3 Summary statistics on the risk exposure estimates

Statistics	β^{fx}		β^{mkt}		β^{smb}		β^{hml}		R^2
A. Cross-sectional statistics of full-sample estimates									
Mean	0.046	(0.107)	0.970	(7.668)	0.971	(4.291)	0.333	(1.505)	0.391
Median	0.034	(0.079)	0.976	(7.284)	0.933	(3.997)	0.350	(1.522)	0.391
Std	0.667	(1.107)	0.277	(4.047)	0.536	(2.696)	0.472	(1.808)	0.158
Minimum	–3.557	(–3.672)	–0.337	(–0.942)	–0.362	(–2.179)	–1.629	(–4.602)	0.043
Maximum	3.095	(3.780)	2.134	(21.870)	3.352	(17.660)	2.350	(5.903)	0.876
Skewness	–0.276	(0.146)	–0.348	(–0.611)	0.475	(1.081)	–0.258	(–0.078)	0.250
Kurtosis	4.797	(0.224)	3.334	(0.278)	0.950	(2.747)	2.832	(0.128)	–0.239
B. Cross-sectional statistics of time-series averages of rolling-window estimates									
Mean	0.108	(0.184)	0.935	(6.157)	0.995	(3.696)	0.243	(0.916)	0.409
Median	0.040	(0.101)	0.943	(5.897)	0.977	(3.514)	0.265	(1.052)	0.403
Std	0.604	(0.970)	0.254	(2.945)	0.541	(2.192)	0.414	(1.314)	0.163
Minimum	–1.834	(–2.172)	–0.097	(–1.159)	–0.307	(–1.615)	–2.278	(–3.053)	0.032
Maximum	2.487	(3.228)	1.862	(14.900)	3.352	(14.959)	1.775	(3.854)	0.883
Skewness	0.498	(0.294)	–0.190	(–0.448)	0.586	(0.906)	–0.688	(–0.339)	0.256
Kurtosis	1.908	(-0.130)	1.379	(0.034)	1.430	(2.714)	4.502	(0.117)	–0.308
C. Time-series statistics of cross-sectional averages of rolling-window estimates									
Mean	0.007	(0.013)	0.976	(6.690)	0.924	(3.931)	0.269	(1.051)	0.415
Median	0.057	(0.076)	0.954	(6.532)	0.951	(3.960)	0.280	(0.985)	0.414
Std	0.127	(0.230)	0.061	(0.835)	0.155	(0.297)	0.136	(0.533)	0.052
Minimum	–0.261	(–0.435)	0.898	(5.268)	0.691	(3.238)	0.053	(0.139)	0.326
Maximum	0.165	(0.359)	1.095	(8.228)	1.143	(4.425)	0.561	(2.049)	0.500
Skewness	–1.032	(–0.661)	0.909	(0.241)	–0.340	(–0.384)	0.087	(0.016)	0.050
Kurtosis	0.089	(0.587)	–0.475	(–0.782)	-1.320	(0.104)	–0.725	(–1.085)	–1.160

Entries report the summary statistics on the slope estimates, Newey-West t-statistics (in parentheses), and R^2 of the following time-series regression on each industry portfolio,

$$ER_t^i = \beta_{i0} + \beta_i^{fx} ER_t^{fx} + \beta_i^{mkt} ER_t^{mkt} + \beta_i^{smb} SMB_t + \beta_i^{hml} HML_t + e_t,$$

where ER^i, ER^{fx}, ER^{mkt} denote the monthly excess returns on the ith industry portfolio, the dollar index, and the market portfolio, respectively, and SMB and HML are the size and book-to-market risk factors. All regressions are performed on monthly returns over the sample period from February 1973 to December 2007. The summary statistics are over 404 industries for the full-sample estimates and 378 for the rolling-window estimates. The last column reports the statistics on the R-squares of the regressions

positive and significant, but with larger cross-sectional standard deviations at 0.536 for SMB and 0.472 for HML.

To account for potentially time-varying risk exposures, we also perform rolling window estimation on Eq. 1. For each industry, we repeat the estimation in July of each year with a rolling window of ten years. The choice of a relatively long rolling window is to cover at least a full business cycle for each rolling regression (Hoberg and Phillips 2006). We require that that within each ten-year rolling window, each industry have at least three annual observations on imports and exports and 24 monthly observations on industry portfolio returns. This requirement reduces the number of industries from 404 to 378. Panel B of Table 3 reports the cross-sectional statistics on the time-series averages of the slope estimates. The statistics are very much similar to those on the full-sample estimates in Panel A, showing that the rolling-window estimation generates sensible results.

Panel C of Table 3 reports the time-series statistics of the cross-sectional averages of the slope estimates across the different industries. The time-series standard deviation of the average dollar exposure is about five times smaller than the cross-sectional standard deviation of the full-sample estimates or time-series averages of the rolling-window estimates. The much smaller time-series variation is partly due to the smoothing effect of the rolling window, but it also reflects the intertemporal stability of the dollar exposure for the average economy.

5 Tracing Dollar Exposure to Import and Export Activities

When we regress industry portfolio returns on dollar index returns, we find that the average dollar exposure is small, but that the exposure estimates show large cross-sectional variations. These cross-sectional variations can come either from sample variation (e.g., large standard errors in the coefficient estimates), or from fundamental differences in the business operations. In this section, we strive to distinguish between the two sources of variation by linking the cross-sectional variations in the risk exposure estimates to economic fundamentals such as international trading activities. A strong, economically meaningful structural linkage between the risk exposure estimates and economic fundamentals would verify that the exposure estimates are not purely noise.

One common conjecture in the literature is that currency exposure is linked to the openness of the economy. For example, Dominguez and Tesar (2006) use bilateral trade to proxy for the openness of an economy. We agree that the degree of openness is important for currency exposure. A completely closed economy should be little affected by exchange rate movements. However, we argue that the direction or imbalance of the international trade is the more relevant source for exchange rate exposure than is the absolute magnitude of openness. A firm that balances imports with exports can have little currency exposure regardless of the aggregate quantity of the international trade. The direction of the currency exposure depends on whether the firm is more export or import oriented.

To test our hypothesis, we regress cross-sectionally the dollar exposure estimates (β^{fx}) on the time-series averages of the imports and exports of the corresponding industry,

$$\beta_i^{fx} = \alpha + \lambda_{IM} \ln(IM/ME)_i + \lambda_{EX} \ln(EX/ME)_i + e_i, \tag{2}$$

where we scale imports and exports by the market capitalization of the corresponding industry to control for the size effect, and we take natural logarithms on the scaled quantity to obtain better distributional behaviors. The cross-sectional regression is over 404 industries. The regression estimates, the heteroskedasticity consistent t-statistics (in parentheses), and the adjusted R-squares are reported in Panel A of Table 4 under specification I. The R^2 from the regression is very low, highlighting the large noise in the dollar exposure estimates. Nevertheless, the regression generates significantly positive slope coefficient estimate on imports and significantly negative slope coefficient estimate on exports. These estimates suggest that import-oriented companies are more likely to have positive exposures to the dollar index variation whereas export-oriented companies are more likely to have negative exposures to the dollar index variation. Stocks of import-oriented companies tend to react positively to dollar appreciation, but stocks of export-oriented companies tend to react negatively to dollar appreciation.

For comparison with the literature, we also regress the dollar exposure estimates against the logarithm of the total trades scaled by the market capitalization, and report the results in Panel A of Table 4 under specification II. In this case, the regression generates a slope coefficient estimate that is not significantly different from zero and an adjusted R-square that is very close to zero. The regression results suggest that the total trades do not explain the dollar exposure.

The results make economic sense. For export-oriented companies, dollar appreciation makes their exports more costly for foreign consumers and hence reduces their sales. As traditional wisdom goes, domestic currency appreciation hurts exports. On the other hand, for import-oriented companies, dollar appreciation makes their imports less expensive and hence increases their profit margins. The regression

Table 4 Tracing dollar exposures to imports and exports

Specifications	Intercept	ln((IM+EX)/ME)	ln(IM/ME)	ln(EX/ME)	ln(IM/EX)	Adj. R^2
A. Full-sample cross-sectional regression						
I	0.042		0.065	–0.056		1.49 %
	(0.84)		(2.67)	(–1.83)		
II	0.042	0.020				0.07 %
	(1.37)	(0.94)				
III	0.042				0.048	0.69 %
	(0.97)				(1.87)	
B. Time-series averages and t-statistics of rolling-window cross-sectional regression estimates						
I	0.026		0.046	–0.028		
	(0.82)		(7.99)	(–3.84)		

Panel A reports the estimates, heteroskedasticity consistent t-statistics (in parentheses), and adjusted R-squares of various cross-sectional regressions that link the dollar exposure β^{fx} to various combinations of exports and exports. The dollar exposure for each industry is estimated by regressing the industry portfolio returns on the dollar index returns and other stock risk factors over the whole sample period from February 1973 to December 2007. The regressors are time-series averages of the imports and export variables. Each cross-sectional regression is over 404 industries. Panel B reports the time-series averages and Newey-West t-statistics of the ten-year rolling-window cross-sectional regression coefficient estimates results reflect the differential impacts of imports and exports on the currency exposure. The results support our argument that it is not the degree of openness that determines currency exposure; instead, it is the imbalance of the trade that generates the exposure.[3]

In principle, when a firm has international trade imbalances that it cannot fully pass through to customers or hedge operationally, it can try to hedge the currency exposure via financial risk management strategies. Such hedging activities will reduce our exposure estimates and the significance of the linkages between the exposures and the trading activities.[4] The fact that we identify significant linkages between the currency exposure and imports and exports activities suggest that the hedging practice is not complete. Indeed, a casual look into the SEC filings of large companies shows that the exchange rate exposure is one of the often-discussed risk factors. As an example, the following is an excerpt from the risk factors section of a recent 10-Q filing from Apple, one of the largest companies in the U.S.: "Demand also could differ materially from the Company's expectations as a result of currency fluctuations because the Company generally raises prices on goods and services sold outside the U.S. to correspond with the effect of a strengthening of the U.S. dollar." The quote epitomize our argument that dollar appreciation hurts exports demand due to increased selling price.

When the sensitivities of dollar exposures to imports and exports are similar in absolute magnitudes, we can use the logarithm of imports-to-exports ratio, ln(IM/EX), to measure the imbalance of the international trade and directly regress the dollar exposure on the imbalance. Under specification III in Panel A of Table 4, we report the results from such a univariate regression. The slope coefficient estimate is significantly positive, showing the informativeness of the trade imbalance measure about currency exposure. Nevertheless, the adjusted R-square of this univariate regression is about half of that from the bivariate regression. Therefore, it is beneficial to allow for different sensitivities of the dollar exposure to imports and exports.

We have experimented with different transformations and scaling of the imports and exports volume. For example, we have used imports and exports without taking logarithms, and without the market capitalization scaling. We have also repeated the analysis by normalizing imports and exports with the book value of total assets. These variations do not alter the qualitative results regarding the direction of the impacts of imports and exports on the dollar risk exposure.

To analyze the time-variation of the relation between dollar exposure and import/export activities, we also perform rolling-window estimation on Eq. 2. Each year from 1983 to 2007, we regress the ten-year rolling-window estimates of the dollar exposure on the ten-year rolling averages of imports and exports. Panel B of Table 4 reports the time-series averages and Newey and West (1987) t-statistic (in

[3]Consistent with our argument, Pritamani et al. (2004) also find that the exposure estimates tend to be positive for import industries and negative for export industries, with or without controlling for the market portfolio return.

[4]For example, Bartram et al. (2010) find that financial hedging with foreign currency debt, and to a lesser extent currency derivatives, reduces the exposure by about 40 %.

parentheses) of the coefficient estimates. The time-series average of the coefficient estimates on imports is strongly positive at 0.046, with a Newey and West (1987) t-statistic of 7.99. The time-series average of the coefficient estimates on exports is strongly negative at −0.028, with a Newey-West t-statistic of −3.84. The average results of the rolling-window estimation are consistent with the results from the unconditional cross-sectional regression in Panel A.

The dollar exposure estimates from the return regressions can have large standard errors, making the estimates for many industries insignificant statistically. The literature often regards this phenomenon as a puzzle. Nevertheless, our cross-sectional analysis in this section shows that the cross-sectional variations of these exposure estimates contain information and can be linked significantly and meaningfully to fundamental trading activities. The fundamental linkage highlights the economic significance of the dollar exposure estimates. Furthermore, the structural linkage can be exploited in reducing the noise in the exposure estimates from return regressions.

6 Linking Dollar Exposure to Expected Stock Returns

So far, our analysis suggests that import- and export-oriented industries have systematically different dollar risk exposures, but does the difference in dollar exposures lead to different expected excess returns on their stocks? Can we use the dollar exposure estimates to predict future stock returns? Can we use the structural linkage to imports and exports to enhance this prediction?

To answer these questions, we first estimate the risk premiums on different types of risk exposures following a standard procedure popularized by Fama and MacBeth (1973). At each month t, we regress cross-sectionally the next month's excess stock portfolio return on the time-t rolling-window estimates of the risk exposures,

$$ER^i_{t+1} = \eta^0_t + \eta^{fx}_t \beta^{fx}_{it} + \eta^{mkt}_t \beta^{mkt}_{it} + \eta^{smb}_t \beta^{smb}_{it} + \eta^{hml}_t \beta^{hml}_{it} + e^i_{t+1}, \quad (3)$$

where η^0_t denotes the intercept of time-t cross-sectional regression and η^k_t denotes the risk premium estimate for each unit of risk exposure on the k-th risk factor, with $k = fx, mkt, smb, hml$ denoting the dollar risk, stock market portfolio, SMB, and HML risk factors, respectively. All risk exposures are estimated based on a ten-year rolling window and updated annually in July of each year. As a concrete example, monthly excess returns from July 1995 to June 1996 are all regressed on risk exposure estimates based on a ten-year window from July 1986 to June 1995.

The time-series averages of the slope estimates capture the average risk premiums charged by the stock market on each unit of risk exposure in the four risk sources. Table 5 reports the time-series averages of the regression estimates and the Newey and West (1987) t-statistics under specification A. The average slope estimates are negative on the dollar risk exposure and SMB, and positive on the market and the HML exposures. Nevertheless, none of the slope averages are statistically significant. One potential reason for the low statistical significance is that the regression in Eq. 3 suffers from severe generated regressor problems as the rolling-window estimation generates noisy risk exposure estimates. As is well-known, return-regression

Table 5 Identifying dollar risk exposures and risk premiums

Specification	η^0	η^{fx}	η^{mkt}	η^{smb}	η^{hml}	λ_{IM}	λ_{EX}
A	0.484	–0.009	0.379	–0.085	0.016		
	(1.38)	(–0.09)	(1.14)	(–0.37)	(0.07)		
B	0.485	–0.066	0.351	–0.062	0.038	1.162	–1.028
	(1.36)	(–2.02)	(1.04)	(–0.27)	(0.15)	(36.8)	(–34.4)

Entries report time-series averages and Newey-West t-statistics (in parentheses) of the coefficient estimates from two sets of cross-sectional regressions. Specification A estimates the following cross-sectional regression,

$$ER^i_{t+1} = \eta^0_t + \eta^{fx}_t \beta^{fx}_{it} + \eta^{mkt}_t \beta^{mkt}_{it} + \eta^{smb}_t \beta^{smb}_{it} + \eta^{hml}_t \beta^{hml}_{it} + e^i_{t+1},$$

where ER^i_{t+1} denotes next month's excess return on the i-th industry portfolio, β^k_t denotes the ten-year rolling-window risk exposure estimates, η^k_t denotes the slope coefficient on each risk exposure, with $k = fx, mkt, smb, hml$ denoting the four sources of systematic risks in the stock market, and η^0_t denotes the intercept of the regression. Specification B incorporates imports and exports to enhance the identification of the currency exposure,

$$ER^i_{t+1} = \eta^0_t + \eta^{fx}_t \left(\beta^{fx}_{it} + \lambda_{IM} \ln(IM/ME)_{it} + \lambda_{EX} \ln(EX/ME)_{it}\right) + \eta^{mkt}_t \beta^{mkt}_{it} + \eta^{smb}_t \beta^{smb}_{it} + \eta^{hml}_t \beta^{hml}_{it} + e^i_{t+1},$$

where the two coefficients (λ_{IM} and λ_{EX}) are estimated via maximum likelihood method

based risk exposure estimates often have large standard errors. The large noise in the exposure estimates can bias the coefficient estimates in the second-stage regression in Eq. 3 toward zero due to the errors-in-variables problem.

To reduce the noise in the dollar risk exposure estimates and to enhance the identification of the dollar risk premium, we resort to our findings in the previous section that the dollar risk exposures are related to the imports and exports of the corresponding industries. The analysis is meant to identify the fundamental economic sources of the dollar risk exposure, but the linkage also suggests that fundamental information about the import and export quantities of an industry can help us enhance the identification of the dollar risk exposure.

To incorporate the information in imports and exports, we propose an alternative estimation method based on the following specification,

$$\begin{aligned} ER^i_{t+1} = {} & \eta^0_t + \eta^{fx}_t \left(\beta^{fx}_{it} + \lambda_{IM} \ln\left(\frac{IM}{ME}\right)_{it} + \lambda_{EX} \ln\left(\frac{EX}{ME}\right)_{it}\right) \\ & + \eta^{mkt}_t \beta^{mkt}_{it} + \eta^{smb}_t \beta^{smb}_{it} + \eta^{hml}_t \beta^{hml}_{it} + e^i_{t+1}, \end{aligned} \tag{4}$$

where we regard the dollar exposure as an average of information from three sources: the original rolling window regression estimates based on stock returns β^{fx}_{it}, the imports, and the exports. As we have done earlier, we scale imports and exports by the market capitalization of each industry and take natural logarithms on the scaled quantities. In line with the rolling-window risk-exposure estimates, we also employ a ten-year rolling window in estimating the averages of the logarithm of the scaled imports and exports to be used in the regression. The imports and exports data are available annually. Corresponding to the risk exposure estimates with a rolling window from July 1986 to June 1995, for example, we use the averages of the log scaled imports and exports from year 1985 and 1994. The half year lag in timing is to make sure that the imports and exports data are available in June of 1995. Furthermore, for identification reasons, we normalize the weighting on β_{it}^{fx} to unity, and hold the weighting coefficients on imports and exports (λ_{IM} and λ_{EX}) to be constant over time. We estimate the system of equations based on an iterative procedure. First, given initial guess on the two coefficients, we perform cross-sectional regressions each month to obtain the risk premiums η_t^k. Then, we estimate the two coefficients by maximizing the likelihood of the forecasting errors from the regression, assuming that the regression errors are independently and identically distributed with a normal distribution. Table 5 reports the maximum likelihood estimates and t-statistics of the two coefficients under specification B. The maximum likelihood estimates on the two coefficients are 1.162 for λ_{IM} and −1.028 for λ_{EX}. The t-statistics for the two estimates are 36.8 and −34.4, respectively. Both the sign and the high statistical significance confirm our earlier findings that imports relate positively to the dollar exposure and exports relate negatively to the dollar exposure.

Table 5 also reports the average risk premiums estimated from Eq. 4 under specification B. With the enhanced identification using information from imports and exports, the time-series average of the dollar risk premium η_t^{fx} becomes negative and statistically significant, with a Newey and West (1987) t-statistic of −2.02. Thus, through Eq. 4, we have not only linked the dollar exposure to fundamental international trading quantities such as imports and exports, but also exploited this linkage in sharpening the identification of the dollar risk exposure and dollar risk premium.

The negative risk premium estimate suggests that in the United States, market participants view dollar appreciation as an adverse shock to the domestic economy. Thus, companies with positive dollar exposures generate higher stock returns during adverse economic conditions. Investors are willing to receive a lower expected excess return to gain positive exposures to dollar appreciation so that they can hedge against adverse movements in the economy.

7 Conclusion

Economic theory suggests that the magnitude and direction of a firm's currency risk exposure depends crucially on its fundamental involvement in international trade. Within the U.S., we find that the stock performance of import-oriented industries moves positively with the performance of the dollar, but the stock performance of export-oriented industries tends to move against the dollar. Based on this finding, we use the imports and exports information to enhance the identification of the dollar risk exposure for different industries, and analyze how each industry's expected stock return varies with its dollar risk exposure. We identify a strongly negative risk premium for bearing positive exposures to the dollar. On average, import-oriented industries generate lower expected stock returns.

Our strong findings rely on three major insights. First, it is not the aggregate trade activity but the unhedged trade imbalance between imports and exports that generates the currency exposure. Second, cross-sectional variations in business characteristics and hence risk exposures are much larger than intertemporal variations within a fixed industry. The first insight leads us to include imports and exports as separate explanatory variables, whereas the second insight motivates us to use cross-sectional regressions instead of time-series regressions to identify the linkage between currency risk exposures and trade fundamentals.

Our third insight is related to various puzzles on risk exposure and risk premium estimates. Risk exposure estimates from stock return regressions tend to have large standard errors, making many estimates statistically insignificant. The lack of significance is often regarded as a puzzle in itself. Furthermore, when one tries to estimate the risk premium on such risk exposures, the risk premium estimates also become insignificant due to errors-in-variable problems. The insignificance of the risk premium is also frequently treated as a puzzle, but the two types of puzzles are inherently linked. Only when we are able to estimate the risk exposure accurately, do we have the chance of identifying the risk premium. We propose that one way to validate the return-regression risk exposure estimates is to investigate whether the cross-sectional variations of these estimates are related to firm fundamentals in economically meaningful ways. Furthermore, the existence of such an economic linkage can also provide a channel to further reduce the noise in the return-regression-based risk exposure estimates. Using the example of dollar risk exposures, we show that doing so can also help make the risk premium estimate more significant.

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References

Aizenman J, Riera-Crichton D (2008) Real exchange rate and international reserves in the era of growing financial and trade integration. Rev Econ Stat 90(4):812–815

Allayannis G (1997) The time-variation of the exchange rate exposure: An industry analysis. Working paper. University of Virginia

Allayannis G, Ihrig J (2001) Exposure and markups. Rev Financ Stud 14:805–835

Allayannis G, Ofek E (2001) Exchange rate exposure, hedging, and the use of foreign currency derivatives. J Int Money Financ 20:273–296

Amihud Y (1994) Exchange rates and valuation of equity shares. In: Amihud Y., Levich R (eds) Exchange Rates and Corporate Performance. Irwin, New York

An L, Wang J (2012) Exchange rate pass-through: Evidence based on vector autoregression with sign restrictions. Open Econ Rev 23:359–380

Bartov E, Bodnar GM (1994) Firm valuation, earnings expectations, and the exchange-rate exposure effect. J Financ 49:1755–1785

Bartram SM (2008) What lies beneath: Foreign exchange rate exposure, hedging and cash flows. J Bank Financ 32:1508–1521

Bartram SM (2015) Corporate hedging and speculation with derivatives. Working paper. Warwick Business School

Bartram SM, Brown GW, Conrad JS (2011) The effects of derivatives on firm risk and value. J Financ Quant Anal 46:967–999

Bartram SM, Brown GW, Minton BA (2010) Resolving the exposure puzzle: The many facets of exchange rate exposure. J Financ Econ 95:148–173

Bartram SM, Karolyi GA (2006) The impact of the introduction of the euro on foreign exchange rate risk exposures. J Empir Financ 13:519–549

Betts CM, Kehoe TJ (2001) Tradability of goods and real exchange rate fluctuations. Working paper. University of South Carolina and University of Minnesota

Betts CM, Kehoe TJ (2006) U.S. real exchange rate fluctuations and relative price fluctuations. J Monet Econ 53:1297–1326

Bodnar GM, Dumas B, Marston RC (2002) Pass-through and exposure. J Financ 57:199–231

Bodnar GM, Gentry WM (1993) Exchange rate exposure and industry characteristics: evidence from Canada, Japan, and the USA. J Int Money Financ 12:29–45

Bodnar GM, Wong MHF (2003) Estimating exchange rate exposures: Issues in model structure. Financ Manag 32:35–67

Boug P, Cappelen A, Eika T (2013) Exchange rate pass-through in a small open economy: the importance of the distribution sector. Open Econ Rev 24(5):853–879

Campa J, Goldberg LS (1999) Investment, pass-through, and exchange rates: a cross-country comparison. Int Econ Rev 40:287–312

Campa J, Goldberg LS (2005) Exchange rate pass through into import prices. Rev Econ Stat 87:679–690

Carrieri F, Errunza V, Majerbi B (2006) Does emerging market exchange risk affect global equity prices? J Financ Quant Anal 41:511–540

De Santis G, Gerard B (1998) How big is the premium for currency risk? J Financ Econ 49:375–412

Didier T, Hevia C, Schmukler SL (2012) How resilient were emerging economies to the global crisis? J Int Money Financ 31:2052–2077

Dominguez KME, Tesar LL (2001) A re-examination of exchange rate exposure. Am Econ Rev Pap Proc 91:396–399

Dominguez KME, Tesar LL (2006) Exchange rate exposure. J Int Econ 68:188–218

Dumas B (1992) Dynamic equilibrium and the real exchange rate in a spatially separated world. Rev Financ Stud 5:153–180

Dumas B, Solnik B (1995) The world price of foreign exchage risk. J Financ 50:445–479

Engel C, Mark NC, West KD (2007) Exchange rate models are not as bad as you think. Working paper. University of Wisconsin, University of Notre Dame, and University of Wisconsin

Engel C, West K (2005) Exchange rates and fundamentals. J Polit Econ 113:485–517

Evans MDD, Lyons RK (2002) Order flow and exchange rate dynamics. J Polit Econ 110:170–180

Fama EF, French KR (1993) Common risk factors in the returns on stocks and bonds. J Financ Econ 33:3–56

Fama EF, French KR (1995) Size and book-to-market factors in earnings and returns. J Financ 50:131–155

Fama EF, French KR (1996) Multifactor explanations for asset pricing anomalies. J Financ 51:55–84

Fama EF, MacBeth JD (1973) Risk return, and equilibrium: Empirical tests. J Polit Econ 81:607–636

Feenstra RC (1996) U.S. imports, 1972-1994: Data and concordances. NBER Working Paper 5515 UC Davis

Feenstra RC (1997) U.S. exports, 1972-1994, with state exports and other U.S. data. NBER Working Paper 5990 UC Davis

Feenstra RC, Romalis J, Schott PK (2002) U.S. imports, exports and tariff data: 1989–2001. NBER Working Paper 9387 UC Davis, University of Chicago, and Yale University

Ferson WE, Harvey CR (1993) The risk and predictability of international equity returns. Rev Financ Stud 6:527–566

Ferson WE, Harvey CR (1994) Sources of risk and expected returns in global equity markets. J Bank Financ 18:755–803

Griffin JM, Stulz RM (2001) International competition and exchange rate shocks: A cross-country industry analysis. Rev Financ Stud 14:215–241

Guay WR (1999) The impact of derivatives on firm risk: An empirical examination of new derivative users. J Account Econ 26:319–351

Harvey CR (1995a) Global risk exposure to a trade-weighted currency index. Working paper

Harvey CR (1995b) Predictable risk and returns in emerging markets. Rev Financ Stud 8:773–816

He J, Ng LK (1998) The foreign exchange exposure of Japanese multinational corporations. J Financ 53:733–753

Hentschel L, Kothari SP (2001) Are corporations reducing or taking risks with derivatives? J Financ Quant Anal 36:93–118

Hoberg G, Phillips G (2006) Real and financial industry booms and busts. Working paper. University of Maryland

Jorion P (1990) The exchange rate exposure of U.S. multinationals. J Bus 63:331–345

Jorion P (1991) The pricing of exchange rate risk in the stock market. J Financ Quant Anal 26:363–373

Kashiwagi M (2013) Implications of exchange rate pass-through and nontradable goods for international policy cooperation. Open Econ Rev 25:771–795

Lothian JR, Taylor MP (1996) Real exchange rate behavior: The recent float from the perspective of the past two centuries. J Polit Econ 104:488–509

Mark N (1995) Exchange rates and fundamentals: Evidence on long-horizon predictability. Am Econ Rev 85:201–218

Newey WK, West KD (1987) A simple positive-definite heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55:703–708

Papell DH, Prodan R (2011) The statistical behavior of gdp after financial crises and severe recessions. B E J Macroecon 12:1–29

Pritamani MD, Shome DK, Singhal V (2004) Foreign exchange exposures of exporting and importing firms. J Bank Financ 28:1697–1710

Sercu P, Uppal R (2000) Exchange Rate Volatility, Trade, and Capital Flows under Alternative Exchange Rate Regimes. Cambridge University Press, Cambridge

Williamson RG (2001) Exchange rate exposure and competition: Evidence from the automotive industry. J Financ Econ 59:441–475