Firm Foreign Activity and the Geography of Exchange Rate Risk

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Abstract

Globally-focused firms, more than domestic ones, are the key drivers of foreign exchange rate (FX) risk. They explain a larger fraction of the factors' variation and have higher FX exposure, specifically during the home currency depreciation. Their exposure is higher in countries more dependent on the export sector but decreases with centrality in the trade network, reflecting benefits from geographically diversified foreign activities. Exposure is relatively larger to neighbors' currencies, in line with gravity effects, and to the currencies of the most distant countries, across the distinct FX factors. Overall, we find the economic origins of FX risk pricing captured by trade rather than investments.

Keywords: International Finance, Foreign Exchange Rate Risk, Currency Exposure, Multinationals, Geography

JEL classification: F31, F23, G12, G15.

1. Introduction

After decades of inconclusive results, evidence is building that foreign exchange rate risk is priced in global equity markets. There is, however, not a clear understanding of the economic origins together with the sources of its statistical significance. As recent issues around the world demonstrate, global risk can stem from a host of real-economy events, ranging from shocks to foreign demand and supply of goods and services, shifts in their relative prices, and disruptions to supply chains. These sources of risk affect firms, especially globally-focused companies operating in open economies, directly or indirectly. We show that those firms with a significant percentage of sales in foreign countries are the drivers of the pricing of foreign exchange (FX) risk. What is more, consistent with the firms' direct exposure to international business activities, aggregate measures of world trade also explain their systematic exposure to FX risk and its geographic properties.

Global economic activity and asset prices are linked. Recent papers have pointed out that heterogeneity in trade participation matters for economic and financial outcomes. The trade literature such as di Giovanni, Levchenko, and Mejean (2022) finds that foreign shocks are transmitted to the domestic economy primarily through the large firms which are the most likely to trade internationally. In the finance literature, models such as Barrot, Loualiche, and Sauvagnat (2019) show that firms' heterogeneity with respect to international trade and its costs is a valuable set-up in asset pricing to study exposure to global shocks. Our main test assets are the aggregation of companies with a high foreign sales ratio (H-FSR firms) that are a key part of the global trade network. For Australia, the sample median country by foreign sales ratio, the H-FSR firms represented 12 percent of the country's listed companies and 45 percent of its market capitalization in 2019. Yet, in all, their foreign activity was equivalent to 57 percent of the credits recorded in the Current Account. This high degree of concentration is likely to have a significant impact on FX risk pricing.[1]

[1]All throughout, we refer to trade to broadly indicate economic activities by firms recorded in the flows of the Current Account, such as sales from exports (from the trade balance) and sales from foreign operations

In this paper, we posit that the international trade linkages of globally-focused firms expose them to shocks from the changing economic activity and relative aggregate prices around the world. As a result, the equity returns of country-level portfolios built only from these firms comove more strongly than domestic ones with global risk factors, which alleviates the challenges in the empirical identification of the risk stemming from currency dislocations. Our framework relies on the basic underpinnings of asset pricing theories of currency risk (e.g., Adler and Dumas, 1983). These models attribute the presence of currency risk to purchasing power parity deviations (PPP) and attach a risk premium to all bilateral exchange rates versus the numeraire currency, based on the relative global wealth of their respective home investors. We construct portfolios for 41 countries from 24,072 H-FSR firms, which we identify based on an exhaustive set of data cleaning filters for the period of 1996 to 2019. Our empirical strategy includes a host of unconditional and conditional estimation approaches to measuring covariances, correlations, and exposures to global systematic risk factors for the large country cross-section of our portfolios. We rely on panel regressions to show how common sensitivity to foreign activity among these kinds of companies matters for global asset pricing. We then use cross-sectional regressions to understand the drivers of FX risk and to show how the geography of foreign trade also shapes its patterns. The results can be summarized as follows.

First, we find that portfolios of H-FSR firms aggregated within the country of their headquarters provide richer information with respect to the global risk factors and their dynamics than country indices. They correlate more strongly with global risk proxies, and their principal components show an underlying more complex factor structure than the broader cross-section of firms in the country indices. Above all, these globally-focused portfolios rather than domestic ones qualify as *strong* test assets for these *weak* risk factors, given that those components explain a larger fraction of FX risk. By exploiting them, one can improve the estimation of the price of FX risk (Giglio, Xiu, and Zhang, 2021).

(from the distributed profits in the primary income balance).

Second, we establish that the H-FSR portfolios contribute significantly to pricing the systematic FX risk. The estimated prices for the exchange rate risk factors have more statistical significance and are economically larger than the measures obtained through the benchmark country indices. This suggests that these firms, which are identified from the underlying characteristics linked to real economic activity, are more sensitive to global shocks. Indeed, we fail to observe as strong as a relationship studying portfolios built from low foreign sales ratio firms (L-FSR portfolios), those aggregated without taking into account geographic domicile, or the most commonly studied country-level indices. Studying the G10 currencies separately (nine bilateral exchange rate risk measures versus the U.S. dollar, henceforth $G10^{-U\$}$), we observe that the comovements with larger currencies, such as the euro, the British pound, and the Swiss franc, significantly explain the returns of the H-FSR firms, consistent with theoretical predictions. We also observe that some of our distinct exchange rate factors have a negative price of risk, representing a hedging component for investors.

In-sample beta sorting of the 41 countries' H-FSR portfolios matches the evidence from the asset pricing regressions. The average returns of portfolios of firms with high sensitivity to FX risk confirm the sign of the estimated prices of risk for the currencies. Furthermore, we uncover that the sensitivities to FX risk in the beta-sorted portfolio aggregation exhibit geographic clustering. Firm portfolios have a higher sensitivity to the bilateral FX risk measure of a neighboring $G10^{-U\$}$ currency, rather than currencies of distant countries. The relative magnitude of the risk sensitivities aligns with the widely established gravity phenomenon at play for global trade. Neighboring countries face lower barriers related to distance, and they experience more aligned and less volatile bilateral exchange rates. These attributes are associated with larger trade between them and can explain the more similar sensitivity across the portfolios within each of the FX risks. At the same time, the level of exposure across the separate FX factors is relatively larger with respect to the risk from currencies of the most distant among the $G10^{-U\$}$ countries.

Third, we find that the time-varying exposures of the H-FSR portfolios are significantly associated with the real global economy through measures of countries' aggregate export intensity and trade centrality, controlling for a range of country and time variables. This sensitivity is stronger for firms in countries with a larger export sector, and interestingly, it is weaker for firms in countries that are central to the global trade network and thus conduct business with more trading partners. The negative association with trade centrality is also in line with the findings of Richmond (2019), who documents that interest rates and FX risk premia are lower for countries which are more central in the network. On the other hand, we find no evidence that relates the risk sensitivities to aggregate measures of capital flows, measured by foreign equity, debt, or direct investment. Analyzing firm characteristics across our sample countries, we observe that higher FX sensitivity is also explained by the extent of the foreign activity measured by the size of firms' export and foreign sales. In addition, this sensitivity is inversely related to home currency depreciations.

Our results on the economic information from the cross-section of H-FSR firms are noteworthy in light of papers like Lustig, Roussanov, and Verdelhan (2011, 2014) and Verdelhan (2018) that have uncovered a factor structure in currency returns and exchange rates, and extracted new currency factors to price the cross-section of currencies. Lustig and Richmond (2019) further relate the risk characteristics of currencies to measures of distance and argue that the factor structure of exchange rates is consistent with a gravity effect. Recently Jiang and Richmond (2023) show that exchange rate correlations increase beyond bilateral linkages in countries that share common trade linkages, and that the latter are related to the new currency factors. Going one step further, Hassan, Loualiche, Reggi Pecora, and Ward (2023) make the trade network and the exchange rate factor structure endogenous. Taken together, evidence is accumulating that the structure of the trade network explained by gravity is related to the structure in currency factors and their risk.

We run several robustness checks for our asset pricing analysis with respect to the composition of the H-FSR portfolios, by excluding the U.S. or countries with a low number of H-FSR firms, and with respect to model specifications, to check for a country-specific effect that instead would manifest itself as home currency risk and for a region-specific effect that could impact the nature of global risks. To further validate trade as a driver, we compute the sensitivities of the firm portfolios to newly introduced measures of aggregate currency factors. Also, with these alternatives, we verify the association of FX risk with aggregate trade intensity and centrality.

Geography has been shown to play a role in institutional investments in the U.S. (see Coval and Moskowitz, 2001 and Bernile, Kumar, and Sulaeman, 2015) and internationally, in cross-border equity flows (Portes and Rey, 2005) and asset holdings through its impact on trade in goods (Aviat and Coeurdacier, 2007). Recently Aloosh and Bekaert (2022) find that a two-block structure underlying currency comovements is also related to distance. However, to our knowledge, there are no papers on the economic geography of exchange rate risk for international equities. We document a clustering effect for the G10 currencies that is driven by distance and a core-periphery effect that depends on countries' worldwide importance for the output of globally tradable goods. Overall, our results indicate a prominent role for the trade channel and geography in explaining how the international equity markets are priced.

This paper contributes to the international asset pricing literature by providing further convincing results on the presence of exchange rate risk. Some papers find support for such risk with stock indices (see Dumas and Solnik, 1995 and De Santis and Gerard, 1998 with the G4 stock indices, Carrieri, Errunza, and Majerbi, 2006, Francis, Hasan, and Hunter, 2008, and Balvers and Klein, 2014 with larger cross-sections of Emerging Markets, U.S. industries, and country equity indices). More recently, with global portfolios sorted on company characteristics, Karolyi and Wu (2020) show that a carry trade risk factor is priced more consistently than a dollar risk factor.[2] Rather than focusing on such benchmark indices or portfolio sorts, we investigate portfolios constructed based on fundamental economic characteristics, namely the extent of firms' foreign sales. Indeed a number of studies have revealed

[2] Fama and French (2012), Hou, Karolyi, and Kho (2011), and Karolyi and Wu (2018) have explored global or local risk factors, omitting FX risk, with portfolios sorted on characteristics like size, value, momentum, and cash-flow to price.

the importance of foreign sales and related economic activity for stocks and their prices, without directly exploiting the extent of the international economic activity for the pricing of FX risk (see Doidge, Griffin, and Williamson, 2006 and Amihud, Bartov, and Wang, 2013 from the perspective of companies, and Bae, Elkamhi, and Simutin, 2019 and Demirci, Ferreira, Matos, and Sialm, 2022 from the perspective of international investors).

We also contribute to the literature that studies the connection of economic quantities of fundamentals like output, trade, and investment flows with currency dynamics and global uncertainty (the so-called exchange rate disconnect starting with the seminal paper by Meese and Rogoff, 1983).[3] Very recently, a few papers have attempted to explain expected returns from exposure to global risk linked to trade activity (see Richmond, 2019, Hoberg and Moon, 2019, Barrot et al., 2019 and Chang, Du, Lou, and Polk, 2022). [4] International trade as an important economic source of exposure motivates us to focus on a stock attribute like foreign sales and to explore its asset pricing implications across international equity portfolios.

In the remainder of the paper, Section 2 presents the framework for our tests, explains the methodology, and covers the data. Results from the asset pricing tests are in Section 3, while those about the risk sensitivities are in Section 4. Section 5 concludes.

2. Empirical Methodology

2.1. Tests of Multiple FX factors

Theoretical models show that international investors who face differences in purchasing power require an additional premium to take on FX risk, along with the premium for the global market risk. The FX risk is capturing a portion of the systematic risk linked to contemporaneous and future shocks in relative prices among different countries. Hence, the expected

[3] Revisiting the failure of standard models of exchange rates, Engel, Mark, and West (2008) show that forecasts can be improved with panel techniques and provide support for the PPP model as the best-performing model.

[4] For other recent papers on macro fundamentals and exchange rates, see Hassan (2013), Gabaix and Maggiori (2015), Colacito, Croce, Gavazzoni, and Ready (2018).

return of global stocks should be linearly related to the exposure to a world equity market portfolio hedged against exchange rate fluctuations.

Our empirical model follows this framework, combining the theoretical insights of Merton (1973) and Adler and Dumas (1983).[5] We employ a conditional approach and investigate the asset pricing relationship through time-varying estimates of covariances, correlations, and risk exposures to global factors. Indeed Zhang (2006) finds that the conditional International CAPM with FX risk performs the best among several global pricing kernels. The relationship between conditional expected excess returns $E_{t-1}\left[\boldsymbol{r_t}\right]$ and risk is formalized as follows:

$$E_{t-1}\left[\boldsymbol{r_t}\right] = \lambda \operatorname{Cov}_{t-1}\left(\boldsymbol{r_t}, r_{m,t}\right) \;+\; \boldsymbol{\gamma}^{'} \operatorname{Cov}_{t-1}\left(\boldsymbol{r_t}, \boldsymbol{X_t}\right) \tag{1}$$

$$X_{j,t} = \left(I_{j,t-1} + 1\right) \frac{S_{j,t}}{S_{j,t-1}} - \left(I_{\$,t-1} + 1\right), \qquad \forall j \in \{\mathrm{G10}^{-U\$}\} \tag{2}$$

where $\operatorname{Cov}_t\left(r^i, \cdot\right)$ denotes the conditional covariance between asset returns of country i and risk factors given the information available at time t, λ is the price of market covariance risk, and $\boldsymbol{\gamma}$ is the vector of the prices of FX covariance risk, X_j. We use excess currency investment returns as proxies for the state variables that help anticipate unexpected changes in relative prices. I_j and $I_\$$ denote the risk-free investment rates in the country of currency j and U.S., respectively and S_j denotes units of U.S. dollar per currency j.

We perform asset pricing tests for different sets of portfolios composed of stocks with high and low foreign sales aggregated along the country dimension, or without accounting for geographic domicile, as well as countrywide portfolios. Given the mounting evidence that FX risk is systematic, and holding the cost of capital constant, we posit that the pricing relationship has stronger statistical significance for globally-focused companies whose cash flows are more affected by global shocks.

[5]The FX risk has also been supported in other theoretical models, starting with Solnik (1974), Sercu (1980), and Stulz (1981, 1984). More recently, papers have explored alternative dimensions of FX risk together with market risk. For instance, Chaieb and Errunza (2007) develop a model of partially segmented markets with PPP deviations for securities accessible and not accessible to foreign investors and show that they command a segflation premium.

Our exercise needs some clarifications. We work from a theory that tells us what the common risk factors are, and in equilibrium, these factors should consistently price any international asset. In other words, in an integrated world, the value of the factor risk premia should be the same, irrespective of what asset or what subset of assets we use for the test. However, the choice of test assets determines how well different factor risk premia can be identified: if only some assets are less exposed to a factor, that factor is weak, which makes standard estimation and inference incorrect (Giglio et al., 2021). Thus in our hypothesis, we do not intend to make definite statements on the magnitude of the estimate of a factor premium. Rather, we want to verify that a smaller cross-section organized from some firm characteristics can be particularly informative about a factor, which in our case is supported by the theory. In the result section, we show that the strength in the factor structure of H-FSR firms helps us in capturing exposure to the FX risk factors.

Applying a fully parameterized conditional setting for asset pricing tests in a large cross-section of assets and with many risk factors has presented estimation challenges. We overcome these obstacles by adopting the approach of Bali and Engle (2010) that allows us to exploit the time-varying information of multiple sources of risk as well as the cross-sectional variation of many portfolios. Our estimation of the asset pricing relationship involves two steps. First, we estimate the time-varying variances of several risk factors, as well as their pairwise covariances with respect to the different sets of test assets. In the second step, we use these conditional covariances as regressors and estimate the prices of risk in a panel regression setting.[6]

Through our methodology, we can empirically study a large number of candidate proxies for FX risk without the need to aggregate the currency factors. This is necessary for our subsequent analysis that provides insight into the currencies' separate importance for firms across geographic regions. At the same time, we keep the risk prices constant, which

[6]We implement the corrected Dynamic Conditional Correlation (cDCC) proposed by Aielli (2013) in our first step, and a Generalized Least Square estimator that corrects for heteroskedasticity and autocorrelation as well as the cross-correlations in the error terms in the second step (see Bali and Engle, 2010).

ultimately imposes a higher hurdle on our asset pricing tests compared to the previously documented evidence.[7] Constant prices of risk allow a direct assessment across model specifications, without large parameter proliferation and with no loss in the interpretation of the economic role of the estimated coefficients. While finance theory has established that there should be a positive tradeoff between expected returns and systematic market risk, i.e., the λ coefficient should be significantly positive, the sign of the prices linked to currency premia cannot be determined ex-ante. The $\boldsymbol{\gamma}$ coefficients will be positive when investors require a premium, as the global assets are positively correlated to those sources of global risk, and will be negative when investors earn hedging benefits from the correlation with the factors. The sign of the separate currency risk coefficients also has implications for investors with respect to the geography of FX risk compensation.

To explore more in-depth the economic origins of the risk characteristics across regions and the world, we construct weekly conditional sensitivity to FX risk (*FX Betas*) from the estimated conditional variance-covariance matrix. Our estimates for the sensitivities are the assets' quantities of risk that we use as the regressors in the asset pricing tests, scaled by the variance of the risk factors:

$$\beta_{j,t}^{i} = \mathrm{Cov}_{t-1}\left(r_t^i, X_{j,t}\right) \,/\, \mathrm{Var}_{t-1}\left(X_{j,t}\right) \tag{3}$$

Where, r^i denotes the H-FSR portfolio excess return in country i. We use the notation $\beta_{j,t}^{FXc}$ when X_j represents the FX risk for the home currency of the H-FSR portfolio i and $\beta_{j,t}^{rest}$ for the cross-sectional average of $\beta_{j,t}^{i}$, excluding the $\beta_{j,t}^{FXc}$.[8]

We study the association of the H-FSR portfolios' time-varying *FX Betas* with the trade channel in a cross-sectional regression framework, where we control for a host of the country- and time-specific variables. In the cross-section of countries, we expect that the larger the

[7] Akbari and Carrieri (2023) estimate a fully conditional model for the three main currencies in a two-step approach, similar to the one in this paper, but with risk prices time-varying as a function of common global financial variables. They find that FX risk is priced in a large cross-section of country indices.

[8] Our estimation of *Beta FX* might be affected by a common latent variable that predicts both r_m and X_j. In Section 4.2, we address this issue and confirm that our findings are unaffected by this concern.

role of the export sector in a country's economy, the higher the sensitivity of its globally-focused firms to systematic FX risk. As these firms are likely to be affected by the shifts in countries' competitiveness as a result of currency swings, they have to offer higher compensation to global investors.[9] At the same time, we explore the importance of other geographical characteristics linked to trade that could mitigate the positive relationship. Indeed, the foreign revenues of firms that belong to a country that trades with multiple countries are likely more diversified across currencies and thus less exposed to each of the FX risk factors. These firms are located in the center of the global trade network, whereas firms that trade in a single currency belong to countries located in the periphery. We expect the H-FSR firms' sensitivity to FX risk factors to be negatively related to the measure of trade centrality.

2.2. Data

We study returns of several firm portfolios aggregated at the country level from January 1996 through December 2019. Based on the FTSE group's classification, we cover 22 Developed Markets (DMs) and 19 Emerging Markets (EMs). Data availability in Datastream for the local market interest rates and the firm-level stock prices dictates the starting point of our time sample and the cross-section of countries. The list of countries in DM and EM groups and their statistics are tabulated in Table A1 in the Appendix. To study some of the geographical implications across our sample, we use the k-nearest neighbor algorithm (k-NN) to cluster countries into three regions, which we call Asia-Pacific (with 14 countries), Europe (20 countries), and America (7 countries).[10]

[9] Cassel's body of work on international trade, starting with Cassel (1918), is in support of our underlying assumption that PPP deviations are linked to trade flows, their volumes, and patterns.

[10] k-NN is a non-parametric classification method that minimizes the aggregate pairwise distance of members in a cluster. In our implementation, we use the square of the Euclidean distance between the capital cities of countries in our sample, based on their longitude and latitudes.

2.2.1. *Test Assets*

We access the universe of stocks in major stock exchanges in countries for which DataStream provides a total market index. Out of this universe of 138,827 securities, we select 69,043 non-financial, common stocks to construct portfolios of globally exposed firms.[11] We collect weekly closing, U.S. dollar-denominated, return index data, and market capitalization. For each firm, we also collect the international sales, exports, and net sales or revenues from WorldScope, available at the annual frequency.[12] We follow Doidge et al. (2006), and for each firm, we compute the foreign sales ratio (FSR) as the ratio of the sum of the international sales and exports of that firm to its net sales or revenue, in percentage. In each country and year, we cluster firms into two mutually exclusive groups: (a) H-FSR, those with at least 10 percent foreign sales ratio, and (b) L-FSR, those with less than 10 percent foreign sales ratio. Firms in the finance and real estate sectors and those with missing foreign sales data are excluded to ensure working with companies with known FSR status. We compute the equally-weighted average returns of firms in each country to construct the H-FSR and L-FSR portfolio excess returns.[13]

Our premise is that, as a result of large foreign sales, the firms in the H-FSR group have higher exposure to global shocks and a higher risk sensitivity to currency movements compared to the firms in the L-FSR group.[14] We acknowledge that importing firms and those with fixed assets abroad derived from foreign direct investments are also highly exposed to global risk factors. However, lacking for these metrics comprehensive and comparable data across countries, we only use firms globally exposed due to their foreign sales. Furthermore,

[11]For this selection, we follow an exhaustive list of filters introduced in Ince and Porter (2006) and Griffin, Kelly, and Nardari (2010). Please refer to Appendix A for the details of the selection criteria in our sample.

[12]Exports represent the revenues generated from the shipment of merchandise to another country for sale, whereas international sales represent sales generated from operations in foreign countries.

[13]Due to the cleaning step in the firm selection, the union of H-FSR and L-FSR firms will not cover all firms in a country. Similar to Dominguez and Tesar (2006), we construct equally-weighted portfolios not to bias the results given that larger companies are also those with a larger share of global business activity.

[14]As documented in Aggarwal and Harper (2010), some domestic companies might have indirect exposures to FX risk through an international competition in the markets for their inputs and/or outputs. In addition, it is plausible that H-FSR firms pass some of their FX risk exposure to their domestic customers.

we use the 10 percent threshold for consistency with accounting rules on segment reporting that identify multinational enterprises among U.S. domiciled firms. Figure A1 in the Appendix presents more information on the level of the FSR for the firms in our portfolios. We observe that, at approximately 40 percent, the median FSR is not substantially changing over time, while there is more disparity between the group of DMs and EMs, with the former showing higher FSR median values.

For the countrywide market portfolios, we collect DataStream weekly closing, U.S. dollar-denominated, total return index data (DS-INDEX).[15] As an alternative, we consider the MSCI Investable Market Indices (INVESTABLE), widely used as benchmarks in asset management, since they allow us to take into account firms with high visibility to foreign investors. To further understand heterogeneity in global risk exposure across different test assets, we construct two other sets of portfolios. For the first, we pool all H-FSR firms and randomly assign them to 41 pseudo-country portfolios (RANDOM). For the second set, we assign H-FSR firms to 34 industry portfolios based on their ICB sector classifications (INDUSTRY).[16] All the firms in these portfolios have high exposure to global risk factors because of their sales characteristics, yet their headquarters countries and, thus, their functional currencies differ. Therefore, aggregation in these two types of portfolios is unlikely to result in a unidirectional exposure to the FX risk factors, and it can further shed light on the importance of a firm's domicile in characterizing FX risks and geographic patterns. We use the weekly Euro-dollar one-month deposit rate, obtained from DataStream, as the risk-free rate to calculate excess returns for all our assets.

Summary statistics on the H-FSR firms are in the Appendix. Table A1 reports the average and standard deviation of the firms' weekly returns (annualized, in percentage), the total number of H-FSR firms in each country over the time sample, as well as their total market

[15] These indexes include the common stocks for which the DataStream's data requirements are met and that have passed its liquidity test. For more details on the index construction, please refer to Thomson Reuters global equity index methodology, available at www.thomsonreuters.com/content/dam/openweb/documents/pdf/tr-com-financial/methodology/global-equity-index-methodology-oct-2015.pdf.

[16] DataStream provides 44 ICB sector indexes. We exclude firms in eight financial and two real estate related sectors.

capitalization as of the last week. There are, on average, 763 H-FSR firms in DMs (68% of the local market's capitalization). On the other hand, EMs have fewer H-FSR firms (384 on average and 62% of local market capitalization). However, exporter countries such as India, South Korea, Taiwan, and Malaysia host significantly more. At the end of our sample, the H-FSR firms in DMs are, on average, two times larger than their EM counterparts. Across our sample countries, the average number of H-FSR firms is smaller than L-FSR (246 versus 398 respectively), but the average market capitalization of the former firms is more than four times the one of the latter group.

Table 1 presents summary statistics for the test portfolios in our study. Our sample spans over 24 years and includes 51,291 week-country observations over 1,251 weeks. Rows 1 and 2 of Table 1 report the cross-sectional averages for the time-series mean and standard deviation (annualized, in percentage) for each set of portfolios. We observe that the H-FSR firms have on average higher returns than the L-FSR firms, and not surprisingly, the mean return of the total local market portfolio is close to the average of the two groups. The volatilities of the portfolios are comparable between series; however, randomly assigning H-FSR firms in pseudo-country portfolios diversifies out some of their risk. Higher mean and lower volatility explain the high cross-sectional average of the Sharpe ratios for the H-FSR portfolios.

[**Place Table 1 about here**]

2.2.2. Foreign Exchange Rate Risk Factors

We use the excess returns earned from currency investments as proxies for the FX risk factors. In the context of the theoretical model, all currency pairs vis-à-vis the currency of denomination should be separately included in Equation (1), with the price of the FX risk for currency j (γ_j) proportional to the wealth share of its country in the world. To reduce dimensionality, most empirical asset pricing research focuses on a few currencies linked to the national markets with the largest capitalization; the German marc (the euro), the British pound, and the Japanese yen have been the most common ones as separate factors in the earlier studies. On the other hand, the cash flow exposure literature, for practical reasons, has studied mostly the aggregated, trade-weighted exchange rate changes or only the country's bilateral vis-à-vis the U.S. dollar. Our methodology allows us to expand the analysis to more FX risk factors, and we focus on the G10 currencies that are gaining more attention in recent research, without locking into pre-determined weights that result in currency aggregation. Keeping the FX factors distinct is also necessary to analyze how the risk from different currencies matters across firms located in different regions. We include, vis-à-vis the U.S. dollar (USD), five European and four non-European currencies. They are the Euro (EUR), Japanese Yen (JPY), and British Pound (GBP), as well as the Australian dollar (AUD), Canadian dollar (CAD), New Zealand dollar (NZD), Norwegian krone (NOK), Swiss Franc (CHF), and Swedish krona (SEK) which are the currency pairs most traded around the world in our time sample.[17,18] We substitute the relative price changes of the theoretical model with the differential in short-term interest rates, since we can reasonably assume that for the G10 currencies, inflation at the weekly frequency is not stochastic.[19] These investments are thus nominally riskless deposits in domestic currency that are risky in dollar terms and provide a readily available hedge for the exposure to the FX risk, when priced. We collect the weekly local interest rate and exchange rates from DataStream. Table 1 also presents the cross-sectional averages for correlations of each portfolio in our sample with these FX risk factors. JPY has negative and smaller correlations, whereas the commodity currencies such as AUD, CAD, and NZD have higher correlations with our test asset portfolios. Table A2 reports the summary statistics of the risk factors.

[17]See, for instance, Mueller, Stathopoulos, and Vedolin (2017), Opie and Riddiough (2020), Panayotov (2020), Sandulescu, Trojani, and Vedolin (2021), Aloosh and Bekaert (2022), and Bank of International Settlements (2015). Major banks also have dedicated G10 foreign exchange strategy teams.

[18]Before the inception of the Euro, we use the German mark and splice it into the Euro series.

[19]While a relevant state variable in our framework, inflation is also not available at a higher frequency. Dumas and Solnik (1995) use the same measure for PPP violations at the monthly frequency.

2.2.3. Risk Exposure Determinants

To study what explains the cross-sectional differences in the FX risk sensitivity, we focus on measures of global trade, international investment, and firms' scope of foreign activities, while we control for measures related to both the domestic and the global economy and to firms' standard characteristics. For our main hypothesis on the trade channel, we collect the export of goods and services scaled by a country's gross domestic product (GDP) from the World Bank's World Development Indicator (WDI) dataset to measure the export intensity of a country (EXP_INTENSITY). We also collect the measure of trade centrality (TR_CENTRALITY) from Richmond (2019), which is computed from pairwise bilateral trade normalized by pairwise total GDP. A country can have high trade intensity, yet low trade centrality, if it trades a lot with one or just a few partners. We also use the median for each country's FSR, as we find it representative of a country's aggregate outward activities. We use the log of the geographic distance between the capital city of a country and that of a currency ($DIST^i_j$). The distance data is computed by the CEPII, which is also widely used in the trade literature. We also construct a measure of distance for currencies ($\overline{\mathrm{DIST}}_j$), which is the average of DIST^i_j for currency j over the countries in the sample. Appendix C lists alternative determinants that we explore, taken from the investment and capital flow channel and from firms' outward activities. We also motivate therein the country-level characteristics and country-level variables from firm characteristics that likely shape the economic and business environment and that we use as controls.

3. Asset Pricing Test Results

Our asset pricing analysis is focused on exploring the contribution of globally-focused firms to the international pricing kernel. The international finance literature has long faced the challenge of identifying empirically FX factors that are strongly backed by the theory, and for the most part, it only used countrywide portfolios to test for such factors. In this section, we investigate different sets of portfolios to verify how the information from second moments in the risk quantities of the H-FSR portfolios is of help.

3.1. Principal Component Analysis

We start to explore the properties of the country portfolios of the H-FSR firms with the help of Principal Components (PC). This analysis is inspired by the recent insights provided in Giglio et al. (2021) on the need to select a set of strong test assets to identify the risk premium of weak factors. To gauge the informativeness of the different portfolios, in Panel A of Table 2, we provide the cross-sectional average of the number of PCs needed to explain variations of returns in each set of portfolios. It is worth noting that with the exception of the US, all these portfolios are translated into USD, so exchange rate changes are affecting them equally. We observe that the percentage of asset variation that the first PC can explain is higher for the broad and diversified portfolios, like the countrywide or investable indices and the industry or random portfolios, than for the subsets built from firms' degree of foreign activity. In addition, the number of PCs needed to explain 70 percent of the variation in the data is lower for the former groupings.

[Place Table 2 about here]

These statistics indicate a low-dimensional factor structure for the broad and diversified portfolios. To further explore the factor structure of the different portfolio sets, we first compute up to the tenth PC from the returns of each set and then regress each one of our observable candidate risk factors on these PCs.

$$X_{j,t} \;=\; \alpha_g \;+\; \sum_{k=1}^{10} \gamma_g^k \, PC_{g,t}^k + \epsilon_{j,g,t} \tag{4}$$

where, PC_g^k denotes the k^{th} principal component of portfolio set g. We interpret a high R-squared in these regressions as an indication that the portfolio set represents strong test assets for that risk factor. Given the variation in the number of PCs in the statistics of asset returns in Panel A, our choice of ten PCs can be viewed as arbitrary. We opt to follow Pukthuanthong and Roll (2009), who retain from the covariance matrix of the country index returns the same number of PCs as proxies for global factors. Panel B reports the R-squared of the time-series regressions and, at the bottom, the sum of the R-squared of the nine FX risk factors for the sets. The world market is the strongest factor as it finds overall the highest explanatory power in the ten PCs. However, we also observe R-squared above 40 percent for many FX factors, indicating that they can explain a substantial fraction of asset returns variation. Of the different sets of test portfolios, H-FSR portfolios show the largest sum from the nine FX regressions' R-squared (3.145), whereas the broad countrywide and the investable indexes have lower values. This validates the strength in the factor structure of H-FSR firms in capturing exposure to FX risk factors when aggregated along the country dimension. The results are consistent with the notion that FX risk acquires relevance in the context of place, in other words, it has a geographic connotation.

3.2. Conditional Asset Pricing Regressions

Table 3 presents our results from the conditional asset pricing tests, based on Equation (5).

$$r_t^i = \alpha \; + \; \lambda \, \mathrm{Cov}_{t-1}\left(r_t^i, r_{m,t}\right) \; + \sum_{j \,\in\, \mathrm{spec}} \gamma_j \, \mathrm{Cov}_{t-1}\left(r_t^i, X_{j,t}\right) + \epsilon_t^i, \qquad \forall j, \forall i \tag{5}$$

We present nine specifications, (1) with only the world market portfolio, and (2) through (9) with also different combinations of the currency investments, proxying for state variables linked to PPP deviations. Specification (2) has the three commonly studied currencies, specifications (3) to (8) add one source of FX risk at a time, and in specification (9), we include them all together. At the bottom of the table, we report the p-values of Wald statistics on the joint significance of all the included FX factor risk coefficients. The results of the table are in support of our key hypothesis that H-FSR portfolios are driving the pricing of FX risk in global equity markets. In specifications (2) to (9), we find that the price of EUR is negative and significant while the one for GBP is positive and significant, with p-values for the t-statistics of these individual estimates ranging from 0.003 to 0.063 depending on the currency and the model. Other currencies, like the NOK or SEK, also command a risk premium, but the evidence is less strong. Most notably, the CHF has a significant negative coefficient (p-value of 0.012). Indeed, when we include all the FX risk proxies, the evidence is robust for the presence of the EUR, GBP, and CHF.[20] This is consistent with the theoretical prediction, for which the important currency premia correspond to those of investors with the largest wealth share in the world. P-values as low as 0.011 and up to 0.094 for the joint Wald tests indicate that these risk proxies are together significant or marginally significant, except for the regression with the AUD. The parameter for the world market risk is always positive and significant at the conventional statistical levels. Even with our smaller cross-section of firms, the magnitude of the prices of risk is comparable with the evidence in the conditional international asset pricing literature.

[Place Table 3 about here]

In all, the evidence shows that the factors proposed as proxies for state variables are capturing significant risk components of the expected returns, as we observe that the intercepts in all the specifications across Table 3 are not statistically significant. It is also useful to interpret the evidence for the risk parameters. Given a negative price for a risk factor, like for the CHF or the EUR risk, an asset with a positive covariation will have a greater hedging demand since it helps against deviations in international parities. In other words, investors can look at the EUR and the CHF as relatively safer currencies than the GBP. This also implies that companies that have positive correlations with similar risk factors would carry a lower cost of capital, everything else equal.

[20] In unreported results, we confirm a structural break for JPY risk during the 2008 global financial crisis. In this period, the comovements of portfolio returns with this currency switch sign (from positive to negative). Fatum and Yamamoto (2016) document the particular importance of JPY as the "safest" of the safe-haven currencies, during the crisis. Subsample analysis finds stronger evidence for the pricing of the JPY risk.

Table 4 helps further assess our hypothesis on the strength of the H-FSR portfolios structure in capturing exposure to factors supported by the theory. It reports the results from regressions of specification (9) for the alternative portfolios. First, look at the country-level portfolios of companies with a low level of foreign sales (L-FSR). These assets command a significant world market price. However, the other proxy coefficients for the large and liquid currencies are smaller than Table 3 and with no or only marginal statistical significance. The second and third regressions are based on the total market index and the investable stocks. Both indexes cover the broad cross-section comprised of large, liquid, and easily accessible stocks in each country and partially overlap with the H-FSR companies. However, with these portfolios, we can only find statistical significance for the price of market risk, differently from the results on the joint Wald tests obtained with the H-FSR country portfolios. The fourth column considers portfolios of the H-FSR firms but are now aggregated internationally within industries. The evidence favoring a model with global risks is not strong since only two marginal currencies are priced, and there is no support of systematic FX risk jointly. This weak significance can be explained through offsetting exposures from their cross-country composition. Lastly, for the portfolios constructed by randomly assigning H-FSR firms to pseudo-countries, only one FX risk is priced individually, and the specification is not supported by the joint statistical test. This suggests that the mechanical portfolio composition washes out the information needed to identify the risk.

[Place Table 4 about here]

Directly comparing the results of Table 4 with those of Table 3, we find support for our hypothesis that the globally-focused companies aggregated along the country dimension are the drivers of the statistical significance of the FX risk. As suggested by the information in Tables 1 and 2, the theoretically motivated FX risk factors co-vary significantly less with the portfolios we study than the world market factor, and we can improve the estimation of their price of risk through *stronger* test assets (Giglio et al., 2021). For instance, differently from the world market risk, for the price of EUR or GBP, we observe a higher statistical significance for the estimated coefficients using the H-FSR country portfolios as test assets, compared to the total market portfolios (DS-Index). That said, the sign and magnitude of these values are qualitatively comparable in Tables 3 and 4, while world market risk is priced similarly, both in magnitude and significance. Furthermore, these results confirm the information provided by the PC analysis on the informativeness in the factor structure of the H-FSR firms when aggregated within countries, rather than industries or pseudo-countries. That evidence also provided the first indication of the other research question in the paper, that firms' geographic attributes through their domicile shape their FX risk. Changes in relative prices and interest rates among different countries as a result of national fiscal, monetary and trade policies are likely to affect companies within the country and with respect to the world in a similar way. An interest in estimating market exposures for global firms aggregated based on "geographic zones" according to the place where they conduct business has recently emerged (see Dumas, Gabuniya, and Marston, 2022). Our analysis instead puts forward the view that portfolio aggregation based on firms' headquarters locations, as for the H-FSR portfolios in their respective countries, is important in identifying FX risk.

The specifications of Tables 3 and 4 are consistent with a world where countries are integrated, and local risk is not priced. Nonetheless, it is conceivable empirically that, for example, the sensitivity of the UK portfolio to an unspecified risk of local nature could result in the GBP risk being significant. We thus re-estimate the regressions of Table 3, adding a country-specific intercept for each portfolio in the model to capture potential country-fixed effects. In untabulated results, only two out of the 41 countries exhibit an intercept that is consistently significant in the specifications (1) through (9), while EUR, GBP, and CHF are priced similarly to Table 3. This suggests that these portfolios have little sensitivity to a time-invariant domestic market component but high sensitivity to global conditions. In addition, for these country-specific intercepts, we calculate a joint Wald test across the three non-overlapping regions defined through the k-NN algorithm explained above. Also, in this case, we fail to reject the null of (jointly) zero intercepts for all specifications, an indication that we find no evidence of regional factors of unspecified nature. We run a few additional tests without reporting the results for brevity. First, in building the H-FSR portfolios, we exclude countries with fewer than 50 firms. Second, we compute these globally-exposed portfolios using only the information on companies' foreign income from the subsidiaries' sales, thus eliminating the information on direct export sales that in WorldScope is quite incomplete. Third, we remove the US firms from the cross-section. In all instances, the results of Table 3 are confirmed. It is worth noting that the sign and the significance of the global risk proxies like the EUR, GBP, and CHF are robust and consistent in all these checks.[21]

Portfolio sorting of assets based on their exposure to the currency factors strengthens our findings from Table 3. We first compute the *FX Betas* of the H-FSR portfolios to each of our risk factors, according to Equation (3). Then, each week we sort the cross-section of the 41 H-FSR portfolios with respect to the median of the contemporaneous beta and build two equally weighted portfolios of high and low sensitivity to the ten risk factors. Figure 1 shows the average of the weekly returns from the time series of the generated high and low beta currency portfolios. If the risk premium for a factor is positive and risk exposure to that factor is positive, we expect to observe a higher average return for the high beta portfolios (β_{Top}). For instance, for the world market risk, we find a positive price of risk in Table 3, and, in Table A2, a positive average for the realized returns. In Figure 1, we also observe that the portfolios of high beta assets with respect to the world market risk have higher realized average returns. Across currencies, the average returns for the two beta portfolios show substantial variation. For the CHF or the euro, the low beta portfolio (β_{Bottom}) has a higher return than the high beta one, opposite what we observe for the GBP or the CAD. Similarly to the world market risk, for each currency, we find that the sign in the average returns of β_{Top} minus β_{Bottom} portfolios matches the sign of the realized returns

[21] These robustness results are available from the authors.

of the corresponding risk factor in all cases, with the exception of the Norwegian krone and Swedish krona. For example, the average of CHF β_{Top} minus β_{Bottom} portfolio returns is negative, like the average of the dollar returns from a currency investment in Swiss francs. Furthermore, those spreads in average portfolio returns are consistent with the estimated sign of seven of the ten prices of risk factors, including the four with statistical significance in Table 3. Given that these portfolios are computed ex-post, they do not represent an investment strategy. Nonetheless, it is reassuring to observe that we can capture the asset pricing relationship in ex-post formation through betas.

[Place Figure 1 about here]

When we dig further into the composition of these β_{Top} and β_{Bottom} portfolios, we uncover a consistent pattern throughout. The β_{Top} portfolios consist primarily of firms located in countries of the European region. For instance, the CHF β_{Top} portfolios are comprised of more than 80 percent of the weeks from firm portfolios of European countries, while firms from countries that are far from Switzerland, like those in Asia or South America are grouped in the currency β_{Bottom} portfolios. Thus the composition of these portfolios reveals a geographic dimension, which we will explore more in Section 4.

The geographical make-up of the β_{Top} portfolios, together with the insight from the sign of the different FX risk prices, has interesting implications for global investors. The asset pricing results imply that investors seek compensation from GBP shocks while obtaining hedging benefits from the CHF ones. Then our sorting exercise reveals that, all else equal, to gain from exposure to GBP risk, investors can load up on British firms, as well as firms of geographically close countries. On the other hand, besides Swiss companies, H-FSR firms in a geographic region close to Switzerland can serve as a hedge. They offer investors some protection from CHF shocks, due to their high sensitivity to the Swiss currency.

4. Determinants of FX Risk Sensitivity

The methodology that we deploy in the previous section delivers quantities that can help in understanding the economic origins of FX risk. To begin, in untabulated regressions, we regress annual changes in the local currencies on changes in exports, in foreign portfolio investment liabilities (debt and equity), and in direct investment liabilities, accounting for country- and year-fixed effects. We find that while exports and portfolio investments are significantly associated with changes in exchange rates both in univariate and multivariate panel regressions, the former have substantially greater economic significance. A one-standard deviation change in the trade channel is associated with 0.87 standard deviation changes in the exchange rates, an order of magnitude larger than the change in the investment channel. In this section, we introduce our estimates for the FX risk sensitivities of the portfolios, analyze their dynamics and explore their geographic properties, together with underlying economic information. Despite the prevalence of universal PPP deviations, in the multifactor setting, there is weak empirical evidence for some of the risk factors. In the analysis that follows, we combine them first. However, given that their economic value is nonetheless supported by the theory, we also highlight their distinctive features.

4.1. FX Risk Factor Sensitivity across Regions

We start by examining the FX risk factor sensitivity, the *FX Beta* of the H-FSR portfolios in the cross-section.[22] Figure 2a presents an example, with the *FX Beta* for CHF risk, displayed through a Hodrick-Prescott (HP) filter for visual appeal.

[Place Figure 2 about here]

The thick black line identifies the one for the Swiss firms' portfolio, the $\beta_{j,t}^{FXc}$, while the

[22] Table A3 reports the time-series averages of the FX Betas. The mechanical relationship between dollar-denominated returns for the stock portfolios and for the currency investments mostly explains the positive sign and large magnitude for almost all betas. The U.S. portfolio, which does not suffer from such a mechanical relationship, shows lower betas and two with a negative sign.

ones of H-FSR portfolios of the other countries are marked in gray. The plot reveals a number of interesting patterns. The higher sensitivity of the Swiss portfolio to the Swiss franc risk aligns with the evidence in Adler and Dumas (1983) that the largest weight of an investor's hedge portfolio is in nominal bank deposits in home currency. Although relatively smaller, many other firm portfolios in our sample countries also have *CHF Betas* that are economically meaningful, with a few instances when the *FX Betas* are negative but sizable, similar in absolute magnitude to the positive measures. This observation is further confirmed in Table 5, Panel A, which reports the average values of *FX Beta* for the portfolio of the home country and for the portfolios of the rest of the countries, $\beta_{j,t}^{rest}$, for all currencies. A test on the respective averages shows that the time-series average of $\beta_{j,t}^{FXc}$ is statistically larger than the average of the risk sensitivity for the rest of the H-FSR country portfolios. We also observe that some currencies like the CAD, the AUD, and to some extent also the NZD, NOK, and SEK represent higher systematic FX risk for both the home country and the rest of the country portfolios.

We further explore the geographic patterns of the individual FX sensitivities for the H-FSR country portfolios. Figure 2b shows, as an example, the average of the historical *CHF Betas* versus a measure of distance between the country of the H-FSR portfolio and the country of the currency. The farthest from the Swiss capital the country of the firm portfolios is, the lowest their *CHF Beta*. The plot clearly shows two clusters which we find to be related to the geographical distribution of the countries, with a cluster of near European countries and the rest made of distant countries. This pattern is remarkable in light of the recent evidence on currency basket comovements in Aloosh and Bekaert (2022) who find European countries grouped within one block of a two-block structure through a clustering technique based on correlations.[23] In untabulated results, with regression analysis for each currency, we observe that in all cases, the *FX Betas* decrease with distance and

[23] Bakshi, Crosby, and Gao (2020) provide a formal measure of exchange rate disconnect from the ratio of two martingales and show that currencies coalesce around a currency in the geographic vicinity, pointing to highly correlated SDFs.

the distance coefficient is statistically significant for seven of our currencies, at 1% for EUR, GBP, NZD, NOK, CHF, and SEK and at 10% for AUD.

Given this evidence and our findings on the geographical nature of the currencies' beta-sorted portfolios, in Table 5 Panel B, we perform a more rigorous test, conditional on distance. First, we calculate the distance between each one of the countries in our sample and the G10$^{-U\$}$ countries. With the (40x9) bilateral measures we define four zones, based on threshold values from bilateral distance quantiles, with Zone 1 being the closest to the currency capital city. Then, for the FX risk of each currency, we group the country portfolios into four sets based on these zones, and we compute the average beta within each group. For instance, for the JPY, we attribute the portfolios from 41 countries to four groups based on their distance to Tokyo with Zone 1 being the closest to it, with an average beta of 0.091. We observe the highest betas in group 1, thus, firms across the sample countries exhibit the highest risk sensitivity with respect to the exchange rate risk of a currency from a G10$^{-U\$}$ country that is close. At the bottom of the table, we report a test for the hypothesis that the average of the *FX Beta* for group 1 is smaller than the rest. The test strongly rejects for the FX risks together, and for all the distinct FX risks, except the one of the JPY.[24] Firms have the highest exposure to the risk of the G10$^{-U\$}$ neighbor currency. Neighboring countries face lower transportation costs and other barriers related to distance, and they experience more aligned and less volatile bilateral exchange rates.[25] These attributes can explain the similar sensitivity to FX risks that we document within regions and are associated with larger trade between the countries. Thus the extent of PPP violations from the G10$^{-U\$}$ bilateral exchange rates against the USD matters also for third country firms' cash flows and whose competitiveness depends on how these firms relate to each other across borders.

[24]For the AUD and the NZD group 1 only includes the country itself. In unreported results, we confirm that excluding the home currency portfolio or all the G10$^{-U\$}$ country portfolios does not change our overall conclusion and results are qualitatively unchanged for the majority of the estimates.

[25]Going back to the seminal paper by Engel and Rogers (1996) on the deviations from the law of one price, the distance between cities explains a large portion of the variability among prices, and a border strengthens this effect. For more recent evidence on closeness and comovements, see Aloosh and Bekaert (2022) who find that currency baskets of nearby countries are highly correlated.

Overall, the evidence suggests that the forces in play for global trade can also be important in explaining the exposure that drives the risk sensitivities to the separate currency factors of the H-FSR firms that are part of the trade network. The patterns in the FX risk covariation align with the widely established gravity effect that explains the size of trade flows around the world from geographical as well as other types of distances (see Tinbergen, 1962). Motivated by these observations, and the recent literature that has found an association between the trade network and the structure in exchange rates and their risk (see Richmond (2019), Lustig and Richmond (2019), Jiang and Richmond, 2023) we explore further the link with the trade channel.

[Place Table 5 about here]

4.2. Determinants of FX Risk Sensitivity

4.2.1. Trade Channel - Country-level Characteristics

We focus on measures of global trade related to both the domestic and the global economy. Specifically, we study two key variables: total export intensity (EXP_INTENSITY), measured by the relative size of the export sector in a country, and trade centrality (TR_CENTRALITY), measured by the centrality of the country in the global trade network. Countries are more central if they have many strong links to countries that are important for the global output of tradable goods. Given the evidence on geography in the previous section, we expect the export intensity to be positively associated with the exporting firms' return covariation with the FX risk, whereas we conjecture that our portfolios' covariation with FX risk should be negatively associated with the extent of a country's trade centrality. We implement the following cross-sectional regression, with the firm portfolios' *FX Betas*:

$$\beta^i_{j,t} \;=\; b_1\,\text{EXP\_INTENSITY}^i_t \;+\; b_2\,\text{TR\_CENTRALITY}^i_t \;+\; \Phi\mathbf{Controls}^i_t + \epsilon^i_{j,t} \qquad (6)$$

Most of our determinants are available only at the annual frequency, while for the others with a higher frequency, we collect their end-of-year observations. We run one regression for all FX risks together, by stacking the end-of-year *FX Betas*, and also investigate each currency separately to infer geographic patterns. Table 6 presents the results where we report the slope coefficients for the independent variables as averages of the period-by-period estimates from the cross-sectional regressions. The corresponding t-statistic for each estimate reported in parentheses is obtained from the cross-sectional regressions' standard errors corrected for the time-dependence, following Petersen (2009).

[Place Table 6 about here]

Overall, we find strong statistical support that *FX Beta* is associated with the global trade channel. We observe that for the totality of FX risk as well as for the nine separate risk proxies, the slope coefficient for EXP_ INTENSITY is positive, suggesting that firms in countries with larger export activities have a higher sensitivity to the systematic risk from dislocations in PPP. The exposures of the H-FSR portfolios to the three main currencies, EUR, JPY, and GBP, and also the one to CHF significantly load on EXP_INTENSITY, with p-values ranging from 0.007 to 0.048, implied from the t-statistics of the table. The coefficient estimates for four more currencies are also marginally significant (with p-values from 0.052 to 0.090). PPP shocks captured through their effects on H-FSR firms' export competitiveness are difficult to diversify also for investors who invest globally but consume at home. The statistical significance points more strongly to the risk exposure of the largest currencies, i.e., those linked to the nationality of investors representing the largest share in world financial markets. At the same time, the magnitude of the coefficient is larger for the currency risk stemming from peripheral countries. Lustig and Richmond (2019) show that currencies of peripheral countries are more exposed to systematic variation than currencies of central countries.

Now consider the measure of international trade built at the global level, TR_ CENTRAL-

ITY. The position of a country in the global trade network is shown to be very significant in explaining the combined currency sensitivities of the portfolios. Looking across the currencies, we find that trade centrality is inversely related to the systematic risk of eight of the nine currencies at least at the five percent level of significance, with p-values ranging from 0.000 to 0.042. Thus firms in countries that are relatively more important in the global trade network are exposed to lower systematic FX risk and would benefit from a lower cost of capital, all other things equal. Our result suggests that a country's centrality allows to better diversify some of the shocks stemming from economic activity around the world and decreases the exposure of the portfolio of the country's firms to the systematic risk attached to currencies. Furthermore, the largest mitigation impact from the country's centrality is found with respect to the exposure to the systematic risk of peripheral currencies. In all, these results echo the message in Richmond (2019) who shows that the currencies of central countries are a good hedge against global consumption risk and thus have lower interest rates and currency premia.

Table 6 also reveals that the firms' measures of systematic FX risk are explained by some other country characteristics, (see Appendix C for their details), yet the trade channel is a very robust determinant across currency risk sensitivity. For example, consumption is also estimated significantly positive for many of the currency risk factors, albeit not for the risk from the main currencies. Interestingly, the stock market capitalization has a negative and significant coefficient for almost all the *FX Betas*, with the exception of the AUD and CAD. This is possibly an indication that firms from countries with more advanced stock markets and greater availability of derivatives are less sensitive to FX risk factors. It strengthens the conjecture in Francis et al. (2008) that hedging on the part of companies and investors could explain the weak evidence on FX risk pricing. We do not find a strong and robust association with the degree of the quality of corporate governance and institutions. Among the three variables, we observe that only law and order enters in six of the nine regressions with a positive and significant coefficient. Capital account openness is positive and significant for three of the main currencies. However, exposure from more openness to capital flows does not drive out the significant exposure to trade openness. Taken together, this evidence indicates that firms' exposures to currency systematic risk are heightened by a country's trade intensity and mitigated by their trade centrality. Some fundamental country characteristics, including some related to macroeconomic variables that in the empirical analysis are often disconnected from spot exchange rates, are important determinants of FX risk factor sensitivities.

A common latent variable is likely to predict both r_m and X_j. To clean of confounding effects on the trade variables, we run two additional tests. First, we control for these effects by adding in our regressions the $\beta_{m,t}$ estimate. Second, we first orthogonalize the H-FSR returns on the world market returns before computing the *FX Betas* to run the trade regressions. In all instances, the significance and size of the trade coefficients are not altered. For an additional robustness check, we change the cutoff of FSR in the cross-section. In constructing the H-FSR set for the portfolios we use throughout the median of each country instead of the 10 percent. The evidence is confirmed. We report the panel results of the specifications with all the currencies in Appendix Table A4.

Another concern is that the results are driven by the high firm exposure to the respective currency, $\beta_{j,t}^{FXc}$, as illustrated in Figure 2a. In unreported analysis, we re-estimate the nine $\text{G10}^{-U\$}$ regressions by removing the country portfolio associated with the currency in the cross-section of test assets. In other words, the cross-sectional regressions of the British pound sensitivity exclude the *FX Betas* of the portfolio of H-FSR firms in the U.K. The results are unchanged.

When we repeat the same analysis in Table 6 using the L-FSR portfolios as the dependent variable, we observe that the coefficients for EXP_INTENSITY are still positive, the economic magnitude is not very different, but the statistical significance is substantially weaker. Trade centrality is still inversely related to the systematic risk betas and significant for the sensitivities to six currencies. Overall, these results conform to our expectations of weaker evidence for this set of portfolios and support the importance of firms' heterogeneity in explaining our asset pricing evidence.[26]

4.2.2. Alternative Channel - Global Capital Flows

We consider alternative types of international flows taken from the countries' Balance of Payments and substitute the trade channel variables. Tables A5 and A6 investigate the equity and debt investments, which measure the extent of foreign capital inflows directed toward domestic equity and bond markets. Table A7 covers the FDI inflows, net of repatriation of capital and repayment of loans, which quantifies the purchases of controlling stakes in domestic companies by foreign residents. These flows thus generate demand for home currency, like the purchase of exports by foreigners at the core of our trade variables.[27]

Differently from Table 6, the coefficients on the investment flows do not have a robust sign and are never statistically significant for all FX risks. Analyzing each currency, for only two currencies (CHF and SEK) the slope coefficients for the equity flows are (marginally) significantly estimated. The slope coefficients for the debt flows are also insignificant, except in the case of only two currencies (EUR and GBP). For the foreign direct investment regressions, none of the slope coefficients are estimated positive and significantly; only for the JPY the coefficient is significant but with a negative sign. Some of the other variables aimed at capturing differences in countries' characteristics appear robust in these regressions from both economic and statistical standpoints, like what we also observed in Table 6.

The Balance of Payments is, of course, a record of both inflows and outflows. We estimate regressions with the remaining broadly classified outflow items, including U.S. outflows in the form of purchases of foreign bonds that have shown some explanatory power in explaining exchange rate changes in Lilley, Maggiori, Neiman, and Schreger (2022). For brevity, do not

[26] Bernard and Jensen (1995) were the first to use firm-level information to explore the role of exporting plants for the US manufacturing sectors, showing that exporters have better performance than other firms. The international trade literature has recently introduced heterogeneous firms into modified gravity models, moving away from the assumption of an infinite number of firms of equal size, and focusing instead on the contribution of large and outstanding exporters. See for example Eaton, Kortum, and Sotelo (2013), Breinlich, Fadinger, Nocke, and Schutz (2021), Gaubert and Itskhoki (2021).

[27] Among recent papers on the links of capital flows with demand and supply of foreign currency, see Gourinchas and Rey (2007), Della Corte, Riddiough, and Sarno (2016), Camanho, Hau, and Rey (2022).

report these results since we also do not find significance. Thus, taken together, our findings validate the importance of the trade channel for the risk exposure of our global assets, while other types of international activities do not have the same explanatory power.

4.2.3. Alternative Currency Factors

We verify the robustness of the relationship between FX risk sensitivities and trade with the help of measures of aggregate currency risk proposed by recent research (Lustig et al., 2011, 2014, and Verdelhan, 2018).[28] Given the success of these risk factors in explaining the cross-section of currency investment returns, other papers have recently used them in pricing currency risk in a panel of country stock indices (Brusa, Ramadorai, and Verdelhan, 2015) and in the cross-section of sorted global equity portfolios (Karolyi and Wu, 2020). We further this line of research and use them in the cross-section of H-FSR portfolios.

More specifically, for each of these factors, first, we estimate the quantities of risk and risk exposures, using the empirical methodology described in Section 2. Then we perform a cross-sectional regression analysis in a similar setup as the one in Table 6 but we substitute the individual FX risks with the aggregate measures of currency risk (*CR Beta*). Results are tabulated in Appendix Table A8, in which Column (1) through (5) use *CR Beta* that we compute with, respectively, the carry factor (`Carry` hereafter), the dollar factor (`Dollar` hereafter), the dollar carry-trade (`USD` hereafter), the dollar risk factor (`RX` hereafter), and the carry-trade risk factor ($\texttt{HML}_{\texttt{FX}}$ hereafter) as alternative measures for the dependent variable. The last two of these measures are built from the aggregation or sorting of currency investment returns, like our own currency-specific FX risk measures. The first two only account for exchange rate changes and given their definition, they have empirically an almost perfect negative correlation with the last two; so we multiply the resulting *CR Beta* by (-1) to run the cross-sectional regressions, for ease of interpretation of coefficient estimates.

[28]These factors are the aggregation of currency changes, their returns or their forward contracts, built through different sorting. Karolyi and Wu (2020) has a detailed explanation of all these factors and the differences between each of them that we also report in Appendix B.

We find that, with the exception of the USD *Beta*, all the other regressions have a significant association with the trade channel similar to what we uncover through our own risk measures. A larger importance in the global trade activity for the economy of a country explains the higher sensitivity of its H-FSR firms to currency exposure, but more trade centrality is associated with lower expected returns. Of all these alternative measures, the ones based on the level of the currency baskets (RX and Dollar) appear more robust than those built on long-short strategies.[29] Because of aggregation, these measures cannot provide us with specific information on the geography of currency risk like what we gather from Table 5, however, the importance of the trade channel is confirmed.

4.2.4. Trade Channel - Alternative Determinants from Firm Characteristics

In our sample, on average, the totality of the H-FSR firms' international activities is equivalent to 64% of the country's export sector.[30] One would expect that also the characteristics of these firms highly representative of a country's outward propensity are associated with the relative patterns in the *FX Betas*. In this section, we focus on country determinants obtained from firm-level characteristics to assess the relative significance of our hypothesis on the importance of the aggregate trade channel.[31]

In Table 7, we present the results from cross-sectional regression similar to those in Table 6 to validate the importance of the export channel as a driver of FX risk, together with determinants built at the country level from firm-level characteristics (see Appendix C).

$$\beta^i_{j,t} \;=\; b\,\mathrm{FSR}^i_t \;+\; \Phi\mathbf{Controls}^i_t + \epsilon^i_{j,t} \tag{7}$$

[29] Among these currency factors $\mathtt{HML_{FX}}$ is the most robust in the pricing of the test assets from double sorted global stocks in Karolyi and Wu (2020), while USD is never significant.

[30] To establish this, for each country, we sum up Export and Foreign Sales data of all H-FSR firms in a country and measure them as a proportion of their country's exports of goods and services (and their country's primary income receipts from the Balance of Payments). Data source: World Bank.

[31] Our test assets, the H-FSR portfolios, overlap with those at the center of the literature on the exchange rate cash flow effects that relate the FX exposure betas to firm and industry determinants. See, among others, He and Ng (1998) for Japanese MNCs, Allayannis, Ihrig, and Weston (2001) for U.S. industries, Dominguez and Tesar (2006) and Doidge et al. (2006) for a sample of international stocks.

Consistent with the message in Table 6, we observe that the extent of firm-level export activity in the cross-section of countries is associated with larger sensitivity to the systematic risk from parity deviations. We find that FSR, the share of firms' international sales, has a positive coefficient, with a p-value of 0.000 for eight currencies. We further find that several firm-level characteristics are also important explanatory variables. The statistical significance of size is strong across the majority of currencies, indicating that larger firms, which based on a large body of literature likely have more extensive foreign activities, have higher risk sensitivity. On the other hand, there is no support for the foreign asset ratio measure, which suggests that risk from currency fluctuations is explained by periodic flows from the firms' operations and less by the stock of fixed assets. Financial leverage is positively associated with FX risk exposure, with a p-value of 0.035 or lower in seven cases, while the evidence on the liquidity proxy provides some support for a negative relationship, although in two instances the coefficient is marginally positive. Finally, we observe that the relationship with book to market ratio is positive and significant in half of the regressions.

On average, across the nine currencies, the coefficient estimates for FSR imply that a one standard deviation increase in this independent variable, which is equivalent to the change in the outward propensity of Mexican firms to the one of German firms, is associated with a 0.091 increase in *FX Beta* (equivalent to 17% of its average). In comparison, the coefficient estimates in Table 6 imply that one standard deviation increase in EXP_INTENSITY, which is equivalent to the difference in export intensity from Mexico to the Netherlands, is associated with a 0.052 unit increase. This corresponds to a 9.8% change compared to the mean of 0.583 across the sample *FX Betas*. The same increase in TR_CENTRALITY, which is equivalent to the difference in the variable between Mexico and the United Kingdom, is associated with a 0.043 decrease on average across the FX risk sensitivities (8.2% change compared to the mean). Thus also the impact derived from quantities of aggregate variables is economically meaningful. Engagement in global trade is an important route to explain the systematic FX risk exposure across countries.

The shortcoming of our analysis is that we only advance our understanding of the role of firms that export and derive income from sales in foreign operations. Companies' import data comparable across countries are not widely available, and thus we are not able to differentiate from other types of activities that could generate different sensitivity to the systematic risk of foreign nature. Indeed firms heterogeneity plays a role in Hoberg and Moon (2019) and Barrot et al. (2019) who have to rely on textual analysis on 10-K filings of only U.S. firms to gather information on offshore and onshore activities and on exporters and non-exporters, respectively.

[Place Table 7 about here]

4.3. Time-varying FX Risk Factor Sensitivity

In the last step, we proceed with the analysis of time-variation of *FX Betas* to shed more light on the cash flow channel that should also be at work through shocks from the global economy. We start studying panels with all the annualized *FX Betas*. We then focus on the exposures $\beta_{j,t}^{FXc}$ to assess how these risk sensitivities change with respect to variations in the value of the home currency (ΔS), and to further identify the impact of firms' heterogeneity with respect to currency movements, we study the difference between the *FX Betas* of the H-FSR and L-FSR firms within a country. We consider the following regression framework and begin by verifying the geographic properties that we uncover in the previous analysis.

$$\beta_{j,t}^{i} = \alpha + b_1\, DIST_j^i + b_2\, \overline{\mathrm{DIST}_j} + c_1 \Delta S_t^i + \Phi \mathbf{Controls}_t^i + \epsilon_{j,t}^i \tag{8}$$

Where, $DIST_j^i$ is the log of the distance between the capital city of country i and that of the currency of country j's, and $\overline{\mathrm{DIST}_j}$ is the average of DIST_j^i for currency j over the countries in the sample. ΔS^i the annual changes in the home currency of a $\mathrm{G10}^{-U\$}$ portfolio, as measured by the bilateral exchange rate vis-à-vis USD. Following Richmond (2019), a currency is deemed distant when it belongs to a country that is far from most other countries. Based on the values of the variable $\overline{\text{DIST}}_j$, we find that the AUD and the NZD are the most distant currencies, while the EUR, the CHF, and the GBP are respectively ranked as the closest currencies. The currency fluctuations proxy for cash flow shocks to the country's firms. Thus a negative change is a currency depreciation versus the USD that is expected to favor the activity of non-US exporters. Results are tabulated in Table 8.

[Place Table 8 about here]

Regression (1) only includes the measure of distance for each G10$^{-U\$}$ currency, $\overline{\text{DIST}}_j$, with the one for each country of our firm portfolios, $DIST_j^i$, as well as country and time fixed effects. Both geographic patterns are confirmed, even after controlling for countries' constant unknown properties. Distant currencies are associated with larger exposures, consistent with our observations in Table 5 Panel A. However, if a country is farther away from the country of one of the G10$^{-U\$}$ currencies, its exposure to that currency is smaller, like our result in Panel B. Since Forbes and Rigobon (2002), and recently Akbari, Ng, and Solnik (2020), argue that correlation coefficients are conditional on market volatility, our measures of risk sensitivity could be biased during periods of high uncertainty. In column (2) we regress the *FX Betas* on the volatilities of the world, of the country of our firm portfolios, and of the G10$^{-U\$}$ currency FX risk factor. We find that the risk sensitivities load positively on the first two measures and load negatively on the latter, which enters in the denominator of the $\beta_{j,t}^i$, and the last two are estimated significantly. We include $\bar{R}^i$ the H-FSR firms' cost of equity as the expected returns for each portfolio implied by our asset pricing model, Equation (5), estimated in column (9) of Table 3. It can be interpreted as a proxy for firms' discount rate movements, while distance that acts as an impediment to trade can also be viewed as a proxy for the cash flow channel.

In columns (3) through (5), we shrink the cross-section of test assets to the $\beta_{j,t}^{FXc}$ of a G10$^{-U\$}$ firm portfolio and explore the association with the change in the home currency as an alternative proxy to capture the cash flow channel. First, in regression (3), we confirm the positive association of *FX Betas* with $\overline{\mathrm{DIST}}_j$ in the smaller cross-section of G10$^{-U\$}$ countries, dropping $DIST^i_j$ which becomes redundant in this specification. In regression (4), we find a negative and significant slope coefficient for ΔS, in other words, larger $\beta^{FXc}_{j,t}$ are associated with home currency depreciations. Dominguez and Tesar (2006) find that firms with high international sales outperform those with no international sales in periods of home currency depreciation but underperform during appreciations. Our analysis of the time-variation in risk exposures aligns with their evidence. This finding is robust to the presence of other state variables that can possibly explain this relationship. The firms' cost of equity, or uncertainty linked to home country and exchange rate volatilities in regression (5), do not alter the relationship between the FX risk sensitivities and home currency changes.

To further isolate the impact of currency movements, we study the difference between the $\beta^{FXc}_{j,t}$ of the H-FSR and L-FSR firms within a country. This allows us to control for common state variables affecting firms' risk sensitivity dynamics. Column (6) documents that the risk sensitivities load negatively on ΔS, after controlling for time and country fixed effects, suggesting that the *FX Betas* of the H-FSR firms in periods of home currency depreciation are affected beyond the conversion effect equally at work for the USD denominated *FX Betas* of all firms in the country. The cash flows of firms with exports and foreign income are shielded through the home currency depreciation, as the activities of these firms will benefit from the exchange rate movements, compared to domestically focused firms. In other words, consistent with the basic insight on firm value in the cash flow exposure literature, these companies become remarkably more valuable in correspondence to currency depreciations, and in the data, this compensates for the conversion effect of the home currency drop. The relationship between the FX risk sensitivities and home currency movements is confirmed in column (7) with the spread between H-FSR and L-FSR firms' cost of equity and home country and exchange rate volatilities.

Figure 3 visualizes this relationship for the CHF risk, where we plot the $\beta^{FXc}_{CHF,t}$ spread on the left axis and the one-year change in the USD/CHF rates on the right axis.

[Place Figure 3 about here]

The figure shows that the relative magnitude of the sensitivities as illustrated through the spread is not constant but changes with the weakening and strengthening of the currency. The *FX Betas* spread tends to covary negatively with the home currency fluctuations and become more positive when the home currency loses value with respect to the US dollar.

In sum, together with Figures 2a and 3, the evidence in Table 8 confirms the geographic properties in the exposures of H-FSR firms to FX risk, and show how these risk sensitivities are higher in periods of home currency depreciation.

5. Conclusion

In a world of high trade integration, the large globally-focused firms aggregated along the country dimension are driving the significance of the price of exchange rate risk. We provide strong empirical evidence for this, studying a global multifactor conditional model and implementing a flexible empirical approach that allows us to broaden the investigation of exchange rate risk to the G10 currencies, beyond the three major currencies or a few currency indices. We find that the risk of the Swiss franc as well as the ones of the euro and the British pound are significantly priced, which further corroborates the theoretical underpinnings of our empirical specifications.

We offer novel insights into the role of the trade channel and geography in driving systematic currency risk exposure. Our study documents on one side a regional clustering effect that is driven by distance and a core-periphery effect that depends on countries' worldwide importance in the trade network, irrespective of their location in different regions. More specifically, we observe that firm portfolios have a higher sensitivity to the FX risk factor of a currency of a neighboring country, rather than a distant one. In other words, also firms from countries that are close to Switzerland, and trade a lot with it, are a good hedge against CHF risk. While we know that distance matters for trade in goods and assets, we show in this paper that it matters also for the FX risk of those firms involved in trade.

We also find that the risk sensitivities to the currency factors of high foreign sales firms are explained by their country's export intensity and its trade centrality. Our evidence suggests that companies are more exposed to systematic foreign exchange rate risk than counterparts in other countries if they belong to a country that has a larger export sector. Furthermore, we observe that firms face a smaller sensitivity to foreign exchange rate risk if they are based in countries that trade with more partners, and are thus more central to the global trade network, relative to firms of countries in the periphery. The effect from distance and from the trade variables is more pronounced with respect to the risk exposure from the currencies of countries in the periphery of the trade network, the "farthest of currencies".

Taken together, our results provide insights that can shape the debate about the effects of pegs and currency zones for investors and firms. They also have implications for policy efforts toward enhancing and strengthening a country's position in the global supply chain.

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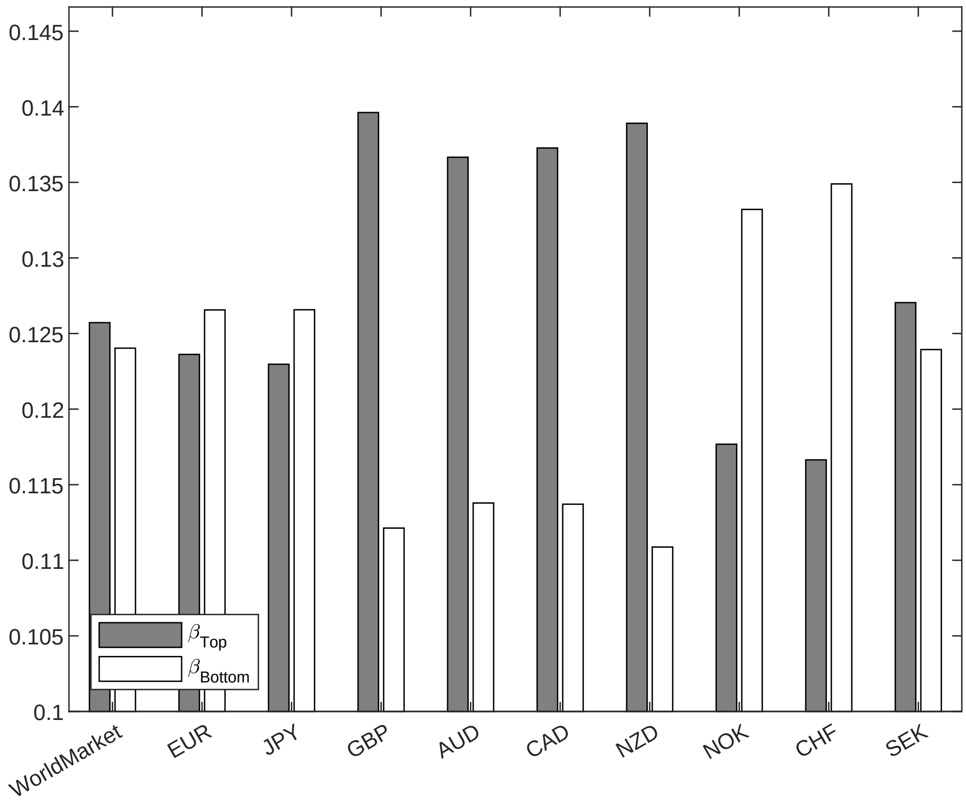
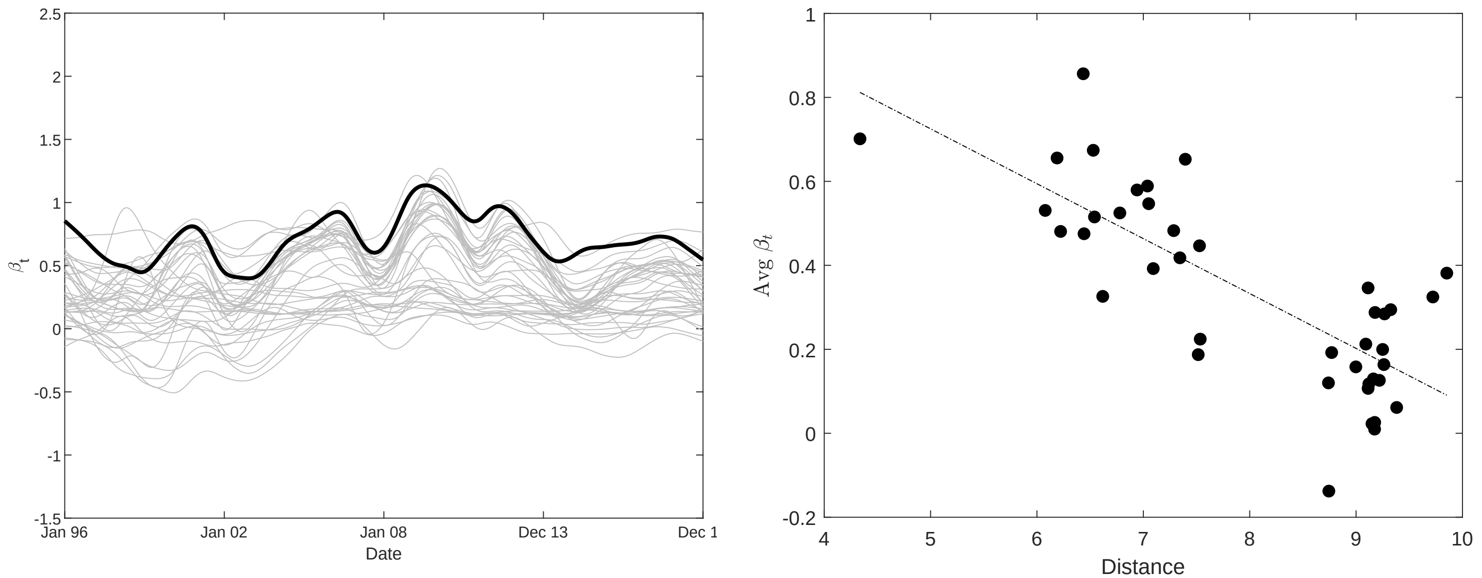


Fig. 1. **Beta Sorted Portfolio Returns.** The figure plots the average annualized return of H-FSR country portfolios sorted based on their time-varying exposure to the risk factors. At each week, portfolios with an exposure larger than the median beta at that week are grouped in β_{Top}, marked in gray. The rest of the H-FSR country portfolios are grouped in β_{Bottom}.



(a) Country *FX Betas*

(b) Average *FX Betas* and Distance

Fig. 2. ***FX Betas.*** Panel (a) presents the conditional risk sensitivity (*FX Betas*) for the H-FSR portfolios in each country to the Swiss Franc risk. The H-FSR portfolio for the Swiss firms is marked with a dark black line. The *FX Betas* are displayed through a Hodrick-Prescott (HP) filter. Panel (b) plots the historical average values of the *FX Betas* to the Swiss Franc risk of H-FSR country portfolios versus the log of the geographic distance of each country and Switzerland.

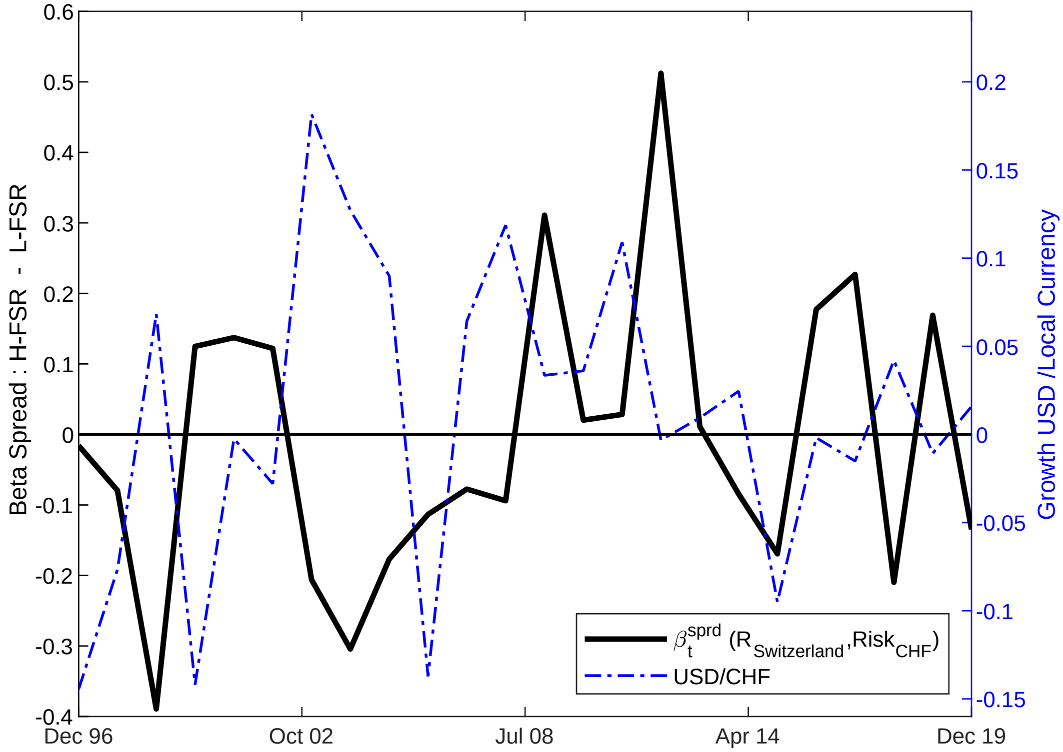


Fig. 3. ***FX Betas* and Currency Fluctuations.** On the left axis and in a solid black line, the the figure plots the difference between the conditional risk sensitivity (*FX Beta*) to the CHF risk of the Swiss H-FSR portfolio and that of the Swiss L-FSR portfolio, at the end of each year. On the right axis and in a dashed blue line, the figure plots the annual growth rate of the CHF currency.

Table 1: Summary Statistics. This table presents the summary statistics for the USD-denominated excess returns of the portfolios in our sample. Panel A reports the cross-sectional averages of mean, standard deviation (St. Dev.), and Sharpe ratio, in annual percentages. Panel B reports the cross-sectional averages of correlations of each portfolio with the risk factors. The row $\sum FX$ reports the sum of these values for the FX risk factors. For each country, H-FSR portfolios are constructed from firms with at least 10 percent foreign sales ratio, and L-FSR portfolios are based on those with less than 10 percent foreign sales ratio. INDUSTRY and RANDOM portfolios are constructed from firms with at least a 10 percent foreign sales ratio which are clustered in 34 industry portfolios and 41 pseudo-country portfolios, respectively. DS-INDEX portfolios are the DataStream's total market indexes and INVESTABLE portfolios are the MSCI's Investable Market indexes. The sample period is from January 1996 to December 2019 at the weekly frequency.

	H-FSR	DS-INDEX	INVESTABLE	L-FSR	INDUSTRY	RANDOM
Panel A						
Mean	9.642	7.952	7.303	7.434	6.330	6.747
St. Dev.	23.623	24.303	25.263	28.550	20.687	19.679
Sharpe Ratio	0.413	0.333	0.293	0.251	0.322	0.344
Panel B						
World Market	0.573	0.654	0.661	0.411	0.728	0.850
EUR	0.302	0.282	0.279	0.213	0.211	0.225
JPY	-0.027	-0.054	-0.057	-0.011	-0.097	-0.109
GBP	0.288	0.282	0.282	0.203	0.238	0.266
AUD	0.458	0.477	0.479	0.327	0.442	0.503
CAD	0.411	0.432	0.436	0.289	0.414	0.482
NZD	0.397	0.414	0.414	0.282	0.375	0.425
NOK	0.368	0.369	0.368	0.259	0.302	0.346
CHF	0.168	0.145	0.141	0.124	0.078	0.076
SEK	0.377	0.377	0.377	0.263	0.329	0.372
$\sum FX$	2.742	2.725	2.719	1.949	2.292	2.587

Table 2: Principal Component Analysis. This table reports the cross-sectional averages for the PC analysis. In Panel A, the first row shows the percentage of asset variation that the first PC explains and the second row shows the number of PCs needed to explain 70 percent of the variation. In Panel B, we report the R-squared of the projection of the risk factors on the first 10 PCs of each set of portfolios. The row $\sum FX$ reports the sum of these values for the FX risk factors. For each country, H-FSR portfolios are constructed from firms with at least 10 percent foreign sales ratio, and L-FSR portfolios are based on those with less than 10 percent foreign sales ratio. INDUSTRY and RANDOM portfolios are constructed from firms with at least a 10 percent foreign sales ratio which are clustered in 34 industry portfolios and 41 pseudo-country portfolios, respectively. DS-INDEX portfolios are the DataStream's total market indexes and INVESTABLE portfolios are the MSCI's Investable Market indexes. The sample period is from January 1996 to December 2019 at the weekly frequency.

	H-FSR	DS-INDEX	INVESTABLE	L-FSR	INDUSTRY	RANDOM
Panel A						
%Var-1stPC	40.401	47.875	48.541	22.999	54.512	74.557
%70Var-NbPC	8.098	6.000	6.000	13.950	3.973	1.000
Panel B						
WorldMarket	0.787	0.922	0.919	0.748	0.972	0.975
EUR	0.419	0.363	0.336	0.324	0.267	0.233
JPY	0.060	0.069	0.071	0.051	0.110	0.063
GBP	0.260	0.217	0.213	0.210	0.217	0.246
AUD	0.519	0.477	0.491	0.474	0.489	0.429
CAD	0.452	0.407	0.415	0.383	0.425	0.399
NZD	0.385	0.357	0.367	0.359	0.364	0.314
NOK	0.396	0.382	0.369	0.346	0.369	0.326
CHF	0.203	0.168	0.152	0.143	0.169	0.132
SEK	0.451	0.403	0.385	0.387	0.324	0.299
$\sum FX$	3.145	2.844	2.800	2.678	2.734	2.441

Table 3: Conditional Asset Pricing Tests. This table presents the slope coefficients for conditional asset pricing tests of the International CAPM (Equation (5)) with the H-FSR country portfolios as test assets. The analysis is based on the two-stage Bali-Engle methodology; first estimating the conditional covariances with the factors using the cDCC specification and then estimating panel regressions using these as covariates. T-statistics, in square brackets, are obtained using the GLS standard errors corrected for heteroskedasticity, autocorrelation, and cross-correlations of assets. We present nine specifications, (1) with only the world market portfolio, and (2) through (9) with different combinations of the currency investment risks, in addition to the market risk. The table also reports Wald statistics on the joint significance of all the included FX factor risk coefficients ($H_0 : joint\ \gamma_j = 0$). H-FSR country portfolios are constructed from firms with at least a 10 percent foreign sales ratio. The sample period is from January 1996 to December 2019 at the weekly frequency.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
intercept	0.032	0.001	-0.005	-0.007	0.001	0.000	0.001	-0.004	-0.016
	[0.87]	[0.03]	[-0.25]	[-0.35]	[0.03]	[0.00]	[0.06]	[-0.16]	[-0.81]
World Market	2.636***	2.310***	2.827***	1.876***	2.094***	1.982***	2.239***	1.864***	2.467***
	[5.68]	[4.41]	[5.32]	[3.26]	[3.76]	[3.63]	[4.30]	[3.42]	[4.67]
EUR		-3.555*	-3.984**	-4.105**	-4.331**	-7.004***	-0.667	-8.411***	-6.002**
		[-1.86]	[-2.05]	[-2.10]	[-2.19]	[-2.59]	[-0.31]	[-2.97]	[-1.98]
JPY		0.492	1.293	0.774	0.910	0.441	1.103	0.116	1.140
		[0.35]	[0.95]	[0.55]	[0.67]	[0.32]	[0.78]	[0.08]	[0.84]
GBP		5.022**	5.094**	3.928*	3.928*	4.432**	5.215***	4.981***	4.174**
		[2.56]	[2.48]	[1.94]	[1.91]	[2.24]	[2.67]	[2.58]	[2.10]
AUD			-0.591						-2.695
			[-0.67]						[-1.58]
CAD				2.354					0.496
				[1.54]					[0.26]
NZD					1.473				2.418
					[1.29]				[1.25]
NOK						4.330*			3.213
						[1.88]			[1.20]
CHF							-3.658**		-3.543**
							[-2.52]		[-2.51]
SEK								5.016**	2.115
								[2.19]	[0.83]
Observations	52,542	56,295	57,546	57,546	57,546	57,546	57,546	57,546	63,801
$H_0 : joint\ \gamma_j = 0$		0.082	0.132	0.052	0.094	0.036	0.011	0.013	0.022

Table 4: Conditional Asset Pricing Tests - other Test Assets. This table presents the slope coefficients for conditional asset pricing tests of the International CAPM (Equation (5)) with the other portfolios in our sample as test assets. The analysis is based on the two-stage Bali-Engle regressions; first estimating the conditional covariances with the factors using the cDCC specification and then estimating panel regressions using these as covariates. T-statistic, in square brackets, are obtained using the GLS standard errors corrected for heteroskedasticity, autocorrelation, and cross-correlations of assets. We present the specification with all the currency investment risks, in addition to the market risk. The table also reports Wald statistics on the joint significance of all the included FX factor risk coefficients ($H_0 : joint\ \gamma_j = 0$). L-FSR country portfolios are based on firms with less than a 10 percent foreign sales ratio. INDUSTRY and RANDOM portfolios are constructed from firms with at least a 10 percent foreign sales ratio which are clustered in 34 industry portfolios and 41 pseudo-country portfolios, respectively. DS-INDEX country portfolios are the DataStream's total market indexes and INVESTABLE country portfolios are the MSCI's Investable Market indexes. The sample period is from January 1996 to December 2019 at the weekly frequency.

	L-FSR	DS-INDEX	INVESTABLE	INDUSTRY	RANDOM
intercept	-0.014	0.014	-0.010	0.001	0.006
	[-0.79]	[0.76]	[-0.51]	[0.07]	[0.28]
World Market	2.492***	2.060***	2.843***	1.194**	2.105***
	[4.48]	[4.04]	[5.56]	[2.18]	[3.58]
EUR	-8.341**	-5.445*	-1.869	-1.074	-0.466
	[-2.27]	[-1.93]	[-0.67]	[-0.29]	[-0.12]
JPY	0.545	-0.990	-1.170	-0.218	-0.189
	[0.39]	[-0.90]	[-1.04]	[-0.15]	[-0.14]
GBP	1.615	2.820	0.831	1.657	-4.518
	[0.75]	[1.53]	[0.47]	[0.59]	[-1.59]
AUD	-0.969	-2.530	-1.338	4.252**	2.248
	[-0.47]	[-1.63]	[-0.86]	[2.15]	[1.01]
CAD	3.415	-1.054	-1.866	-1.387	3.475
	[1.43]	[-0.63]	[-1.08]	[-0.48]	[1.33]
NZD	-2.895	1.292	1.569	-4.975**	-5.596**
	[-1.24]	[0.75]	[0.89]	[-1.99]	[-2.13]
NOK	5.749*	2.297	-0.118	-1.723	1.143
	[1.79]	[0.97]	[-0.05]	[-0.52]	[0.36]
CHF	1.104	0.468	0.130	1.976	1.441
	[0.53]	[0.31]	[0.08]	[1.02]	[0.69]
SEK	2.746	4.245*	2.778	2.825	0.959
	[0.82]	[1.79]	[1.17]	[0.94]	[0.31]
Observations	62,550	63,801	63,801	58,797	63,801
$H_0 : joint\ \gamma_j = 0$	0.103	0.117	0.797	0.439	0.276

Table 5: *FX Beta* and Geographic Regions. The table reports the cross-sectional statistics of the conditional foreign exchange rate risk sensitivities (*FX Beta*) for the H-FSR country portfolios. Panel A reports the historical average values of *FX Beta* to the home currency risk for each country and for the rest of the sample. In addition, it reports the p-value for the null that *FX Beta* to the home currency risk is smaller ($H_0 : \beta_j^{FXc} < \beta_j^{rest}$). Panel B reports the cross-sectional averages for each geographic zones. It also reports the p-value for the null that *FX Beta* of countries closer to the home currency risk is smaller ($H_0 : \beta_j^{\text{Zone 1}} < \beta_j^{rest}$). H-FSR country portfolios are constructed from firms with at least a 10 percent foreign sales ratio. For each currency, we define four geographic zones based on a measure of distance between the country of the currency (its capital) and the country of the H-FSR portfolio (its capital). Zone 1 identifies countries closest to the country of the currency. The sample period is from January 1996 to December 2019 at the annual frequency.

	All FX	EUR	JPY	GBP	AUD	CAD	NZD	NOK	CHF	SEK
Panel A										
Mean[β_j^{FXc}]	1.078	0.899	0.376	1.052	1.299	1.759	1.209	1.265	0.701	1.143
Mean[β_j^{rest}]	0.564	0.643	-0.048	0.588	0.748	0.990	0.576	0.644	0.327	0.657
H_0 : $\beta_j^{FXc} < \beta_j^{rest}$	0.000	0.050	0.025	0.001	0.000	0.000	0.000	0.001	0.001	0.000
Panel B										
Zone 1	0.882	0.949	0.091	0.804	1.299	1.339	1.209	0.843	0.513	0.893
Zone 2	0.474	0.356	-0.067	0.355	0.712	1.040	0.681	0.574	0.083	0.529
Zone 3	0.456	0.386	-0.022	0.437	0.702	0.915	0.522	0.496	0.156	0.513
Zone 4	0.516	0.549	-0.063	0.529	0.755	0.876	0.578	0.595	0.265	0.558
H_0 : $\beta^{\text{Zone 1}} < \beta_j^{rest}$	0.000	0.001	0.193	0.010	0.000	0.005	0.000	0.007	0.000	0.000

Table 6: ***FX Beta* and Trade.** The table reports the averages of period-by-period slope coefficients from cross-sectional regressions of conditional foreign exchange rate risk sensitivity (*FX Beta*) for H-FSR country portfolios on the exports of goods and services, as % of GDP (EXP_INTENSITY), Trade Centrality (TR_CENTRALITY), IFRS adoption date dummy, Anti-director index (ANTI_DIR), capital account openness measure (CAP_OPEN), the degree of law and order (LAW), as well as domestic consumption (CONS), market capitalization of listed companies (MCAP), and domestic credit to the private sector (P_CREDIT), all as % of GDP. T-statistics, in square brackets, are obtained using the Fama-MacBeth standard errors corrected for time-dependence following Petersen (2009). H-FSR country portfolios are constructed from firms with at least a 10 percent foreign sales ratio. The sample period is from January 1996 to December 2019 at the annual frequency.

	All FX	EUR	JPY	GBP	AUD	CAD	NZD	NOK	CHF	SEK
EXP_INTENSITY	0.125**	0.144**	0.064**	0.090**	0.172*	0.130	0.190*	0.104*	0.103***	0.126*
	[1.96]	[2.30]	[2.31]	[1.98]	[1.71]	[0.88]	[1.95]	[1.67]	[2.68]	[1.70]
TR_CENTRALITY	-0.148***	-0.156***	-0.049**	-0.079	-0.233***	-0.132**	-0.264***	-0.215***	-0.071**	-0.134***
	[-5.61]	[-2.98]	[-2.10]	[-0.98]	[-7.33]	[-2.35]	[-7.58]	[-7.17]	[-2.03]	[-3.40]
IFRS	12.058*	19.173*	5.657	16.786*	8.045*	10.918	5.873	14.109**	14.504	13.458*
	[1.86]	[1.78]	[1.24]	[1.83]	[1.74]	[1.10]	[1.41]	[2.05]	[1.45]	[1.76]
ANTI_DIR	-2.482***	-7.361***	-2.095**	-2.329	1.286*	2.630***	1.011	-4.029***	-6.331***	-5.116***
	[-3.31]	[-4.77]	[-2.45]	[-0.93]	[1.68]	[3.13]	[0.77]	[-3.28]	[-9.10]	[-5.96]
CAP_OPEN	0.050	0.375***	0.123	0.144**	-0.240***	-0.285	-0.040	0.047	0.231***	0.090
	[0.69]	[3.64]	[1.60]	[2.02]	[-3.67]	[-1.17]	[-0.76]	[0.46]	[4.25]	[1.14]
LAW	5.467***	6.838***	-2.013	5.381***	6.848*	9.277**	3.779	6.734***	3.508***	8.849***
	[4.13]	[3.62]	[-1.47]	[3.81]	[1.89]	[2.40]	[1.46]	[3.52]	[4.49]	[6.03]
MCAP	-0.067***	-0.092***	-0.064**	-0.092***	-0.044	-0.020	-0.086*	-0.050***	-0.084***	-0.070***
	[-2.89]	[-3.33]	[-2.38]	[-3.33]	[-1.62]	[-0.92]	[-1.91]	[-5.44]	[-3.03]	[-2.63]
P_CREDIT	-0.043	-0.105	0.128*	-0.054*	-0.045	-0.126*	0.012	-0.088	-0.025	-0.084*
	[-0.74]	[-1.58]	[1.91]	[-1.67]	[-0.59]	[-1.65]	[0.13]	[-1.45]	[-0.91]	[-1.68]
CONS	0.598***	0.493*	-0.062	0.497	0.928***	1.113***	0.699***	0.771***	0.299***	0.640***
	[4.31]	[1.69]	[-0.55]	[1.61]	[5.61]	[3.77]	[4.70]	[5.90]	[3.25]	[4.91]
Observations	6417	713	713	713	713	713	713	713	713	713
Adjusted R2	0.674	0.866	0.656	0.884	0.900	0.859	0.872	0.898	0.799	0.904

Table 7: *FX Beta* and Firm-level Characteristics. The table reports the averages of period-by-period slope coefficients from cross-sectional regressions of the conditional foreign exchange rate risk sensitivity (*FX Beta*) for the H-FSR country portfolios on the median characteristics of the H-FSR firms in their country. FSR is the foreign sales ratio, SIZE is the log of the USD-denominated market capitalization on the last observation of each year, FAR is the foreign asset ratio, B/M is the book to market ratio, and LEVERAGE is the ratio of a firm's value of total debt to its total assets. We compute the trading volume by summing the volume of shares traded over the year, in log (VOLUME). T-statistics, in square brackets, are obtained using the Fama-MacBeth standard errors corrected for time-dependence following Petersen (2009). H-FSR country portfolios are constructed from firms with at least a 10 percent foreign sales ratio. The sample period is from January 1996 to December 2019 at the annual frequency.

	All FX	EUR	JPY	GBP	AUD	CAD	NZD	NOK	CHF	SEK
FSR	0.515***	0.802***	0.002	0.594***	0.421***	0.689***	0.330***	0.673***	0.414***	0.705***
	[8.57]	[11.02]	[0.02]	[9.09]	[3.50]	[7.99]	[4.30]	[8.47]	[7.16]	[13.69]
SIZE	5.131***	7.827**	0.506	5.076**	3.834*	9.034***	3.194**	7.057***	2.822*	6.833***
	[3.07]	[2.23]	[0.44]	[2.39]	[1.94]	[6.72]	[2.40]	[4.77]	[1.80]	[3.39]
VOLUME	-1.398*	-4.932***	-1.218*	-2.429***	1.928**	0.835	0.752**	-2.160**	-2.911***	-2.446**
	[-1.85]	[-3.23]	[-1.93]	[-4.32]	[2.13]	[0.89]	[2.28]	[-2.04]	[-4.01]	[-2.38]
FAR	-0.020	-0.143	0.249*	-0.097	0.131	-0.129	0.296	-0.433**	0.063	-0.119
	[-0.09]	[-0.65]	[1.72]	[-0.47]	[0.29]	[-0.43]	[0.65]	[-2.49]	[1.33]	[-0.39]
B/M	0.455***	0.872***	0.282	0.503*	0.220	-0.014	0.166	0.289	1.178***	0.601***
	[4.14]	[4.70]	[1.31]	[1.89]	[1.41]	[-0.08]	[1.34]	[1.38]	[9.06]	[3.46]
LEVERAGE	0.559***	0.910***	0.078	0.795***	0.505**	0.427	0.554***	0.569**	0.658***	0.534**
	[3.11]	[2.83]	[0.49]	[3.29]	[2.10]	[0.82]	[3.13]	[2.17]	[4.50]	[2.33]
Observations	8757	973	973	973	973	973	973	973	973	973
Adjusted R2	0.627	0.812	0.547	0.822	0.871	0.829	0.853	0.843	0.750	0.844

Table 8: *FX Beta*, Distance, and Currency Fluctuations. The table reports the slope coefficients for regressions of the conditional foreign exchange rate risk sensitivity (*FX Beta*) on measures of distance and local currency fluctuations. Distance (DIST_j^i) is the log of the geographic distance between the capital cities of the currency country j and the country portfolio i. $\overline{\mathrm{DIST}_j}$ is the average of DIST_j^i for currency j over the countries in the sample. ΔS^i is the annual changes in the home currency, as measured by the bilateral exchange rate vis-à-vis USD. The dependent variables in regressions (1) to (5) are the *FX Beta* for H-FSR country portfolios, and in regressions (6) and (7) are the spread between *FX Beta* for H-FSR and L-FSR portfolios for each country. Regressions in columns (1) and (2) cover the whole cross-section of the H-FSR portfolios. Regressions (3) to (7) only include portfolios of the G10 countries, minus the U.S. The control variables are the model implied expected returns of the H-FSR portfolios from column 9 of Table 3 ($\bar{R}^i$), world market volatility (σ_{G}), local market volatility (σ_{L}^i), and FX risk factors volatility (σ_{Sj}), as well as country and year fixed effects. $\bar{R}^i{}_{\mathrm{SPREAD}}$ is the difference between the model-implied expected returns of the H-FSR and L-FSR country portfolios. T-statistics, in square brackets, are obtained using the Newey-West standard errors. H-FSR (L-FSR) country portfolios are constructed from firms with at least (less than) a 10 percent foreign sales ratio. The sample period is from January 1996 to December 2019 at the annual frequency.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\overline{\mathrm{DIST}_j}$	0.152***	0.200***	0.280***	0.203***	0.278***	0.100	0.060
	[13.01]	[16.86]	[5.00]	[4.12]	[4.99]	[1.54]	[1.38]
DIST_j^i	-0.105***	-0.133***					
	[-17.92]	[-21.75]					
ΔS^i				-1.019**	-0.618**	-0.807***	-0.412*
				[-2.24]	[-2.15]	[-2.72]	[-1.84]
$\bar{R}^i$		2.348***	2.069		2.396**		
		[9.99]	[1.63]		[2.14]		
$\bar{R}^i{}_{\mathrm{SPREAD}}$							1.341**
							[2.02]
σ_{G}		-0.017	-4.039***		-4.040***		-0.144
		[-0.07]	[-4.52]		[-4.64]		[-0.22]
σ_{L}^i		0.397***	4.818***		4.488***		1.546**
		[2.69]	[4.79]		[4.73]		[2.54]
σ_{Sj}		-2.322***	-5.069***		-4.926***		-1.958*
		[-7.81]	[-3.66]		[-3.68]		[-1.96]
Country FE	YES			YES		YES	
Year FE	YES			YES		YES	
Observations	7983	7983	216	216	216	216	216
Adjusted R2	0.231	0.159	0.269	0.534	0.280	0.065	0.086

Supplementary Material to

Firm Foreign Activity and the Geography of Exchange Rate Risk

This document presents supplementary information not included in the main body of the manuscript. It describes firm-level data cleaning procedure, the set of new currency risk factors and their sources, the determinant variables for the conditional foreign exchange rate risk sensitivity (*FX Beta*) and their sources, and additional tables.

OnlineAppendix

A. Firm-level Data Cleaning

We access the universe of stocks in major stock exchanges in countries for which DataStream provides a total market index. A country's major stock exchange is the one with the highest number of listed stocks. To be more inclusive, we follow Chaieb, Langlois, and Scaillet (2021) and include more than one stock exchange in some countries: Brazil (Rio de Janeiro and Bovespa), Canada (Toronto and TSX Venture), China (Shanghai and Shenzhen), France (Paris and NYSE Euronext), Germany (Deutsche Boerse and Xetra), India (BSE and National Stock Exchange), Japan (Tokyo and Osaka), South Korea (Korea and KOSDAQ), Switzerland (Swiss Exchange and Zurich), and the U.S. (NYSE, NYSE Arca, Amex, and Nasdaq).

To limit the effect of survivorship bias, we include dead stocks in the sample. To identify delisting dates for dead stocks, for each stock, we verify each day if the rest of the time series has the same unadjusted price (UP) in local currency denomination and remove the rest of the time series in such a case.

We follow Ince and Porter (2006) and Lee (2011) and perform the following filters for cleaning the firm-level data based on their price information. For a firm at each week, first, we require that the value of its total return index for either the previous or the current period be above 0.01. Second, we require non-missing and non-zero market capitalization for the firm during those periods. Third, if any weekly return greater than or equal to 100% is reversed in the following period, we assume them to be missing and exclude these observations. Specifically, the returns for both period t and $t-1$ are set to be missing if $(1 + r_{j,t}) \times (1 + r_{j,t-1}) \leq 1.5$ and at least one of the two returns are 200% or greater, where $r_{j,t}$ denotes the weekly return of firm j at week t. Fourth, observations with a weekly returns above 300% are assumed as data errors and are excluded.

Lastly, we follow Griffin et al. (2010) and Karolyi, Lee, and van Dijk (2012), and exclude depositary receipts, real estate investment trusts, preferred stocks, investment funds, and other stocks with special features. DataStream does not provide any code for discerning noncommon shares from common shares. Therefore, we manually examine the names of the securities and exclude stocks with names including ADR, GDR, REIT, REAL EST, PF, PREF, or PRF. Also, we drop stocks with names including terms provided in Table B.1 of Griffin et al. (2010) due to various special features. For this step, we also collect the Industry Classification Benchmark (ICB) level 4 for each firm from DataStream and exclude firms with ICB classification of REITS (REITs'), and RLISV (Real Estate Inv and Svs) as well as those with CEINV (Closed-End Invest.), OMINV (Open, Misc. Invest.), UNCLS (Unclassified), and UQEQS (Unquoted equities). We also implement country-specific filters provided in Table B.2 of Griffin et al. (2010) to identify special stocks. Chaieb et al. (2021) update this list, which is detailed in their online Appendix.

B. New Currency Risk Factors and Their Sources

We consider the dollar risk factor (`RX`) and the carry-trade risk factor ($\texttt{HML}_{\texttt{FX}}$) from Lustig et al. (2011), the dollar carry-trade (`USD`) from Lustig et al. (2014), and dollar factor (`Dollar`) and a carry factor (`Carry`) from Verdelhan (2018).

`RX` and $\texttt{HML}_{\texttt{FX}}$ are the first two principal components of the currency portfolio returns, sorted by their forward discounts. The log currency returns are defined as $Rx^j_{t+1} = f^j_t - s^j_{t+1}$, Where f^j is the log of the forward return and s^j is the log of the spot exchange rate, expressed in units of foreign currency j per U.S. dollar. Therefore, assuming covered interest parity holds, we have:

$$Rx^j_{t+1} = i^j_t - \Delta s^j_{t+1} - i^{\$}_t$$

where, i and $i^{\$}$ denote the log of risk free investment in the country of currency j and U.S. respectively. `RX` corresponds to the average excess return on all foreign currency portfolios and $\texttt{HML}_{\texttt{FX}}$ is similar to the returns on a zero-cost strategy that goes long on the high interest rate currency portfolio and short in the low interest rate currency portfolio. USD is the excess returns on the investment strategy that goes long all available 1-month ahead currency forward contracts when the average forward discount of developed countries is positive, and it goes short the same contracts, otherwise. Dollar is the average change in exchange rates across portfolios sorted according to their interest rate levels, at each point in time. Carry is the average change in the exchange rate between countries in the last portfolio (high interest rate countries) and those in the first portfolio (low interest rate countries). More formally we have:

$$\texttt{Dollar}_{t+1} = \frac{1}{J}\sum_{J}\Delta s^{j}_{t+1}$$
$$\texttt{Carry}_{t+1} = \frac{1}{J_H}\sum_{j\in H}\Delta s^{j}_{t+1} - \frac{1}{J_L}\sum_{j\in L}\Delta s^{j}_{t+1}$$

where J, J_H, and J_L denote the number of all, only high, and only low interest currencies. Given their definitions, Dollar and Carry only account for exchange rate changes and thus have empirically an almost perfect negative correlation with RX and $\texttt{HML}_{\texttt{FX}}$.

C. Risk Exposure Determinants and Their Sources

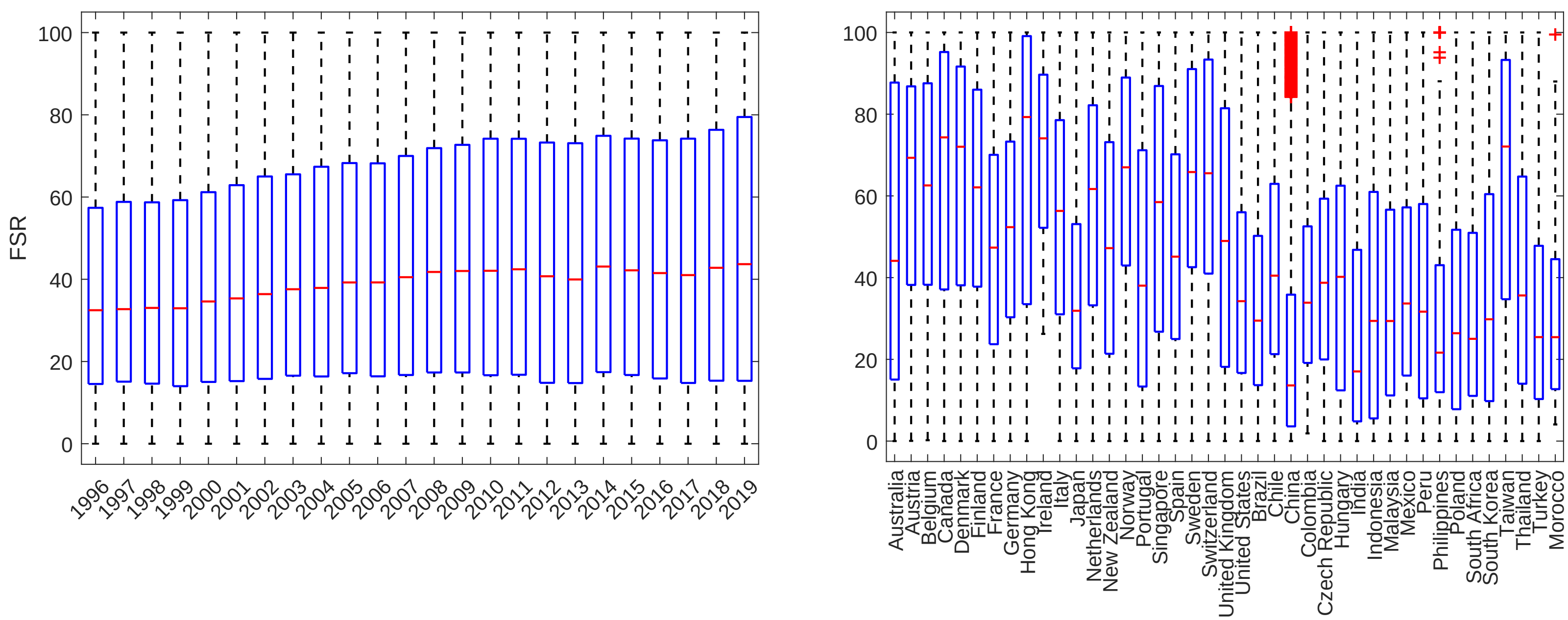
We explore alternative determinants. Most of these variables are available only at the annual frequency, while for the others with a higher frequency, we collect their end-of-the-year observations.

We consider several variables to control for country-level characteristics. To characterize the corporate governance environment and the quality of institutions of the country, we consider the International Financial Reporting System adoption date (IFRS), the anti-director index (ANTI_DIR) introduced by Pagano and Volpin (2005), and the degree of law and order from the International Country Risk Guide (LAW). For all these variables, a higher value indicates a better environment. We also collect from WDI the domestic consumption (CONS), the market capitalization of listed companies (MCAP), and the domestic credit to the private sector (P_CREDIT), all as a percentage of the local GDP. Domestic consumption measures a country's economic development. Economies with a higher share of consumption, like the advanced ones, could be more sensitive to the deviations in relative prices, which affect asset holders who might invest internationally but consume at home. Local stock market capitalization and credit to the private sector are intended to explain countries' economic environment and financial development. Countries with deeper financial markets and more credit availability provide better conditions for the business activity of both domestic and foreign firms. Financial development can be viewed as a proxy for access to financial derivatives, which is an important portion of the risk management of firms in our portfolios. This could be relevant given that a large literature documents that the use of FX derivatives is prevalent around the world among firms with exchange rate exposure. We include the capital account openness measure introduced by Quinn and Toyoda (2008) and later updated by Fernández, Klein, Rebucci, Schindler, and Uribe (2016), since it is conceivable that the cross-section of assets' risk sensitivities to currency factors is associated with the easiness of capital movements, besides trade flows (CAP_OPEN). The index is constructed from the IMF's annual publications on capital controls. A high score indicates less restricted capital flows. For the distance-based variables, we consider Germany and Berlin as the reference for the euro because the CEPII method cannot provide a measure of distance for the eurozone as one single nation.

We also construct a set of country-level variables from firm characteristics that we collect from WorldScope and DataStream firm-level data. We use the median across the H-FSR firms in each country. The foreign sales ratio (FSR) is the sum of exports and international sales from foreign operations divided by total sales. To measure a firm's size, we collect the log of the U.S. dollar-denominated market capitalization on the last observation of each year (SIZE). We compute the trading volume by summing the volume of shares traded over the year, in log (VOLUME). We take high volume as a proxy for the firm's liquidity in the absence of a more reliable measure of liquidity across our large sample of global firms. We use the foreign assets ratio (FAR) and book to market ratio (B/M) as provided by WorldScope in the year. We construct financial leverage as the ratio of a firm's value of total debt to its total assets for the year (LEVERAGE).

For the investment channel, we consider different types of international capital flows. From the International Monetary Fund's (IMF) Balance of Payments dataset, we collect the extent of domestic equity and debt purchases by foreign investors, i.e., the liabilities item from Foreign Portfolio Investment, scaled by the country's GDP (FEPI) & (FDPI). From WDI, we collect the Foreign Direct Investment inflow and outflow metrics, scaled by the country's GDP (FDI_IN).

D. Additional Figures and Tables



(a) Firms' FSR through Time

(b) Firms' FSR in the Cross-section

Fig. A1. ***FSR.*** The figure presents the boxplot of the foreign sales ratio (FSR) of firms with foreign activity in our sample, grouped for each year in Panel (a) and for each country in Panel (b). Each blue box shows the lower and upper quartiles for each group. The median values of each group are marked with a horizontal red line. The vertical black dotted lines mark the minimum and maximum values in each group.

Table A1: H-FSR Summary Statistics. This table presents the summary statistics for the H-FSR country portfolios. It reports the mean and the standard deviation (St. Dev.) of the USD-denominated excess returns, in annual percentages, for each country. It also reports the number of unique firms (# Firms) as well as the total market capitalization, in USD, of each portfolio (Mcap) at the end of our sample. The total market capitalizations, in USD, of the DataStream's total market index portfolios ([DS-INDEX]) on the same date are also reported. The cross-sectional averages of these statistics for developed markets (DM) and emerging markets (EM) are reported below each group. H-FSR country portfolios are constructed from firms with at least a 10 percent foreign sales ratio. The sample period is from January 1996 to December 2019 at the weekly frequency.

Country	Mean	St. Dev.	# Firms	Mcap	[DS-INDEX]	Country	Mean	St. Dev.	# Firms	Mcap	[DS-INDEX]
Australia	9.023	21.509	878	601,852	1,324,769	Brazil	14.655	26.006	118	321,430	1,047,145
Austria	9.682	16.874	93	58,672	127,819	Chile	10.248	23.434	69	84,308	173,040
Belgium	4.749	17.388	100	234,715	377,940	China	17.781	31.911	1818	2,585,382	1,622,437
Canada	11.884	20.928	1081	924,945	2,040,521	Colombia	4.419	27.100	15	56,141	128,292
Denmark	9.232	17.264	162	369,405	431,625	Czech Republic	8.580	24.810	37	13,412	27,106
Finland	10.753	19.265	153	214,683	275,929	Hungary	9.361	27.362	25	12,343	31,918
France	9.456	17.285	779	2,177,154	2,759,249	India	15.920	27.878	1560	841,159	1,878,213
Germany	7.586	17.625	1271	3,280,270	2,126,147	Indonesia	14.147	33.663	152	52,448	389,708
Hong Kong	11.627	22.354	1312	1,104,845	2,795,222	Malaysia	6.715	31.111	507	159,439	339,824
Ireland	12.931	25.211	10	51,637	100,088	Mexico	8.918	22.276	99	179,635	391,981
Italy	5.656	20.066	299	360,099	710,670	Morocco	2.388	12.830	5	14,003	64,624
Japan	6.979	21.368	1646	3,822,761	5,944,290	Peru	13.791	28.480	34	11,112	99,447
Netherlands	8.613	19.604	189	634,029	886,153	Philippines	8.657	28.717	41	37,466	236,925
New Zealand	6.480	20.100	81	41,457	102,616	Poland	9.678	26.976	245	56,975	131,961
Norway	6.645	24.050	247	208,426	283,206	South Africa	7.538	25.507	151	232,725	423,834
Portugal	8.188	19.374	56	50,720	61,088	South Korea	15.863	36.934	1275	1,008,769	1,064,109
Singapore	9.262	24.851	537	215,804	526,108	Taiwan	1.783	29.987	696	71,162	914,475
Spain	8.582	19.834	144	479,563	747,678	Thailand	10.316	20.810	272	124,932	401,239
Sweden	12.055	22.337	449	513,843	648,545	Turkey	16.932	41.334	170	25,841	145,381
Switzerland	9.374	16.648	248	1,460,335	1,822,230						
United Kingdom	4.871	16.459	1995	2,231,321	3,345,069						
United States	14.020	21.035	5053	21,722,023	32,297,490						
Mean DM	8.984	20.065	763	1,852,662	2,715,202	Mean EM	10.405	27.743	384	309,931	500,614

Table A2: Summary Statistics Risk Factors. This table presents the summary statistics for the risk factors in our sample. World Market risk is the excess return of the world market index from DataStream. The foreign exchange rate risk factors are the currency investment excess returns vis-à-vis the US dollar. The table reports time-series averages (Mean) and standard deviation (St. Dev.) of each risk factor as well as their minimum (Min), 25th percentile, median, 75th percentile, and maximum (Max) values. The column Interest Rate reports the average values of the Euro-dollar one-month deposit rate, obtained from DataStream, in the country of each currency in our sample. The sample period is from January 1996 to December 2019 at the weekly frequency.

	Mean	St. Dev.	Min	25th	Median	75th	Max	Interest Rate
World Market	0.068	0.189	-0.420	-0.051	0.088	0.189	0.348	
EUR	-0.010	0.107	-0.167	-0.086	-0.040	0.070	0.222	0.018
JPY	-0.019	0.108	-0.172	-0.136	0.006	0.051	0.167	0.001
GBP	0.004	0.097	-0.248	-0.050	0.005	0.093	0.144	0.031
AUD	0.025	0.142	-0.181	-0.083	0.028	0.087	0.390	0.043
CAD	0.006	0.097	-0.171	-0.061	0.002	0.057	0.235	0.025
NZD	0.032	0.133	-0.197	-0.049	0.025	0.111	0.308	0.049
NOK	0.001	0.128	-0.200	-0.076	-0.013	0.070	0.350	0.033
CHF	-0.007	0.090	-0.176	-0.038	0.001	0.031	0.174	0.007
SEK	-0.012	0.118	-0.178	-0.101	-0.033	0.086	0.239	0.022
USD								0.025

Table A3: Summary *FX Beta*. The table reports the mean of the conditional foreign exchange rate risk sensitivity (*FX Beta*) for the H-FSR country portfolios to each currency risk. Risk sensitivities with respect to the home currency, β_j^{FXc}, are shown in a bold font and correspond to the figures reported in Table 5. H-FSR country portfolios are constructed from firms with at least a 10 percent foreign sales ratio. The sample period is from January 1996 to December 2019 at the annual frequency.

	EUR	JPY	GBP	AUD	CAD	NZD	NOK	CHF	SEK
Australia	0.647	-0.012	0.708	**1.299**	1.236	0.909	0.708	0.325	0.691
Austria	1.143	0.095	0.893	0.720	0.970	0.583	0.911	0.674	0.925
Belgium	0.945	0.069	0.719	0.705	0.859	0.556	0.748	0.656	0.814
Brazil	0.441	-0.204	0.522	0.842	1.183	0.633	0.608	0.129	0.561
Canada	0.499	-0.115	0.554	0.871	**1.759**	0.654	0.691	0.192	0.616
Chile	0.321	-0.070	0.288	0.734	0.932	0.562	0.451	0.061	0.375
China	0.277	-0.078	0.206	0.381	0.567	0.210	0.316	0.158	0.300
Colombia	0.403	-0.209	0.496	0.751	0.957	0.596	0.562	0.107	0.369
Czech Republic	1.291	0.051	0.997	0.840	1.045	0.702	0.981	0.856	1.064
Denmark	1.006	0.012	0.790	0.662	0.835	0.529	0.801	0.580	0.880
Finland	0.887	-0.022	0.719	0.773	1.175	0.588	0.816	0.447	0.864
France	0.976	-0.007	0.724	0.740	1.018	0.573	0.796	0.531	0.852
Germany	**0.899**	-0.019	0.725	0.700	0.993	0.539	0.729	0.481	0.812
Hong Kong	0.178	-0.155	0.223	0.509	0.679	0.340	0.293	0.023	0.239
Hungary	1.031	0.117	0.854	0.882	1.394	0.691	0.977	0.525	0.995
India	0.309	-0.182	0.348	0.603	0.629	0.445	0.408	0.120	0.407
Indonesia	0.559	0.131	0.480	0.711	0.691	0.626	0.463	0.294	0.522
Ireland	0.738	-0.068	0.674	0.667	0.863	0.486	0.611	0.392	0.748
Italy	0.939	-0.006	0.751	0.731	1.015	0.555	0.813	0.515	0.885
Japan	0.455	**0.376**	0.491	0.600	0.699	0.479	0.422	0.288	0.488
Malaysia	0.310	-0.027	0.425	0.738	0.903	0.550	0.385	0.126	0.527
Mexico	0.278	-0.174	0.293	0.660	1.079	0.489	0.487	0.010	0.385
Morocco	0.715	0.166	0.456	0.345	0.371	0.307	0.471	0.414	0.494
Netherlands	0.887	-0.079	0.723	0.757	1.073	0.583	0.817	0.475	0.855
New Zealand	0.670	0.064	0.639	1.106	1.145	**1.209**	0.676	0.381	0.720
Norway	0.955	-0.107	0.856	1.043	1.590	0.781	**1.265**	0.483	1.032
Peru	0.497	0.030	0.472	0.704	0.907	0.521	0.547	0.284	0.447
Philippines	0.277	-0.144	0.372	0.602	0.717	0.509	0.429	0.164	0.373
Poland	1.006	0.015	0.858	0.977	1.417	0.764	0.950	0.589	0.943
Portugal	0.988	0.037	0.900	0.777	0.912	0.604	0.832	0.653	0.862
Singapore	0.438	0.020	0.387	0.699	0.875	0.588	0.423	0.200	0.511
South Africa	0.729	-0.004	0.667	1.121	1.510	0.834	0.969	0.346	0.856
South Korea	0.258	-0.193	0.562	1.012	1.461	0.785	0.465	0.212	0.546
Spain	0.981	-0.019	0.823	0.764	1.078	0.592	0.863	0.547	0.867
Sweden	0.900	-0.127	0.754	0.932	1.274	0.726	0.908	0.418	**1.143**
Switzerland	0.866	0.125	0.655	0.676	0.888	0.523	0.729	**0.701**	0.801
Taiwan	0.329	-0.197	0.424	0.621	0.609	0.458	0.453	0.026	0.388
Thailand	0.295	0.022	0.351	0.526	0.646	0.415	0.381	0.118	0.382
Turkey	0.662	-0.176	0.564	1.060	1.294	0.745	0.939	0.187	0.835
United Kingdom	0.648	-0.081	**0.564**	0.697	0.929	0.533	0.609	0.326	0.659
United States	0.097	-0.374	0.211	0.541	0.920	0.376	0.305	-0.138	0.329

Table A4: ***FX Beta* and Trade–Robustness.** The table reports the averages of period-by-period slope coefficients from cross-sectional regressions of conditional foreign exchange rate risk sensitivity (*FX Beta*) on the exports of goods and services, as % of GDP (EXP_INTENSITY), Trade Centrality (TR_CENTRALITY), IFRS adoption date dummy, Anti-director index (ANTI_DIR), capital account openness measure (CAP_OPEN), the degree of law and order (LAW), as well as domestic consumption (CONS), market capitalization of listed companies (MCAP), and domestic credit to the private sector (P_CREDIT), all as % of GDP. Column (1) reports the results for the pooled panel of all *FX Beta* for H-FSR country portfolios, as in Table 6. Column (2) reports the results of the same analysis, controlling for the conditional world market risk sensitivity (β^{Rw}). Columns (3) and (4) report the results for the pooled panel of all *FX Beta* for H-FSR^{Ortho} and H-FSR^{median} country portfolios. H-FSR country portfolios are constructed from firms with at least a 10 percent foreign sales ratio. H-FSR^{Ortho} are also orthogonalized on the world market risk factor. H-FSR^{median} are constructed from firms with above the median foreign sales ratio in each country. T-statistics, in square brackets, are obtained using the Fama-MacBeth standard errors corrected for time-dependence following Petersen (2009). The sample period is from January 1996 to December 2019 at the annual frequency.

	(1)	(2)	(3)	(4)
EXP_INTENSITY	0.125**	0.122**	0.108***	0.149**
	[1.96]	[2.42]	[4.50]	[2.47]
TR_CENTRALITY	-0.148***	-0.130***	-0.157***	-0.178***
	[-5.61]	[-4.14]	[-6.99]	[-7.35]
IFRS	12.058*	9.828**	9.973**	12.217**
	[1.86]	[2.19]	[2.01]	[1.96]
ANTI_DIR	-2.482***	-2.325***	-3.720***	-2.374***
	[-3.31]	[-4.21]	[-5.33]	[-3.01]
CAP_OPEN	0.050	0.063	0.034	0.054
	[0.69]	[0.85]	[0.71]	[0.61]
LAW	5.467***	2.881*	4.637***	5.149***
	[4.13]	[1.67]	[6.64]	[2.79]
MCAP	-0.067***	-0.058***	-0.041***	-0.065***
	[-2.89]	[-3.78]	[-7.38]	[-3.81]
P_CREDIT	-0.043	-0.006	-0.046***	-0.047
	[-0.74]	[-0.24]	[-4.23]	[-0.73]
CONS	0.598***	0.292***	0.284***	0.639***
	[4.31]	[3.30]	[5.64]	[4.89]
β^{Rw}		30.655		
		[1.40]		
Observations	6417	6417	6417	6417
Adjusted R2	0.674	0.695	0.630	0.663

Table A5: *FX Beta* and Foreign (Equity) Portfolio Capital Flows. The table reports the averages of period-by-period slope coefficients from cross-sectional regressions of the conditional foreign exchange rate risk sensitivity (*FX Beta*) for the H-FSR country portfolios on the extent of domestic equity purchases by foreign investors (FEPI), as % of GDP, IFRS adoption date dummy, Anti-director index (ANTI_DIR), capital account openness measure (CAP_OPEN), the degree of law and order (LAW), as well as domestic consumption (CONS), market capitalization of listed companies (MCAP), domestic credit to the private sector (P_CREDIT), all as % of GDP. T-statistics, in square brackets, are obtained using the Fama-MacBeth standard errors corrected for time-dependence following Petersen (2009). H-FSR country portfolios are constructed from firms with at least a 10 percent foreign sales ratio. The sample period is from January 1996 to December 2019 at the annual frequency.

	All FX	EUR	JPY	GBP	AUD	CAD	NZD	NOK	CHF	SEK
FEPI	0.044	0.126	-0.038	0.132	-0.000	-0.158	0.032	0.065	0.138*	0.097*
	[0.92]	[1.11]	[-0.86]	[1.11]	[-0.00]	[-1.32]	[0.52]	[1.22]	[1.78]	[1.69]
IFRS	10.189*	16.716*	4.255	13.413*	6.407	9.969	4.753	11.527**	12.853	11.810*
	[1.93]	[1.73]	[1.21]	[1.90]	[1.54]	[1.31]	[1.44]	[2.07]	[1.50]	[1.84]
ANTI_DIR	-2.443	-8.891***	9.142	-6.540	4.010	-4.031	2.291	-2.365	-8.027***	-7.573***
	[-1.49]	[-4.44]	[0.58]	[-1.61]	[1.58]	[-1.11]	[1.37]	[-0.44]	[-4.18]	[-4.64]
CAP_OPEN	-0.006	0.314***	0.081	0.221*	-0.299***	-0.358	-0.096***	-0.095	0.190***	-0.017
	[-0.12]	[3.38]	[0.71]	[1.76]	[-6.20]	[-1.61]	[-2.67]	[-1.35]	[3.02]	[-0.34]
LAW	5.240***	5.969***	-1.431	3.256***	7.347***	10.227***	4.376***	6.457***	2.422**	8.538***
	[5.44]	[3.79]	[-0.66]	[2.86]	[3.16]	[3.06]	[2.75]	[3.82]	[2.31]	[9.12]
MCAP	-0.064***	-0.102***	-0.035**	-0.129*	-0.042	0.034	-0.066**	-0.059***	-0.109***	-0.069***
	[-3.69]	[-3.96]	[-2.28]	[-1.91]	[-1.36]	[0.53]	[-2.09]	[-4.01]	[-2.86]	[-3.70]
P_CREDIT	-0.000	-0.051	0.126	0.014	-0.020	-0.059	0.019	-0.042	0.037	-0.024
	[-0.00]	[-1.32]	[1.42]	[0.56]	[-0.42]	[-1.08]	[0.40]	[-1.50]	[1.30]	[-0.76]
CONS	0.591***	0.505**	-0.247*	0.504**	0.884***	1.242***	0.592***	0.819***	0.322***	0.700***
	[6.75]	[2.32]	[-1.68]	[2.20]	[10.17]	[3.53]	[5.96]	[7.32]	[4.55]	[8.32]
Observations	6831	759	759	759	759	759	759	759	759	759
Adjusted R2	0.661	0.878	0.699	0.897	0.899	0.863	0.880	0.889	0.812	0.904

Table A6: *FX Beta* and Foreign (Debt) Portfolio Capital Flows. The table reports the averages of period-by-period slope coefficients from cross-sectional regressions of the conditional foreign exchange rate risk sensitivity (*FX Beta*) for the H-FSR country portfolios on the extent of domestic debt purchases by foreign investors (FDPI), as % of GDP, IFRS adoption date dummy, Anti-director index (ANTI_DIR), capital account openness measure (CAP_OPEN), the degree of law and order (LAW), as well as domestic consumption (CONS), market capitalization of listed companies (MCAP), domestic credit to the private sector (P_CREDIT), all as % of GDP. T-statistics, in square brackets, are obtained using the Fama-MacBeth standard errors corrected for time-dependence following Petersen (2009). H-FSR country portfolios are constructed from firms with at least a 10 percent foreign sales ratio. The sample period is from January 1996 to December 2019 at the annual frequency.

	All FX	EUR	JPY	GBP	AUD	CAD	NZD	NOK	CHF	SEK
FDPI	0.091	0.203**	-0.014	0.100*	0.058	0.136	0.073	0.124	-0.007	0.145
	[0.96]	[2.08]	[-0.19]	[1.67]	[0.62]	[0.86]	[0.58]	[1.37]	[-0.11]	[1.55]
IFRS	11.411*	17.365*	4.603	14.073*	8.220*	12.398	6.769*	12.839**	13.718	12.717*
	[1.93]	[1.74]	[1.34]	[1.95]	[1.76]	[1.45]	[1.87]	[2.13]	[1.50]	[1.87]
ANTI_DIR	-1.121	-6.199***	4.519	-4.293**	5.254	1.874	2.318	-1.018	-6.784***	-5.761**
	[-0.25]	[-3.20]	[0.52]	[-2.44]	[1.16]	[0.90]	[0.97]	[-0.11]	[-6.29]	[-2.18]
CAP_OPEN	-0.038	0.247***	0.104	0.173*	-0.343***	-0.398**	-0.170***	-0.125*	0.226***	-0.054
	[-0.98]	[3.25]	[0.93]	[1.86]	[-8.18]	[-2.43]	[-5.88]	[-1.96]	[3.40]	[-1.21]
LAW	4.759***	4.503**	-1.141	2.659***	7.498***	8.936**	4.744**	5.554**	2.453**	7.623***
	[3.40]	[2.38]	[-0.67]	[2.66]	[3.26]	[2.52]	[2.39]	[2.46]	[2.47]	[5.58]
MCAP	-0.050***	-0.062***	-0.047**	-0.083***	-0.041*	-0.021	-0.058***	-0.039***	-0.061***	-0.038***
	[-4.52]	[-4.30]	[-2.36]	[-3.46]	[-1.90]	[-1.09]	[-3.00]	[-5.24]	[-3.77]	[-3.03]
P_CREDIT	0.010	-0.026	0.122	0.027	-0.013	-0.040	0.033	-0.027	0.025	-0.010
	[0.27]	[-0.59]	[1.40]	[0.95]	[-0.27]	[-0.59]	[0.55]	[-0.86]	[1.52]	[-0.28]
CONS	0.590***	0.513**	-0.195*	0.517***	0.878***	1.196***	0.634***	0.814***	0.263***	0.691***
	[6.23]	[2.25]	[-1.93]	[2.67]	[9.46]	[3.60]	[6.35]	[6.03]	[3.02]	[6.49]
Observations	6867	763	763	763	763	763	763	763	763	763
Adjusted R2	0.663	0.880	0.688	0.895	0.902	0.864	0.883	0.890	0.811	0.905

Table A7: *FX Beta* and Foreign Investment Capital Flows. The table reports the averages of period-by-period slope coefficients from cross-sectional regressions of the conditional foreign exchange rate risk sensitivity (*FX Beta*) for the H-FSR country portfolios on foreign direct investment inflows (FDI_IN), as % of GDP, IFRS adoption date dummy, Anti-director index (ANTI_DIR), capital account openness measure (CAP_OPEN), the degree of law and order (LAW), as well as domestic consumption (CONS), market capitalization of listed companies (MCAP), domestic credit to the private sector (P_CREDIT), all as % of GDP. T-statistics, in square brackets, are obtained using the Fama-MacBeth standard errors corrected for time-dependence following Petersen (2009). H-FSR country portfolios are constructed from firms with at least a 10 percent foreign sales ratio. The sample period is from January 1996 to December 2019 at the annual frequency.

	All FX	EUR	JPY	GBP	AUD	CAD	NZD	NOK	CHF	SEK
FDI_IN	-0.054	-0.078	-0.347**	-0.146	0.124	0.094	0.170	-0.213	-0.034	-0.058
	[-0.27]	[-0.42]	[-2.06]	[-0.84]	[0.41]	[0.13]	[0.40]	[-1.39]	[-0.17]	[-0.26]
IFRS	11.761	17.309	2.202	16.232*	9.647*	13.915	7.069*	13.579*	12.212	13.688
	[1.64]	[1.59]	[0.88]	[1.72]	[1.80]	[1.35]	[1.66]	[1.68]	[1.29]	[1.55]
ANTI_DIR	-1.826**	-7.248***	6.199	-6.325	3.763***	1.561	0.618	-3.127**	-6.434***	-5.443***
	[-2.42]	[-3.41]	[0.57]	[-1.14]	[3.59]	[0.40]	[0.33]	[-2.57]	[-8.52]	[-2.75]
CAP_OPEN	0.214***	0.383***	0.050	0.326***	0.134*	0.158	0.189***	0.198**	0.250***	0.240***
	[3.86]	[5.39]	[0.61]	[5.02]	[1.68]	[1.09]	[2.95]	[2.54]	[5.17]	[3.66]
Law & Order	3.772***	7.103***	-0.020	3.377***	2.123	4.068*	1.177	4.930***	4.126***	7.067***
	[7.44]	[5.26]	[-0.02]	[4.06]	[1.49]	[1.80]	[1.38]	[6.48]	[4.35]	[11.68]
MCAP	-0.058**	-0.078***	-0.030	-0.081***	-0.048*	-0.031	-0.071*	-0.057***	-0.067***	-0.058***
	[-2.51]	[-3.26]	[-1.31]	[-2.94]	[-1.87]	[-1.12]	[-1.83]	[-2.89]	[-2.64]	[-2.78]
P_CREDIT	-0.046	-0.116	0.079	-0.045	-0.036	-0.100	0.002	-0.092*	-0.031	-0.077
	[-0.81]	[-1.52]	[1.25]	[-1.32]	[-0.47]	[-1.30]	[0.02]	[-1.69]	[-0.98]	[-1.51]
CONS	0.427***	0.435	-0.145	0.420*	0.617***	0.799***	0.455***	0.577***	0.224**	0.457**
	[2.82]	[1.49]	[-1.43]	[1.85]	[5.08]	[3.33]	[3.26]	[3.68]	[2.52]	[2.44]
Observations	8640	960	960	960	960	960	960	960	960	960
Adjusted R2	0.647	0.849	0.600	0.862	0.875	0.838	0.847	0.869	0.775	0.871

Table A8: *FX Beta* and Trade-New Currency Risk Factors The table reports the averages of period-by-period slope coefficients from cross-sectional regressions of the new currency risk factors conditional sensitivities (*CR Beta*) for the H-FSR country portfolios on the exports of goods and services, as % of GDP (EXP_INTENSITY), Trade Centrality (TR_CENTRALITY), IFRS adoption date dummy, Anti-director index (ANTI_DIR), capital account openness measure (CAP_OPEN), the degree of law and order (LAW), as well as domestic consumption, market capitalization of listed companies (MCAP), and domestic credit to the private sector (P_CREDIT), all as % of GDP. T-statistics, in square brackets, are obtained using the Fama-MacBeth standard errors corrected for time-dependence following Petersen (2009). H-FSR country portfolios are constructed from firms with at least a 10 percent foreign sales ratio. The sample period is from January 1996 to December 2019 at the annual frequency.

	Carry	Dollar	USD	RX	HML_{FX}
EXP_INTENSITY	0.536	0.748***	0.071	0.760***	0.627*
	[1.53]	[2.89]	[0.97]	[2.96]	[1.85]
TR_CENTRALITY	-0.244***	-0.313***	0.106	-0.289***	-0.291***
	[-6.86]	[-3.94]	[1.30]	[-3.90]	[-4.75]
IFRS	-9.618	11.842	0.249	10.319	-8.350
	[-1.25]	[1.35]	[0.06]	[1.26]	[-1.08]
ANTI_DIR	6.584***	6.435**	5.591***	6.463**	5.532*
	[4.11]	[1.99]	[3.30]	[2.04]	[1.85]
CAP_OPEN	-0.579***	-0.598***	0.078	-0.599**	-0.666***
	[-5.27]	[-2.62]	[0.69]	[-2.57]	[-6.40]
LAW	0.517	10.705	4.502	10.387*	-0.181
	[0.04]	[1.59]	[0.96]	[1.67]	[-0.01]
MCAP	-0.020	-0.158	0.013	-0.152	-0.008
	[-0.30]	[-1.37]	[0.74]	[-1.35]	[-0.16]
P_CREDIT	-0.282	-0.204	-0.195***	-0.208	-0.249
	[-1.25]	[-0.63]	[-3.77]	[-0.64]	[-1.36]
CONS	2.232***	2.496***	-0.285**	2.483***	2.272***
	[15.57]	[9.04]	[-2.24]	[8.99]	[16.55]
Observations	713	713	509	713	713
Adjusted R2	0.837	0.911	0.349	0.911	0.834