

Digesting FOREXS: Information Transmission across Asset Classes and Return Predictability*

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First version: November 12, 2019

This version: May 24, 2022

Abstract

We provide novel evidence that equity investors react to currency shocks with a delay. Using the cross-section of currency returns and the relative presence of U.S. firms in foreign economies, we compute a foreign operations related exchange shock (*FOREXS*) measure. We find *FOREXS* to predict firms' future cash flows and stock returns, driving much of the previously documented underreaction to foreign information. A *FOREXS* based long-short strategy yields a 6.74% annualized abnormal return. *FOREXS* predictive power comes from firms' incomplete hedging and investors' limited attention, highlighting the challenges involved when processing information from a different asset class.

JEL Classification: G12, G15

Keywords: return predictability, currency information, foreign operations

*For valuable comments we thank Söhnke Bartram, Lauren Cohen, Tom George, Anurag Gupta, Jerry Hoberg, Peter Kelly, Quoc Nguyen, John Shim, Sophie Shive, Hui-Ju Tsai and seminar participants at University of Notre Dame, Korea University, Case Western Reserve University, and the 2020 Lone Star Finance, 2020 Financial Management Association Annual Meetings, 2021 Eastern Finance Association Annual Meetings, 2021 Northern Finance Association conferences. Zhi Da acknowledges financial support from Beijing Outstanding Young Scientist Program (BJJWZYJH01201910034034) and the 111 Project (B20094).

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1 Introduction

Firms today operate in an increasingly inter-connected economy. As a result, equity valuation is affected by shocks across many different asset classes. For example, commodity prices affect firms' input costs and interest rates affect firms' financing costs and discount rates. How do equity investors respond to shocks from a different asset class that they are potentially unfamiliar with and less likely to pay attention? Despite its importance, this question has not been extensively studied.

In this paper, we approach this question by focusing on the cross-section of currency exposure of U.S. firms and their relative presence in foreign economies. Cohen, Gurun and Malloy (2017) note that almost half of all sales of firms in the S&P 500 composite are generated abroad. Foreign exchange rate fluctuations, while largely unpredictable (see, for example, Rossi (2013)), can have a significant impact on firms' cash flow especially when they are not fully hedged. We provide novel evidence that equity investors of U.S. multinationals underreact to firms' currency shocks from countries in which they operate.

Shocks to the cross-section of currency rates slowly diffuse to U.S. stock prices, which is consistent with firms and investors challenges to digest complex information. To build intuition for our approach, consider the following example using the Brexit referendum. On June 23, 2016, the U.K. held the referendum about its withdrawal from the European Union, with voters supporting its exit. The result triggered a sell-off of the British pound and a rally of the Japanese yen.¹ How did this change affect U.S. firms with operations in the U.K. and Japan? Foreign economies with weaker currencies make U.S. firms' goods relatively more expensive, while the opposite happens with stronger currencies. In Figure 1, we plot the cumulative excess returns adjusted for domestic market beta and cumulative changes in the

¹“Pound Down 13% Against the Yen - Investors are selling the pound as Brexit becomes more of a reality, and buying the yen as a safe haven,” Dow Jones Newswires, June 23, 2016; “Brexit! Pound at 3 decades low, yen surges to 2013 high,” Dow Jones Newswires, June 24, 2016. Contrary to currency returns, FTSE 100 index rose about 4.3% and Nikkei 225 fell over 9% in the month of June 2016.

return on asset (ROA), for two portfolios of U.S. firms with significant foreign operations in the U.K. and Japan, respectively.² The exchange rate shock in this example is salient and impacts firms' future ROAs in a predictable direction (Panel A), but investors still seem to underreact to such information, generating post-event return drift (Panel B). This is because figuring out the precise impact of a currency shock on firms is a non-trivial task, especially when the firms have partially hedged such a shock.

While this example is illustrative and refers specifically to a single foreign economy and currency, it still highlights the main feature of our strategy: foreign information related to relevant currencies impacts on domestic firms with a delay. Moreover, return predictability is more pronounced with less salient events and for firms that carry foreign operations with a multitude of countries because of investors' limited access and capabilities to efficiently process foreign exchange rate shocks.

[Insert Figure 1 Here]

Our empirical strategy examines the link between the equity returns of multinational corporations and the information embedded in the cross-section of currency returns. The relevance of a currency is determined by the relative presence of the U.S. firm in the foreign economy. Specifically, we compute a firm's exposure to foreign exchange rate shocks as the cross-sectional mean of lagged currency returns, weighted by the relative sales of the U.S. company in each foreign country. We label the resulting measure *FOREXS* (foreign operations related exchange shocks).

We find *FOREXS* to have a strong predictive power for firms' future returns. Individual stocks with high *FOREXS* exhibit higher future returns than stocks with low *FOREXS*. We implement the following portfolio strategy to investigate the economic significance of the

²To construct the average excess return, we first select a group of firms with greater than 10% foreign sales to the target country (e.g., the U.K. and Japan). We then take a target country sales-weighted average of excess returns. We implement a similar procedure for the changes in ROA.

return predictability induced by *FOREXS*. Each month, our proposed trading strategy buys a set of stocks with high *FOREXS* and shorts a set of stocks with low *FOREXS*, based on the previous month *FOREXS* estimates. The long-short strategy generates a 6.74% annualized abnormal return and is statistically significant after controlling for the 3-factor model of Fama and French (1993), the 4-factor model of Carhart (1994), the 5-factor model of Fama and French (2015), the 4-factor model of Stambaugh and Yuan (2017), and the 4-factor model of Hou, Xue and Zhang (2015).

For emphasis, *FOREXS* measures a transitory shock rather than a persistent firm characteristic. The transitory and directional nature of *FOREXS* alleviates missing risk factor concerns. Future returns increase monotonically from stocks with large and negative *FOREXS* to those with large and positive *FOREXS*, even though both sets of stocks are likely experiencing higher uncertainty and risk.³ Furthermore, our strategy returns accrue disproportionately on future earnings announcement days and persist up to seven months after the portfolio formation with no reversals in the long run, consistent with the notion that investors initially underreact to the fundamental information embedded in *FOREXS*. For example, *FOREXS* positively predicts analysts' forecast error, suggesting that analysts initially underreact to currency shocks.

Huang (2015) and Nguyen (2016) document that investors of U.S. multinational firms underreact to foreign information, measured using dollar returns of foreign market or industry returns.⁴ Using cross-sectional regressions, therefore, we further investigate if the predictive power of a multinational's *FOREXS* is driven by alternative characteristics of the firm, industry, market or country. First, we find that the exposure of a company to the cross-section of currency rates remains economically and statistically unaffected by the firm's size as well as contemporaneous or lagged domestic and foreign industries and stock

³In our empirical analysis, we confirm the importance of a directional measure for the construction of *FOREXS*, as using currency volatility (instead of currency returns) does not provide return predictability.

⁴We use interchangeably the terms dollar return or dollarized to define the monthly local currency return of the foreign industry or market after converting it to U.S. dollars.

markets. Second, when we decompose these foreign industry and stock market (dollar) returns into a stock return component (measured in local currency) and a foreign exchange return component, only the latter remains with strong predictive power. In other words, investors seem to underreact mostly to information contained in foreign exchange rates, not in foreign market or industry returns. Third, the regressions also confirm that *FOREXS* has predictable impact on firms' future cash flows, since an appreciation of the foreign currency elevates the purchasing power of consumers. A one-standard deviation change in *FOREXS* results in a 1.24% increase in the quarterly growth rate of sales, suggesting that firms, on average, do not fully hedge their currency exposures.

In our framework, two conditions are needed in order to obtain return predictability induced by *FOREXS*. First, U.S. firms should be fundamentally exposed to the cross-section of relevant currency rates. Second, investors should underreact to such information, relevant for firms' operational performance, generating post-event return drift. Indeed, if multinational firms fully hedge their exchange rate exposure, *FOREXS* should not affect stock returns. Changing firms' hedging costs, via financial or operational hedging, therefore directly impacts the prospect of U.S. firms' with foreign operations. Different degrees of currency hedging therefore generate interesting cross-sectional variations. We use currency option and spot prices to estimate firms' cost to financially insure against future changes in FX volatility and find *FOREXS* return effect to increase with the cost to hedge against currency volatility. We confirm this result when looking into firms' 10K reports following Hoberg and Moon (2017), with a stronger effect of *FOREXS* in firms with fewer mentions of financial derivatives for hedging purposes. We then study firms' operational hedging levels implied by the company 10K's documents and find that stock return predictability increases when firms' operational hedging is lower. Consistent with these findings on hedging policies, we document a much stronger *FOREXS* return predictive power among firms with high currency exposures using the cash-flow sensitivity to *FOREXS* as a measure of firms' effective net currency exposure

(Adler and Dumas (1984)).

Incomplete hedging could explain *FOREXS*'s predictive power on firms' future cash flows, but it alone does not explain the return predictability. The delayed price adjustment may arise from investors' challenges in understanding the net effect of cross-sectional currency shocks on individual firms. Investors can exhibit limited capabilities to process information (Jensen and Meckling (1992)) and thus their specialization in either the equity market or the currency market deters the speedy information flows across asset classes, which results in informational segmentation (Menzly and Ozbas (2010)). Moreover, searching for publicly available information that is relevant for investors' decision making process can also be costly (Hong, Stein, and Yu (2007)).

We provide several pieces of evidence supporting investors limitations in first accessing and then processing information from the currency market. First, we examine the impact of currency risk disclosure by firms in their annual reports. We find the predictive power of *FOREXS* to decrease among firms that mention the words "currency", "foreign exchange" or "FX" in the Risk Factors section of their 10-K reports, consistent with the notion that such disclosure encourages investor attention to currency shocks, thus reducing underreaction to *FOREXS*. Second, we rely on several textual analytics and use computational linguistic methods to identify and isolate news coverage specific to currency rates. To the extent that currency news coverage triggers investor attention to exchange rate fluctuations, it should weaken the return predictability of *FOREXS*. This is exactly what we find. As a placebo test, the return predictability of *FOREXS* does not vary with other news coverage about foreign equity markets. Third, the return predictability of *FOREXS* also weakens when stock ownership by hedge funds and foreign investors increases, since these investors are more likely to allocate resources (time and specialized labor) to the cross-section of currency rates. Fourth, the return predictability of *FOREXS* becomes stronger when the multinational firms are exposed to more currencies and these currencies are less correlated

with each other. In these situations, the failure to rapidly access and process the effects of currency shocks is likely to have a large impact on price efficiency and cause more return predictability by *FOREXS*.

When there is little uncertainty or disagreement in the direction of FX movements, it is relatively straightforward to incorporate information contained in *FOREXS*. Intuitively, limited attention has a bigger effect when volatility and uncertainty across currencies increase. We compute foreign exchange rate volatilities and empirically confirm the importance of information uncertainty. As uncertainty about currency rates increases, the processing of information becomes more complex, resulting in greater return predictability. We further validate our results using FX forecasts dispersion measures implied by FX analyst forecasts, which arguably measure uncertainty about future changes in the foreign exchange rate, and show that stock return predictability increases with the dispersion of analysts' forecasts.

The structure of the paper is as follows. Section 2 describes the literature related to the paper. Section 3 presents the data sources utilized for the empirical analysis. Section 4 studies the return effect of *FOREXS* in the cross-section individual stocks and equity portfolio strategies. Section 5 explores the mechanisms underlying the return predictability of *FOREXS*. Section 6 concludes.

2 Related Literature

Our paper contributes to different strands of literature, starting with studies on information flows between segmented asset classes. From a theoretical perspective, capital immobility, limits of arbitrage, and delegated portfolio management can all result in segmented asset classes (Gabaix, Krishnamurty, and Vigneron (2007), Duffie (2010), Greenwood, Hanson, and Liao (2018), He and Xiong (2013) among others). Empirically, there is evidence of such slow diffusion between the equity market and the bond market (Gebhardt, Hvidkjaer, and

Swaminathan (2005); Pitkajarvi, Suominen, and Vaittinen (2020)).⁵ The literature also documents the link between the equity market with the CDS market (Han, Subrahmanyam, and Zhou (2017)) and with the options market (Barras and Malkhozov (2016)). More recently, Addoum and Murfin (2020) document the information lag from syndicated loan prices to equity prices. We show that information in the foreign exchange market travels to the equity market with a delay.

Our paper also intersects with a broader literature on slow information diffusion in financial markets due to investors' limited attention and information processing capacity. A growing literature relaxes the assumption of instantaneous information incorporation into stock prices, and instead argue that investors react to new information with a delay because of limited attention (Hirshleifer and Teoh (2003), Hirshleifer, Lim and Teoh (2009) and DellaVigna and Pollet (2009)) or because of information being difficult to process (Cohen and Lou (2012) and Akbas, Markov, Subasi and Weisbord (2018)).⁶ Our paper is among the first to document that equity investors have limited attention to exchange-rate-related information. Our results thus highlight the important role of investor attention in facilitating information transmission across asset classes.

Focusing on multinational firms, existing literature finds that firms with presence in foreign economies are particularly sensitive to the transmission of foreign markets' developments into U.S. stocks prices (Albuquerque, Ramadorai and Watugala (2015), Bae, Elkamhi and Simutin (2019), Bai, Garg and Wan (2020), Huang (2015), Nguyen (2016) and Wagner, Zeckhauser and Ziegler (2018)). In this paper, we show that the cross-section of foreign exchange rates, weighted by the relative presence of the multinational in each foreign economy,

⁵Additional studies on the equity-bond cross-markets link include Auh and Bai (2020), Collin-Dufresne, Goldstein and Martin (2001), Chordia, Goyal, Nozawa, Subrahmanyam and Tong (2017) and Choi and Kim (2018).

⁶A non-exhaustive literature on (investors) limited attention and information processing capacity includes the theoretical studies of Merton (1987), Hong and Stein (1999), Peng and Xiong (2006) and Andrei and Hasler (2015). Empirical studies include Cohen and Frazzini (2008), Coval and Moskowitz (1999), Da, Engelberg, and Gao (2011) and Hoberg and Phillips (2018).

contains relevant information that is not captured by foreign returns in individual stocks, industries, markets, or economies. In other words, we show that shocks specific to currency rates slowly diffuse to U.S. firms and play a critical role in previously-documented return predictability.

We find that return predictability decreases with financial hedging, proxied with the cost of FX volatility insurance (Della Corte, Ramadorai and Sarno (2016) and Drechsler and Yaron (2011)), and decreases with operational hedging (Hoberg and Moon (2017)). In line with Tetlock (2007), Engelberg and Parsons (2011), Dougal, Engelberg, Garcia and Parsons (2012), Peress (2014), Da, Gurun and Warachka (2014), Ahern and Sosyura (2015) and Kaniel and Parham (2017) among others, we show that press coverage plays an important role in alleviating investors' attention constraints.

Several studies document a risk-based explanation for the future return of multinationals, given their exposure to risks originated overseas (e.g., see Barrot, Loualiche and Sauvagnat (2019), Fillat and Garetto (2015) and Hoberg and Moon (2018)). Different from these papers, we provide evidence for an explanation based on investors' challenges to access and understand relevant foreign news in a timely manner. We find that *FOREXS* predictability is transitory and directional in nature and different from multinational firms' persistent exposure to foreign countries or stock markets. Furthermore, our trading strategy carries negligible exposure to well established risk factors, accrues disproportionately on future earnings announcement days and persists up to seven months after the portfolio formation, supporting the hypothesis for a slow diffusion of information between asset classes.

Lastly, our paper is related to earlier work investigating the exposure of firms to foreign exchange rates. This literature either uses both U.S. and non-U.S. firms, a specific number of currencies or index, or trade-weights that are country rather than firm-specific and fixed over time (e.g., see Bartram, Brown and Minton (2010), Bodnar, Dumas and Marston (2002)

and Dominguez and Tesar (2001)).⁷ While insightful, we find that aggregation of firms and countries can yield inconclusive results. U.S. firms' exposure to foreign currency information is substantially different from the exposure of non-U.S. firms, and explicitly accounting for a firm's relative presence in different countries is crucial to understand investors' delayed reaction to currency shocks.

More related to our work, Bartov and Bodnar (1994) study the time-series effects of changes in a trade-weighted currency index on a subset of 208 firms reporting foreign currency adjustments in their financial statements. Our approach is different in several important dimensions. Indeed, our results show that despite the increasing usage of currency hedging in the past 30 years, currency shocks can still predict future stock returns. More importantly, the added cross-sectional dimension in our analyses including more than 3,000 companies helps us better understand why equity investors underreact to currency shocks. Specifically, it allows us to take advantage of heterogeneity among firms with different operating and financial hedging strategies, different exposures to currency baskets and different investor clienteles. Finally, by allowing time-varying and firm-specific weights, our *FOREXS* measure seems to better capture firms' dynamic currency exposures.⁸

3 Data

We next describe our data sources related to U.S. firms' foreign operations, domestic and foreign industries and stock markets, foreign exchange rates, hedging policies and specialized news flows.

We obtain firm-level geographic revenue with different countries from FactSet Revere

⁷Other important studies include Desai, Foley and Forbes (2008) and Griffin and Stulz (2001).

⁸In Section 4.3, we show that using fixed, equal-weights across currencies generates non-significant return effects. Moreover, the predictability of *FOREXS* is stronger than an alternative based on return currency loadings.

database. FactSet Revere Geographic Exposure provides firm-level geographic footprint of a company based on sources of revenue. For firms domiciled in the U.S., firm-level price and financial accounting information are obtained from CRSP and Compustat respectively. For firms with a domicile of origin outside of the U.S., we follow Hou, Karolyi and Kho (2011) to obtain firm-level price and total return series, market value of equity, and four-digit SIC codes from Datastream.⁹ We then construct value-weighted portfolios for each two-digit SIC code and each country in our sample.¹⁰ We construct the portfolios using 30 countries.¹¹ The list of countries utilized is based on (i) the top sales partners of U.S. firms, and (ii) the availability of data on these countries to conduct the required tests.

Table 1 reports the summary statistics for the set of U.S. firms with foreign operations. In Panel A, each period we compute the ratio of each U.S. firms' sales to foreign economies over its total sales, and compute the value-weighted and equal-weighted average across all firms. We find that U.S. firms generate 36 and 22 percent of their revenues from foreign economies using value weights and equal weights, respectively. While the ratio is significantly lower among below median size firms, 20 (18) percent using value (equal) weights, the gap is mostly driven by small size firms without having any foreign sales exposure. Conditional on firms having positive foreign sales, below median size firms still have considerable sales exposure to foreign economies (36 and 35 percent using value weights and equal weights respectively). Panel B reports the top 10 sales partners of U.S. firms based on value-weights across firms.

⁹We apply several screening procedures as suggested by Ince and Porter (2003). First, at least one of the financial variables above must be available for a minimum of one year, for a stock to be included in our dataset. Second, we only select common stocks that are traded on the country's major exchange(s), excluding preferred stocks, REITs, depositary receipts, warrants, closed-end funds. Multiple exchanges are included in samples for China (Shanghai and Shenzhen Stock Exchanges), Japan (Osaka and Tokyo Stock Exchanges), and the United States (NYSE, AMEX and NASDAQ). Third, we set both R_t and R_{t+1} to missing if R_t or R_{t+1} is greater than 300% and $(1 + R_t)(1 + R_{t+1}) - 1 \leq 50\%$. Fourth, we drop observations with previous month price less than \$1.00 to avoid picking up errors in Datastream. Fifth, firms are required to have at least 12 monthly returns.

¹⁰We confirm that our findings are robust to re-defining the industry set to one-digit SIC codes.

¹¹The set of countries include Argentina, Australia, Austria, Belgium, Brazil, Canada, China, Denmark, France, Germany, Hong Kong, India, Indonesia, Italy, Japan, Mexico, the Netherlands, Norway, Poland, Russia, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Thailand, Turkey, the U.K., and the U.S.

[Insert Table 1 Here]

We obtain end of month foreign exchange spot prices from Datastream and at-the-money option implied FX volatilities from Bloomberg. All of the foreign exchange rates are quoted against the U.S. dollar. The risk factors of Fama and French (2015), Hou, Xue and Zhang (2015), Stambaugh and Yuan (2017), and Daniel, Hirshleifer and Sun (2020) are collected from the authors' websites. We use firms' FX hedging data based on firm-year textual mentions in 10-k filings from the Hoberg and Moon (2017) database. We also hand-collect data on analysts' currency forecasts from Bloomberg, and follow Della Corte and Krcetovs (2019) to compute monthly analysts' forecast dispersion for each currency.¹²

We develop a time-varying nation-security-month network to isolate specialized news flows. We compile a list of words that connect three arguments in our network: countries, asset classes, and relevant actions. For the first argument, we use the list of nations where U.S. firms exhibit a positive flow of sales. For the second argument, we generate a list of words related to foreign exchange rates, specific to each foreign country. We implement a similar strategy for news specific to each foreign stock market. For example, for the case of Japan we use Japan or Japanese for the first argument. For the second argument, for currency specific news we use foreign exchange, FX, currency, its official currency name (Yen) or its ISO 4217 currency code (JPY). For stock market specific news the list includes words such as Nikkei, JPX, TOPIX. For the third argument, we search for actions that indicate developments in the foreign asset class. For currencies, the list includes words such as depreciation or appreciation, and includes bearish or bullish for stock markets. We augment our list with the financial dictionary of words developed by Loughran and McDonald (2011). Our source of news comes from top newspapers where U.S. investors obtain relevant information.¹³ The

¹²At time period t and for country k , let $f_{k,t}^H, f_{k,t}^L$, be the next-quarter top and bottom forecast respectively, we compute the currency forecast dispersion as $[\ln(1 + f_{k,t}^H) - \ln(1 + f_{k,t}^L)]^{0.5}$. Using alternative definitions for forecast dispersion yield similar results.

¹³We search asset class specific news from the Wall Street Journal, New York Times, Washington Post,

sample period utilized for the construction of all variables is from 2003 to 2018, and we define them in Table 2.

[Insert Table 2 Here]

4 Foreign Operations Related Exchange Shocks

In this section, we first define the main information measure (*FOREXS*), its components, and study the performance of a long-short strategy based on *FOREXS* using portfolio quantiles. We then investigate its explanatory power in the cross-section of individual stocks.

4.1 FOREXS

We define the variables used to construct cross-sectional measures of currency shocks. The foreign exchange rate is the number of U.S. dollars that buys 1 unit of local currency. Thus, an appreciation of the foreign exchange rate indicates that more U.S. dollars are exchanged for the same amount of local currency. Foreign stock market and industry indices are originally denominated in their local currencies (e.g., the Nikkei is denominated in Japanese yens, while the FTSE is denominated in British pounds). Converting foreign market indices to U.S. dollar greatly simplifies the cross-country analysis when comparing among different economies. However, for our purposes, it can also veil the sources of information transmission to U.S. firms.

Los Angeles Times and USA Today. See for example Fang and Peress (2009) and Hillert, Jacobs and Müller (2014). We restrict our search to articles where words referring to the three arguments are within 5 words of distance. Hoberg and Moon (2017) implement a similar strategy and use a 25-word window to search for hedging related words in 10-K filings. Without a nearest neighbor algorithm restriction, the results bring news that are not specifically referring to country, currency and relevant actions. Manual inspection reveals that our reduced word window, instead of using simpler word connectors (e.g., AND, OR), significantly improves the success rate in selecting specialized news. Our combined set totals 3174 words that we apply to each country in our list.

Note that a foreign entity (firm, industry or market) that experienced a positive return in U.S. dollar terms potentially indicates that: (i) the foreign exchange rate increased in value more than any change in the foreign entity value, (ii) the foreign entity increased in value more than any change in the foreign exchange rate, (iii) the foreign exchange rate and the foreign entity increased in value. For example, the first case may indicate that the Japanese yen appreciated more than any change (positive or negative) in the Nikkei index.

Our goal is to disentangle the effects of different sources of foreign information on the value of U.S. based multinational firms. The main hypothesis of the paper is that information embedded in the cross-section of currencies generates strong return predictability for firms with sales abroad due to slow information diffusion between segmented asset classes. This specialized asset class information is different from developments in the foreign country, stock market or industry.

We define our information measure as the cross-sectional mean of currency returns, where each currency is weighted by the ratio of foreign sales to total sales. Specifically, for each firm i and period t , the foreign operations related exchange shocks (*FOREXS*) measure is the cross-sectional average of currency returns CR for each relevant foreign country k , weighted by the ratio w of foreign sales to total sales

$$FOREXS_{i,t} = \sum_{k=1}^N w_{i,k,t} CR_{k,t} \quad (1)$$

where N is the total number of countries where firm i generates foreign sales. For example, if a firm's sales ratio to the U.K. is 30% and Japan is 40%, and the British pound appreciated by 2% while the Japanese yen depreciated by 1%, then *FOREXS* equals to 0.2% ($0.3 \times 0.02 - 0.4 \times 0.01$). By construction, if the firm generates little sales outside U.S., its *FOREXS* will be close to zero.¹⁴

¹⁴In Section 4.3, we replace currency returns with their unexpected components after removing the carry and momentum effects and find that the alternative measure generates similar results.

We compute additional measures of foreign information using foreign stock market and industry returns. We also control for domestic information using market and industry returns. In all cases, the computation of the information variable follows the above equation, where we replace currency returns by its alternatives.

4.2 Portfolio Sorts

We now investigate *FOREXS*' predictive power with portfolio sorts. Our main finding is that stocks with relatively high *FOREXS* exhibit higher returns months ahead, and this information is different from alternative sources of foreign news and controls. Intuitively, a U.S. firm with operations in economies that exhibit stronger currencies will be benefited by larger future sales. However, due to frictions between two different asset classes, this information may be incorporated into stock prices with a delay.

Each month, we form quintile portfolios by sorting individual stocks based on their *FOREXS*. Quintile 5 (high) contains stocks with the highest *FOREXS* during the previous month, while quintile 1 (low) contains stocks with the lowest *FOREXS* during the previous month. The difference portfolio (High minus Low) results from holding a long position in the high *FOREXS* portfolio and a short position in the low *FOREXS* portfolio. The sample period is from December 2003 to January 2018 and the number of firms-months is 277,831.

Table 3 reports the summary statistics for portfolios 1 (low) to 5 (high) along with the high minus low portfolio. We report portfolios mean, standard deviation, skewness, kurtosis and Sharpe ratio, as well as the average *FOREXS* per quintile. From the Table, we observe portfolio returns monotonically increase between quintiles. Portfolios with higher previous-month *FOREXS* yield significantly larger average returns. The long-short portfolio strategy yields an annualized return of 6.73% and shows close to normally distributed returns, with

skewness of 0.18 and kurtosis of 3.27.¹⁵

[Insert Table 3 Here]

We investigate the possibility that return predictability generated by *FOREXS* decreases once we incorporate well established risk factors. We therefore account for the three factors of Fama and French (1993), the Carhart (1997) momentum factor, the 5 factors in Fama and French (2015), the 4 factors in Stambaugh and Yuan (2017), the 4 factors of Hou, Xue and Zhang (2014) and the 3 factors of Daniel, Hirshleifer and Sun (2020). Table 4 reports the annualized, abnormal returns (alphas) for value-weighted portfolio quintiles and the long-short strategy. The portfolios are sorted by firms' cross-sectional currency lagged information (*FOREXS*). We report in parentheses the Newey-West corrected t -statistics.

[Insert Table 4 Here]

Panel A in Table 4 reports that the long-short strategy yields significant returns, with alphas ranging from 6% to 7.9% annual, even after controlling for different risk factor models. In all seven specifications, the abnormal return of the long-short strategy exceeds the statistical significance of 3, the recently proposed threshold by Harvey, Liu, and Zhu (2016).

The loadings (betas) on portfolio quintiles are close to zero and statistically insignificant except for the loading on the market factor, where in all cases portfolio quintiles have positive loadings around one, indicating that these individual portfolios have average market risk. Moreover, the long-short strategy has neutral factor loadings with respect to all factors considered. We report these results in Table A.1.

As illustrated in Section 1 using the Brexit referendum, exchange rate shocks can have a predictable impact on firms' fundamentals, with investors underreacting to such shocks. To

¹⁵In untabulated results, we obtain similar from the strategy when we sort stocks using equal-weighted (instead of value-weighted) portfolios. We also sort stocks based on the cross section of foreign markets and industries measured in local currency returns. The strategies yield at best a quarter of *FOREXS* performance.

the extent that this fundamental information is revealed through a firm’s earnings announcement, investors assess the effects on the firm of developments in foreign economies and begin to incorporate this information into the firm’s stock price more aggressively. We therefore expect to find greater divergence of firms’ returns between those with high *FOREXS* and low *FOREXS* around the earnings announcement window. In Panels B and C of Table 4, we construct two separate quintile portfolios sorted on *FOREXS*: one using individual stocks with scheduled earnings announcements in the coming month and the other without such events. In line with our hypothesis, we find supporting evidence that the abnormal returns of the high-minus-low *FOREXS* portfolios are largely accrued through those firms in the earnings announcements window. The economic magnitude of the abnormal return in the announcement window doubles the non-announcement window, with an average abnormal return across factor models of 10.02% in the first case and 5.37% in the second case.

Abnormal returns estimated from intercepts of regressions using factor models implicitly assume that benchmark returns depend only on factor realizations and sensitivities to those. The extant literature, however, shows that firm characteristics have significant predictive power for the cross-section of stock returns potentially beyond those factor sensitivities (see for example Green, Hand, and Zhang (2017)). Therefore, we test whether the high-minus-low *FOREXS* portfolio returns are abnormal by comparing them to the realized returns of characteristics-matched benchmark portfolios.¹⁶ We consider various sets of benchmark portfolios: 25 portfolios sorted on size and book-to-market ratio (SizeBM) and 125 portfolios sorted on size, book-to-market, momentum (DGTW) as defined by Daniel, Grinblatt, Titman and Wermers (1997). We also employ Bessembinder, Cooper, and Zhang (2019)’s multivariate cross-sectional regression approach to circumvent the curse of dimensionality.¹⁷

¹⁶In order to generate a characteristics-based benchmark adjusted return for each firm-month, we take the difference between an individual firm’s return and a characteristic-matched portfolio’s return. We then calculate abnormal portfolio returns as value-weighted average of individual firms’ characteristics-based benchmark adjusted returns in each *FOREXS* quintile.

¹⁷Specifically, we use both of 5-characteristics and 14-characteristics models in the paper (denoted as BCZ_{C5} and BCZ_{C14} respectively), and augment C14 model with foreign-to-total-sales ratio (BCZ_{C15}) since

In Table 4, Panel D shows that the characteristics-adjusted returns of the high-minus-low *FOREXS* portfolio are still statistically significant and economically comparable to those using factor-sensitivity-based alphas.

Is *FOREXS* return effect a consequence of investors' overreaction to currency information? If so, we can expect a reversal of the return performance at longer horizons. To answer this, in Figure 2 we plot the cumulative returns of the portfolio strategy over horizons longer than 1-month. The return in $n = 1$ corresponds to a monthly portfolio return of 0.56%, with its annual counterpart reported in Table 3. The cumulative returns increase monotonically, 12-months after portfolio formation the return climbs to 1.50%. We find no reversal in cumulative returns, suggesting that *FOREXS* captures delays in information transmission that is fundamental to determine firms' future values. We therefore cannot attribute the performance of *FOREXS* to investors' overreaction to currency information, and instead confirm that investors access and process information with delay.

[Insert Figure 2 Here]

A potential caveat for the *FOREXS* strategy comes from U.S. firms dealing with countries with historically large currency oscillations. U.S. firms with stronger ties to these countries may be the ones always included in the long or short legs of the strategy, and thus the composition of the quintile portfolios does not change over time.

To investigate this argument, in Figure 3 we plot the portfolios' persistence score. At the beginning of every calendar month, we rank firms in ascending order by their *FOREXS* in the previous month. The ranked stocks are assigned to one of the quintile portfolios. After n months (with $n = 1, 2, \dots, 6$) from the portfolio formation period, we keep track of all the constituents of portfolio k (with $k = 1, 2, \dots, 5$) and assign a score to each of the stocks based on their new membership out of 5 portfolios.

the high *FOREXS* portfolio return could primarily reflect compensation for priced offshoring risk.

[Insert Figure 3 Here]

In Figure 3, each line is the average score of firms in portfolio k at the initial formation period. Interestingly, we find that stocks switch from portfolio quintiles with relative high frequency, suggesting that the strategy is not composed of the same set of firms over time. It provides evidence that the long-short portfolio is not systematically related to (persistent) firm-risk characteristics which may be positively correlated with *FOREXS*.

4.3 Cross Sectional Regressions

Does *FOREXS* capture information from foreign economies that is relevant for individual U.S. firms? Perhaps U.S. firms do exhibit exposure to foreign economies, but the distinction between foreign country, stock market, industry and currency is trivial. To answer this question we implement cross-sectional Fama-Macbeth (1973) monthly, predictive regressions

$$R_{i,t+1} = \lambda_{1,t} + \lambda_{2,t}FOREXS_{i,t} + \lambda_{3,t}X_{i,t} + \varepsilon_{i,t+1} \quad (2)$$

where the dependent variable $R_{i,t+1}$ is the realized return on firm i in month $t+1$, $FOREXS_{i,t}$ is the cross-sectional currency lagged information measure of firm i in month t , and $X_{i,t}$ is a set of firm-specific control variables observed in month t . Specifically, we control for firm's size (log of market cap.) and the following sales-weighted variables: foreign market return, domestic market return, foreign industry return and domestic industry return. Industry variables are adjusted from market variables, and foreign variables are denominated in local currency units. All explanatory variables are one-period lagged except contemporaneous (ctmp.) controls.

Table 5 reports the time series averages for the slope coefficients using monthly observations. The sample period is from December 2003 to January 2018. Column 1 reports the

regression on *FOREXS* after controlling for firm size, and indicates a positive and statistically significant relation between *FOREXS* and the cross-section of future stock returns. The average slope from the monthly regressions of realized returns on *FOREXS* is 0.42 with a Newey-West t -statistic of 3.80.

[Insert Table 5 Here]

In specification 2, we include cross-sectional lagged information about the foreign and domestic stock market. Both measures are insignificant, whereas *FOREXS* remain positively (0.64) and statistically ($t = 4.22$) significant to future stock returns. We obtain similar results with specification 3, which further includes lagged information about foreign and domestic industries (orthogonalized to stock market returns).

Burt and Hrdlicka (2020) argue that cross-firm predictability among economically linked firms can arise when both firms, leaders and laggards, exhibit own-momentum and their returns are contemporaneously correlated. As the firm's *FOREXS* is contemporaneously correlated with the focal firm's return, the predictability can give rise to a mechanical reason. In column 4, we therefore augment the regression with the contemporaneous version of *FOREXS* and find that our main predictor, lagged *FOREXS*, remains economically and statistically significant. We also include the contemporaneous version of *Foreign Market*, which shows a significant positive effect on returns, while *Foreign Market*'s lagged version shows an insignificant effect, supporting our hypothesis that equity investors underreact to information in the currency market. In column 5, we control for contemporaneous foreign and domestic economy measures and obtain similar results.¹⁸ In sum, firms with higher *FOREXS* exhibit higher future returns.¹⁹ To interpret the economic significance of *FOREXS*, note that

¹⁸The foreign economy measure is computed as the sum of the (sales-weighted average of) foreign currency, foreign market, and foreign industry returns. The domestic economy measure is computed in a similar fashion.

¹⁹When we contrast our *FOREXS* measure based on currency returns with an alternative based on currency volatility, the latter renders non-significant and suggests that *FOREXS* directional nature is critical to determine firms' future returns. Table A.2 reports these results.

its coefficient of 0.42 in column 1 indicates that a one-standard deviation increase in *FOREXS* is associated with an average increase in firm return of 23 basis points per month.

What would be the change in next-month average return for a stock that moves from portfolio 1 to 5? Using the average values of *FOREXS* in the quintile portfolios of Table 3, we can further determine the economic significance of the average slope coefficient of 0.42 in column 1 of Table 5. Table 3 reports that the difference between the *FOREXS* measure in the top and bottom quintile is 1.26%. This implies that the increase in expected return for a stock moving from portfolio 1 to 5 amounts to 0.53% per month ($1.26\% \times 0.42$).

Next, we examine if a firm's relative presence in the foreign country is irrelevant when analyzing its cross sectional exposure to currencies. Specifically, we test if the weight (foreign sales to total sales) of a firm matters for the construction of *FOREXS*. For each firm, instead of using its actual foreign sales ratio for the construction of the information measure, we assign equal weights to each country where the company reports foreign sales. In Table 5, column 6 replicates column 5 but using an equally-weighted version of *FOREXS*, labeled \overline{FOREXS} . Column 7 includes both *FOREXS* and \overline{FOREXS} . In both cases, columns 6 and 7 show that \overline{FOREXS} coefficients render insignificant, suggesting that the relative foreign presence of a multinational does matter when constructing *FOREXS*. Alternatively, we can fix currency rates (instead of foreign sales) to construct \overline{FOREXS} . Column 8 controls for this measure, labeled Foreign Sales Ratio, which follows Amihud, Bartov and Wang (2014) methodology to investigate firms' exposure to systematic foreign trade risk. *FOREXS* continue to exhibit strong statistical and economic significance. These results reinforce our hypothesis that the predictive power of *FOREXS* comes from both of its components, currency rates and foreign sales.

We further investigate whether the predictability of *FOREXS* is contaminated by the inclusion of other variables previously known to predict returns. As additional control variables, we first include the one-month lagged return of firm i to account for a possible short-

term reversal effect, its return between $t - 12$ and $t - 2$ to control for the momentum effect, and the book-to-market ratio to control for the value effect. Second, we rely on Ang, Hodrick, Xing, and Zhang (2006) and estimate the monthly idiosyncratic volatility as the standard deviation of the daily residuals from the regression of daily excess stock returns on the three factors of Fama and French (1993) over the past one month. Overall, column 8 in Table 5 reports that those additional controls do not affect the magnitude and significance of the *FOREXS* predictability.

The predictive power of *FOREXS* supports our hypothesis that shocks to relevant currencies are incorporated with a delay into firm values. We further study this finding and compute *FOREXS* using only its unexpected component by removing the expected returns (or currency risk premiums) from the realized currency returns. Following Lustig and Verdelhan (2007), we define the unexpected component of currency returns as the residual after removing its carry and momentum components.²⁰ Carry and momentum have shown to contain important predictive power for the cross-section of several asset classes (Asness, Moskowitz and Pedersen (2013); Kojien, Moskowitz, Pedersen and Vrugt (2018)). In addition, to the extent that the Fisher effect holds, we remove potential effects of changes in inflation expectations between the domestic and foreign countries by including interest rate differentials. Table A.3 reports that $FOREXS_{Resid}$ is statistically significant and has predictability on future stock returns economically as strong as *FOREXS*, which confirms our prior that investors react with a delay to unexpected currency shocks.

As an alternative way to capture foreign exposure, we compute $FOREXS_{\beta}$ by replacing a firm’s foreign sales ratio with its return beta on that currency. In other words, we measure the firm’s foreign exposure using its return sensitivity to recent exchange rate fluctuations.

²⁰Specifically, we implement the following cross-sectional predictive regression: $CR_{k,t+1} = E_t[CR_{k,t+1}] + \epsilon_{k,t+1} = \beta_{1,t} + \beta_{2,t}Carry_{k,t} + \beta_{3,t}Momentum_{k,t} + \epsilon_{k,t+1}$. We measure carry as 1-month interest rate differential between a foreign country k and the U.S. (proxied by 1-month forward discount) and momentum as the past 12-month currency return. See also Burt and Hrdlicka (2020) and Menkhoff, Sarno, Schmelling and Schrimpf (2012).

Table A.4 in the Appendix reports that $FOREXS_\beta$ does not significantly predict stock returns in the cross-section. The result implies that betas are estimated with errors and are not as robust as foreign sales ratios in capturing a firm’s exposure to currency shocks.²¹

4.4 Decomposing Foreign Information

The results from Table 5 indicate that different sources of foreign information require different processing times and capabilities by U.S. investors. Distinguishing between these sources can provide significant results and further avoid potentially confounding effects when using broader information measures. As discussed, a positive change in a foreign stock market that has been previously converted to U.S. dollars may imply a positive month for the foreign stock market denominated in local currency units, an appreciation of the foreign currency, or any combination such that the overall change is positive.

Huang (2015) and Nguyen (2016) document that investors of U.S. multinational firms underreact to foreign information, measured using dollar return of foreign market or industry returns. When we decompose these dollarized returns into their original, local currency returns and their foreign exchange returns in Table 5, only the latter remains with strong predictive power.²² In other words, investors seem to underreact mostly to information contained in foreign exchange rates, while information on foreign markets or industries is readily incorporated into firms’ values.

To understand the sources of $FOREXS$ ’ predictability more clearly, we use the contemporaneous version of equation (2) and decompose the return of the individual firm into

²¹Currency return beta can be also largely driven by salient factors (such as commodity prices and macroeconomic states) that affect both stock and currency returns. Therefore, its firm-specific effect can be significantly diluted and information related to these salient factors is processed immediately, which results in no return predictability.

²²Tables A.5 and A.6 in the Appendix confirm the findings of Huang (2015) and Nguyen (2016) in our sample. The results also confirm that return predictability mostly comes from $FOREXS$, rather than foreign equity returns measured in local currencies.

sub-components: the information from the foreign currency return (*FOREXS*) and its industry information counterparts. The foreign (domestic) industry measure is the cross-sectional average of foreign (domestic) industry return, weighted by the ratio of foreign (domestic) sales to total sales. We complete equation (2) with its residual, the firm-specific component.

Following the methodology in Chen, Da and Zhao (2013), we first compute the proportion of the individual firm’s contemporaneous variance explained by those sub-components. We find that 6%, 2.5%, 11%, and 80.5% of the total variance are explained by *FOREXS*, foreign industry, domestic industry and firm specific return, respectively.²³ We then ask which of the four components of the individual firm return is *FOREXS* predicting. We present the predictive regression results in Table 6. In this table, as in Table 5, we run the Fama-MacBeth cross-sectional regression. However, instead of using a firms’ return as the dependent variable, we use each of its four components.

[Insert Table 6 Here]

We find that the lagged *FOREXS* predicts neither foreign nor domestic industry return. This evidence suggests that *FOREXS*’s predictability of individual firms’ returns is not mainly originated from its economic implication on the future stock market or industry condition in the foreign countries to which the firms is exposed. Contrary to that, the coefficient on the firm-specific component is positive and statistically significant ($t = 2.3$), implying that *FOREXS* predictability is closely associated with its relation to firm specific fundamentals. Its positive predictability on the firm-specific fundamentals can be interpreted as follows. First, an appreciation of the currency of a foreign country elevates the purchasing power of consumers in that foreign country. Second, even with the same quantity of expected sales to the foreign country, every earnings or cash flows harvested in foreign currency unit would

²³Note that *FOREXS* and Foreign Industry are two constituents of the Foreign Industry return denominated in U.S. dollars. From the same variance decomposition analysis performed on Foreign Industry (in U.S. dollars), we find that about 40% (60%) of the return variation is explained by *FOREXS* (Foreign Industry returns).

be translated into higher dollar earnings for the U.S. firm. Note that the marginal benefits from an appreciation of the foreign currency would only be transferred to the firms which have a considerable sales-exposure to the country. This further highlights the importance of the foreign sales weights in the construction of our *FOREXS* information measure.

4.5 The Real Impact of FOREXS

Sections 4.2 and 4.3 explore the predictive power of *FOREXS* regarding equity portfolios and individual stock prices. Given that firms' fair values are determined by discounting their future cash flows, we next study if the cross-section of currency rates contains information relevant for firms' future operational performance. Because in this exercise the dependent variable is an accounting measure, we investigate the real effects of *FOREXS* within a panel data framework (Petersen (2009)). Therefore, instead of firms' returns, the dependent variables are firms' quarterly sales growth, quarterly changes in return on assets and the quarterly earnings surprise (SUE).²⁴ Control variables include firms' size (log of market cap.), stock returns, book to market, investment ratio, profitability (Novy-Marx (2013)), R&D expenditure and Altman's z-score. In Table 7, we report the panel regression coefficients, with *t*-statistics controlling for the firm-fixed effect and clustering standard errors at the firm level.

[Insert Table 7 Here]

We find that *FOREXS* exhibits strong predictability in firms' future operational performance. In column 1, firms with larger *FOREXS* generate larger growth of sales in the following quarter. The loading on *FOREXS* is 0.37 ($t=16.2$), indicating that a one-standard deviation change in *FOREXS* results in a 1.24% increase in the quarterly growth rate of

²⁴We define SUE as actual earnings minus expected earnings from IBES analyst forecasts, normalized by the standard deviation of those analysts forecasts.

sales. We obtain similar results using firms' return on assets as the dependent variable. In column 2, the coefficient of *FOREXS* equals 0.01 and is statistically significant ($t=4.19$). These results are consistent with return predictability coming from investors' limited attention to the cash-flow implication of *FOREXS*. Furthermore, the significant predictability of *FOREXS* on SUE in column 3 implies that analysts also suffer the lack of sufficient attention to the value relevant information regarding the firms' foreign operations, revealed through the actual earnings announcement.

Note that, in addition to *FOREXS*, the Foreign Market variable also loads significantly. This implies that not only *FOREXS* predict real effects for the U.S. firms, but also foreign stock markets contain important information regarding future cash-flows of firms, such as the demand condition of foreign economies. However, investors seem to readily incorporate it into stock prices, which ultimately leads to weak predictability in returns after controlling for *FOREXS*' effect.

Overall, Section 4 shows that not all information about foreign markets is alike, supporting our prior that information specific to the cross-section of currency rates is incorporated with significant delay into U.S. firms with foreign operations. In Section 5, we investigate the mechanisms underlying this delay.

5 The Channels

The previous section suggests that investors incorporate information about the cross-section of currency returns with a delay, and that *FOREXS* predicts future cash flows and returns of U.S. firms. In this section, we examine the sources of the predictability and conjecture that the significance of *FOREXS* is driven by two conditions. First, U.S. firms should be fundamentally exposed to the cross-section of relevant currency rates. Second, U.S. investors should exhibit limitations in processing relevant currency information in a timely manner.

5.1 Incomplete Hedging

To the extent that currency fluctuation imposes a risk to U.S. multinational firms, one would expect firms to offset such a risk via either financial hedging (through the FX derivatives market) or operational hedging (via the purchase of foreign inputs in the country where they operate). Earlier empirical evidence on the effects of these types of hedging on multinationals is varied (e.g., see Allayanis, Ihrig and Weston (2001), Bartram, Brown and Conrad (2011) and de Jong, Ligterink, and Macrae (2006)). Intuitively, if U.S. firms do a good job with hedging, currency shocks should not affect their equity valuation and *FOREXS* should not predict future stock returns. We therefore expect the return predictive power of *FOREXS* to increase as the degree of hedging decreases.

We empirically study the impact of hedging on multinationals' returns using cross-sectional regressions that interact *FOREXS* with a categorical variable related to hedging. We report the results in Table 8.

[Insert Table 8 Here]

First, we investigate the importance of financial hedging. Using data from the derivatives markets, a recent literature studies the importance of financial insurance against oscillations in asset prices (see for example Carr and Wu (2016) and Della Corte, Ramadorai and Sarno (2016)). Our prior is that the return effect of *FOREXS* is specially stronger when we observe a higher cost of financial hedging through derivatives.

The insurance cost for currency volatility is estimated as the difference between the option implied volatility and the realized volatility of FX returns. For each firm, we construct a categorical variable (*ICV*) that equals 1 if the sales-weighted average of the insurance cost for currency volatility is above the median across firms and equals 0 otherwise. In Table 8, column 1 reports that the interaction term $FOREXS \times ICV$ exhibits a positive loading

of 0.4 with t -statistic of 2.11.²⁵ This result supports the hypothesis that as the cost of FX volatility insurance increases, firms are less inclined to hedge, and thereby the return effect of *FOREXS* increases. We also analyze the impact of financial hedging on firms returns by looking into the company’s 10K reports. We follow Hoberg and Moon (2017) and extract the firm’s mentions of currency derivatives. We construct the firm-level categorical variable (*CDM*) that equals 1 if the firm reports above median mentions of currency derivatives across firms and 0 otherwise. Column 2 reports the regression results using this textual measure, with the interaction term *FOREXS* \times *CDM* reporting the negative sign (-0.30) and statistical significance ($t=-2.09$). This evidence suggests that *FOREXS* return effect to be stronger in firms with relatively fewer mentions of financial derivatives.

Next, we examine the importance of operational hedging. Note that columns 1 and 2 show that the return predictability of *FOREXS* increases with FX volatility insurance cost and fewer mentions of FX derivatives in the firm’s 10K reports. This entails trading in the currency derivatives market, but some firms may be reluctant to participate in these markets. This observation motivates us to question whether U.S. firms would try to hedge FX volatility through alternative ways. For many multinationals, this hedge can be operational instead of financial. Thus, we study whether *FOREXS* return effect is related to firms’ varying degrees of operational hedging. We measure operational hedging using the number of mentions about input in firms’ financial statements (Hoberg and Moon (2017)). The operational hedging indicators (*OHIN* and *OHIN**) are computed based on the firm’s mentions of purchasing inputs in the foreign nation, provided that the firm also mentions (IN) or does not mention (*IN**) owning assets in the foreign nation.

Our conjecture is that *FOREXS* return effect is more pronounced for firms with less operational hedging. In column 3, we find that the interaction term is negative (-0.42) and significant ($t=-2.00$), while column 4 reports even larger magnitude and significance for

²⁵In all columns, the categorical dummy variable along with the control variables are also included in the regression but unreported for brevity.

the interaction term (-0.79 and $t=-2.37$). Interestingly, while in both cases the coefficients are with expected negative sign, the magnitude of the interaction $OHIN^*$ almost doubles that of $OHIN$. This result is consistent with Hoberg and Moon (2017), who find that the counter-cyclical benefits of purchase of input are weakened when operational hedging is simultaneously involved with ownership of foreign assets since offshore asset values are pro-cyclical to foreign economic conditions.

Lastly, we study the sensitivity of cash flows to exchange rates in the spirit of Adler and Dumas (1984) in order to capture total residual exposure after accounting for any other forms of hedging in place. For example, Bartram, Brown, and Fehle (2009) and Bartram, Brown and Minton (2010) find that FX exposure can be mitigated, especially for firms domiciled outside the U.S., through the use of foreign currency debt. In the case of U.S. firms, Francis, Hasan, and Hunter (2008) find that they have fewer natural hedges (e.g., foreign currency liabilities) than firms based in foreign countries since U.S. based corporations issue a small proportion of their debt in non-U.S. dollar denominated currencies.²⁶ Firms' cash-flow sensitivity to currency rates would give an indication of the total residual exposure, after all the hedging is accounted for, including operational hedges. Since fundamentals of firms with high sensitivities are vulnerable to movements in their respective exchange rates, we expect *FOREXS*'s return predictability to be more pronounced for those firms. To empirically measure the cash-flow sensitivity, we use the firm's quarterly operating income before depreciation and amortization (OIBDPQ) year-over-year percentage change to proxy for its free cash flow growth. For each firm at each point in time, we estimate its regression coefficient of percentage changes in OIBDPQ on *FOREXS* using a rolling window of 32 quarters. We then construct the firm-level categorical variable (*CFS*) that equals 1 if the firm cash-flow sensitivity is above the median across firms and 0 otherwise. Column 5 reports the coefficient of the interaction term is 0.71 ($t=2.13$), indicating that return predictability

²⁶The Bank for International Settlements reports that non-financial U.S. firms' debt issued in U.S. dollars was 90.7% in 2020 (<https://stats.bis.org/statx/srs/table/c1?f=pdf>).

increases for firms in which their cash-flow growth exhibits high exposure to *FOREXS*.

Taken together, these results show that the magnitude of *FOREXS* return effect changes according to firms' hedging alternatives. Return predictability increases with decreasing degrees of financial and operational hedging, as well as with increasing cash-flow exposure to *FOREXS*.

5.2 Limited Attention And Information Complexity

Limitations in information processing capabilities and attention by investors may also give rise to slow diffusion of information related to *FOREXS*. To the extent that the foreign exchange market and the stock market might be segmented due to capital immobility, limits of arbitrage, and delegated portfolio management (e.g., Acharya, Lochstoer and Ramadorai (2013) and Greenwood, Hanson, and Liao (2018)), equity investors may not allocate sufficient attention to the the development (and implications) of currency shocks or have limited resources to collect, interpret and trade based on the information. Such limitations generate an initial underreaction to *FOREXS*. Under this channel, we would expect the return predictive power associated with *FOREXS* to strengthen when investors' limited attention and information processing capacity are more likely to be binding.

We begin by studying how investors react to currency risks disclosed by firms in their annual reports. This allows us to determine whether the firm acknowledges potential risks of currency fluctuations in its overall performance, regardless of whether the company decides to hedge these risks or not.²⁷ We therefore construct a firm-level indicator variable (10K1A) that equals 1 if a given firm mentions the words “currency”, “foreign exchange” or “FX” in the Risk Factors section (Section 1A) of the 10-K report.²⁸ The textual data is downloaded

²⁷We thank Quoc Nguyen for bringing examples of such currency risk disclosure to our attention.

²⁸Cohen, Malloy and Nguyen (2020) discuss on the importance of the Risk Factors section of the annual report to predict future returns.

from the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR). Ex-ante, the impact of the 10K1A dummy is not clear. On one hand, positive 10K1A dummies likely identify firms more exposed to extreme *FOREXS* in the future and we therefore expect *FOREXS* predictability to increase among these firms. On the other hand, currency risk disclosure prompts investor to pay attention to future *FOREXS*, we should then expect *FOREXS* predictability to decrease.

In Table 9, column 1 reports on the predictive power of *FOREXS* along with the interaction term $FOREXS \times 10K1A$, whose coefficient has a negative sign and is statistically significant ($t=-2.28$). The result suggests that after controlling for the magnitude of *FOREXS*, the attention effect dominates. Currency risk disclosure generates investor attention, and this allows investors to better process the information embedded in *FOREXS*, ultimately reducing its return predictive power.

[Insert Table 9 Here]

Press coverage facilitates investor attention. We therefore hypothesize that more press coverage specifically related to foreign exchange rates should weaken the return predictability indicated by *FOREXS*. In contrast, the relative scarcity of specialized information significantly impact on investors' processing capabilities. We further argue that the abnormal news channel is specific to foreign exchange rates, and unrelated to foreign markets or industries.

To test this hypothesis, we collect foreign news, specific to foreign exchange rates, from articles published in the Wall Street Journal, New York Times, Los Angeles Times, Washington Post and USA Today. We compute the foreign-currency specific abnormal news measure as the spread of the last month's foreign-currency specific news count over its previous 12-month average, adjusted by its 12-month standard deviation. We construct an indicator variable (*ANFX*) that equals 1 if the sales-weighted average of the abnormal currency news measure is above the median across firms and equals 0 otherwise. The main explanatory

variables are *FOREXS* and the news interaction variable $FOREXS \times ANFX$. To distinguish foreign information between asset classes, we repeat the procedure using foreign stock market specific news (*ANFM*). We present the predictive regression results in Table 9.

Column 2 reports the coefficients from the cross-sectional, predictive regression with independent variables *FOREXS* and the interaction term $FOREXS \times ANFX$ along with control variables. The interaction term exhibits the expected sign and significance, $FOREXS \times ANFX$ coefficient equals -0.48 with a Newey-West corrected t -statistic of -2.42. This implies that in times when news coverage is below the recent news trend, investors have relatively less access to information about future changes in currency values, and thus the return predictability of *FOREXS* is more pronounced. Interestingly, note that when we repeat the analysis but instead focus on news specific to foreign stock markets (column 3), the interaction term $FOREXS \times ANFM$ is not significant ($t = -0.76$).

These results indicate that not any foreign information is alike for U.S. investors. Distinguishing between the types of foreign specialized news does matter for the return predictability of individual stocks. Changes in specialized currency news flows carry a differential effect for the return effect of *FOREXS*, consistent with the role of limited investor attention.

The impact of limitations in accessing and processing relevant information on future asset prices should also weaken when more investors are attentive. In the case of *FOREXS*, when more equity investors are paying attention to currency news, *FOREXS*'s return predictive power should be reduced. We expect foreign equity investors and sophisticated investors such as hedge funds to have higher processing capacity dedicated to the currency market. Therefore, U.S. multinational firms with more foreign ownership or hedge fund ownership are less likely to suffer from underreaction to *FOREXS*.

The results from Table 9 confirm our priors. In column 4, we observe that the interaction term *FOREXS* with hedge fund ownership is statistically significant ($t = -2.28$) and with

expected negative sign (-0.41). Likewise, interacting *FOREXS* with foreign institutional ownership in column 5 yields similar conclusions in terms of sign and significance. The two specifications imply that the overall magnitude of the return effect induced by *FOREXS* decreases between 69% and 74% for U.S. firms largely held by hedge funds or foreign institutional investors.

Using the broader definition of all institutional ownership (column 6), the interaction term $FOREXS \times IO$ is not significant.²⁹ Investors' limitations matter for the speed of information diffusion through firms' foreign operations. However, due to the complex nature of information, not all market participants' attention exhibit similar effects on *FOREXS* predictability. Attention from those who are more likely understand and better process foreign information seems to significantly impact on *FOREXS* return effect, as columns 4 and 5 suggest. In all, columns 4 to 6 suggest that efficient processing of *FOREXS* requires specialized resources to the currency market.

Finally, the degree of limited attention and complexity of processing information should vary based on the nature of the currency portfolio to which the firm is exposed. We conjecture that *FOREXS* does not require too much attention to process if the currency portfolio contains only one or two currencies, or is concentrated in a few currencies, or contains currencies that are highly correlated with each other. Columns 7 to 9 in Table 9 tests these conjectures.

We construct the Herfindahl index using firms' foreign sales ratios. Firms with high index levels indicate that their foreign operations are concentrated in a smaller group of nations. For investors, this implies allocating resources to a smaller currency set, which makes the processing of information relatively easier. We therefore expect that as the Herfindahl index increases, the return effect of *FOREXS* is less pronounced. In column 7, we confirm our hypothesis. The interaction term is with the expected sign (-0.49) and statistically significant

²⁹We orthogonalize ownership variables to firms' size in all specifications.

($t = -1.97$). Likewise, in column 8 we find *FOREXS*' return effect to be stronger if its construction involves more countries and is consistent with Fraser and Pantzalis (2004), who find a similar result using the number of subsidiaries for a subset of 310 firms.

In column 9, we examine whether the results are stronger or weaker among firms whose currency set is not highly correlated. Each month, we compute the firm's cross sectional standard deviation of its currency set involved.³⁰ Higher standard deviation means that the set of currency shocks are not highly correlated among themselves, thus requires more investor attention to process and leads to stronger return predictability when resources are limited. On the other hand, uncorrelated currency shocks result in diversification, hence a smaller *FOREXS* and potentially weaker return predictability. Empirically, we find return predictability to increase as the cross-sectional standard deviation across currencies increases. In column 9 we find the interacting term to be positive (0.45) and statistically significant ($t = 2.39$), further supporting the channel of investors' limited resources (in terms of time and labor needed).

If exchange rates are relatively stable, investors should have less difficulty in processing related information, even if they suffer from limited attention. In contrast, larger oscillations in the value of the currency lead to a more complicated assessment by investors of the future value of the currency, and make limited attention more costly. We therefore hypothesize that the predictability of *FOREXS* should be stronger if there is large uncertainty or disagreement in the future direction of the currency movements among financial analysts in the market.

To test this channel, we use a specification similar to the cross-sectional regression of Section 4.3, but decompose *FOREXS* into $FOREXS^H$ and $FOREXS^L$. $FOREXS^H$ comprises the set of economies where previous month currency volatility is above median across currencies. $FOREXS^L$ comprises the set of economies where previous month currency

³⁰Each month t , the *FOREXS* measure of firm i is comprised of k currencies. We thus compute the cross sectional standard deviation of k currencies for firm i in month t .

volatility is below median across currencies. Likewise, we repeat *FOREXS* decomposition but replace historical volatility with the dispersion of analysts forecasts about the future value of each currency, which represents a forward-looking measure of currency uncertainty. We test our prediction that return predictability increases with volatile currencies and report cross-sectional regression results in Table 10.

[Insert Table 10 Here]

Columns 1 to 3 decompose *FOREXS* into $FOREXS^H$ and $FOREXS^L$ based on the cross-section of currency volatilities. Columns 2 and 3 augment column 1 by adding contemporaneous *FOREXS* and foreign and domestic economy variables. Consistent with our priors, $FOREXS^H$ coefficient is positive and statistically significant. As uncertainty about the cross-section of FX volatility increases, so does the return predictability of *FOREXS* because investors face more complicated tasks in determining the expected direction of the currency. We obtain similar conclusions in columns 4 to 6 by implementing the decomposition based on currency forecast dispersions. For example, column 6 reports a $FOREXS^H$ coefficient equal to 1.33 ($t=3.22$) while $FOREXS^L$ is not statistically different than zero. These results are consistent with the hypothesis that in times of higher uncertainty about future currency values, investors deal with more complicated information to process and thus firm values react with a lag.

Overall, results in this section are consistent with the idea that investors do allocate time and effort in processing information specific to currency rates. However, it is firms' incomplete hedging and investors' limitations in accessing and processing information what generates a delayed reaction from cross-sectional currency shocks to individual firms' values.

6 Conclusion

We investigate on the importance of the transmission of foreign information into the value of U.S. firms with foreign operations. By decomposing the information contained in foreign stock prices into foreign market prices, industry specific prices and exchange rates, we demonstrate that the latter slowly diffuses into firms' values.

We compute a firm's foreign operations related exchange shocks (*FOREXS*) using the previous month cross-sectional currency mean return, weighted by the relative sales of the firm in the foreign economies. We show that stocks with high *FOREXS* exhibit higher future returns than stocks with low *FOREXS*. Buying stocks with high *FOREXS* while shorting stocks with low *FOREXS* generates a 6.74% annualized abnormal return, which is statistically significant after controlling for a battery of risk factors and characteristics.

We find *FOREXS*'s predictive power to arise from firms' limitations (in terms of risk-management) and investors' limitations (in terms of accessing and processing information). Our results thus highlight the important role of investor attention in facilitating information transmission across asset classes.

References

- [1] Acharya, Viral, Lochstoer, Lars, and Tarun Ramadorai. 2013. Limits to arbitrage and hedging: Evidence from commodity markets. *Journal of Financial Economics*, 109, 441-465.
- [2] Addoum, Jawad and Justin Murfin. 2020. Equity Price Discovery with Informed Private Debt. *Review of Financial Studies*, 33, 3766-3803.
- [3] Adler, Michael, and Bernard Dumas. 1984. Exposure to Currency Risk: Definition and Measurement. *Financial Management*, 13, 41-50.
- [4] Ahern, Kenneth, and Denis Sosyura. 2015. Rumor Has It: Sensationalism in Financial Media. *Review of Financial Studies*, 28, 7, 2050-2093.
- [5] Akbas, Ferhat, Markov, Subasi, Musa, and Eric Weisbrod. 2018. Determinants and consequences of information processing delay: Evidence from the Thomson Reuters Institutional Brokers' Estimate System. *Journal of Financial Economics*, 127, 366-388.
- [6] Albuquerque, Rui, Ramadorai, Tarun, and Sumudu Watugala. 2015. Trade credit and cross-country predictable firm returns. *Journal of Financial Economics*, 115, 592-613.
- [7] Allayannis, George, and Jane Ihrig. 2001. Exposure and Markups. *Review of Financial Studies*, 14, 805-835
- [8] Allayannis, George, Ihrig, Jane, and James Weston. 2001. Exchange rate hedging: Financial versus operational strategies. *American Economic Review*, 91, 2, 391-395.
- [9] Amihud, Yakov, Bartov, Eli, and Baolian Wang. 2014. The pricing of corporate foreign trade risk. Working Paper.
- [10] Andrei Daniel, and Michael Hasler. 2015. Investor Attention and Stock Market Volatility. *Review of Financial Studies*, 28, 1, 33-72.
- [11] Ang, Andrew, Hodrick, Robert, Xing, Yuhang, and Xiaoyan Zhang. 2006. The cross section of volatility and expected returns. *Journal of Finance*, 61, 1, 259-299.
- [12] Asness, Clifford, Moskowitz, Tobias, and Lasse Pedersen. 2013. Value and Momentum Everywhere. *Journal of Finance*, 68, 3, 929-985.
- [13] Auh, Jun Kyung, and Jennie Bai. 2020. Cross-Asset Information Synergy in Mutual Fund Families. Working Paper.
- [14] Bae, Joon Woo, Elkamhi, Redouane, and Mikhail Simutin. 2019. The Best of Both Worlds: Accessing Emerging Economies via Developed Markets. *Journal of Finance*, 74, 2579-2617.
- [15] Bai, John, Garg, Priya and Chi Wan. 2020. Offshore sales networks and stock return predictability. Working Paper.

- [16] Bali, Turan, Brown, Stephen, and Yi Tang. 2017. Is economic uncertainty priced in the cross-section of stock returns? *Journal of Financial Economics*, 126, 471-489.
- [17] Barrot, Jean-Noel, Loualiche, Erik, and Julien Sauvagnat. 2019. The Globalization Risk Premium. *Journal of Finance*, 74, 5, 2391-2439.
- [18] Barras, Laurent and Aytok Malkhozov. 2016. Does variance risk have two prices? Evidence from the equity and option markets. *Journal of Financial Economics*, 121, 79-92.
- [19] Bartram, Söhnke, Brown, Gregory, and Jennifer Conrad. 2011. The Effects of Derivatives on Firm Risk and Value. *Journal of Financial and Quantitative Analysis*, 46, 4, 967-999.
- [20] Bartram, Söhnke, Brown, Gregory, and Frank Fehle. 2009. International Evidence on Financial Derivatives Usage. *Financial Management*, 185-206.
- [21] Bartram, Söhnke, Brown, Gregory, and Bernardette Minton. 2010. Resolving the exposure puzzle: The many facets of exchange rate exposure. *Journal of Financial Economics*, 95, 148-173.
- [22] Bartov, Eli and Gordon Bodnar. 1994. Firm Valuation, Earnings Expectations, and the Exchange-Rate Exposure Effect. *Journal of Finance*, 49, 5, 1755-1785.
- [23] Bessembinder, Hendrik and Cooper, Michael, and Feng Zhang. 2019. Characteristic-Based Benchmark Returns and Corporate Events. *Review of Financial Studies*, 32, 75-125.
- [24] Bodnar, Gordon, Dumas, Bernard and Richard Marston. 2002. Pass-through and exposure. *Journal of Finance*, 57, 199-231.
- [25] Burt, Aaron, and Christopher Hrdlicka. 2020. Where Does the Predictability from Sorting on Returns of Economically Linked Firms Come From? *Journal of Financial and Quantitative Analysis*, 1-25.
- [26] Carhart, Mark. 1997. On persistence in mutual fund performance. *Journal of Finance*, 52, 57-82.
- [27] Carr, Peter and Liuren Wu. 2016. Analyzing volatility risk and risk premium in option contracts: A new theory. *Journal of Financial Economics*, 120, 1-20.
- [28] Chen, Long, Da, Zhi, and Xinlei Zhao. 2013. What Drives Stock Price Movements? *Review of Financial Studies*, 26, 4, 841-876.
- [29] Choi, Jaewon, and Yongjun Kim. 2018. Anomalies and market (dis)integration. *Journal of Monetary Economics*, 100, 16-34.
- [30] Chordia, Tarun, Goyal, Amit, Nozawa, Yoshio, Subrahmanyam, Avanidhar and Qing Tong. 2017. Are Capital Market Anomalies Common to Equity and Corporate Bond Markets? *Journal of Financial and Quantitative Analysis*, 52, 1301-1342.

- [31] Cohen, Lauren, and Andrea Frazzini. 2008. Economic links and predictable returns. *Journal of Finance*, 63, 1977-2011.
- [32] Cohen, Lauren, Gurun, Umit, and Christopher Malloy. 2017. Resident Networks and Corporate Connections: Evidence from World War II Internment Camps. *Journal of Finance*, 72, 1, 207-248.
- [33] Cohen, Lauren, and Dong Lou. 2012. Complicated firms. *Journal of Financial Economics*, 104, 383-400.
- [34] Cohen, Lauren, Malloy, Christopher, and Quoc Nguyen. 2020. Lazy Prices. *Journal of Finance*, 75, 3, 1371-1415.
- [35] Collin-Dufresne, Pierre, Goldstein, Robert, and Spencer Martin. 2001. The Determinants of Credit Spread Changes. *Journal of Finance*, 56, 2177-2207.
- [36] Da, Zhi, Engelberg, Joseph, and Pengjie Gao. 2011. In search of attention. *Journal of Finance*, 66, 1461-99.
- [37] Da, Zhi, Gurun, Umit, and Mitch Warachka. 2014. Frog in the pan: Continuous information and momentum. *Review of Financial Studies*, 27, 2171-2218.
- [38] Daniel, Kent, Grinblatt, Mark, Titman, Sheridan, and Russ Wermers. 1997. Measuring Mutual Fund Performance with Characteristic-Based Benchmarks. *Journal of Finance*, 52, 1035-1058.
- [39] Daniel, Kent, Hirshleifer, David and Lin Sun. 2020. Short- and Long-Horizon Behavioral Factors. *Review of Financial Studies*, 33, 4, 1673-1736.
- [40] de Jong, Abe, Ligterink, Jeroen and Victor Macrae. 2006. A Firm-Specific Analysis of the Exchange-Rate Exposure of Dutch Firms. *Journal of International Financial Management and Accounting*, 1-17.
- [41] Della Corte, Pasquale, Ramadorai, Tarun and Lucio Sarno. 2016. Volatility risk premia and exchange rate predictability. *Journal of Financial Economics*, 120, 1, 21-40.
- [42] Della Corte, Pasquale and Aleksejs Krecetovs. 2019. Macro Uncertainty and Currency Premia. Working Paper.
- [43] DellaVigna, Stefano, and Joshua Pollet. 2009. Investor inattention and Friday earnings announcements. *Journal of Finance*, 64, 709-749.
- [44] Desai, Mihir, Foley, Fritz and Kristin Forbes. 2008. Financial Constraints and Growth: Multinational and Local Firm Responses to Currency Depreciations. *Review of Financial Studies*, 21, 6, 2857-2888.
- [45] Dominguez, Kathryn, and Linda Tesar. 2001. A reexamination of exchange-rate exposure. *American Economic Review*, 91, 2, 396-400.

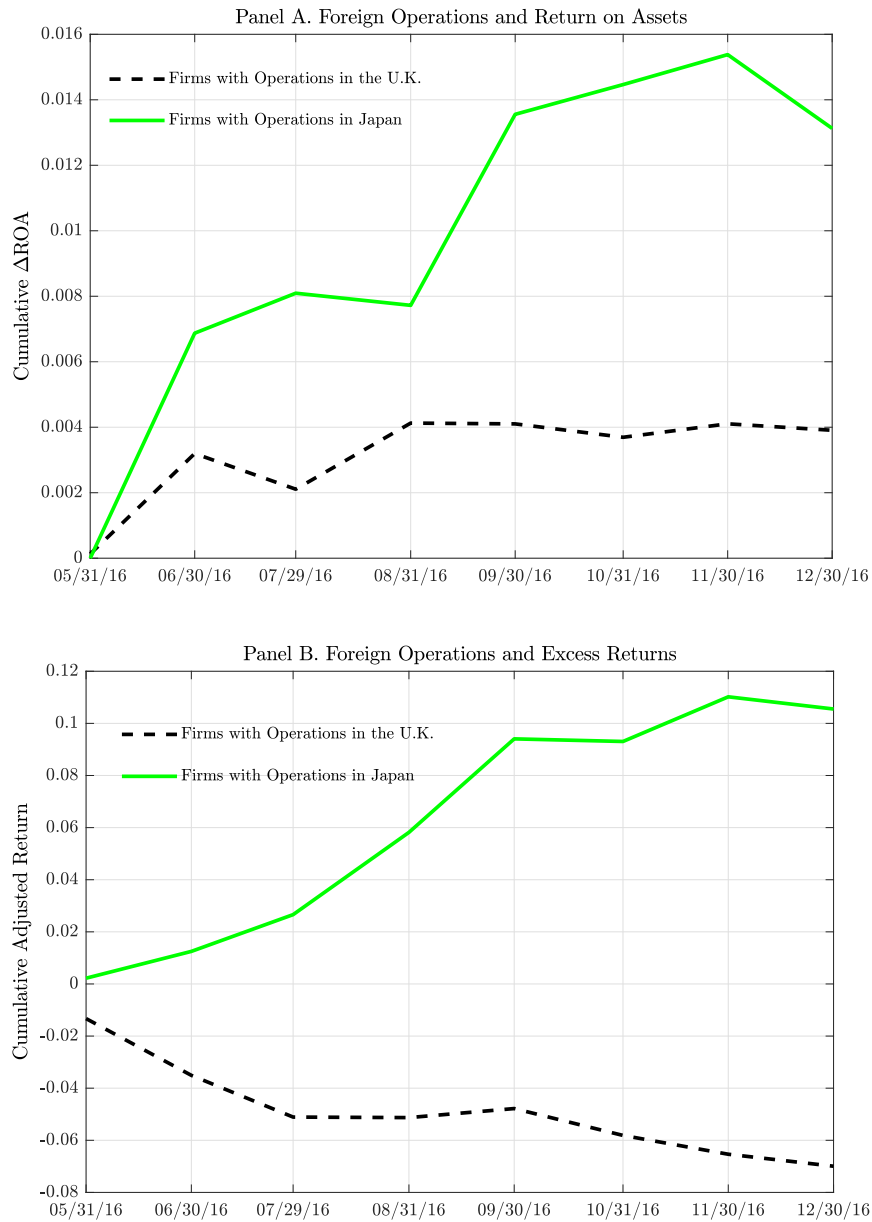
- [46] Dougal, Casey, Engelberg, Joseph, Garcia, Diego and Christopher Parsons, 2012, Journalists and the stock market. *Review of Financial Studies*, 25, 639-679.
- [47] Drechsler, Itamar, and Amir Yaron. 2011. What's Vol Got to Do with It. *Review of Financial Studies*, 24, 1, 1-45.
- [48] Duffie, Darrell. 2010. Presidential address: Asset price dynamics with slow-moving capital. *Journal of Finance*, 65,1237-67.
- [49] Engelberg, Joseph, and Christopher Parsons. 2011. The causal impact of media in financial markets. *Journal of Finance*, 66, 67-97.
- [50] Fama, Eugene, and Kenneth French. 1992. The cross-section of expected stock returns. *Journal of Finance*, 47, 427-465.
- [51] Fama, Eugene, and Kenneth French. 2015. A five-factor asset pricing model. *Journal of Financial Economics*, 116-122.
- [52] Fama, Eugene, and James MacBeth. 1973. Risk, return and equilibrium: empirical tests. *Journal of Political Economy*, 81, 607-636.
- [53] Fang, Lily, and Joel Peress. 2009. Media coverage and the cross-section of stock returns. *Journal of Finance*, 64, 2023-2052.
- [54] Fillat, Jose, and Stefania Garetto. 2015. Risk, Returns, and Multinational Production. *Quarterly Journal of Economics*, 130, 2027-2073.
- [55] Francis, Bill, Hasan, Iftekhar, and Delroy Hunter. 2008. Can hedging tell the full story? Reconciling differences in United States aggregate- and industry-level exchange rate risk premium, *Journal of Financial Economics*, 90, 169-196.
- [56] Fraser, Steve, and Christos Pantzalis. 2004. Foreign exchange rate exposure of US multinational corporations: a firm-specific approach. *Journal of Multinational Financial Management*, 14, 261-281.
- [57] Gabaix, Xavier, Krishnamurthy, Arvind and Olivier Vigneron. Limits of Arbitrage: Theory and Evidence from the Mortgage-Backed Securities Market. *Journal of Finance*, 62, 2, 557-595.
- [58] Gebhardt, William, Hvidkjaer, Soeren, and Bhaskaran Swaminathan. 2005. Stock and bond market interaction: Does momentum spill over? *Journal of Financial Economics*, 75, 651-690.
- [59] Green, Jeremiah and Hand, John R. M. and Zhang, X. Frank. 2017. The Characteristics that Provide Independent Information about Average U.S. Monthly Stock Returns, *Review of Financial Studies*, 30, 12, 4389-4436.
- [60] Greenwood, Robin, Hanson, Samuel, and Gordon Liao. 2018. Asset Price Dynamics in Partially Segmented Markets. *Review of Financial Studies*, 31, 3307-3343.

- [61] Griffin, John, and René Stulz. 2001. International Competition and Exchange Rate Shocks: A Cross-Country Industry Analysis of Stock Returns. *Review of Financial Studies*, 14, 1, 215-241.
- [62] Han, Bing, Subrahmanyam, Avanidhar, and Yi Zhou. 2017. The term structure of credit spreads, firm fundamentals, and expected stock returns. *Journal of Financial Economics*, 124, 147-171.
- [63] Harvey, Campbell, Liu, Yan, and Heqing Zhu. 2016. ...and the cross-section of expected returns, *Review of Financial Studies*, 29, 5-68.
- [64] He, Zhiguo, and Wei Xiong. 2013. Delegated asset management, investment mandates, and capital immobility. *Journal of Financial Economics*, 107, 239-258.
- [65] Hillert, Alexander, Jacobs, Heiko and Sebastian Müller. 2014. Media Makes Momentum. *Review of Financial Studies*, 27, 12, 3467-3501.
- [66] Hirshleifer, David, and Siew Hong Teoh. 2003. Limited attention, information disclosure, and financial reporting. *Journal of accounting and economics*, 36, 337-386.
- [67] Hirshleifer, David, Sonya Lim, and Siew Hong Teoh. 2009. Driven to distraction: extraneous events and underreaction to earnings news. *Journal of Finance*, 64, 2289-2325.
- [68] Hoberg, Gerard, and Katie Moon. 2017. Offshore activities and financial vs operational hedging. *Journal of Financial Economics*, 125, 217-244.
- [69] Hoberg, Gerard, and Katie Moon. 2018. The Offshoring Return Premium. *Management Science*, 1-24.
- [70] Hoberg, Gerard, and Gordon Phillips. 2016. Text-Based Network Industries and Endogenous Product Differentiation. *Journal of Political Economy*, 124, 5, 1423-1465.
- [71] Hoberg, Gerard, and Gordon Phillips. 2018. Text-Based Industry Momentum. *Journal of Financial and Quantitative Analysis*, 53, 2355-2388.
- [72] Hoberg, Gerard, Phillips, Gordon, and Nagpurnanand Prabhala. 2014. Product Market Threats, Payouts, and Financial Flexibility, *Journal of Finance*, 69, 1, 293-324.
- [73] Hong, Harrison, Terence Lim, and Jeremy Stein. 2000. Bad news travels slowly: size, analyst coverage, and the profitability of momentum strategies. *Journal of Finance*, 55, 265-295.
- [74] Hong, Harrison, and Jeremy Stein, and Jialin Yi. 2007. Simple forecasts and paradigm shifts. *Journal of Finance*, 62, 1207-1242.
- [75] Hou, Kewei. 2007. Industry Information Diffusion and the Lead-Lag Effect in Stock Returns. *Review of Financial Studies*, 20, 1113-1138.
- [76] Hou, Kewei, Karolyi, Andrew, and Bong-Chan Kho. 2011. What Factors Drive Global Stock Returns? *Review of Financial Studies*, 24, 2525-2574.

- [77] Hou, Kewei, Xue, Chen and Lu Zhang. 2015. Digesting anomalies: An investment approach. *Review of Financial Studies*, 28, 650-705.
- [78] Huang, Xing. 2015. Thinking outside the borders: Investors' underreaction to foreign operations information. *Review of Financial Studies*, 3109-3152.
- [79] Ince, Ozgur and Burt Porter. 2003. Individual Equity Return Data from Thomson Datastream: Handle with Care! *Journal of Financial Research*, 29, 463-479.
- [80] Jensen, Michael and William Meckling. 1992. Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, 48, 65-91.
- [81] Kaniel, Ron and Robert Parham. 2017. WSJ category kings—the impact of media attention on consumer and mutual fund investment decisions. *Journal of Financial Economics*, 132, 337-356.
- [82] Koijen, Ralph, Moskowitz, Tobias, Pedersen, Lasse, and Evert Vrugt. 2018. Carry. *Journal of Financial Economics*, 127, 2, 197-225.
- [83] Lustig, Hanno and Adrien Verdelhan. 2007. The Cross Section of Foreign Currency Risk Premia and Consumption Growth Risk. *American Economic Review*, 97, 1, 89-117.
- [84] Menkhoff, Lukas, Sarno, Lucio, Schmeling, Maik, and Andreas Schrimpf. 2012. Currency momentum strategies. *Journal of Financial Economics*, 106, 660-684.
- [85] Menzly, Lior and Oguzhan Ozbas. 2010. Market Segmentation and Cross-predictability of Returns. *Journal of Finance*, 65, 1555-1580.
- [86] Merton, Robert. 1987. A simple model of capital market equilibrium with incomplete information. *Journal of Finance*, 42, 483-510.
- [87] Newey, Whitney and Kenneth West. 1987. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, 55, 3, 703-708.
- [88] Nguyen, Quoc. 2016. Does Investor Attention Stop at the Water's Edge? The Predictability of Multinational Firms' Returns. Working Paper.
- [89] Novy-Marx, Robert. 2013. The Other Side of Value: The Gross Profitability Premium. *Journal of Financial Economics*, 108, 1, 1-28.
- [90] Peng, Lin, and Wei Xiong. 2006. Investor attention, overconfidence and category learning. *Journal of Financial Economics*, 80, 563-602.
- [91] Peress, Joel. 2014. The media and the diffusion of information in financial markets: Evidence from newspaper strikes. *Journal of Finance*, 69, 2007-43.
- [92] Petersen, Mitchell. 2009. Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *Review of Financial Studies*, 22, 1, 435-480.

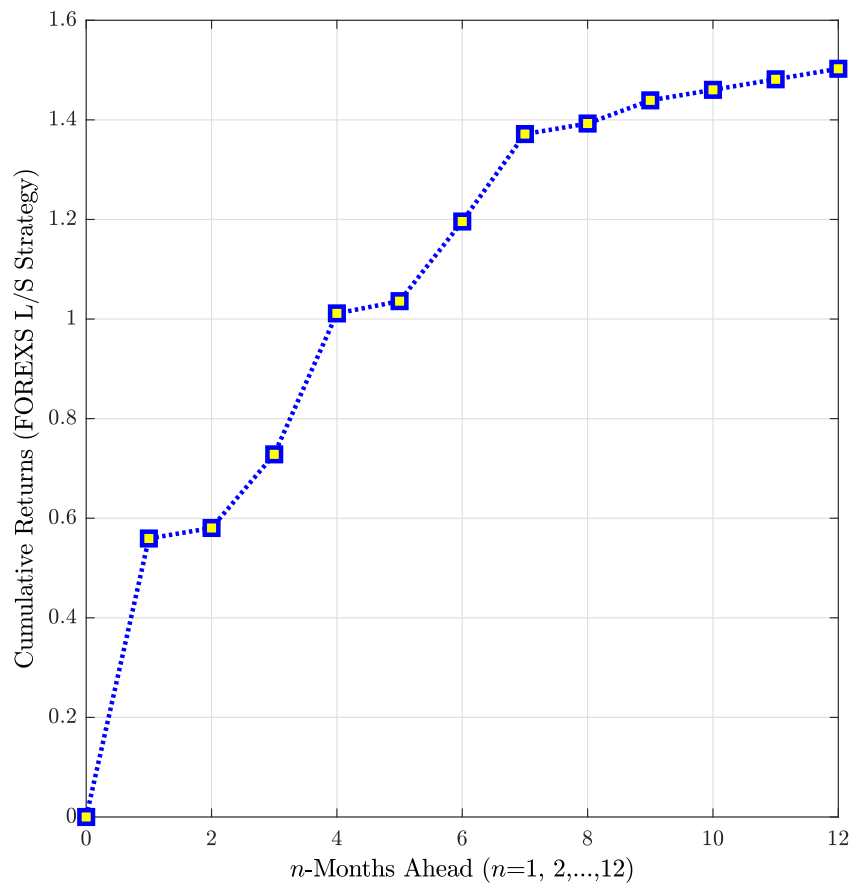
- [93] Pitkäjärvi, Aleksi, Suominen, Matti, and Lauri Vaittinen. 2020. Cross-asset signals and time series momentum. *Journal of Financial Economics*, 136, 63-85.
- [94] Rossi, Barbara. 2013. Exchange Rate Predictability. 2013. *Journal of Economic Literature*, 51, 1063-1119.
- [95] Tetlock, Paul. 2007. Giving content to investor sentiment: The role of media in the stock market. 2007. *Journal of Finance*, 62, 1139-1168.
- [96] Stambaugh, Robert and Yu Yuan. 2017. Mispricing factors. *Review of Financial Studies*, 30, 1270-1315.
- [97] Wagner, Alexander, Zeckhauser, Richard and Alexandre Ziegler. 2018. Company stock price reactions to the 2016 election shock: Trump, taxes, and trade. *Journal of Financial Economics*, 130, 428-451.

Figure 1. Foreign Currencies and Operations: The Brexit Case



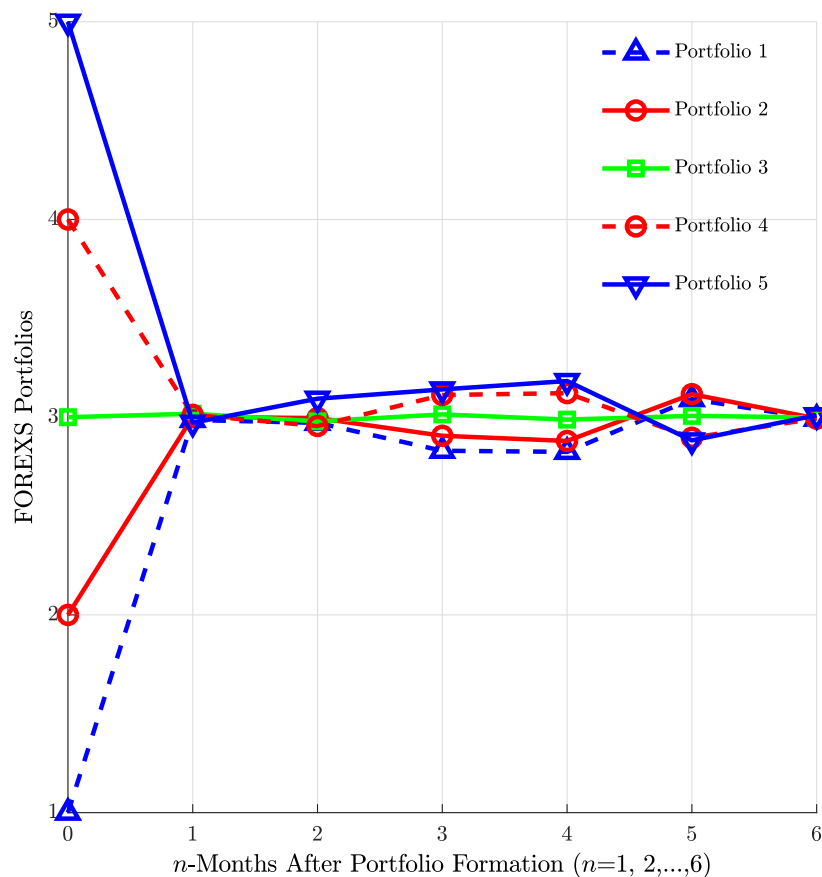
We plot the cumulative excess returns from May to December of 2016 for U.S. firms with operations in the U.K. and Japan. The returns are domestic market beta-adjusted. The Brexit referendum was held in June 23, 2016. Panel A (B) shows the average cumulative Δ ROA (excess returns) for U.S. firms with operations in the U.K. and Japan. To compute the average Δ ROA (excess returns), we first select a group of firms with greater than 10% foreign sales to target country (the U.K. and Japan). We then take a target country sales-weighted average of Δ ROA (excess returns).

Figure 2. Cumulative Portfolio Returns



We plot the cumulative returns of the *FOREXS* long-short strategy in the next twelve months after portfolio formation. We compute a firm's *FOREXS* as the previous month cross-sectional currency mean return, weighted by the relative sales of the firm in the foreign economy. The value-weighted strategy buys stocks with high *FOREXS* and sells stocks with low *FOREXS*. The portfolios are rebalanced on a monthly basis.

Figure 3. Portfolio Persistence Score



We plot the portfolio persistence score. At the beginning of every calendar month, all firms are ranked in an ascending order by their *FOREXS* in the previous month. The ranked stocks are assigned to one of 5 quintile portfolios. The portfolios are rebalanced every calendar month. After n months (with $n = 1, 2, \dots, 6$) from the portfolio formation period, we keep track of all the constituents of portfolio k (with $k = 1, 2, \dots, 5$) and assign a score to each of the stocks based on their new membership out of 5 quintile portfolios. Each line in the figure presents the average score of firms in portfolio k at the initial formation period.

Table 1. Summary Statistics

We report the summary statistics for the set of U.S. firms with foreign operations. Panel A reports the number of all U.S. firms, and the subset of U.S. firms with positive foreign sales. The statistics are computed using value weights (VW) and equal weights (EW) across firms. Panel B reports the top 10 sales partners of U.S. firms based on value-weights across firms. In both panels, the first column indicates the foreign economy where U.S. firms generate sales revenues. The second column reports foreign sales over total sales. Each period we compute the ratio of each U.S. firm's sales to the foreign economy over its total sales, and compute the period-average across all firms. We repeat the analysis for all periods, and report the average across all periods. The third column reports foreign sales over total sales, excluding domestic sales. Each period we compute the ratio of each U.S. firm's sales to the foreign economy over its total sales to foreign economies (excluding domestic sales) and compute the period-average across all firms. We repeat the analysis for all periods, and report the average across all periods. The sample period is from December 2003 to January 2018.

Panel A. Firms Foreign Sales		
	Unique Firms	Unique Firms (Foreign Sales >0)
Total Firms	5477	3464
Avg. Foreign Sales (VW)	35.6%	42.6%
Above Median Size Firms	36.2%	42.9%
Below Median Size Firms	19.6%	35.6%
Avg. Foreign Sales (EW)	22.2%	36.4%
Above Median Size Firms	26.1%	37.4%
Below Median Size Firms	18.4%	34.9%
Panel B. Foreign Sales by Country		
Country	Total	Ex. Domestic
China	5.0%	14.0%
Japan	4.8%	13.5%
United Kingdom	3.6%	10.3%
Germany	3.5%	10.0%
Canada	2.9%	8.3%
France	2.4%	6.8%
Italy	1.9%	5.4%
Brazil	1.8%	5.1%
Mexico	1.4%	4.1%
Russia	1.3%	3.6%

Table 2. Variable Definitions

We report the description of variables used in the paper.

Variables related to foreign operations	
<i>FOREXS</i>	Foreign operations related exchange shocks, which is measured by the cross-sectional average of currency returns for each relevant foreign country, weighted by the ratio of foreign sales to total sales
<i>FOREXS</i>	Equal-weighted version of <i>FOREXS</i>
Foreign Market	Similar to <i>FOREXS</i> except that the cross-sectional average is taken on foreign stock market return in local currency
Domestic Market	Domestic market return times domestic sales to total sales
Foreign Industry	Similar to <i>FOREXS</i> except that the cross-sectional mean is taken on foreign industry (in excess of foreign market) return in local currency
Domestic Industry	Domestic industry (in excess of domestic market) return times domestic sales to total sales
Foreign Economy	Sum of (sales weighted avg.) foreign currency, market and industry
Domestic Economy	Sum of (sales weighted avg.) domestic market and industry
Variables for controlling factors	
FF 3	Fama and French (1993) factors: MKT, SMB, HML
Carhart 4	FF 3 with Carhart (1997) factors: MKT, SMB, HML, MOM
FF 5	Fama and French (2015) factors: MKT, SMB, HML, RMW, CMA
SY 4	Stambaugh and Yuan (2017) factors: MKT, SMB, MGMT, PERF
HXZ 4	Hou, Xue and Zhang (2014) factors: MKT, SMB, INV, ROE
DHS 3	Daniel, Hirshleifer and Sun (2019) factors: MKT, FIN, PEAD
Variables related to characteristics-based benchmarks	
SizeBM	Characteristics-based benchmark adjusted return: individual firm's return minus characteristic-matched portfolio's return. Benchmark portfolios: 25 portfolios sorted on size and BM ratio
DGTW	Similar to SizeBM except that benchmark portfolios: 125 portfolios sorted on size, BM, momentum as defined by Daniel et. al. (1997)
BCZ _{C5}	Characteristics-based benchmark adjusted return following Bessembinder, Cooper and Zhang (2019). C5 model includes log size, log BM ratio, momentum, ROA and asset growth
BCZ _{C14}	C5 characteristics plus beta, accrual, dividend, log LR return, idiosyncratic risk, illiquidity, turnover, leverage, sales-to-price ratio
BCZ _{C15}	C14 characteristics plus foreign-sales-to-total-sales ratio
Variables for firm fundamentals	
Size	Log of market capitalization
Sales Gr.	Quarter-over-quarter growth rate of total sales
ROA	Return on asset, which is the ratio of firms' income before extraordinary item to total assets

Table 2 (cont.). Variable Defini-

Variables for firm fundamentals (cont.)	
Book to Market	Book to market ratio as in Fama and French (1993)
Profitability	Gross profitability as in Novy-Marx (2013)
Investment	Investment as in Chen and Zhang (2010): change in property, plant, and equipment plus changes in inventories scaled by lagged total assets
R&D	R&D expense divided by lagged total assets
Z-score	Altman's Z-score as in Mackie-Mason (1990)
SUE	Actual minus expected earnings over the std. dev. of analysts forecasts
Variables related to firm-level hedging	
CDM	Mentions of FX futures derivatives in the 10-K report, orthogonalized by retrieving residuals from the cross-sectional regression on log of market capitalization. Dummy variable
ICV	Sales-weighted avg. of option implied minus realized FX volatility. Dummy variable
IN	Firm-country level indicator equal to 1 if the firm mentions purchasing inputs from the given nation (Hoberg and Moon (2017))
OHIN	Firm level indicator variable equals 1 if the sales-weighted average of IN is greater than 30 percent
IN*	Similar to IN except that IN* equals 1 if the firm mentions purchasing inputs and does not mention owning assets in the given nation
OHIN*	Indicator variable equals 1 if the sales-weighted average of IN* is greater than 30 percent
CFS	Regression coefficient of percentage changes in OIBDPQ on <i>FOREXS</i> . Dummy variable
FX Forecast	Dispersion of analysts' forecasts about the future value of the currency, following Della Corte and Krecetovs (2019)
Variables related to firm-level information processing environment	
10K1A	Mentions of currency, foreign exchange or FX in the Risk Factors section of the 10K report. Dummy variable
ANFX	Sales-weighted average of the abnormal FX news measure. Dummy variable
ANFM	Similar to ANFX except that ANFM uses foreign stock market news
HFO	Hedge fund ownership as a percentage of outstanding shares
FIO	Foreign institutional ownership as a percentage of outstanding shares
IO	Total institutional ownership as a percentage of outstanding shares. All 3 ownership variables are orthogonalized by retrieving residuals from the cross-sectional regression on log of market capitalization. Dummy variables
Herfin.	Herfindahl index based on the firm's geographic segment sales. Dummy variable
Countr.	Countries in which the firm has foreign operations. Dummy variable
CSDFX	Firm-month cross-sectional std. dev. of FX returns. Dummy variable

Table 3. Summary Statistics for Portfolio Quintiles

We report the summary statistics for the returns of value-weighted portfolios of stocks, sorted by their cross-sectional currency lagged information (*FOREXS*) measure. The statistics include the portfolio's annualized mean, standard deviation, skewness, kurtosis and Sharpe ratio. The bottom row reports the average *FOREXS* measure per quintile. Portfolio 1 includes stocks with relative low *FOREXS*, and portfolio 5 includes stocks with relative high *FOREXS*. Portfolios are rebalanced on a monthly basis. The right-most column reports the long-short strategy, the difference between portfolio 5 and portfolio 1 (high - low). The strategy longs a portfolio of stocks with high *FOREXS* and shorts a portfolio of stocks with low *FOREXS*. The sample period is from December 2003 to January 2018.

	Low	2	3	4	High	High - Low
Mean	7.13	9.50	9.65	11.56	13.86	6.73
Std. Dev.	14.99	14.76	15.60	14.75	14.67	6.86
Skewness	-0.74	-0.53	-0.81	-0.70	-1.18	0.18
Kurtosis	4.82	5.25	5.36	4.86	7.04	3.27
Sharpe Ratio	0.48	0.64	0.62	0.78	0.95	0.98
<i>FOREXS</i>	-0.65%	-0.25%	-0.02%	0.21%	0.60%	

Table 4. Abnormal Returns of FOREXS Portfolios

We report in Panel A the annualized abnormal returns for value-weighted portfolio quintiles and the long-short *FOREXS* strategy accounting for the three-factor model (FF 3) of Fama and French (1993), the four-factor model (Carhart 4) of Carhart (1994), the five-factor model (FF 5) of Fama and French (2015), the four-factor model (SY 4) of Stambaugh and Yuan (2017), the four-factor model (HXZ 4) of Hou, Xue and Zhang (2014), and the three-factor model (DHS 3) of Daniel, Hirshleifer and Sun (2019). Stocks are sorted by their cross-sectional currency lagged information (*FOREXS*) measure. Portfolio 1 (low) includes stocks with relative low *FOREXS*, and portfolio 5 (high) includes stocks with relative high *FOREXS*. Portfolios are rebalanced on a monthly basis. Panels B and C report annualized abnormal returns in relation to firms earnings announcements. Panel B (C) reports quintile portfolios for firms with (without) scheduled earnings announcements in the coming month. Panel D reports the characteristics-based benchmark adjusted returns of value-weighted portfolio stocks. We take the difference between an individual firm’s return and a characteristic-matched portfolio’s return to generate a characteristics-based benchmark adjusted return for each firm-month. We then calculate abnormal portfolio returns as value-weighted average of individual firms’ characteristics-based benchmark adjusted returns in each *FOREXS* quintile. For benchmark portfolios, we use 25 portfolios sorted on size and book-to-market ratio (SizeBM) and 125 portfolios sorted on size, book-to-market, momentum (DGTW) as defined by Daniel, Grinblatt, Titman and Wermers (1997). For BCZ, we employ Bessembinder, Cooper, and Zhang (2019)’s multivariate cross-sectional regression approach to circumvent the curse of dimensionality. We use both of 5-characteristics and 14-characteristics models in the paper (denoted as BCZ_{C5} and BCZ_{C14} respectively), and augment C14 model with foreign-to-total-sales ratio (BCZ_{C15}). We report the Newey-West corrected *t*-statistics in parentheses using four lags.

	Low	2	3	4	High	High - Low
Panel A. Abnormal Returns						
CAPM	-2.97 (-2.14)	-0.96 (-0.91)	-1.09 (-0.89)	1.24 (1.27)	3.78 (2.88)	6.74 (3.55)
FF 3	-3.10 (-2.28)	-1.02 (-0.98)	-1.01 (-0.83)	1.22 (1.28)	3.71 (2.99)	6.81 (3.59)
Carhart 4	-3.33 (-2.47)	-0.84 (-0.81)	-1.00 (-0.82)	1.13 (1.18)	3.62 (2.91)	6.95 (3.65)
FF 5	-2.54 (-1.79)	-0.75 (-0.68)	-0.44 (-0.35)	0.71 (0.73)	3.46 (2.66)	6.00 (3.04)
SY 4	-4.16 (-3)	-1.12 (-0.97)	-1.23 (-0.92)	0.71 (0.69)	3.76 (2.82)	7.92 (3.94)
HXZ 4	-3.25 (-2.27)	-0.70 (-0.61)	-1.29 (-0.96)	0.87 (0.82)	4.22 (3.24)	7.47 (3.78)
DHS 3	-2.55 (-1.80)	-0.87 (-0.79)	-0.47 (-0.38)	1.60 (1.60)	4.32 (3.30)	6.86 (3.49)

	Low	2	3	4	High	High - Low
Panel B. Abnormal Returns (Earnings Announc. Window)						
CAPM	-3.88	2.38	2.58	4.80	6.88	10.76
	(-1.20)	(0.90)	(1.08)	(1.81)	(2.42)	(2.73)
FF 3	-4.05	2.24	2.58	4.81	6.86	10.92
	(-1.26)	(0.85)	(1.07)	(1.82)	(2.47)	(2.78)
Carhart 4	-3.92	2.59	2.39	4.82	6.70	10.62
	(-1.21)	(1.00)	(0.99)	(1.81)	(2.40)	(2.71)
FF 5	-3.10	2.65	2.01	4.84	5.28	8.38
	(-0.93)	(0.98)	(0.80)	(1.75)	(1.84)	(2.07)
SY 4	-4.77	2.64	1.19	4.21	5.36	10.13
	(-1.39)	(0.94)	(0.48)	(1.49)	(1.86)	(2.43)
HXZ 4	-2.94	3.97	2.22	4.94	6.35	9.29
	(-0.89)	(1.45)	(0.88)	(1.77)	(2.27)	(2.31)
DHS 3	-3.13	2.29	1.75	4.95	7.02	10.15
	(-0.93)	(0.84)	(0.72)	(1.80)	(2.39)	(2.49)
Panel C. Abnormal Returns (Non-Earnings Announc. Window)						
CAPM	-2.41	-2.23	-2.15	0.07	2.35	4.76
	(-1.53)	(-1.95)	(-1.45)	(0.05)	(1.56)	(2.16)
FF 3	-2.59	-2.26	-2.02	0.03	2.41	4.99
	(-1.68)	(-1.96)	(-1.39)	(0.03)	(1.68)	(2.30)
Carhart 4	-2.92	-2.18	-1.80	-0.07	2.64	5.56
	(-1.94)	(-1.89)	(-1.25)	(-0.05)	(1.86)	(2.66)
FF 5	-1.96	-1.61	-1.79	-0.12	1.85	3.81
	(-1.23)	(-1.35)	(-1.19)	(-0.09)	(1.24)	(1.70)
SY 4	-2.91	-2.66	-2.39	-0.66	3.51	6.42
	(-2.51)	(-2.13)	(-1.51)	(-0.48)	(2.32)	(3.32)
HXZ 4	-3.12	-2.64	-2.41	-0.37	3.53	6.65
	(-1.95)	(-2.13)	(-1.52)	(-0.26)	(2.44)	(3.03)
DHS 3	-2.20	-1.76	-1.32	0.58	3.68	5.88
	(-1.38)	(-1.49)	(-0.89)	(0.44)	(2.47)	(2.61)
Panel D. Characteristics-based benchmark adjusted returns						
SizeBM	-2.51	-0.09	-0.19	1.18	3.01	5.52
	(-1.98)	(-0.09)	(-0.17)	(1.41)	(2.55)	(3.11)
DGTW	-2.26	-0.21	-0.75	0.65	2.12	4.38
	(-2.29)	(-0.24)	(-0.77)	(0.87)	(2.07)	(3.06)
BCZ _{C5}	-0.67	2.79	2.45	4.94	5.85	6.51
	(-0.11)	(0.46)	(0.41)	(0.83)	(0.98)	(3.51)
BCZ _{C14}	-5.65	-3.37	-3.18	-0.64	1.29	6.94
	(-0.86)	(-0.52)	(-0.49)	(-0.10)	(0.20)	(3.79)
BCZ _{C15}	-5.52	-3.30	-3.26	-1.04	0.81	6.32
	(-0.85)	(-0.52)	(-0.51)	(-0.17)	(0.13)	(3.33)

Table 5. FOREXS and Stock Return Predictability

We report the Fama-MacBeth cross-sectional regressions. The dependant variable is the firm's monthly stock return. The main explanatory variable is *FOREXS*. All variables are summarized in Table 2. All explanatory variables are one-period lagged except contemporaneous (ctmp.) variables. The sample period is from December 2003 to January 2018. We report the Newey-West corrected *t*-statistics in parentheses using four lags, adjusted R-squared and total firm-month observations.

Dependent Variable	Firm Return							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.0002 (0.02)	0.0010 (0.09)	0.0028 (0.24)	0.0022 (0.19)	0.0029 (0.26)	0.0039 (0.34)	0.0029 (0.26)	0.0280 (2.06)
<i>FOREXS</i>	0.4221 (3.80)	0.6404 (4.22)	0.5882 (3.86)	0.5000 (2.88)	0.5298 (3.44)		0.5396 (3.33)	0.3893 (2.40)
\overline{FOREXS}						0.0490 (0.48)	-0.0051 (-0.05)	
Size	0.0007 (1.36)	0.0006 (1.27)	0.0006 (1.12)	0.2913 (2.66)	0.0005 (0.99)	0.0005 (1.01)	0.0005 (0.98)	-0.0010 (-2.27)
Foreign Market		-0.0529 (-0.45)	0.0900 (0.59)	0.0082 (0.05)	0.0104 (0.05)	0.0614 (0.34)	0.0141 (0.07)	-0.0187 (-0.13)
Domestic Market		-0.2354 (-0.30)	-0.2122 (-0.32)	0.1497 (0.13)	0.7129 (0.42)	0.3293 (0.16)	0.8451 (0.47)	2.6323 (0.96)
Foreign Industry			0.1871 (1.62)	0.1564 (1.28)	0.1082 (0.92)	0.1655 (1.35)	0.1044 (0.89)	0.0848 (0.84)
Domestic Industry			0.0281 (0.44)	0.0163 (0.25)	0.0337 (0.77)	0.0328 (0.76)	0.0383 (0.87)	0.0014 (0.02)
<i>FOREXS</i> (ctmp.)				0.6406 (4.70)				
Foreign Market (ctmp.)				0.2913 (2.66)				
Foreign Economy (ctmp.)					0.3678 (4.64)	0.3387 (3.97)	0.3579 (4.62)	0.3681 (5.31)
Domestic Economy (ctmp.)					0.6706 (16.14)	0.6782 (16.52)	0.6728 (16.21)	0.6754 (17.04)
Foreign Sales Ratio								-0.0216 (-3.04)
Momentum								-0.0032 (-0.95)
Firm Return								-0.0049 (-1.94)
Idio Volatility								-0.0013 (-2.14)
Book-to-Market								(-0.00) (-0.25)
R_{Adj}^2	0.008	0.011	0.016	0.017	0.020	0.019	0.020	0.044
N	274,059	269,317	262,312	259,364	259,336	259,441	259,336	243,198

Table 6. FOREXS and Stock Return Decomposition

We report the Fama-MacBeth cross-sectional regressions. We decompose the firm's return into the sales-weighted foreign currency returns (*FOREXS*), foreign industry returns (Foreign Industry), domestic industry returns (Domestic Industry) measures and the residual firm-specific (Firm Specific) measure. The firm-specific measure is the difference between the firm's return and the three information measures: *FOREXS*, Foreign Industry and Domestic Industry. We use each of the four sub-components as the dependent variable and report the regression coefficients in their respective columns. All explanatory variables are one-period lagged and summarized in Table 2. The sample period is from December 2003 to January 2018. We report the Newey-West corrected *t*-statistics in parentheses using four lags, adjusted R-squared and total firm-month observations.

Dependent Variable	<i>FOREXS</i>	Foreign Industry	Domestic Industry	Firm Specific
	(1)	(2)	(3)	(4)
Intercept	0.0002 (0.71)	0.0012 (2.01)	0.0056 (2.28)	-0.0054 (-0.58)
<i>FOREXS</i>	0.0204 (0.41)	0.0399 (1.08)	-0.0402 (-0.80)	0.3551 (2.35)
Foreign Industry	0.0340 (1.59)	0.1561 (3.01)	-0.0581 (-1.08)	0.0954 (1.00)
Domestic Industry	0.0026 (0.30)	-0.0043 (-0.37)	0.0487 (1.20)	0.0099 (0.19)
Firm Specific	0.0002 (1.66)	0.0003 (1.79)	0.0003 (0.67)	-0.0161 (-2.71)
Size	0.0000 (-0.46)	0.0000 (1.01)	0.0000 (-0.83)	0.0005 (0.95)
R^2_{Adj}	0.413	0.458	0.382	0.020
N	258,301	258,387	258,388	257,968

Table 7. Real Effects and FOREXS

We report the quarterly panel regressions. The dependent variables are firms' quarterly sales growth, quarterly changes in return on assets and quarterly earnings surprise. The main explanatory variable is *FOREXS*. All variables related to firm fundamentals are summarized in Table 2. For Sales Gr. (column 1), we use the percentage change in total sales in the current quarter to sales in the previous quarter. Δ ROA (column 2) is the difference between ROA in the current and the previous quarter and ROA is the ratio of firms' income before extraordinary item to total assets. SUE (column 3) is the actual earnings minus expected earnings, normalized by the standard deviation of analysts forecasts. We report in parentheses the *t*-statistics controlling for firm-fixed effects and clustering standard errors at the firm level, adjusted R-squared and total firm-quarter observations. All explanatory variables are one-quarter lagged. The sample period is from December 2003 to January 2018.

Dependent Variable	Sales Gr.	Δ ROA	SUE
	(1)	(2)	(3)
Intercept	-0.094 (-2.23)	-0.002 (-0.42)	-1.597 (-3.45)
<i>FOREXS</i>	0.377 (16.29)	0.011 (4.19)	4.817 (14.22)
Foreign Market	0.245 (12.57)	0.009 (5.18)	3.073 (11.27)
Firm Return	0.139 (7.62)	0.010 (4.37)	2.943 (20.34)
Book-to-market	-0.018 (-2.84)	0.001 (1.52)	-0.364 (-4.96)
Profitability	-0.056 (-3.11)	-0.011 (-5.25)	-1.387 (-7.21)
Investment	-0.001 (-0.31)	-0.002 (-4.38)	-0.417 (-6.77)
R&D	-0.117 (-1.64)	-0.005 (-0.73)	2.804 (4.72)
Z-score	-0.066 (-7.91)	-0.009 (-7.69)	-0.189 (-6.30)
Size	0.014 (4.72)	0.001 (2.73)	0.170 (5.41)
R^2_{Adj}	0.078	0.057	0.128
N	40,566	40,663	37,750

Table 8. FOREXS and Currency Hedging

We report the Fama-Macbeth cross-sectional regressions. The dependent variable is the firm's monthly stock return. The explanatory variables are interaction terms between *FOREXS* and a number of dummy variables. The interaction variables are summarized in Table 2. Column 1 interacts *FOREXS* with the insurance cost for FX volatility, measured by the difference between the option implied and historical spot currency volatility. Column 2 interacts *FOREXS* with firms' financial hedging information. We measure financial hedging using the number of financial derivatives mentions in firms' 10K reports (Hoberg and Moon (2017)). Columns 3 and 4 interact *FOREXS* with firms' operational hedging information. We measure operational hedging using the number of mentions in firms' financial statements (Hoberg and Moon (2017)) about input purchases (column 3) and input purchases without owning foreign assets (column 4). Column 5 interacts *FOREXS* with firm's cash-flow exposure. Cash-flow beta is computed using firms' quarterly operating income before depreciation and amortization (OIBDPQ) year-over-year percentage change. Control variables include firm's size (log of market cap.) and the following sales-weighted variables: foreign market return, domestic market return, foreign industry return and domestic industry return. The sample period is from December 2003 to January 2018. We report the Newey-West corrected *t*-statistics in parentheses using four lags, adjusted R-squared and total firm-month observations.

Dependent Variable	Firm Return				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.0129 (0.85)	0.0165 (1.2)	0.0127 (0.93)	0.0145 (1.07)	0.0076 (0.72)
<i>FOREXS</i>	0.1971 (0.99)	0.5483 (3.48)	0.4848 (2.51)	0.555 (2.17)	0.4862 (3.18)
<i>FOREXS</i> × <i>ICV</i>	0.4004 (2.11)				
<i>FOREXS</i> × <i>CDM</i>		-0.3042 (-2.09)			
<i>FOREXS</i> × <i>OHIN</i>			-0.4235 (-2.00)		
<i>FOREXS</i> × <i>OHIN</i> *				-0.7909 (-2.34)	
<i>FOREXS</i> × <i>CFS</i>					0.7132 (2.13)
Controls	Y	Y	Y	Y	Y
R^2_{Adj}	0.016	0.015	0.015	0.015	0.020
N	238,353	273,122	265,567	269,067	108,842

Table 9. FOREXS and Information Processing Environment

We report the Fama-Macbeth cross-sectional regressions. The dependant variable is the firm's monthly stock return. The explanatory variables are interaction terms between *FOREXS* and a number of dummy variables. The interaction variables are summarized in Table 2. Column 1 interacts *FOREXS* with mentions about currency risk in the firm's 10K-1A section. Columns 2 and 3 interact *FOREXS* with abnormal news flows about foreign currency news (ANFX) and foreign stock market news (ANFM), collected monthly, of foreign-currency specific news and foreign-stock-market specific news from the top 5 U.S. newspapers. Columns 4 to 9 respectively interact *FOREXS* with firm size orthogonalized measures of hedge fund institutional ownership (HFO), foreign institutional ownership (FIO), institutional ownership (IO), the Herfindahl index of foreign sales (Herfin.), number of countries involved (Countr.) the and cross-sectional standard deviation among currencies (CSDFX). Control variables include firm's size (log of market cap.) and the following sales-weighted variables: foreign market return, domestic market return, foreign industry return and domestic industry return. The sample period is from December 2003 to January 2018. We report the Newey-West corrected *t*-statistics in parentheses using four lags, adjusted R-squared and total firm-month observations.

Dependent Variable	Firm Return								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.0027 (0.24)	0.0014 (0.12)	0.0017 (0.15)	-0.0003 (-0.03)	0.0013 (0.11)	0.0015 (0.13)	0.0019 (0.17)	0.0019 (0.16)	0.0016 (0.14)
<i>FOREXS</i>	0.5531 (3.16)	0.5509 (3.13)	0.6230 (2.62)	0.5496 (3.59)	0.5201 (2.95)	0.5693 (3.59)	0.6667 (2.53)	0.5947 (3.33)	0.5863 (3.18)
<i>FOREXS</i> × 10K1A	-0.3791 (-2.28)								
<i>FOREXS</i> × ANFX		-0.4841 (-2.42)							
<i>FOREXS</i> × ANFM			-0.2863 (-0.76)						
<i>FOREXS</i> × HFO				-0.4147 (-2.28)					
<i>FOREXS</i> × FIO					-0.3608 (-2.11)				
<i>FOREXS</i> × IO						-0.1216 (-0.73)			
<i>FOREXS</i> × Herfin.							-0.4871 (-1.97)		
<i>FOREXS</i> × Countr.								0.4098 (2.40)	
<i>FOREXS</i> × CSDFX									0.4461 (2.39)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
R^2_{Adj}	0.016	0.016	0.017	0.017	0.016	0.018	0.016	0.016	0.016
N	262,121	262,160	262,312	262,105	262,066	262,222	262,069	262,119	262,139

Table 10. FOREXS and the Cross Section of Currency Uncertainty

We report the Fama-Macbeth cross-sectional regressions. The dependant variable is the firm's monthly stock return. Columns 1 to 6 report the decomposition of *FOREXS* into *FOREXS^H* and *FOREXS^L*. In columns 1 to 3, *FOREXS^H* comprises the set of economies where previous month currency volatility is above median across currencies and *FOREXS^L* comprises the set of economies where previous month currency volatility is below median across currencies. In columns 4 to 6, *FOREXS^H* comprises the set of economies where previous month currency forecast dispersion is above median across currencies and *FOREXS^L* comprises the set of economies where previous month currency forecast dispersion is below median across currencies. All variables are summarized in Table 2. All explanatory variables are with one-month lag except contemporaneous (ctmp.) variables. The sample period is from December 2003 to January 2018. We report the Newey-West corrected *t*-statistics in parentheses using four lags, adjusted R-squared and total firm-month observations.

Dependent Variable	Firm Return					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0039 (0.33)	0.0065 (0.55)	0.0047 (0.39)	0.0000 (-0.00)	0.0021 (0.15)	0.0012 (0.09)
<i>FOREXS^H</i>	0.5287 (2.15)	0.5372 (1.91)	0.6456 (2.05)	1.3045 (3.49)	1.1396 (2.95)	1.3311 (3.22)
<i>FOREXS^L</i>	0.0381 (0.12)	-0.0305 (-0.09)	0.0356 (0.10)	0.3938 (1.36)	0.2690 (0.90)	0.3995 (1.27)
Size	0.0006 (1.14)	0.0005 (1.01)	0.0005 (0.96)	0.0008 (1.40)	0.0008 (1.28)	0.0007 (1.26)
Foreign Market	0.1477 (0.86)	0.0796 (0.49)	-0.0077 (-0.04)	-0.0142 (-0.09)	-0.0858 (-0.59)	-0.1746 (-1.16)
Domestic Market	-0.2149 (-0.21)	-0.4325 (-0.35)	0.6593 (0.34)	0.3693 (0.51)	0.0859 (0.11)	1.7586 (0.84)
Foreign Industry	0.2089 (1.77)	0.1737 (1.43)	0.1070 (0.92)	0.2039 (1.47)	0.2489 (1.82)	0.1148 (1.05)
Domestic Industry	0.0353 (0.60)	0.0267 (0.46)	0.0147 (0.32)	0.0637 (1.05)	0.0507 (0.85)	0.0447 (0.84)
<i>FOREXS</i> (ctmp.)		0.6811 (3.69)			0.6054 (4.22)	
Foreign Economy (ctmp.)			0.4716 (4.93)			0.4227 (5.70)
Domestic Economy (ctmp.)			0.6741 (17.24)			0.6860 (14.80)
R^2_{Adj}	0.016	0.017	0.021	0.017	0.018	0.022
N	262,418	259,498	259,440	204,259	201,706	201,659

Table A.1. Portfolio Loadings

We report in Panels A to D the loadings on risk factors models of Fama and French (2015), Stambaugh and Yuan (2017), Hou, Xue and Zhang (2015) and Daniel, Hirshleifer and Sun (2019). Portfolio 1 (low) includes stocks with relative low *FOREXS* and portfolio 5 (high) includes stocks with relative high *FOREXS*. Portfolios are rebalanced on a monthly basis. The sample period is from December 2003 to January 2018. We report the Newey-West corrected *t*-statistics in parentheses using four lags.

	Low	2	3	4	High	High - Low
Panel A. Loadings on Fama and French (2015)						
MKT	1.01 (33.12)	1.03 (50.51)	1.04 (39.26)	1.04 (48.46)	0.99 (25.21)	-0.02 (-0.43)
SMB	0.01 (-0.84)	-0.12 (-2.96)	0.10 (0.61)	0.12 (1.17)	0.16 (1.57)	0.15 (1.62)
HML	-0.15 (-2.24)	0.01 (0.13)	0.01 (0.15)	-0.10 (-2.32)	-0.17 (-3.14)	-0.02 (-0.27)
RMW	-0.09 (-1.01)	-0.06 (-0.75)	-0.04 (-0.45)	0.15 (2.17)	0.02 (0.32)	0.11 (1)
CMA	0.01 (0.1)	0.01 (0.19)	-0.03 (-0.22)	0.06 (0.71)	0.06 (0.59)	0.05 (0.29)
Panel B. Loadings on Stambaugh and Yu (2017)						
MKT	1.07 (30.14)	1.03 (36.28)	1.03 (29.38)	1.01 (38.24)	1.00 (23.56)	-0.06 (-1.02)
SMB	0.01 (-0.82)	-0.09 (-2.53)	0.10 (0.41)	0.10 (0.85)	0.14 (0.91)	0.13 (1.3)
MGMT	-0.11 (-1.79)	-0.05 (-0.89)	-0.05 (-0.79)	-0.04 (-0.76)	-0.11 (-1.54)	0.00 (0.02)
PERF	0.12 (2.93)	-0.01 (-0.21)	-0.01 (-0.33)	0.03 (1.41)	0.08 (2.55)	-0.04 (-0.87)
Panel C. Loadings on Hou, Xue and Zhang (2015)						
MKT	1.04 (31.03)	1.01 (33.38)	1.03 (35.89)	1.02 (50.98)	0.98 (24.08)	-0.07 (-1.12)
SMB	0.00 (-0.95)	-0.10 (-2.87)	0.13 (1.22)	0.12 (1.59)	0.13 (1.28)	0.12 (1.16)
INV	-0.09 (-1.19)	0.18 (2.43)	0.13 (1.63)	0.10 (1.58)	-0.15 (-1.57)	-0.06 (-0.43)
ROE	0.17 (1.94)	-0.05 (-0.78)	0.07 (1.47)	0.16 (3.10)	0.10 (1.52)	-0.07 (-0.71)
Panel D. Loadings on Daniel, Hirshleifer and Sun (2019)						
MKT	0.99 (36.63)	1.01 (39.94)	1.04 (36.77)	1.01 (40.27)	0.97 (21.44)	-0.02 (-0.44)
FIN	0.06 (-0.18)	-0.03 (-1.45)	-0.08 (-2.28)	-0.03 (-1.50)	0.08 (0.60)	0.02 (0.21)
PEAD	-0.10 (-2.23)	0.00 (-0.04)	-0.06 (-1.53)	-0.04 (-1.27)	-0.13 (-2.44)	-0.03 (-0.40)

Table A.2. Regression based *FOREXS*_{Vol} Measure

We report the Fama-MacBeth cross-sectional regressions. The dependant variable is the firm's monthly stock return. The explanatory variables are the firm's *FOREXS*_{Vol}, which is measured by the cross-sectional average of currency volatility for each relevant foreign country, weighted by the ratio of foreign sales to total sales. We include the following sales-weighted variables: foreign market return, domestic market return, foreign industry return and domestic industry return. Industry variables are adjusted from market variables except gross industry (incl. Mkt) variables and all explanatory variables are one-period lagged except contemporaneous (ctmp.) variables. The sample period is from December 2003 to January 2018. We report the Newey-West corrected *t*-statistics in parentheses using four lags.

Dependent Variable	Firm Return			
	(1)	(2)	(3)	(4)
Intercept	0.0001 (0.01)	0.0015 (0.12)	0.0033 (0.26)	0.0050 (0.39)
<i>FOREXS</i> _{Vol}	-0.0205 (-0.75)	0.0129 (0.21)	0.0133 (0.21)	0.0140 (0.20)
Size	0.0007 (1.36)	0.0006 (1.31)	0.0006 (1.17)	0.0005 (1.00)
Foreign Market		-0.0298 (-0.24)	0.0539 (0.34)	0.0149 (0.07)
Domestic Market		-0.0924 (-0.04)	-0.1839 (-0.08)	1.3739 (0.49)
Foreign Industry			0.1247 (1.02)	0.0921 (0.74)
Domestic Industry			0.0324 (0.53)	0.0163 (0.35)
Foreign Economy (ctmp.)				0.4765 (4.76)
Domestic Economy (ctmp.)				0.6722 (16.99)

Table A.3. Regression based $FOREXS_{Resid}$ Measure

We report the Fama-MacBeth cross-sectional regressions. The dependant variable is the firm's monthly stock return. The explanatory variables are the firm's $FOREXS_{Resid}$, an alternative regression based $FOREXS$ measure, and the following sales-weighted variables: foreign market return, domestic market return, foreign industry return and domestic industry return. $FOREXS_{Resid}$ is the same as $FOREXS$ except that we replace a currency's return ($CR_{k,t+1}$) with its residual component ($\epsilon_{k,t+1}$) from the following cross-sectional predictive regression: $CR_{k,t+1} = E_t[CR_{k,t+1}] + \epsilon_{k,t+1} = \beta_{1,t} + \beta_{2,t}Carry_{k,t} + \beta_{3,t}Momentum_{k,t} + \epsilon_{k,t+1}$. We measure a currency's carry as the 1-month interest rate differential between a foreign country k and the U.S. and its momentum as the past 12-month currency return. Industry variables are adjusted from market variables except gross industry (incl. Mkt) variables and all explanatory variables are one-period lagged except contemporaneous (ctmp.) variables. The sample period is from December 2003 to January 2018. We report the Newey-West corrected t -statistics in parentheses using four lags.

Dependent Variable	Firm Return			
	(1)	(2)	(3)	(4)
Intercept	0.0033 (0.26)	0.0036 (0.25)	0.0044 (0.30)	0.0063 (0.45)
$FOREXS_{Resid}$	0.6912 (4.00)	0.6334 (3.13)	0.6194 (3.16)	0.4592 (2.39)
Size	0.0004 (0.72)	0.0004 (0.74)	0.0004 (0.63)	0.0004 (0.59)
Foreign Market		-0.0339 (-0.28)	0.1633 (0.93)	0.0911 (0.41)
Domestic Market		-1.2014 (-0.98)	-1.3661 (-1.25)	-1.8221 (-1.33)
Foreign Industry			0.2640 (2.06)	0.1732 (1.17)
Domestic Industry			0.0064 (0.09)	-0.0126 (-0.27)
Foreign Economy (ctmp.)				0.3501 (3.96)
Domestic Economy (ctmp.)				0.6323 (14.35)

Table A.4. Regression based $FOREXS_{\beta}$ Measure

We report the Fama-MacBeth cross-sectional regressions. The dependant variable is the firm's monthly stock return. The explanatory variables are the firm's $FOREXS_{\beta}$, an alternative regression based $FOREXS$ measure, and the following sales-weighted variables: foreign market return, domestic market return, foreign industry return and domestic industry return. $FOREXS_{\beta}$ is the same as $FOREXS$ except that we replace a firm's foreign sales ratio with its return beta on that currency. We measure the firm's foreign exposure using its return sensitivity to recent exchange rate fluctuations (rolling 60-months window). Industry variables are adjusted from market variables except gross industry (incl. Mkt) variables and all explanatory variables are one-period lagged except contemporaneous (ctmp.) variables. The sample period is from December 2003 to January 2018. We report the Newey-West corrected t -statistics in parentheses using four lags.

Dependent Variable	Firm Return			
	(1)	(2)	(3)	(4)
Intercept	0.0224 (2.05)	0.0221 (1.82)	0.0209 (1.67)	0.0213 (1.77)
$FOREXS_{\beta}$	0.0152 (1.02)	0.0148 (1.03)	0.0133 (0.94)	0.0123 (0.88)
Size	-0.0009 (-1.56)	-0.0009 (-1.49)	-0.0008 (-1.35)	-0.0008 (-1.39)
Foreign Market		-0.1251 (-1.17)	-0.0825 (-0.58)	-0.1263 (-1.00)
Domestic Market		-0.3272 (-0.40)	-0.9512 (-1.26)	-0.0848 (-0.05)
Foreign Industry			0.0956 (0.78)	0.0146 (0.14)
Domestic Industry			0.0555 (0.86)	0.0735 (1.56)
Foreign Economy (ctmp.)				0.3691 (3.33)
Domestic Economy (ctmp.)				0.6312 (13.31)

Table A.5. Stock Return Predictability and Foreign Industries

We report the Fama-MacBeth cross-sectional regressions. The dependant variable is the firm's monthly stock return. The explanatory variables are the firm's *FOREXS* and the following sales-weighted variables: foreign market return, domestic market return, foreign industry return and domestic industry return. Industry variables are adjusted from market variables except gross industry (incl. Mkt) variables. All explanatory variables are one-period lagged except contemporaneous (ctmp.) variables. Returns denominated in local currency except dollarized (USD) returns. Additional, unreported control variables include firm's size (log of market cap.), lagged monthly stock return, momentum (lagged cumulative return from $t-12$ to $t-2$) and the ratio of foreign sales to total sales. The sample period is from December 2003 to January 2018. We report the Newey-West corrected t -statistics in parentheses using four lags.

Dependent Variable	Firm Return					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.008 (0.96)	0.006 (0.72)	0.008 (1.01)	0.006 (0.78)	0.012 (1.31)	0.012 (1.31)
<i>FOREXS</i>			0.3341 (2.07)	0.3848 (2.31)	0.4116 (2.36)	0.3434 (2.01)
Foreign Industry (incl. Mkt)			0.1758 (1.72)	0.0804 (0.73)		
Foreign Industry (USD, incl. Mkt)	0.2166 (2.9)	0.1663 (2.26)				
Domestic Industry (incl. Mkt)	0.0839 (1.45)	0.0212 (0.47)	0.0736 (1.19)	0.0154 (0.31)		
Foreign Industry					0.1417 (1.23)	0.0554 (0.49)
Foreign Market					0.0904 (0.64)	-0.0292 (-0.18)
Domestic Industry					0.0419 (0.58)	0.0474 (1.03)
Domestic Market					0.1697 (0.14)	0.1955 (0.82)
Foreign Economy (ctmp.)		0.4202 (5.72)		4.26 (11.22)		0.3289 (4.01)
Domestic Economy (ctmp.)		0.5152 (11.52)		0.5057 (11.22)		0.6617 (14.09)
Controls	Y	Y	Y	Y	Y	Y

Table A.6. Firms Foreign Exposure Based on 10K Reports

We report the Fama-MacBeth cross-sectional regressions. The dependant variable is the firm's monthly stock return. The explanatory variables are the firm's mentions-weighted variables: *FOREXS*, foreign market return, foreign industry return and domestic industry return. The weights are constructed as the number of mentions (in 10K reports) of the firm selling to or purchasing from a foreign nation over total mentions of all foreign nations (Hoberg and Moon (2017)). Industry variables are adjusted from market variables. All explanatory variables are one-period lagged except contemporaneous (ctmp.) variables. Returns denominated in local currency except dollarized (USD) returns. Additional, unreported control variables include firm's size (log of market cap.), lagged monthly stock return, momentum (lagged cumulative return from $t-12$ to $t-2$) and the ratio of foreign sales to total sales. The sample period is from December 2003 to December 2017. We report the Newey-West corrected t -statistics in parentheses using four lags.

Dependent Variable	Firm Return					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.033 (4.65)	0.032 (4.65)	0.033 (4.71)	0.034 (4.84)	0.032 (4.51)	0.028 (4.2)
<i>FOREXS</i>			0.439 (3.58)	0.4044 (2.94)	0.3952 (3.24)	0.3518 (2.74)
Foreign Market			0.0607 (0.76)	-0.0759 (-0.95)	-0.0505 (-0.39)	-0.1836 (-1.24)
Foreign Market (USD)	0.1514 (2.46)	0.1166 (2.01)				
Foreign Industry					0.078 (0.55)	0.0436 (0.22)
Domestic Industry						-0.0391 (-0.57)
Foreign Market (ctmp.)		0.1762 (2.26)				
Foreign Economy (ctmp.)				0.3188 (4.46)		0.3205 (3.75)
Domestic Economy (ctmp.)				0.5773 (14.66)		0.5439 (13.1)
Controls	Y	Y	Y	Y	Y	Y