Digesting FOREXS*

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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. multinational 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 strategy that buys stocks with high *FOREXS* and shorts stocks with low *FOREXS* yields a 6.74% annualized abnormal return. We show that the predictive power comes from incomplete hedging by the firms and limited attention by the investors. Our results thus highlight the important role of investor attention in facilitating information transmission across asset classes.

JEL Classification: G12, G15

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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.

We show that investors' attention is limited because of the availability of relevant information as well as its complexity to digest, and both features can lead to a delayed reaction of U.S. firms to currency shocks. To build intuition for our approach, consider the following example. 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, Panel A, we plot the cumulative excess returns, adjusted for domestic market

[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.

beta, for two U.S. firms. Consider Chicago based FTD Companies, Inc. Among its sales in foreign countries, the U.K. (Japan) represented 25.6% (0%) of its foreign operations. Since Brexit's result, the firm's cumulative return steadily drifted downward. Moreover, FTD's foreign sales ratio to U.K. halved to 12.5%. In contrast, consider semi-conductor company Intersil Corp., with high (no) presence in Japan (the U.K.). At the outset of Brexit, the firm exhibits increasing cumulative returns, with its foreign sales ratio to Japan increasing by 17.8%. Panels B and C of Figure 1 suggests these are not isolated cases; we obtain similar results when grouping all U.S. firms with significant foreign operations in the U.K. and Japan.[2] The exchange rate shock in this example is salient and has a predictable impact on firms' future ROAs, but investors still seem to underreact to such information. Whereas this example is illustrative, similar return predictability is obtained for firms that carry foreign operations with a multitude of countries. Moreover, while foreign events can have an instantaneous effect on their respective local markets, their effects on individual U.S. firms' valuation can be far from immediate because of investors' limited access or 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).

[2]To 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.

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 return predictability induced by *FOREXS*. Each month, we buy a set of stocks with high *FOREXS* and short 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, in-

[3]In 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.

[4]We 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.

dustry, 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 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 1% increase in *FOREXS* this month is associated with a 2.4% increase in sales growth and a 0.3% increase in return-on-asset (ROA) next quarter, suggesting that firms, on average, do not fully hedge their currency exposures.

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. In line with these findings on firms' hedging policies, we document stronger *FOREXS* effects in firms with lower pricing power, as these firms struggle to pass-through currency shocks to consumers. Finally, using past cash flow sensitivity to *FOREXS* as a measure of firm's effective currency exposure after hedging (Adler and Dumas (1984)), we document a much stronger *FOREXS* return predictive power among firms with high currency exposures.

Incomplete hedging could explain *FOREXS*'s predictive power on firms' future cash flows, but it does not explain the return predictability. The delayed price adjustment may arise from equity investors' limited attention to the impact of currency shocks. 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 limited attention to information in the currency market. First, 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. Second, the return predictability of *FOREXS* also weakens when stock ownership by hedge funds and foreign investors increases, since these investors are more likely to pay attention to exchange rate fluctuations. Third, 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 pay attention to some currencies 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 (Collin-Dufresne, Goldstein, and Martin (2001), Gebhardt, Hvidkjaer, and Swaminathan (2005), Chordia, Goyal, Nozawa, Subrahmanyam, and Tong (2017), Choi and Kim (2018), Pitkajarvi, Suominen, and Vaittinen (2020) among others), between the equity market and the CDS market (Han, Subrahmanyam, and Zhou (2017)), and between the equity market and the options market (Barras and Malkhozov (2016)). 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 limited investor attention. 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)).[5] 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, contains relevant information that is not captured by foreign returns in individual stocks, industries, markets, or economies. In other words, different from existing studies, we show that only shocks to currency returns 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

[5] A non-exhaustive literature on investors' limited attention 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).

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. Moreover, we find that investors' limited attention for digesting foreign information is specific to the cross-section of currency news.

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)).[6] While insightful, we find that aggregation of firms and countries can yield inconclusive results. U.S. firms' exposure to foreign currency information is very 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 effects of changes in a trade-weighted currency index on a subset of 208 firms reporting foreign currency adjustments in their financial statements. In their analysis, importance is given to the time-series dimension of the currency exposure effect, with multinationals' presence in foreign economies assumed to be fixed and identical across firms. Instead, our interest is centered on the effects of changes in relevant foreign currency information on the cross-section of U.S. firms, and therefore analyze over 3,000 companies with foreign operations.

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

Importantly, we find that time-varying, firm-specific weights prove critical to determine a firm's exposure to currency rates.[7]

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, operational hedging and specialized news flows.

We obtain firm-level geographic revenue with different countries from FactSet Revere 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.[8] We then construct value-weighted portfolios for each two-digit SIC code and each country in our sample.[9] We construct the portfolios using 30 countries.[10] Our choice of this set of countries is driven by (i) the top sales partners of U.S. firms, and (ii)

[7]In 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 that of an alternative based on return currency loadings.

[8]We 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.

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

[10]Our choice of countries are 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.

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.

[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 (2019) 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 Krecetovs (2019) to compute monthly analysts' forecast dispersion for each currency.[11]

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

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

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.[12] Table 2 defines all variables used in this paper.

[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.

[12]We search asset class specific news from the Wall Street Journal, New York Times, Washington Post, 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.

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.

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 the by the ratio w of foreign sales to total sales

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

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.[13]

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

[13]In 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.

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.

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.[14]

[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 (2019). 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 mod-

[14] For robustness purposes, we 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.

els. 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 non-significant 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 have a predictable impact on firms' fundamentals, with investors underreacting to such shocks. To the extent that this fundamental information is revealed through a firm's earnings announcement, investors asses 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.[15] 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.[16] 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%.

[Insert Figure 2 Here]

Figure 2 shows no reversal in cumulative returns, suggesting *FOREXS* captures delays in information transmission to firm values. This information, related to foreign economies, is specific to currency rates and 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.

[15] In 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.

[16] Specifically, 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 the high *FOREXS* portfolio return could primarily reflect compensation for priced offshoring risk.

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, ..., 6) from the portfolio formation period, we keep track of all the constituents of portfolio k (with k =1, 2, ..., 5) and assign a score to each of the stocks based on their new membership out of 5 portfolios.

[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

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

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 foreign and domestic economy variables.

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 0.30 with a Newey-West $t-$statistic of 2.45.

[Insert Table 5 Here]

In specification 2, we include cross-sectional lagged information about the foreign and domestic stock market. Both measures yield non-significant, whereas *FOREXS* remain positively (0.52) and statistically (t = 2.98) 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).

In column 4 we augment the regression with contemporaneous foreign and domestic economy control variables, which yield significant coefficients, and find that *FOREXS* continues to exhibit strong relation to future returns of individual stocks. In sum, firms with higher *FOREXS* exhibit higher future returns.[17] To interpret the economic significance of *FOREXS*,

[17]When we contrast our *FOREXS* measure based on currency returns with an alternative based on currency

note that its coefficient of 0.428 in column 4 indicates that a one-standard deviation increase in *FOREXS* is associated with an average increase in firm return of 23 basis points per month.[18]

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 0.428 in column 4 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 0.55% per month (1.26%×0.428).[19]

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 5 replicates column 4 but using an equally-weighted version of *FOREXS*, labeled $\overline{FOREXS}$. Column 6 includes both *FOREXS* and $\overline{FOREXS}$. In both cases, columns 5 and 6 show that $\overline{FOREXS}$ coefficients render non-significant, suggesting that the relative foreign presence of a multinational does matter when constructing *FOREXS*.

Lastly, we 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,

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.

[18]In Table 5, column 4, *FOREXS* standard deviation equals 0.53%.

[19]The 0.55% monthly return increases with alternative specifications (columns 1 to 3 in Table 5) and is consistent with the literature on relative portfolio strategies. For example, Bali, Brown and Tang (2017) obtain a 0.68% monthly return when sorting stocks on their covariances with macro-uncertainty measures.

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. Third, we add the total sales fraction from foreign countries to account for firms' exposure to systematic foreign trade risk (Amihud, Bartov, and Wang (2014)). Overall, column 7 in Table 5 reports that those additional controls do not affect the magnitude and significance of the *FOREXS* predictability.

Given that the predictive power of *FOREXS* arises from the delay in incorporating shocks to relevant currencies into the firm value, we next 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) and Menkhoff, Sarno, Schmelling and Schrimpf (2012), we define the unexpected component of currency returns as the residual after removing its carry and momentum components.[20] 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. Table A.4 in the Appendix reports that $FOREXS_{\beta}$ does not significantly predict stock returns in the cross-section. The result suggests 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]

[20]Specifically, 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.

[21]Currency 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.

4.4 Decomposing Foreign Information

The results from Table 5 confirm our hypothesis that different sources of foreign information require different processing times and capabilities by U.S. investors. Distinguishing between these sources seems to provide significant results. It can 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, not in foreign market or industry returns.

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 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*,

[22]Tables 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.

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 ($t = 2.2$), 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 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.

[23] Note 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).

4.5 The Real Impact of FOREXS

Sections 4.2 and 4.3 show 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. To investigate the real effects of *FOREXS*, we implement Fama-Macbeth predictive regressions where instead of firms' returns, the dependent variables are firms' quarterly sales growth, quarterly changes in return on assets and the quarterly earnings surprise (SUE) defined as actual earnings minus expected earnings from IBES analyst forecasts, normalized by the standard deviation of those analysts forecasts. 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. We report the results in Table 7.

[Insert Table 7 Here]

In column 1, the Table reports that *FOREXS* exhibit strong return predictability. Cross sectionally, firms with larger *FOREXS* generate larger growth of sales in the following quarter. We obtain similar results using firms' return on assets as the dependent variable. In column 2, the coefficient of *FOREXS* equals 0.29 and is statistically significant ($t = 2.3$), which implies that a one-standard deviation change in *FOREXS* results in a 49 basis points change of the same sign in ROA.[24] This confirms that return predictability comes from investors having 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.

[24] We further investigate if alternative measures of foreign information generate similar real effects. We repeat the analysis using the cross-section of foreign markets and industries instead of *FOREXS* and find no significant relations to future changes in sales or ROA.

Overall, Section 4 shows that not all information about foreign markets is alike; 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.

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 vary with the degree of hedging. Specifically, we expect a stronger predictive power among firms with relatively less foreign exchange hedging.

We first 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)). The difference between FX volatilities implied by the options and spot market indicates the cost to insure against currency oscillations. Therefore, we expect the return effect of *FOREXS* to be specially stronger when we observe a higher cost of financial hedging through derivatives.

The cost of financial hedging is empirically measured by the difference between the option implied volatility and the realized volatility of FX returns. We split our sample period based on the average cost of FX hedging using option contracts across countries. In Table 8, column 1 reports the cross-sectional regressions for the low insurance cost state, in which the cost of insurance is below the median. Likewise, column 2 reports the regression for the high insurance cost state, where the cost of insurance is above the median. Column 1 reports that in the low insurance state *FOREXS* return predictability is not statistically significant (t=1.1), whereas in the high insurance cost state (column 2) *FOREXS* shows strong economic (0.723) and statistical significance (t=2.9). When the cost of financial hedging increases, so does the return effect of *FOREXS*.

[Insert Table 8 Here]

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 financial derivatives. We expect *FOREXS* return effect to be stronger in firms with relatively fewer mentions of financial derivatives. Column 3 and 4 report the cross-sectional regression for firms with below and above median 10K's mentions. *FOREXS* returns effect is economically and statistically significant for firms with low levels of financial hedging (column 3), while this effect is attenuated as firms increase financial hedging (column 4).

Next, we examine the importance of operational hedging. Columns 1 to 4 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' operational hedging by splitting our sample into firms with and without operational hedging. We measure operational hedging using the number of mentions 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. We test this idea using two measures of operational hedging. In columns 5 to 8 of Table 8, we report the cross-sectional regressions using firms without operational hedging (columns 5 and 7) and firms with operational hedging (columns 6 and 8). First, comparing columns 5 and 6, the predictability of *FOREXS* is significant (0.70) and statistically different than 0 (t=2.39) for firms that lack operational hedging (OHIN=0 or Low Input Purchases), while it is not for firms with operational hedging in place (0.32 and t=1.38). Second, this conclusion holds when we use the alternative measure of operational hedging (OHIN*). In columns 7 and 8, the return effect of *FOREXS* is statically significant only for the firms without operational hedging in place (t=2.6). The difference in coefficients on *FOREXS* is larger for the case of OHIN* (1.01) than that of OHIN (0.38). This evidence is consistent with Hoberg and Moon (2017) 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.

As an alternative form of operational hedging, we consider firms' pricing power and ability to pass-through currency shocks to consumers. To this end, we test whether firm dominance in the product market within an industry has any effect on *FOREXS* predictability. We rely on Hoberg, Phillips and Prabhala (2014) firm-level variable TNIC-HHI, computed using firms sales and the Herfindahl-Hirschmann sum of squared market shares, to empirically measure a firm's pricing power. Intuitively, we expect *FOREXS* predictability to weaken with firms' pricing power as these firms can pass-through currency shocks to their consumers without worrying about consumers shifting away from their products (see for example, Allayanis and Ihrig (2001)). Table 8 reports the cross sectional regressions for firms with low (column 9) and high (column 10) pricing power. Column 9 reports a *FOREXS* loading equal to 0.684 and statistically significant (t=2.76), whereas the loading in column 10 yields non-statistically significant. The results from columns 9 and 10 suggest that return predictability is stronger among firms in competitive industries (i.e., low pricing power) and that as firms pricing power decrease so does their ability to pass-through currency shocks to consumers.

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.[25] 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 sensitivity, we use the firm's quarterly income before extraordinary items (IBQ) year-over-year percentage change to proxy for its free cash flow growth. For

[25]The 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).

each firm at each point in time, we estimate its regression coefficient of percentage changes in IBQ on *FOREXS* using a rolling window of 20 quarters. We then split firms based on their cash-flow beta. Column 11 and 12 report the cross-sectional regressions for the low-beta and high-beta cash-flow exposure to *FOREXS*. Consistent with our prior, return predictability increases for firms in which their cash-flow growth exhibits high exposure to *FOREXS*. Its loading is positive and statistically significant (0.38 and t=2.32), while the coefficient is not statistically significant in the low cash-flow beta case.

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

Limited investor attention 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 development and implications of currency shocks. Such a limited attention generates initial underreaction to $FOREXS$. Under this channel, we would expect the return predictive power associated with $FOREXS$ to weaken when investor attention constraints are alleviated.

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.

[Insert Table 9 Here]

Column 1 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 -0.33 with a Newey-West corrected $t-$statistic of -1.98. 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 2), the interaction term *FOREXS* $\times$ $ANFM$ is not significant ($t = -0.57$).

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 limited attention on 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 be more attentive 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 3, we observe that the interaction term *FOREXS* with hedge fund ownership is statistically significant ($t = -2.41$) and with expected negative sign (-0.16). Likewise, interacting *FOREXS* with foreign institutional ownership in column 4 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 19% and 24% for U.S. firms largely held by hedge funds or foreign institutional investors.

Using the broader definition of all institutional ownership (column 5), the interaction term *FOREXS* $\times$ *Own.I* is not significant.[26] Investors' inattention 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 3 and 4 suggest. In all, columns 3 to 5 suggest that efficient processing of *FOREXS* requires specialized attention to the currency market.

Finally, the degree of limited attention 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

[26]We orthogonalize ownership variables to firms' size in all specifications.

other. Columns 6 to 8 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 attention 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 6, we confirm our hypothesis. The interaction term is with the expected sign (-0.67) and statistically significant ($t = -2.07$). Likewise, in column 7 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 8, 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.[27] 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 attention is 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 8 we find the interacting term to be positive (0.30) and statistically significant ($t = 2.03$), further supporting the limited attention channel.

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

[27]Each 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.

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 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 include our benchmark specification (non-decomposed *FOREXS*) for comparison purposes. We test our prediction that return predictability increases with volatile currencies and report cross-sectional regression results in Table 10.

[Insert Table 10 Here]

Column 1 reports the benchmark specification, identical to column 1 of Table 5. In columns 2 and 3 we decompose *FOREXS* into $FOREXS^H$ and $FOREXS^L$, and control for lagged and contemporaneous variables. Similar to Table 5, we also test whether return predictability results from delays in incorporating information from the cross-section of foreign markets and industries, as well as domestic markets and industries. In column 2, the $FOREXS^H$ coefficient is equal to 0.56 and statistically significant ($t = 2.16$). $FOREXS^L$ coefficient, while similar in magnitude, is not statistically significant ($t = 1.09$). We obtain similar results for the case of currency forecasts dispersion in columns 4 and 5. In column 4, $FOREXS^H$ coefficient equals to 0.74 and is statistically significant ($t = 2.15$), while $FOREXS^L$ coefficient yields non significant ($t = 1.27$). These results indicate that 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. 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 incomplete hedging and limited attention that result in investors incorporating their assessment into stock prices with a significant delay.

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 only 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 come from incomplete hedging by the firms and attention by the investors, limited by the availability and complexity of relevant 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] Adler, Michael, and Bernard Dumas. 1984. Exposure to Currency Risk: Definition and Measurement. *Financial Management*, 13, 41-50.

[3] Ahern, Kenneth, and Denis Sosyura. 2015. Rumor Has It: Sensationalism in Financial Media. *Review of Financial Studies*, 28, 7, 2050-2093.

[4] 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.

[5] Albuquerque, Rui, Ramadorai, Tarun, and Sumudu Watugala. 2015. Trade credit and cross-country predictable firm returns. *Journal of Financial Economics*, 115, 592-613.

[6] Allayannis, George, and Jane Ihrig. 2001. Exposure and Markups. *Review of Financial Studies*,14, 805-835

[7] Allayannis, George, Ihrig, Jane, and James Weston. 2001. Exchange rate hedging: Financial versus operational strategies. *American Economic Review*, 91, 2, 391-395.

[8] Amihud, Yakov, Bartov, Eli, and Baolian Wang. 2014. The pricing of corporate foreign trade risk. Working Paper.

[9] Andrei Daniel, and Michael Hasler. 2015. Investor Attention and Stock Market Volatility. *Review of Financial Studies*, 28, 1, 33-72.

[10] Ang, Andrew, Hodrick, Robert, Xing, Yuhand, and Xiaoyan Zhang. 2006. The cross section of volatility and expected returns. Journal of Finance, 61, 1, 259-299.

[11] 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.

[12] Bai, John, Garg, Priya and Chi Wan. 2020. Offshore sales networks and stock return predictability. Working Paper.

[13] 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.

[14] Barrot, Jean-Noel, Loualiche, Erik, and Julien Sauvagnat. 2019. The Globalization Risk Premium. *Journal of Finance*, 74, 5, 2391-2439.

[15] Barras, Laurent and Aytek Malkhozov. 2016. Does variance risk have two prices? Evidence from the equity and option markets. *Journal of Financial Economics*, 121, 79-92.

[16] 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.

[17] Bartram, Söhnke, Brown, Gregory, and Frank Fehle. 2009. International Evidence on Financial Derivatives Usage. *Financial Management,* 185-206.

[18] 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.

[19] Bartov, Eli and Gordon Bodnar. 1994. Firm Valuation, Earnings Expectations, and the Exchange-Rate Exposure Effect. *Journal of Finance*, 49, 5, 1755-1785.

[20] Bessembinder, Hendrik and Cooper, Michael, and Feng Zhang. 2019. Characteristic-Based Benchmark Returns and Corporate Events. *Review of Financial Studies*, 32, 75-125.

[21] Bodnar, Gordon, Dumas, Bernard and Richard Marston. 2002. Pass-through and exposure. *Journal of Finance*, 57, 199-231.

[22] Carhart, Mark. 1997. On persistence in mutual fund performance. *Journal of Finance*, 52, 57-82.

[23] 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.

[24] Chen, Long, Da, Zhi, and Xinlei Zhao. 2013. What Drives Stock Price Movements? *Review of Financial Studies*, 26, 4, 841-876.

[25] Choi, Jaewon, and Yongjun Kim. 2018. Anomalies and market (dis)integration. *Journal of Monetary Economics*, 100, 16-34.

[26] 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.

[27] Cohen, Lauren, and Andrea Frazzini. 2008. Economic links and predictable returns. *Journal of Finance,* 63, 1977-2011.

[28] 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.

[29] Cohen, Lauren, and Dong Lou. 2012. Complicated firms. *Journal of Financial Economics*, 104, 383-400.

[30] Collin-Dufresne, Pierre, Goldstein, Robert, and Spencer Martin. 2001. The Determinants of Credit Spread Changes. *Journal of Finance*, 56, 2177-2207.

[31] Da, Zhi, Engelberg, Joseph, and Pengjie Gao. 2011. In search of attention. *Journal of Finance*, 66,1461-99.

[32] Da, Zhi, Gurun, Umit, and Mitch Warachka. 2014. Frog in the pan: Continuous information and momentum. *Review of Financial Studies*, 27, 2171-2218.

[33] Daniel, Kent, Grinblatt, Mark, Titman, Sheridan, and Russ Wermers. 1997. Measuring Mutual Fund Performance with Characteristic-Based Benchmarks. *Journal of Finance*, 52, 1035-1058.

[34] Daniel, Kent, Hirshleifer, David and Lin Sun. 2019. Short- and Long-Horizon Behavioral Factors. *Review of Financial Studies*, 1-64.

[35] 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.

[36] Della Corte, Pasquale, Ramadorai, Tarun and Lucio Sarno. 2016. Volatility risk premia and exchange rate predictability. *Journal of Financial Economics*, 120, 1, 21-40.

[37] Della Corte, Pasquale and Aleksejs Krecetovs. 2019. Macro Uncertainty and Currency Premia. Working Paper.

[38] DellaVigna, Stefano, and Joshua Pollet. 2009. Investor inattention and Friday earnings announcements. *Journal of Finance,* 64, 709-749.

[39] 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.

[40] Dominguez, Kathryn, and Linda Tesar. 2001. A reexamination of exchange-rate exposure. *American Economic Review*, 91, 2, 396-400.

[41] Dougal, Casey, Engelberg, Joseph, Garcia, Diego and Christopher Parsons, 2012, Journalists and the stock market. *Review of Financial Studies,* 25, 639-679.

[42] Drechsler, Itamar, and Amir Yaron. 2011. What's Vol Got to Do with It. *Review of Financial Studies*, 24, 1, 1-45.

[43] Duffie, Darrell. 2010. Presidential address: Asset price dynamics with slow-moving capital. *Journal of Finance*, 65,1237-67.

[44] Engelberg, Joseph, and Christopher Parsons. 2011. The causal impact of media in financial markets. *Journal of Finance*, 66, 67-97.

[45] Fama, Eugene, and Kenneth French. 1992. The cross-section of expected stock returns. *Journal of Finance,* 47, 427-465.

[46] Fama, Eugene, and Kenneth French. 2015. A five-factor asset pricing model. *Journal of Financial Economics*, 116-122.

[47] Fama, Eugene, and James MacBeth. 1973. Risk, return and equilibrium: empirical tests. *Journal of Political Economy,* 81, 607-636.

[48] Fang, Lily, and Joel Peress. 2009. Media coverage and the cross-section of stock returns. *Journal of Finance*, 64, 2023-2052.

[49] Fillat, Jose, and Stefania Garetto. 2015. Risk, Returns, and Multinational Production. *Quarterly Journal of Economics*, 130, 2027-2073.

[50] 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.

[51] 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.

[52] 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.

[53] Gebhardt, William, Hvidkjaer, Soeren, and Bhaskaran Swaminathan. 2005. Stock and bond market interaction: Does momentum spill over? *Journal of Financial Economics*, 75, 651-690.

[54] 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.

[55] Greenwood, Robin, Hanson, Samuel, and Gordon Liao. 2018. Asset Price Dynamics in Partially Segmented Markets. *Review of Financial Studies*, 31, 3307-3343.

[56] 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.

[57] 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.

[58] Harvey, Campbell, Liu, Yan, and Heqing Zhu. 2016. ...and the cross-section of expected returns, *Review of Financial Studies*, 29, 5-68.

[59] He, Zhiguo, and Wei Xiong. 2013. Delegated asset management, investment mandates, and capital immobility. *Journal of Financial Economics*, 107, 239-258.

[60] Hillert, Alexander, Jacobs, Heiko and Sebastian Müller. 2014. Media Makes Momentum. *Review of Financial Studies*, 27, 12, 3467-3501.

[61] Hirshleifer, David, and Siew Hong Teoh. 2003. Limited attention, information disclosure, and financial reporting. *Journal of accounting and economics*, 36, 337-386.

[62] 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.

[63] Hoberg, Gerard, and Katie Moon. 2017. Offshore activities and financial vs operational hedging. *Journal of Financial Economics*, 125, 217-244.

[64] Hoberg, Gerard, and Katie Moon. 2018. The Offshoring Return Premium. *Management Science*, 1-24.

[65] Hoberg, Gerard, and Gordon Phillips. 2016. Text-Based Network Industries and Endogenous Product Differentiation. *Journal of Political Economy*, 124, 5, 1423-1465.

[66] Hoberg, Gerard, and Gordon Phillips. 2018. Text-Based Industry Momentum. *Journal of Financial and Quantitative Analysis*, 53, 2355-2388.

[67] Hoberg, Gerard, Phillips, Gordon, and Nagpurnanand Prabhala. 2014. Product Market Threats, Payouts, and Financial Flexibility, *Journal of Finance*, 69, 1, 293-324.

[68] 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.

[69] Hong, Harrison, and Jeremy Stein, and Jialin Yi. 2007. Simple forecasts and paradigm shifts. *Journal of Finance,* 62, 1207-1242.

[70] Hou, Kewei. 2007. Industry Information Diffusion and the Lead-Lag Effect in Stock Returns. *Review of Financial Studies,* 20, 1113-1138.

[71] Hou, Kewei, Karolyi, Andrew, and Bong-Chan Kho. 2011. What Factors Drive Global Stock Returns? *Review of Financial Studies*, 24, 2525-2574.

[72] Hou, Kewei, Xue, Chen and Lu Zhang. 2015. Digesting anomalies: An investment approach. *Review of Financial Studies*, 28, 650-705.

[73] Huang, Xing. 2015. Thinking outside the borders: Investors' underreaction to foreign operations information. *Review of Financial Studies*, 3109-3152.

[74] Ince, Ozgur and Burt Porter. 2003. Individual Equity Return Data from Thomson Datastream: Handle with Care! *Journal of Financial Research*, 29, 463-479.

[75] Jensen, Michael and William Meckling. 1992. Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, 48, 65-91.

[76] 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.

[77] 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.

[78] Menkhoff, Lukas, Sarno, Lucio, Schmeling, Maik, and Andreas Schrimpf. 2012. Currency momentum strategies. *Journal of Financial Economics*, 106, 660-684.

[79] Menzly, Lior and Oguzhan Ozbas. 2010. Market Segmentation and Cross-predictability of Returns. *Journal of Finance*, 65, 1555-1580.

[80] Merton, Robert. 1987. A simple model of capital market equilibrium with incomplete information. *Journal of Finance*, 42, 483-510.

[81] Nguyen, Quoc. 2016. Does Investor Attention Stop at the Water's Edge? The Predictability of Multinational Firms' Returns. Working Paper.

[82] Novy-Marx, Robert. 2013. The Other Side of Value: The Gross Profitability Premium. *Journal of Financial Economics*, 108, 1, 1-28.

[83] Peng, Lin, and Wei Xiong. 2006. Investor attention, overconfidence and category learning. *Journal of Financial Economics*, 80, 563-602.

[84] Peress, Joel. 2014. The media and the diffusion of information in financial markets: Evidence from newspaper strikes. *Journal of Finance,* 69, 2007-43.

[85] Pitkäjärvi, Aleksi, Suominen, Matti, and Lauri Vaittinen. 2020. Cross-asset signals and time series momentum. *Journal of Financial Economics*, 136, 63-85.

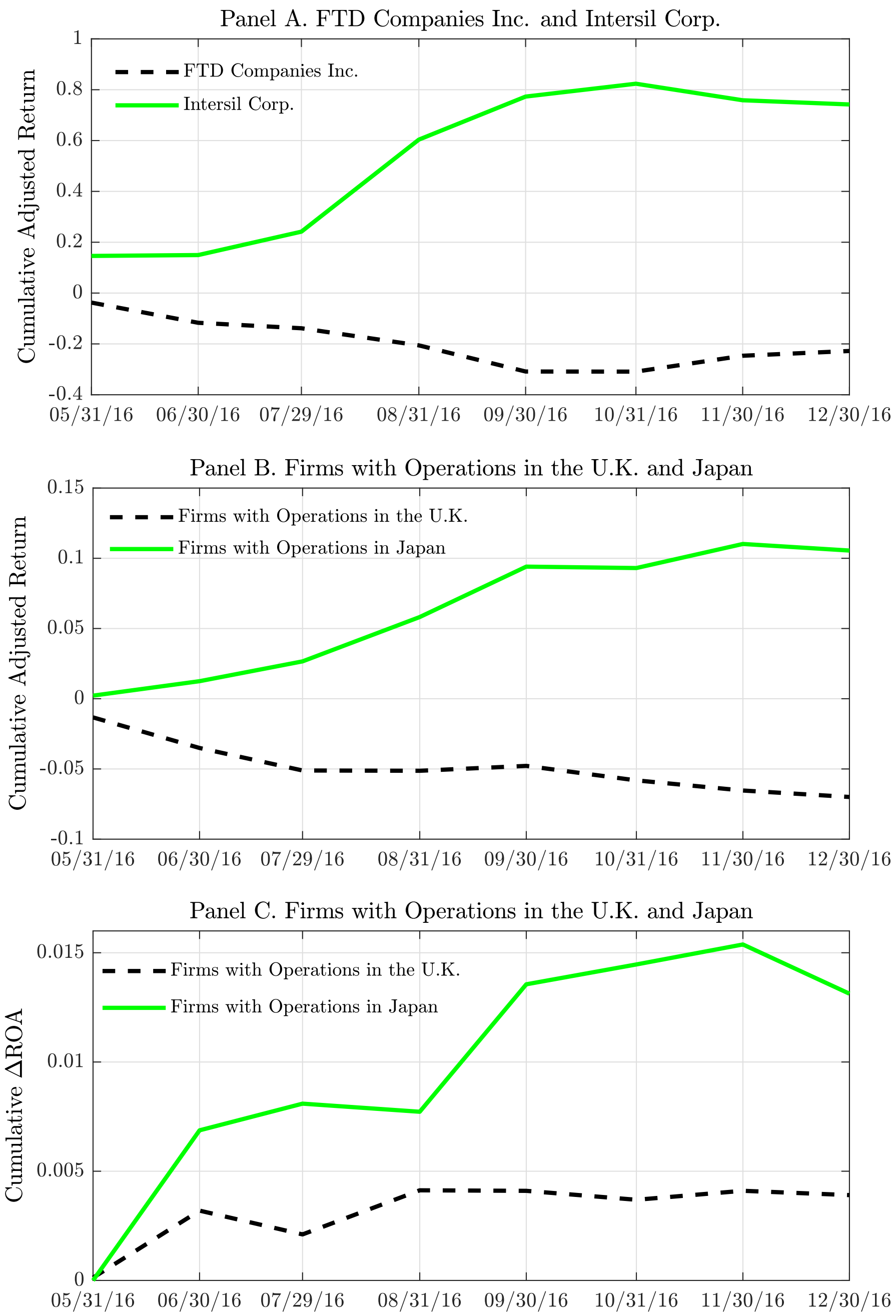
[86] Rossi, Barbara. 2013. Exchange Rate Predictability. 2013. *Journal of Economic Literature*, 51, 1063-1119.

[87] Tetlock, Paul. 2007. Giving content to investor sentiment: The role of media in the stock market. 2007. *Journal of Finance*, 62, 1139-1168.

[88] Stambaugh, Robert and Yu Yuan. 2017. Mispricing factors. *Review of Financial Studies*, 30, 1270-1315.

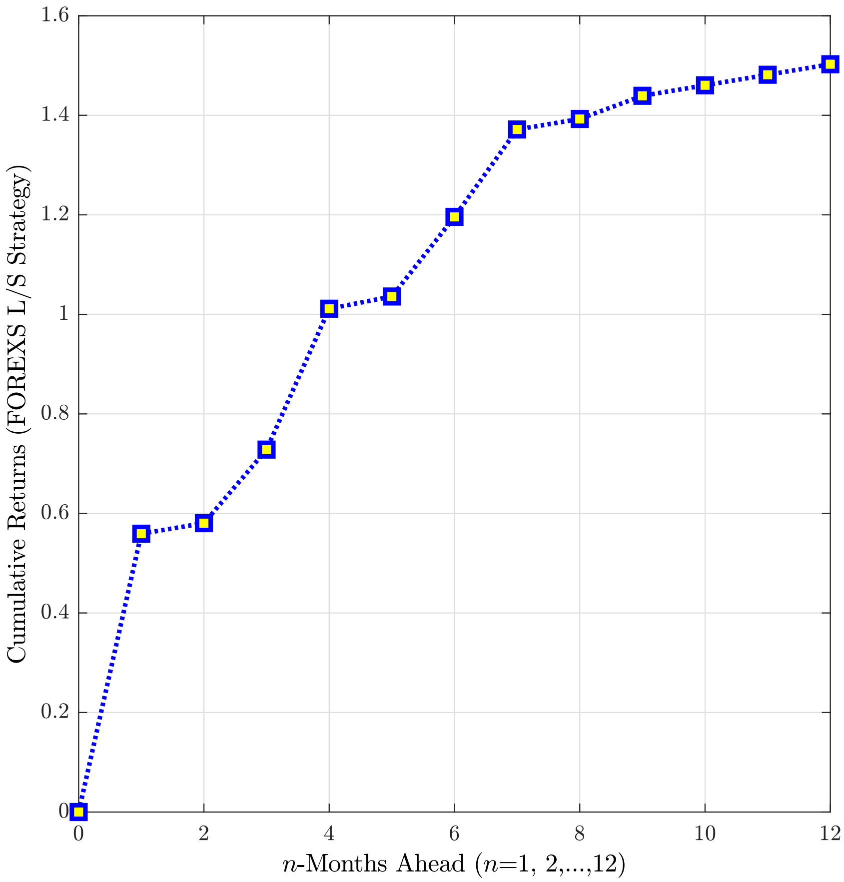
[89] Wagner, Alexander, Zeckhauser, Richard and Alexandre Ziegler. 2018. Company stock price reactions to the 2016 election shock: Trump, taxes, and trade. *Journal of Financial Economics*, 130, 428-451.

Figure 1. Foreign Currencies and Operations: The Brexit Case



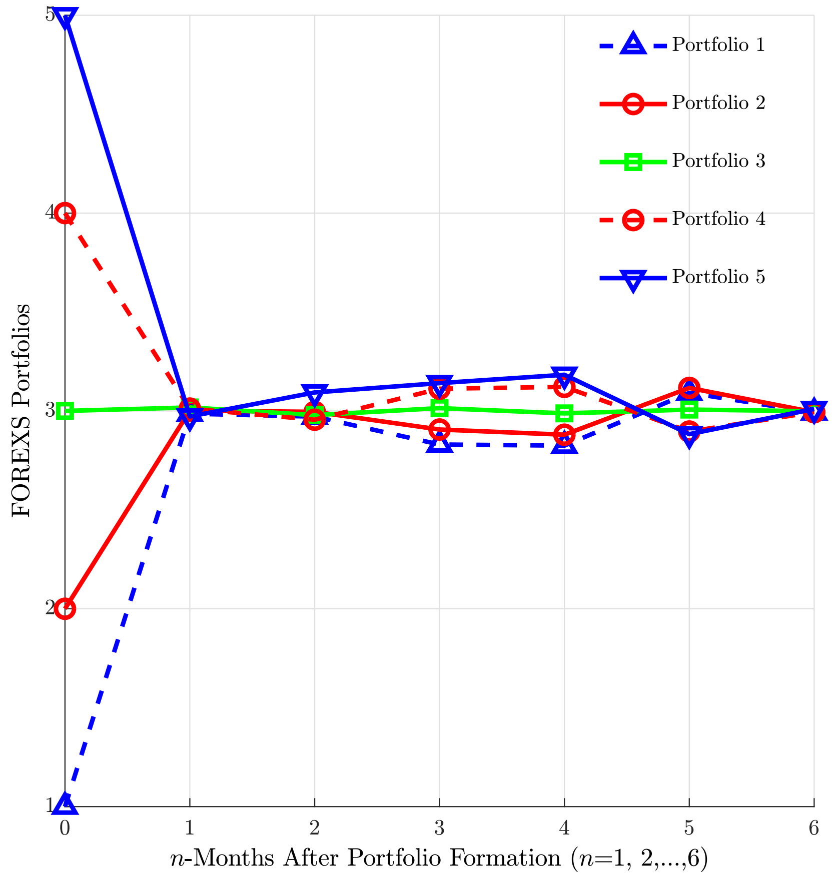
We plot the cumulative excess returns from May to December of 2016 for U.S. firms with operations in the U.K. and Japan. The returns are domestic market beta-adjusted. The Brexit referendum was held in June 23, 2016. Panel A shows the cumulative excess returns for FTD Companies, Inc. and Intersil Corp. Panel B (C) shows the average cumulative excess returns (ΔROA) for U.S. firms with operations in the U.K. and Japan. To compute the average excess return (ΔROA), 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 excess returns (ΔROA).

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 $n = 1, 2, ..., 6$) from the portfolio formation period, we keep track of all the constituents of portfolio k (with $k = 1, 2, ..., 5$) 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	
$FOREXS$	Foreign operations related exchange shocks, which is measured by the cross-sectional average of currency returns for each relavant foreign country, weighted by the ratio of foreign sales to total sales
$\overline{FOREXS}$	Equal-weighted version of $FOREXS$
Foreign Market	Similar to $FOREXS$ 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 $FOREXS$ 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	Combination of $FOREXS$, Foreign Market, and Foreign Industry
Domestic Economy	Combination of Domestic Market and Domestic 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, Xui 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 bechmark portfolios: 125 portfolios sorted on size, BM, momentum as defined by Daniel, Grinblatt, Titman and Wermers (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.	Percentage change in total sales in the current quarter to sales in the previous quarter.

Table 2 (cont.). Variable Definitions

Variables for firm fundamentals (cont.)	
ROA	Return on asset, which is the ratio of firms' income before extraorid-nary item to total assets
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 hedging	
FX Derivatives	Number of mentions of the firm using foreign currency futures derivative in the 10-K report, orthogonalized by retrieving residuals from the cross-sectional regression on log of market capitalization
FX Forecast	Dispersion of analysts' forecasts about the future value of the currency, following Della Corte and Krecetovs (2019)
FX Volatility	Realized and option implied volatility of the foreign exchange rate
IN	The firm-country level indicator variable as in Hoberg and Moon (2017), which equals 1 if if the firm mentions purchasing inputs from the given nation, and 0 otherwise
OHIN	The firm level indicator variable equals 1 if the sales-weighted average of IN is greater than 10 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*	The firm level indicator variable equals 1 if the sales-weighted average of IN* is greater than 10 percent
HHI	Pricing power proxy based on Hoberg, Phillips and Prabhala (2014) Herfindahl-Hirschmann Index
Cash-flow Beta	Regression coefficient of percentage changes in IBQ on $FOREXS$
Variables related to information processing environment	
ANFX	The indicator variable equals 1 if the sales-weighted average of the abnormal currency news measure is above the median across firms and equals 0 otherwise
ANFM	Similar to ANFX except that ANFM uses foreign stock market news
Own.HF	Hedge fund ownership as a percentage of outstanding shares
Own.FI	Foreign institutional ownership as a percentage of outstanding shares
Own.I	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
Herfin	Herfindahl index based on the firm's geographic segment sales
Countries	Number of countries in which the firm has foreign operations
CSDFX	Cross-sectional standard deviation of FX returns for each and month

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
$FOREXS$	-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 (Cahart 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.

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

Dependent Variable	Firm Return						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.0167	0.0167	0.0171	0.0167	0.0176	0.0168	0.028
	(1.86)	(1.69)	(1.71)	(1.66)	(1.72)	(1.67)	(3.37)
$FOREXS$	0.3048	0.5218	0.4923	0.4284		0.4506	0.400
	(2.45)	(2.98)	(2.83)	(2.5)		(2.5)	(2.40)
$\overline{FOREXS}$					-0.0029	-0.0705	
					(-0.03)	(-0.65)	
Size	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.001
	(-0.95)	(-0.99)	(-0.98)	(-1.05)	(-1.03)	(-1.06)	(-2.40)
Foreign Market		-0.0437	0.0799	-0.0402	-0.0022	-0.0294	-0.046
		(-0.37)	(0.54)	(-0.23)	(-0.01)	(-0.17)	(-0.31)
Domestic Market		-0.4448	-0.6816	1.0323	0.7088	1.1486	2.856
		(-0.56)	(-1.07)	(0.52)	(0.31)	(0.54)	(0.99)
Foreign Industry			0.1515	0.059	0.1254	0.0557	0.057
			(1.29)	(0.49)	(1.01)	(0.47)	(0.54)
Domestic Industry			0.0261	0.0342	0.0346	0.0383	-0.005
			(0.37)	(0.84)	(0.84)	(0.94)	(-0.06)
Foreign Economy (ctmp.)				0.3603	0.3381	0.3514	0.366
				(4.55)	(4.07)	(4.5)	(4.76)
Domestic Economy (ctmp.)				0.6667	0.6717	0.6679	0.667
				(13.04)	(13.01)	(12.9)	(15.79)
Firm Return							-0.022
							(-3.09)
Momentum							-0.004
							(-1.28)
Foreign Sales Ratio							-0.004
							(-1.56)
Idiosyncratic Volatility							-0.001
							(-2.33)
Book-to-Market							0.000
							(-0.25)

Table 6. FOREXS and Stock Return Decomposition

We report the Fama-MacBeth cross-sectional regressions. The dependent variables are the firm's monthly *FOREXS* and the sales-weighted foreign industry, domestic industry, and firm-specific information measures. The firm-specific measure is the difference between firm return and the three information measures. All explanatory variables are one-period lagged and defined in Table 2. The sample period is from December 2003 to January 2018. We report the Newey-West corrected t-statistics in parentheses.

Dependent Variable	*FOREXS*	Foreign Industry	Domestic Industry	Firm Specific
	(1)	(2)	(3)	(4)
Intercept	0.0002	0.0012	0.0056	0.0073
	(0.76)	(2.27)	(2.36)	(0.87)
FOREXS	0.0204	0.0394	-0.0397	0.3408
	(0.45)	(0.91)	(-0.65)	(2.22)
Foreign Industry	0.0339	0.1562	-0.0574	0.071
	(1.5)	(3.29)	(-1.01)	(0.76)
Domestic Industry	0.0026	-0.0045	0.0486	0.0093
	(0.32)	(-0.39)	(1.04)	(0.16)
Firm Specific	0.0002	0.0002	0.0002	-0.0199
	(1.49)	(1.54)	(0.49)	(-2.69)
Size	0.0000	0.0000	0.0000	-0.0004
	(-0.49)	(0.95)	(-0.82)	(-0.88)

Table 7. Real Effects and FOREXS

We report the Fama-MacBeth cross-sectional regressions. The dependant 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 defined in Table 2. For Sales Gr., we use the percentage change in total sales in the current quarter to sales in the previous quarter. ΔROA 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 is the actual earnings minus expected earnings, normalized by the standard deviation of analysts forecasts. The sample period is from December 2003 to January 2018. We report the Newey-West corrected $t-$statistics in parentheses.

Dependent Variable	Sales Gr.	ΔROA	SUE
	(1)	(2)	(3)
Intercept	0.100	-0.018	-2.440
	(2.83)	(-2.83)	(-7.79)
$FOREXS$	2.398	0.291	16.850
	(2.25)	(2.33)	(2.63)
Size	-0.001	0.001	0.196
	(-0.48)	(3.17)	(2.66)
Firm Return	0.140	0.017	0.538
	(4.44)	(5.72)	(1.46)
Book-to-market	-0.086	0.006	0.309
	(-7.59)	(1.73)	(2.29)
Profitability	0.098	0.036	5.847
	(0.87)	(5.89)	(15.42)
Investment	0.580	-0.009	-2.504
	(3.23)	(-0.64)	(-6.01)
R&D	0.317	0.004	5.703
	(0.85)	(0.11)	(3.54)
Z-score	-0.018	-0.002	0.084
	(-1.92)	(-2.99)	(4.16)

Table 8. FOREXS and Currency Hedging

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 defined in Table 2. In columns 1 and 2, the sample period is split in two groups based on the insurance cost for FX volatility, measured by the difference between the option implied and historical spot currency volatility. Column 1 reports the results for the low insurance cost of volatility state. Column 2 reports the results for the high insurance cost of volatility state. In columns 3 and 4, based on firms' financial hedging information we split the sample into firms with financial hedging and firms without financial hedging. We measure financial hedging using the number of financial derivatives mentions in firms' 10K reports (Hoberg and Moon (2017)). In columns 5 to 8, based on firms' operational hedging information, we split the sample into firms with no operational hedging (OHIN=0) and firms with operational hedging (OHIN=1) when the firm purchases inputs (columns 5 and 6) as well as mentions of input purchases without owning foreign assets (OHIN*=0 and OHIN*=1 in columns 7 and 8). We measure operational hedging using the number of mentions in firms' financial statements (Hoberg and Moon (2017)). In columns 9 and 10, we split the sample into firms with low pricing power and high pricing power. Pricing power measures the (inverse) level of current product market competition faced by firms. We follow Hoberg, Phillips, Prabhala (2014) and compute each firms' Herfindahl-Hirschmann Index (HHI) sum of squared market shares based on the "Textual Network Industry Classification (TNIC)" industries formed using firm-by-firm similarity measures as in Hoberg and Phillips (2016). In columns 11 and 12, we split the sample into firms with low and high cash-flow exposure to *FOREXS*. Cash-flow beta is computed using firms quarterly income before extraordinary items (IBQ) year-over-year percentage change. The sample period is from December 2003 to December 2017. We report the Newey-West corrected t-statistics in parentheses.

Dependent Variable	Firm Return											
	Financial Hedging				Operational Hedging						Cash-Flow Beta	
	Insurance Cost		10K Mentions		Input Purchases		Input Purchases*		Pricing Power		Sensitivity	
	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.0051	0.0309	0.014	0.0211	0.0115	0.0243	0.0149	0.0252	0.0007	0.0035	0.0295	0.0338
	(0.49)	(1.73)	(0.95)	(2.16)	(1.09)	(2.07)	(1.47)	(1.47)	(0.06)	(0.39)	(1.53)	(1.65)
$FOREXS$	0.2755	0.7235	0.6055	0.4135	0.7054	0.3272	0.5217	-0.4959	0.684	0.4649	0.0109	0.3800
	(1.11)	(2.95)	(2.71)	(1.63)	(2.39)	(1.38)	(2.6)	(-0.53)	(2.76)	(1.52)	(0.07)	(2.32)
Size	0.0001	-0.0012	0.3142	-0.0933	-0.0005	-0.0008	-0.0005	-0.0003	0.0007	0.0005	-0.0011	-0.0012
	(0.17)	(-1.4)	(1.27)	(-0.5)	(-0.95)	(-1.36)	(-0.98)	(-0.3)	(1.53)	(1.01)	(-1.13)	(-1.18)
Foreign Market	-0.1098	0.2824	-0.1754	-1.0913	0.4541	-0.1737	0.0799	-2.1356	0.4169	-0.3709	0.3304	-0.3056
	(-0.6)	(1.17)	(-0.16)	(-1.14)	(1.56)	(-1.1)	(0.47)	(-1.11)	(1.49)	(-1.45)	(1.18)	(-1.69)
Domestic Market	0.167	-1.5742	0.4639	-0.1174	-0.4083	-1.4559	-1.0302	-1.238	-0.2782	0.2321	-1.4337	-0.9819
	(0.16)	(-2.46)	(2.43)	(-0.79)	(-0.26)	(-1.44)	(-1.45)	(-0.64)	(-0.41)	(0.28)	(-1.38)	(-1.05)
Foreign Industry	0.1651	0.1528	0.0253	0.2173	0.3648	0.0127	0.2132	-0.5879	0.3749	-0.0299	0.2166	0.1616
	(1.03)	(0.88)	(0.36)	(1.57)	(2.05)	(0.09)	(1.63)	(-1.63)	(1.97)	(-0.19)	(0.88)	(0.91)
Domestic Industry	0.1778	-0.1471	-0.0004	-0.0006	0.0528	0.0755	0.0384	-0.2472	0.0141	0.0195	0.0698	0.0750
	(2.27)	(-1.21)	(-0.57)	(-1.09)	(0.75)	(0.8)	(0.53)	(-1.77)	(0.15)	(0.29)	(0.83)	(1.12)

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 benchmark explanatory variable is *FOREXS*. All the interaction variables are defined in Table 2. Specifications 1 and 2 interact *FOREXS* with abnormal news flows about foreign currency news and foreign stock market news. For each foreign economy, we collect monthly, foreign-currency specific news and foreign-stock-market specific news from the top 5 U.S. newspapers: 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 repeat the analysis for foreign-stock-market specific news. Specifications 3 to 8 respectively interact *FOREXS* with firm size orthogonalized measures of hedge fund institutional ownership, foreign institutional ownership, institutional ownership, the Herfindahl index of foreign sales, number of countries involved, and cross-sectional standard deviation among currencies. 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.

Dependent Variable	Firm Return							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.0151	0.0145	0.0111	0.0087	0.0124	0.003	0.0093	0.0178
	(1.53)	(1.47)	(1.11)	(0.85)	(1.19)	(0.33)	(1.1)	(1.76)
$FOREXS$	0.4627	0.5285	0.6766	0.6318	0.6086	1.0247	0.3879	0.3783
	(2.34)	(2.21)	(2.94)	(2.83)	(2.43)	(3.55)	(2.1)	(2.1)
$FOREXS \times ANFX$	-0.3302							
	(-1.98)							
$FOREXS \times ANFM$		-0.143						
		(-0.57)						
$FOREXS \times Own.HF$			-0.1637					
			(-2.41)					
$FOREXS \times Own.FI$				-0.1206				
				(-2.26)				
$FOREXS \times Own.I$					-0.0593			
					(-0.59)			
$FOREXS \times Herfin.$						-0.671		
						(-2.07)		
$FOREXS \times Countries$							0.1796	
							(1.91)	
$FOREXS \times CSDFX$								0.3096
								(2.03)

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. Column 1 reports the benchmark explanatory variable *FOREXS* and controls. The variables are defined in Table 2. Columns 2 and 3 report the decomposition of *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 volatility is below median across currencies. In columns 4 and 5, $FOREXS^H$ comprises the set of economies where previous month currency forecast dispersion is above median across currencies. $FOREXS^L$ comprises the set of economies where previous month currency forecast dispersion is below median across currencies. All explanatory variables 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.

Dependent Variable	Firm Return				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.0167	0.0181	0.0182	0.0164	0.0166
	(1.86)	(1.75)	(1.75)	(1.47)	(1.5)
$FOREXS$	0.3048				
	(2.45)				
$FOREXS^H$		0.5604	0.6676	0.7466	0.691
		(2.16)	(2.13)	(2.15)	(2.07)
$FOREXS^L$		0.5241	0.5401	0.3149	0.2468
		(1.09)	(1.06)	(1.27)	(0.92)
Size	-0.0005	-0.0005	-0.0005	-0.0003	-0.0003
	(-0.95)	(-0.98)	(-1.08)	(-0.54)	(-0.59)
Foreign Market		0.1351	-0.0472	-0.0818	-0.2506
		(0.85)	(-0.27)	(-0.5)	(-1.59)
Domestic Market		-0.7004	1.0651	-0.108	2.0137
		(-0.73)	(0.48)	(-0.14)	(0.83)
Foreign Industry		0.1615	0.0415	0.1451	0.0645
		(1.31)	(0.34)	(1.14)	(0.59)
Domestic Industry		0.0332	0.016	0.0735	0.0506
		(0.5)	(0.35)	(1.25)	(1.13)
Foreign Economy (ctmp.)			0.4834		0.3289
			(4.14)		(3.99)
Domestic Economy (ctmp.)			0.6679		0.6759
			(13.27)		(11.58)

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.

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

Dependent Variable	Firm Return			
	(1)	(2)	(3)	(4)
Intercept	0.0167	0.0173	0.0175	0.0185
	(1.88)	(1.59)	(1.61)	(1.69)
$FOREXS_{Vol}$	-0.013	-0.0039	0.0051	0.0167
	(-0.5)	(-0.06)	(0.08)	(0.24)
Size	-0.0005	-0.0005	-0.0005	-0.0005
	(-0.97)	(-0.99)	(-0.98)	(-1.07)
Foreign Market		-0.0439	0.0232	-0.0524
		(-0.32)	(0.14)	(-0.29)
Domestic Market		-0.6497	-0.9905	1.3938
		(-0.28)	(-0.47)	(0.49)
Foreign Industry			0.074	0.0249
			(0.58)	(0.21)
Domestic Industry			0.0292	0.0238
			(0.43)	(0.56)
Foreign Economy (ctmp.)				0.436
				(4.18)
Domestic Economy (ctmp.)				0.6644
				(13.22)

Table A.3. Regression based $\boldsymbol{FOREXS_{Resid}}$ 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.

Dependent Variable	Firm Return			
	(1)	(2)	(3)	(4)
Intercept	0.0033	0.0037	0.0044	0.0042
	(0.35)	(0.34)	(0.4)	(0.38)
$FOREXS_{Resid}$	0.6986	0.6347	0.6215	0.5181
	(4.04)	(2.82)	(2.8)	(2.51)
Size	0.0004	0.0004	0.0004	0.0003
	(0.84)	(0.89)	(0.77)	(0.62)
Foreign Market		-0.0341	0.1634	0.0915
		(-0.27)	(1.01)	(0.47)
Domestic Market		-1.2023	-1.3673	-2.2954
		(-1.09)	(-1.39)	(-1.49)
Foreign Industry			0.265	0.196
			(2.25)	(1.44)
Domestic Industry			0.0062	-0.0125
			(0.07)	(-0.26)
Foreign Economy (ctmp.)				0.3929
				(3.92)
Domestic Economy (ctmp.)				0.6328
				(12.7)

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.

Dependent Variable	Firm Return			
	(1)	(2)	(3)	(4)
Intercept	0.0224	0.0221	0.0209	0.0213
	(2.61)	(2.32)	(2.13)	(2.19)
$FOREXS_\beta$	0.0152	-0.0009	0.0133	0.0123
	(1.03)	(-1.81)	(0.94)	(0.88)
Size	-0.0009	0.0148	-0.0008	-0.0008
	(-1.87)	(1.02)	(-1.67)	(-1.72)
Foreign Market		-0.1251	-0.178	-0.1263
		(-0.96)	(-1.3)	(-0.79)
Domestic Market		-0.3272	-1.0068	-0.0848
		(-0.43)	(-1.39)	(-0.05)
Foreign Industry			0.0956	0.0146
			(0.82)	(0.13)
Domestic Industry			0.0555	0.0735
			(0.79)	(1.68)
Foreign Economy (ctmp.)				0.3691
				(3.78)
Domestic Economy (ctmp.)				0.6312
				(12.44)

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.

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

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