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Digesting FOREXS: Information Transmission Across Asset Classes and Return Predictability

Joon Woo Bae,[a] Zhi Da,[b,*] Virgilio Zurita[c]

[a] Weatherhead School of Management, Case Western Reserve University, Cleveland, Ohio 44106; [b] Mendoza College of Business, University of Notre Dame, Notre Dame, Indiana 46556; [c] Hankamer School of Business, Baylor University, Waco, Texas 76706

*Corresponding author

Contact: joon.bae@case.edu, https://orcid.org/0000-0002-7389-2113 (JWB); zda@nd.edu, https://orcid.org/0000-0003-2815-1516 (ZD); virgilio_zurita@baylor.edu, https://orcid.org/0009-0002-4136-9181 (VZ)

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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. 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. An *FOREXS*-based long-short strategy yields a 6.74% annualized abnormal return. *FOREXS* predictive power comes from firms' incomplete hedging and investors' limited attention, highlighting the challenges involved when processing information from a different asset class.

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1. Introduction

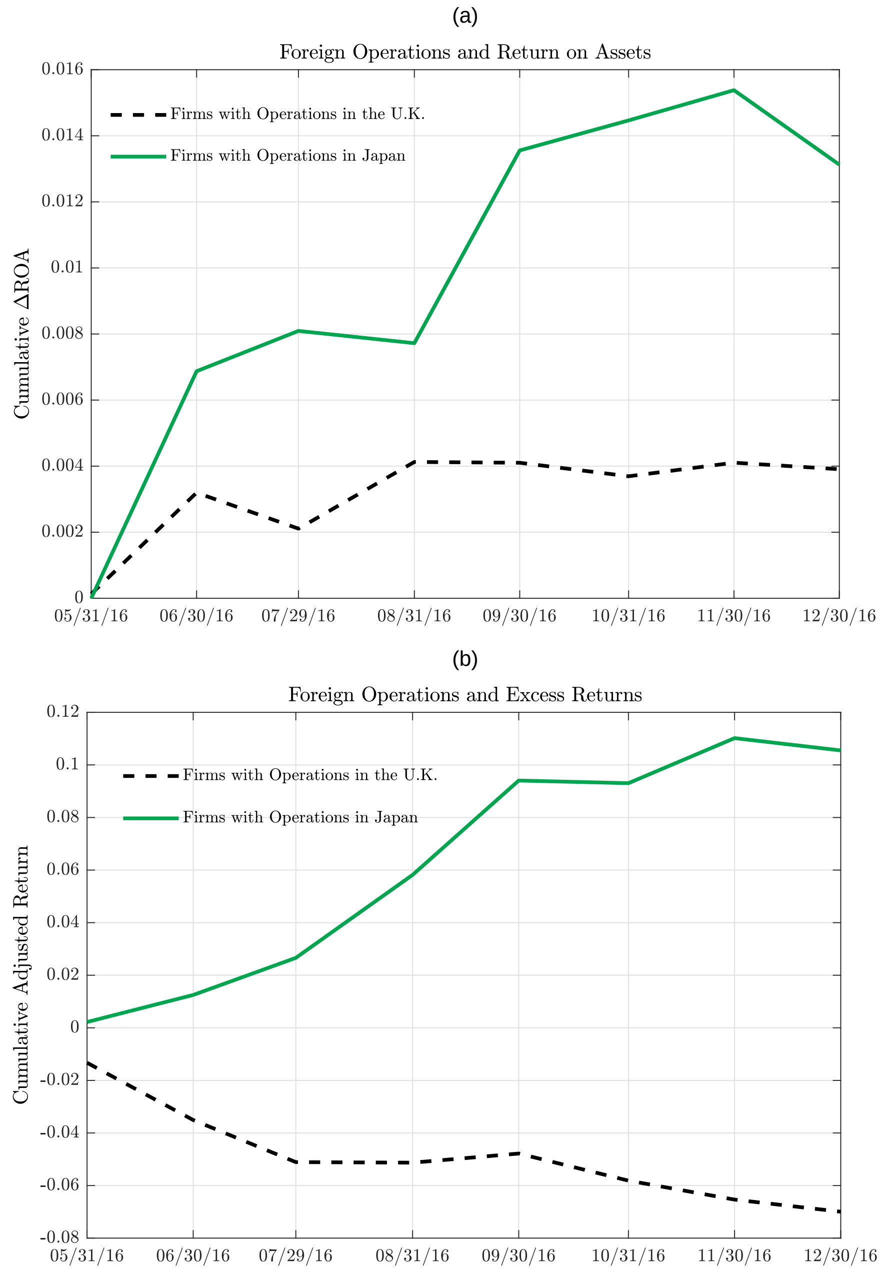
Firms today operate in an increasingly interconnected economy. As a result, equity valuation is affected by shocks across many different asset classes. For example, commodity prices affect firms' input costs, and interest rates affect firms' financing costs and discount rates. How do equity investors 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 et al. (2017) note that almost half of all sales of firms in the S&P 500 composite are generated abroad. Foreign exchange rate fluctuations, although largely unpredictable (see, for example, Rossi 2013), can have a significant impact on firms' cash flow, especially when they are not fully hedged. We provide novel evidence that equity investors of U.S. multinationals underreact to firms' currency shocks from countries in which they operate.

Shocks to the cross-section of currency rates slowly diffuse to U.S. stock prices, which is consistent with firm and investor challenges to digest complex information. To build intuition for our approach, consider the following example using the Brexit referendum. On June 23, 2016, the United Kingdom 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 United Kingdom and Japan? Foreign economies with weaker currencies make U.S. firms' goods relatively more expensive, whereas the opposite happens with stronger currencies. In Figure 1, we plot the cumulative excess returns adjusted for domestic market β and cumulative changes in the return on asset (ΔROA) for two portfolios of U.S. firms with significant foreign operations in the United Kingdom and Japan, respectively.[2] The exchange rate shock in this example is salient and impacts firms' future *ROA*s in a predictable direction (Figure 1(a)), but investors still seem to underreact to such information, generating postevent return drift (Figure 1(b)). This is because figuring out the precise impact of a currency shock on firms is a nontrivial task, especially when the firms have partially hedged such a shock.

Although this example is illustrative and refers specifically to a single foreign economy and currency, it still highlights the main feature of our strategy; foreign information related to relevant currencies impacts domestic firms with a delay. Moreover, return predictability is more pronounced with less salient events and for firms that carry foreign operations with a multitude of countries

Figure 1. (Color online) Foreign Currencies and Operations: The Brexit Case



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

because of investors' limited access and capabilities to efficiently process foreign exchange rate shocks.

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 foreign operations-related exchange shocks (*FOREXS*).

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, our proposed trading strategy buys a set of stocks with high *FOREXS* and shorts a set of stocks with low *FOREXS* based on the previous month *FOREXS* estimates. The long-short strategy generates a 6.74% annualized abnormal return and is statistically significant after controlling for the three-factor model of Fama and French (1992), the four-factor model of Carhart (1997), the five-factor model of Fama and French (2015), the four-factor model of Stambaugh and Yuan (2017), and the four-factor model of Hou et al. (2015).

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

Huang (2015) and Nguyen (2016) document that investors of U.S. multinational firms underreact to foreign information, measured using dollar returns of foreign market or industry returns.[4] Using cross-sectional regressions, therefore, we further investigate if the predictive power of a multinational's *FOREXS* is driven by alternative characteristics of the firm, industry, market, or country. First, we find that the exposure of a company to the cross-section of currency rates remains economically and statistically unaffected by the firm's size as well as contemporaneous (ctmp.) 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 because an appreciation of the foreign currency elevates the purchasing power of consumers. A one-standard deviation change in *FOREXS* results in a 1.24% increase in the quarterly growth rate of sales, suggesting that firms, on average, do not fully hedge their currency exposures.

In our framework, two conditions are needed in order to obtain return predictability induced by *FOREXS*. First, U.S. firms should be fundamentally exposed to the cross-section of relevant currency rates. Second, investors should underreact to such information, relevant for firms' operational performance, generating postevent return drift. Indeed, if multinational firms fully hedge their exchange rate exposure, *FOREXS* should not affect stock returns. Changing firms' hedging costs, via financial or operational hedging, therefore directly impacts the prospect of U.S. firms with foreign operations. Different degrees of currency hedging, therefore, generate interesting cross-sectional variations. We use currency option and spot prices to estimate firms' cost to financially insure against future changes in FX volatility and find the *FOREXS* return effect to increase with the cost to hedge against currency volatility. We confirm this result when looking into firms' 10K reports following Hoberg and Moon (2017), with a stronger effect of *FOREXS* in firms with fewer mentions of financial derivatives for hedging purposes. We then study firms' operational hedging levels implied by the company 10K's documents and find that stock return predictability increases when firms' operational hedging is lower. Consistent with these findings on hedging policies, we document a much stronger *FOREXS* return predictive power among firms with high currency exposures using the cash-flow sensitivity to *FOREXS* as a measure of firms' effective net currency exposure (Adler and Dumas 1984).

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

We provide several pieces of evidence supporting investors limitations in first accessing and then processing information from the currency market. First, we examine the impact of currency risk disclosure by firms in their annual reports. We find the predictive power of *FOREXS* to decrease among firms that mention the words "currency," "foreign exchange," or "FX" in the risk factors section of their 10K reports, consistent with the notion that such disclosure encourages investor attention to currency shocks, thus reducing underreaction to *FOREXS*. Second, we rely on several textual analytics and use computational linguistic methods to identify and isolate news coverage specific to currency rates. To the extent that currency news coverage triggers investor attention to exchange rate fluctuations, it should weaken the return predictability of *FOREXS*. This is exactly what we find. As a placebo test, the return predictability of

FOREXS does not vary with other news coverage about foreign equity markets. Third, the return predictability of *FOREXS* also weakens when stock ownership by hedge funds and foreign investors increases because these investors are more likely to allocate resources (time and specialized labor) to the cross-section of currency rates. Fourth, the return predictability of *FOREXS* becomes stronger when the multinational firms are exposed to more currencies, and these currencies are less correlated with each other. In these situations, the failure to rapidly access and process the effects of currency shocks is likely to have a large impact on price efficiency and cause more return predictability by *FOREXS*.

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

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

2. Related Literature

Our paper contributes to different strands of literature, starting with studies on information flows between segmented asset classes. From a theoretical perspective, capital immobility, limits of arbitrage, and delegated portfolio management can all result in segmented asset classes (Gabaix et al. 2007, Duffie 2010, He and Xiong 2013, Greenwood et al. 2018 among others). Empirically, there is evidence of such slow diffusion between the equity market and the bond market (Gebhardt et al. 2005, Pitkäjärvi et al. 2020).[5] The literature also documents the link of the equity market with the CDS market (Han et al. 2017) and with the options market (Barras and Malkhozov 2016). More recently, Addoum and Murfin (2020) document the information lag from syndicated loan prices to equity prices. We show that information in the foreign exchange market travels to the equity market with a delay.

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

Focusing on multinational firms, existing literature finds that firms with a presence in foreign economies are particularly sensitive to the transmission of foreign markets' developments into U.S. stocks prices (Albuquerque et al. 2015, Huang 2015, Nguyen 2016, Wagner et al. 2018, Bae et al. 2019, Bai et al. 2020). 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, we show that shocks specific to currency rates slowly diffuse to U.S. firms and play a critical role in previously documented return predictability.

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

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

Lastly, our paper is related to earlier work investigating the exposure of firms to foreign exchange rates. This literature 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 Dominguez and Tesar 2001, Bodnar et al. 2002, Bartram et al. 2010).[7] Although insightful, we find that aggregation of firms and countries can yield inconclusive results. U.S. firms' exposure to foreign currency information is substantially different from the exposure of non-U.S. firms, and explicitly accounting for a firm's relative presence in different countries is crucial to understand investors' delayed reaction to currency shocks.

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

3. Data

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

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

Table 1 reports the summary statistics for the set of U.S. firms with foreign operations. In panel A, for 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% of their revenues from foreign economies using value weights and equal weights, respectively. Although the ratio is significantly lower among below median-size firms, 20% (18%) 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% 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.

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 et al. (2015), Stambaugh and Yuan (2017), and Daniel et al. (2020) are collected from the authors' websites. We use firms' FX hedging data based on firm-year textual mentions in 10K 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.[12]

We develop a time-varying nation-security-month network to isolate specialized news flows. We compile a list of words that connect three arguments in our network: countries, asset classes, and relevant actions. For the first argument, we use the list of nations where U.S. firms exhibit a positive flow of sales. For the second argument, we generate a list of words related to foreign exchange rates, specific to each foreign country. We implement a similar strategy for news specific to each foreign stock market. For example, for the case of Japan, we use Japan or Japanese for the first argument. For the second argument, for currency-specific news we use foreign exchange, FX, currency, its official currency name (yen), or its ISO 4217 currency code (JPY). For stock market-specific news, the list includes words such as "Nikkei", "JPX", and "TOPIX". For the third argument, we search for actions that indicate developments in the foreign asset class. For currencies, the list includes words such as depreciation or appreciation and includes bearish or bullish for stock markets. We augment our list with the financial dictionary of words developed by Loughran and McDonald (2011). Our source of news comes from top newspapers where U.S. investors obtain relevant information.[13] The sample period utilized for the construction of all variables is from 2003 to 2018, and we define them in Table 2.

4. Foreign Operations-Related Exchange Shocks

In this section, we first define the main information measure (*FOREXS*) and its components, and we study the performance of a long-short strategy based on *FOREXS*

Table 1. Summary Statistics

Panel A: Firms foreign sales		
	Unique firms	Unique firms (foreign sales > 0)
Total firms	5,477	3,464
Average foreign sales (VW), %	35.6	42.6
Above median-size firms, %	36.2	42.9
Below median-size firms, %	19.6	35.6
Average 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, %		
	Total	Excluding 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

Notes. 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 (VWs) and equal weights (EWs) across firms. Panel B reports the top 10 sales partners of U.S. firms based on VWs 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.

using portfolio quantiles. We then investigate its explanatory power in the cross-section of individual stocks.

4.1. *FOREXS*

We define the variables used to construct cross-sectional measures of currency shocks. The foreign exchange rate is the number of U.S. dollars that buys one 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, whereas the Financial Times Stock Exchange (FTSE) is denominated in British pounds). Converting foreign market indices to the U.S. dollar greatly simplifies the crosscountry 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, and (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 United States-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 because of 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 *FOREXS* measure is the cross-sectional average of currency returns CR for each relevant foreign country k weighted by the ratio w of foreign sales to total sales:

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

where N is the total number of countries where firm i generates foreign sales. For example, if a firm's sales ratio to the United Kingdom is 30% and Japan is 40% and if

Table 2. Variable Definitions

Variables	Definition
Variables related to foreign operations	
FOREXS	Foreign operations-related exchange shocks, which is measured by the cross-sectional average of currency returns for each relevant foreign country weighted by the ratio of foreign sales to total sales
$\overline{FOREXS}$	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	Sum of (sales-weighted avg.) foreign currency, market, and industry
Domestic Economy	Sum of (sales-weighted avg.) domestic market and industry
Variables for controlling factors	
FF 3	Fama and French (1992) 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 et al. (2015) factors: *MKT*, *SMB*, *INV*, *ROE*
DHS 3	Daniel et al. (2020) 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 benchmark portfolios: 125 portfolios sorted on size, BM, momentum as defined by Daniel et al. (1997)
BCZ_{C5}	Characteristics-based benchmark adjusted return following Bessembinder et al. (2019). *C*5 model includes log size, log BM ratio, momentum, ROA, and asset growth
BCZ_{C14}	*C*5 characteristics plus β, accrual, dividend, log LR return, idiosyncratic risk, illiquidity, turnover, leverage, and sales-to-price ratio
BCZ_{C15}	*C*14 characteristics plus foreign sales-to-total sales ratio
Variables for firm fundamentals	
Size	Log of market capitalization
Sales Gr.	Quarter over quarter growth rate of total sales
ROA	Return on asset, which is the ratio of firms' income before extraordinary item to total assets
Book to Market	Book to market ratio as in Fama and French (1992)
Profitability	Gross profitability as in Novy-Marx (2013)
Investment	Investment as in Chen et al. (2013): change in property, plant, and equipment plus changes in inventories scaled by lagged total assets
R&D	Research and development (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 standard deviation of analysts' forecasts
Variables related to firm-level hedging	
CDM	Mentions of FX futures derivatives in the 10K report, orthogonalized by retrieving residuals from the cross-sectional regression on log of market capitalization. Dummy variable
ICV	Sales-weighted avg. of option implied minus realized FX volatility. Dummy variable
IN	Firm-country–level indicator equal to 1 if the firm mentions purchasing inputs from the given nation (Hoberg and Moon 2017)
OHIN	Firm-level indicator variable equals 1 if the sales-weighted average of *IN* is greater than 30%
*IN**	Similar to *IN* except that *IN** equals 1 if the firm mentions purchasing inputs and does not mention owning assets in the given nation
*OHIN**	Indicator variable equals 1 if the sales-weighted average of *IN** is greater than 30%
CFS	Regression coefficient of percentage changes in OIBDPQ on *FOREXS*. Dummy variable
FX Forecast	Dispersion of analysts' forecasts about the future value of the currency, following Della Corte and Krecetovs (2019)
Variables related to firm-level information processing environment	
10K1A	Mentions of currency, foreign exchange, or FX in the risk factors section of the 10K report. Dummy variable
ANFX	Sales-weighted average of the abnormal FX news measure. Dummy variable
ANFM	Similar to *ANFX* except that *ANFM* uses foreign stock market news

Table 2. (Continued)

Variables	Definition
HFO	Hedge fund ownership as a percentage of outstanding shares
FIO	Foreign institutional ownership as a percentage of outstanding shares
IO	Total institutional ownership as a percentage of outstanding shares. All 3 ownership variables are orthogonalized by retrieving residuals from the cross-sectional regression on log of market capitalization. Dummy variables
Herfin.	Herfindahl index based on the firm's geographic segment sales. Dummy variable
Countr.	Countries in which the firm has foreign operations. Dummy variable
CSDFX	Firm-month cross-sectional standard deviation of FX returns. Dummy variable

Note. We report the description of variables used in the paper.

the British pound appreciated by 2%, whereas 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 United States, its *FOREXS* will be close to zero.[14]

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 equation, where we replace currency returns by its alternatives.

4.2. Portfolio Sorts

We now investigate *FOREXS*'s 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, because of frictions between two different asset classes, this information may be incorporated into stock prices with a delay.

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

Table 3 reports the summary statistics for portfolios 1 (low) to 5 (high) along with the high minus low portfolio. We report portfolio mean, standard deviation, skewness, kurtosis, and Sharpe ratio, as well as the average *FOREXS* per quintile. From the table, we observe that portfolio returns monotonically increase between quintiles. Portfolios with higher previous-month *FOREXS* yield significantly larger average returns. The long-short portfolio strategy yields an annualized return of 6.73% and shows close to normally distributed returns, with skewness of 0.18 and kurtosis of 3.27.[15]

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 (1992), the Carhart (1997) momentum factor, the five factors in Fama and French (2015), the four factors in Stambaugh and Yuan (2017), the four factors of Hou et al. (2015), and the three factors of Daniel et al. (2020). Table 4 reports the annualized, abnormal returns (α) 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 (Newey and West 1987).

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

Table 3. Summary Statistics for Portfolio Quintiles

	Low	2	3	4	High	High − low
Mean	7.13	9.50	9.65	11.56	13.86	6.73
Standard deviation	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	

Notes. 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 relatively low *FOREXS*, and portfolio 5 includes stocks with relatively 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.

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

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

Table 4. Abnormal Returns of FOREXS Portfolios

	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)
			Panel B: Abnormal returns (earnings announcement 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 announcement 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)

Table 4. (Continued)

	Low	2	3	4	High	High − low
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)

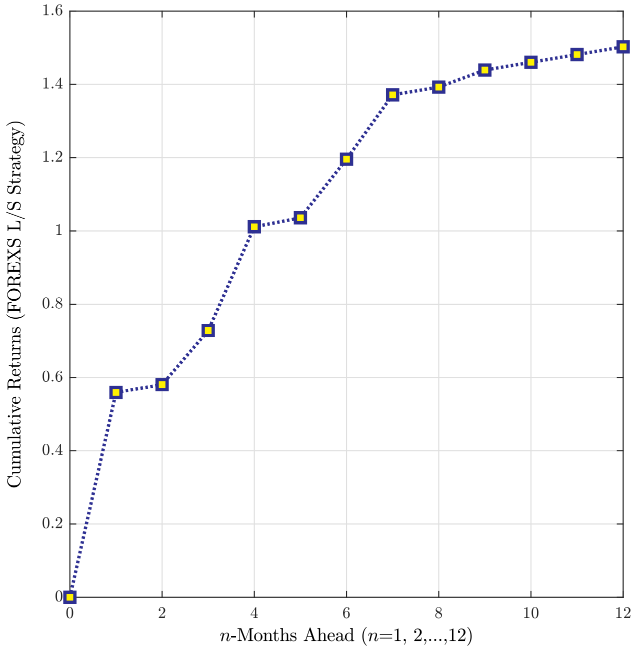
Notes. We report in panel A the annualized abnormal returns for value-weighted portfolio quintiles and the long-short *FOREXS* strategy accounting for the three-factor model (*FF 3*) of Fama and French (1992), the four-factor model (*Carhart 4*) of Carhart (1997), the five-factor model (*FF 5*) of Fama and French (2015), the four-factor model (*SY 4*) of Stambaugh and Yuan (2017), the four-factor model (*HXZ 4*) of Hou et al. (2015), and the three-factor model (*DHS 3*) of Daniel et al. (2020). Stocks are sorted by their cross-sectional currency lagged information (*FOREXS*) measure. Portfolio 1 (low) includes stocks with relatively low *FOREXS*, and portfolio 5 (high) includes stocks with relatively 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 (panel 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 the 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 ratio, and momentum (*DGTW*) as defined by Daniel et al. (1997). For *BCZ*, we employ the Bessembinder et al. (2019) multivariate cross-sectional regression approach to circumvent the curse of dimensionality. We use both the 5-characteristics and 14-characteristics models in the paper (denoted as BCZ_{C5} and BCZ_{C14}, respectively) and augment the C14 model with the foreign-to-total sales ratio (BCZ_{C15}). We report the Newey–West corrected t statistics in parentheses using four lags.

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 nonannouncement 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 et al. 2017). Therefore, we test whether the high minus low *FOREXS* portfolio returns are abnormal by comparing them with the realized returns of characteristics-matched benchmark portfolios.[16] We consider various sets of benchmark portfolios: 25 portfolios sorted on size and book-to-market ratio (*SizeBM*) and 125 portfolios sorted on size, book to market, and momentum (*DGTW*) as defined by Daniel et al. (1997). We also employ the Bessembinder et al. (2019) multivariate cross-sectional regression approach (BCZ) to circumvent the curse of dimensionality.[17] 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 with those using factor sensitivity-based α.

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

Figure 2. (Color online) Cumulative Portfolio Returns



Notes. We plot the cumulative returns of the *FOREXS* long-short strategy in the next 12 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. L/S, Long-short strategy.

overreaction to currency information, and instead, we confirm that investors access and process information with delay.

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

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*.

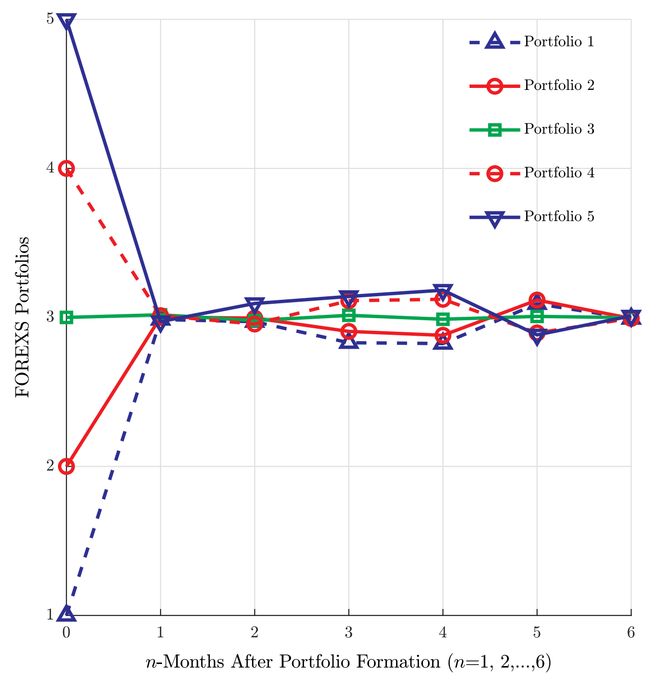
4.3. Cross-Sectional Regressions

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 and Macbeth (1973) monthly predictive regressions:

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

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 capitalization) 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.

Figure 3. (Color online) Portfolio Persistence Score



Notes. 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 five quintile portfolios. The portfolios are rebalanced every calendar month. After n months (with $n = 1, 2, \ldots, 6$) from the portfolio formation period, we keep track of all the constituents of portfolio k (with $k = 1, 2, \ldots, 5$) and assign a score to each of the stocks based on their new membership of five quintile portfolios. Each line in the figure presents the average score of firms in portfolio k at the initial formation period.

All explanatory variables are one-period lagged except ctmp. controls.

Table 5 reports the time series averages for the slope coefficients using monthly observations. The sample period is from December 2003 to January 2018. Column (1) reports the regression on *FOREXS* after controlling for firm size and indicates a positive and statistically significant relation between *FOREXS* and the cross-section of future stock returns. The average slope from the monthly regressions of realized returns on *FOREXS* is 0.42 with a Newey–West t statistic of 3.80.

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

Burt and Hrdlicka (2020) argue that crossfirm predictability among economically linked firms can arise when both firms, leaders and laggards, exhibit own momentum

Table 5. *FOREXS* and Stock Return Predictability

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

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

and their returns are contemporaneously correlated. As the firm's *FOREXS* is contemporaneously correlated with the focal firm's return, the predictability can give rise to a mechanical reason. In column (4), we, therefore, augment the regression with the contemporaneous version of *FOREXS* and find that our main predictor, lagged *FOREXS*, remains economically and statistically significant. We also include the contemporaneous version of *Foreign Market*, which shows a significant positive effect on returns, whereas *Foreign Market*'s lagged version shows an insignificant effect, supporting our hypothesis that equity investors underreact to information in the currency market. In column (5), we control for contemporaneous foreign and domestic economy measures and obtain similar results.[18] In sum, firms with higher *FOREXS* exhibit higher future returns.[19] To interpret the economic significance of *FOREXS*, note that its coefficient of 0.42 in column (1) indicates that a one-standard deviation increase in *FOREXS* is associated with an average increase in firm return of 23 basis points per month.

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

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

We further investigate whether the predictability of *FOREXS* is contaminated by the inclusion of other variables previously known to predict returns. As additional control variables, we first include the one-month lagged return of firm i to account for a possible short-term reversal effect, its return between $t-12$ and $t-2$ to control for the momentum effect, and the book-to-market ratio to control for the value effect. Second, we rely on Ang et al. (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 (1992) over the past one month. Overall, column (8) in Table 5 reports that those additional controls do not affect the magnitude and significance of the *FOREXS* predictability.

The predictive power of *FOREXS* supports our hypothesis that shocks to relevant currencies are incorporated with a delay into firm values. We further study this finding and compute *FOREXS* using only its unexpected component by removing the expected returns (or currency risk premiums) from the realized currency returns. Following Lustig and Verdelhan (2007), we define the unexpected component of currency returns as the residual after removing its carry and momentum components.[20] Carry and momentum have been shown to contain important predictive power for the cross-section of several asset classes (Asness et al. 2013, Koijen et al. 2018). In addition, to the extent that the Fisher effect holds, we remove potential effects of changes in inflation expectations between the domestic and foreign countries by including interest rate differentials. Table A.3 reports that $FOREXS_{Resid}$ is statistically significant and has predictability on future stock returns economically as strong as *FOREXS*, which confirm 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 β 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 implies that β values are estimated with errors and are not as robust as foreign sales ratios in capturing a firm's exposure to currency shocks.[21]

4.4. Decomposing Foreign Information

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

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

To understand the sources of *FOREXS*'s predictability more clearly, we use the contemporaneous version of Equation (2) and decompose the return of the individual firm into subcomponents: 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 et al. (2013), we first compute the proportion of the individual firm's contemporaneous variance explained by those subcomponents. We find that 6%, 2.5%, 11%, and 80.5% of the total variance are explained by *FOREXS*, foreign industry, domestic industry, and firm-specific return, respectively.[23] We then ask which of the four components of the individual firm return is *FOREXS* predicting. We present the predictive regression results in Table 6. In this table, as in Table 5, we run the Fama–MacBeth cross-sectional regression. However, instead of using a firm's return as the dependent variable, we use each of its four components.

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

4.5. The Real Impact of *FOREXS*

Sections 4.2 and 4.3 explore the predictive power of *FOREXS* regarding equity portfolios and individual

Table 6. *FOREXS* and Stock Return Decomposition

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

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

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. We investigate the real effects of FOREXS within a panel data framework (Petersen 2009), because the dependent variable is an accounting measure in this exercise. Therefore, instead of firms' returns, the dependent variables are firms' quarterly sales growth, quarterly changes in return on assets, and the quarterly earnings surprise (*SUE*).[24] Control variables include firms' size (log of market capitalization), stock returns, book to market, investment ratio, profitability (Novy-Marx 2013), R&D expenditure, and Altman's z score. In Table 7, we report the panel regression coefficients, with t statistics controlling for the firm fixed effect and clustering standard errors at the firm level.

Table 7. Real Effects and *FOREXS*

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

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

We find that *FOREXS* exhibits strong predictability in firms' future operational performance. In column (1), firms with larger *FOREXS* generate larger growth of sales in the following quarter. The loading on *FOREXS* is 0.37 (t = 16.2), indicating that a one-standard deviation change in *FOREXS* results in a 1.24% increase in the quarterly growth rate of sales. We obtain similar results using firms' return on assets as the dependent variable. In column (2), the coefficient of *FOREXS* equals 0.01 and is statistically significant (t = 4.19). These results are consistent with return predictability coming from investors' limited attention to the cash-flow implication of *FOREXS*. Furthermore, the significant predictability of *FOREXS* on SUE in column (3) implies that analysts also suffer the lack of sufficient attention to the value-relevant information regarding the firms' foreign operations, revealed through the actual earnings announcement.

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

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

5. The Channels

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

5.1. Incomplete Hedging

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

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

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

Table 8. *FOREXS* and Currency Hedging

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

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

The insurance cost for currency volatility is estimated as the difference between the option implied volatility and the realized volatility of FX returns. For each firm, we construct a categorical variable (*ICV*) that equals one if the sales-weighted average of the insurance cost for currency volatility is above the median across firms and equals zero otherwise. In Table 8, column (1) reports that the interaction term *FOREXS* × *ICV* exhibits a positive loading of 0.4 with a t statistic of 2.11.[25] This result supports the hypothesis that as the cost of FX volatility insurance increases, firms are less inclined to hedge, and thereby, the return effect of *FOREXS* increases. We also analyze the impact of financial hedging on a firm's returns by looking into the company's 10K reports. We follow Hoberg and Moon (2017) and extract the firm's mentions of currency derivatives. We construct the firm-level categorical variable (*CDM*) that equals one if the firm reports above-median mentions of currency derivatives across firms and zero otherwise. Column (2) reports the regression results using this textual measure, with the interaction term *FOREXS* × *CDM* reporting the negative sign (−0.30) and statistical significance (t = −2.09). This evidence suggests that *FOREXS* return effect to be stronger in firms with relatively fewer mentions of financial derivatives.

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

Our conjecture is that the *FOREXS* return effect is more pronounced for firms with less operational hedging. In column (3), we find that the interaction term is negative (−0.42) and significant (t = −2.00), whereas column (4) reports even larger magnitude and significance for the interaction term (−0.79 and t = −2.37). Interestingly, although in both cases, the coefficients are with the expected negative sign, the magnitude of the interaction *OHIN** almost doubles that of *OHIN*. This result is consistent with Hoberg and Moon (2017), who find that the countercyclical benefits of purchase of input are weakened when operational hedging is simultaneously involved with ownership of foreign assets because offshore asset values are procyclical to foreign economic conditions.

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

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

5.2. Limited Attention and Information Complexity

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

We begin by studying how investors react to currency risks disclosed by firms in their annual reports. This allows us to determine whether the firm acknowledges potential risks of currency fluctuations in its overall performance, regardless of whether the company decides to hedge these risks or not.[27] We, therefore, construct a firm-level indicator variable (10K1A) that equals one if a given firm mentions the words "currency," "foreign exchange," or "FX" in the risk factors section (section 1A) of the 10K report.[28] The textual data are downloaded from the SEC's Electronic Data Gathering, Analysis, and Retrieval. Ex ante, the impact of the 10K1A dummy is not clear. On one hand, positive 10K1A dummies likely identify firms more exposed to extreme *FOREXS* in the future, and we, therefore, expect *FOREXS* predictability to increase among these firms. On the other hand, if currency risk disclosure prompts investors to pay attention to future *FOREXS*, we should then expect *FOREXS* predictability to decrease.

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

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 impacts 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 one if the sales-weighted average of the abnormal currency news measure is above the median across firms and equals zero otherwise. The main explanatory variables are *FOREXS* and the news interaction variable *FOREXS* × *ANFX*. To distinguish foreign information between asset classes, we repeat the procedure using foreign stock market-specific news (*ANFM*). We present the predictive regression results in Table 9.

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

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

The impact of limitations in accessing and processing relevant information on future asset prices should also weaken when more investors are attentive. In the case of *FOREXS*, when more equity investors are paying attention to currency news, *FOREXS*'s return predictive power should be reduced. We expect foreign equity investors and sophisticated investors such as hedge funds to have higher processing capacity dedicated to the currency

Table 9. *FOREXS* and Information Processing Environment

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

Notes. We report the Fama–Macbeth cross-sectional regressions. The dependent variable is the firm's monthly stock return. The explanatory variables are interaction terms between *FOREXS* and a number of dummy variables. The interaction variables are summarized in Table 2. Column (1) interacts *FOREXS* with mentions about currency risk in the firm's 10K1A section. Columns (2) and (3) interact *FOREXS* with abnormal news flows about foreign currency news (*ANFX*) and foreign stock market news (*ANFM*), collected monthly, of foreign currency-specific news and foreign stock market-specific news from the top five U.S. newspapers. Columns (4)–(9) interact *FOREXS* with firm size orthogonalized measures of hedge fund institutional ownership (*HFO*), foreign institutional ownership (*FIO*), institutional ownership (*IO*), the Herfindahl index of foreign sales (*Herfin.*), number of countries involved (*Countr.*), and cross-sectional standard deviation among currencies (*CSDFX*), respectively. Control variables include firm's size (log of market cap.) and the following sales-weighted variables: foreign market return, domestic market return, foreign industry return, and domestic industry return. The sample period is from December 2003 to January 2018. We report the Newey–West corrected t statistics in parentheses using four lags, adjusted R^2, and total firm-month observations.

market. Therefore, U.S. multinational firms with more foreign ownership or hedge fund ownership are less likely to suffer from underreaction to *FOREXS*.

The results from Table 9 confirm our priors. In column (4), we observe that the interaction term *FOREXS* with hedge fund ownership is statistically significant (t = −2.28) and with the expected negative sign (−0.41). Likewise, interacting *FOREXS* with foreign institutional ownership in column (5) yields similar conclusions in terms of sign and significance. The two specifications imply that the overall magnitude of the return effect induced by *FOREXS* decreases between 69% and 74% for U.S. firms largely held by hedge funds or foreign institutional investors.

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

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

We construct the Herfindahl index using firms' foreign sales ratios. Firms with high index levels indicate that their foreign operations are concentrated in a smaller group of nations. For investors, this implies allocating resources to a smaller currency set, which makes the processing of information relatively easier. We, therefore, expect that as the Herfindahl index increases, the return effect of *FOREXS* is less pronounced. In column (7), we confirm our hypothesis. The interaction term is with the expected sign (−0.49) and statistically significant (t = −1.97). Likewise, in column (8), we find the *FOREXS* return effect to be stronger if its construction involves more countries, and it is consistent with Fraser and Pantzalis (2004), who find a similar result using the number of subsidiaries for a subset of 310 firms.

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

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

To test this channel, we use a specification similar to the cross-sectional regression of Section 4.3 but decompose *FOREXS* into $FOREXS^H$ and $FOREXS^L$. $FOREXS^H$ comprises the set of economies where previous month currency volatility is above the median across currencies. $FOREXS^L$ comprises the set of economies where previous month currency volatility is below the median across currencies. Likewise, we repeat *FOREXS* decomposition but replace historical volatility with the dispersion of analysts' forecasts about the future value of each currency, which represents a forward-looking measure of currency uncertainty. We test our prediction that return predictability increases with volatile currencies and report cross-sectional regression results in Table 10.

Columns (1)–(3) decompose *FOREXS* into $FOREXS^H$ and $FOREXS^L$ based on the cross-section of currency volatilities. Columns (2) and (3) augment column (1) by adding contemporaneous *FOREXS* and foreign and domestic economy variables. Consistent with our priors, the $FOREXS^H$ coefficient is positive and statistically significant. As uncertainty about the cross-section of FX volatility increases, so does the return predictability of *FOREXS* because investors face more complicated tasks in determining the expected direction of the currency. We obtain similar conclusions in columns (4)–(6) by implementing the decomposition based on currency forecast dispersions. For example, column (6) reports an $FOREXS^H$ coefficient equal to 1.33 (t = 3.22), whereas

Table 10. *FOREXS* and the Cross-Section of Currency Uncertainty

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

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

$FOREXS^L$ is not statistically different than 0. These results are consistent with the hypothesis that in times of higher uncertainty about future currency values, investors deal with more complicated information to process and thus, firm values react with a lag.

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

6. Conclusion

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

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

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

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Appendix. Tables

Table A.1. Portfolio Loadings

	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 Yuan (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 et al. (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 et al. (2020)			
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)

Notes. We report in panels A–D the loadings on risk factor models of Fama and French (2015), Hou et al. (2015), Stambaugh and Yuan (2017), and Daniel et al. (2020). Portfolio 1 (low) includes stocks with relatively low *FOREXS*, and portfolio 5 (high) includes stocks with relatively high *FOREXS*. Portfolios are rebalanced on a monthly basis. The sample period is from December 2003 to January 2018. We report the Newey–West corrected t statistics in parentheses using four lags.

Table A.2. Regression-Based $FOREXS_{Vol}$ Measure

	Firm Return			
Dependent variable	(1)	(2)	(3)	(4)
Intercept	0.0001	0.0015	0.0033	0.0050
	(0.01)	(0.12)	(0.26)	(0.39)
$FOREXS_{Vol}$	−0.0205	0.0129	0.0133	0.0140
	(−0.75)	(0.21)	(0.21)	(0.20)
Size	0.0007	0.0006	0.0006	0.0005
	(1.36)	(1.31)	(1.17)	(1.00)

Table A.2. (Continued)

	Firm Return			
Dependent variable	(1)	(2)	(3)	(4)
Foreign Market		−0.0298	0.0539	0.0149
		(−0.24)	(0.34)	(0.07)
Domestic Market		−0.0924	−0.1839	1.3739
		(−0.04)	(−0.08)	(0.49)
Foreign Industry			0.1247	0.0921
			(1.02)	(0.74)
Domestic Industry			0.0324	0.0163
			(0.53)	(0.35)
Foreign Economy (ctmp.)				0.4765
				(4.76)
Domestic Economy (ctmp.)				0.6722
				(16.99)

Notes. We report the Fama–MacBeth cross-sectional regressions. The dependent 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 (including Mkt) variables, and all explanatory variables are one-period lagged except ctmp. variables. The sample period is from December 2003 to January 2018. We report the Newey–West corrected *t* statistics in parentheses using four lags.

Table A.3. Regression-Based $FOREXS_{Resid}$ Measure

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

Notes. We report the Fama–MacBeth cross-sectional regressions. The dependent 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 United States and its momentum as the past 12-month currency return. Industry variables are adjusted from market variables except gross industry (including Mkt) variables, and all explanatory variables are one-period lagged except ctmp. variables. The sample period is from December 2003 to January 2018. We report the Newey–West corrected *t* statistics in parentheses using four lags.

Table A.4. Regression-Based $FOREXS_\beta$ Measure

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

Notes. We report the Fama–MacBeth cross-sectional regressions. The dependent 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 β on that currency. We measure the firm's foreign exposure using its return sensitivity to recent exchange rate fluctuations (rolling 60-month window). Industry variables are adjusted from market variables except gross industry (including Mkt) variables, and all explanatory variables are one-period lagged except ctmp. variables. The sample period is from December 2003 to January 2018. We report the Newey–West corrected t statistics in parentheses using four lags.

Table A.5. Stock Return Predictability and Foreign Industries

	Firm Return					
Dependent variable	(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)

Table A.5. (Continued)

	Firm Return					
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
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	Yes	Yes	Yes	Yes	Yes	Yes

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

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

	Firm Return					
Dependent variable	(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	Yes	Yes	Yes	Yes	Yes	Yes

Notes. We report the Fama–MacBeth cross-sectional regressions. The dependent 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 ctmp. variables. Returns are denominated in local currency except dollarized (USD) returns. Additional unreported control variables include firm's size (log of market cap.), lagged monthly stock return, momentum (lagged cumulative return from $t-12$ to $t-2$), and the ratio of foreign sales to total sales. The sample period is from December 2003 to December 2017. We report the Newey–West corrected t statistics in parentheses using four lags.

Endnotes

[1] See "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) and "Brexit! Pound at 3 decades low, yen surges to 2013 high" (Dow Jones Newswires, June 24, 2016). Contrary to currency returns, the FTSE 100 index rose about 4.3% and Nikkei 225 fell over 9% in the month of June 2016.

[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 United Kingdom and Japan). We then take a target country sales-weighted average of excess returns. We implement a similar procedure for the changes in ROA.

[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.

[5] Additional studies on the equity-bond crossmarkets link include Collin-Dufresne et al. (2001), Chordia et al. (2017), Choi and Kim (2018), and Auh and Bai (2020).

[6] A nonexhaustive literature on (investors) limited attention and information processing capacity includes the theoretical studies of Merton (1987), Hong et al. (2000), Peng and Xiong (2006), and Andrei and Hasler (2015). Empirical studies include Coval and Moskowitz (1999), Cohen and Frazzini (2008), Da et al. (2011), and Hoberg and Phillips (2018).

[7] Other important studies include Griffin and Stulz (2001) and Desai et al. (2008).

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

[9] We apply several screening procedures as suggested by Ince and Porter (2003). First, at least one of the financial variables must be available for a minimum of one year for a stock to be included in our data set. Second, we only select common stocks that are traded on the country's major exchange(s), excluding preferred stocks, real estate investment trusts, depositary receipts, warrants, and 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 (New York Stock Exchange, American Stock Exchange, and Nasdaq Stock Market). 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 (dollar)1.00 to avoid picking up errors in Datastream. Fifth, firms are required to have at least 12 monthly returns.

[10] We confirm that our findings are robust to redefining the industry set to one-digit SIC codes.

[11] The set of countries includes 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 United Kingdom, and the United States.

[12] At time period t and for country k, let $f^H_{k,t}, f^L_{k,t}$ be the next-quarter top and bottom forecasts, 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 yields similar results.

[13] 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 et al. (2014). We restrict our search to articles where words referring to the three arguments are within five words of distance. Hoberg and Moon (2017) implement a similar strategy and use a 25-word window to search for hedging-related words in 10K 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 3,174 words that we apply to each country in our list.

[14] 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.

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

[16] 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 the value-weighted average of individual firms' characteristics-based benchmark adjusted returns in each *FOREXS* quintile.

[17] Specifically, we use both the 5-characteristics and 14-characteristics models in the paper (denoted as BCZ_{C5} and BCZ_{C14}, respectively) and augment the C14 model with the foreign-to-total sales ratio (BCZ_{C15}) because the high *FOREXS* portfolio return could primarily reflect compensation for priced offshoring risk.

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

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

[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 United States (proxied by 1-month forward discount) and momentum as the past 12-month currency return. See also Menkhoff et al. (2012) and Burt and Hrdlicka (2020).

[21] Currency return β can also be 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.

[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.

[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).

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

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

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

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

[28] Cohen et al. (2020) discuss the importance of the risk factors section of the annual report to predict future returns.

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

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

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