# Currency and Stock Returns: An Example of Market Inattention

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**Abstract**

Currency shocks affect future corporate earnings: companies exporting in countries with an appreciating currency see their earnings increase. Using company-level data on geographic sales, we document that analysts fail to fully integrate currency shocks into their firm-level forecasts: their forecast errors can therefore be predicted by past currency movements. We also show that stock prices do not respond immediately to currency shocks: prices take about two weeks to integrate them. This is true for small to medium size shocks but not for larger shocks, in line with a bounded rationality interpretation. Finally, we find some evidence that arbitrage capital exploiting this anomaly has increased in recent years.

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# 1 Introduction

A major function of financial markets is to ensure that prices incorporate information in real time. Under the efficient market hypothesis, the reaction of prices to public news should be immediate: at any given time, prices should reflect expected fundamental values conditional on available information. This idealized view of markets imperfectly represents reality. A large body of literature documents that markets sometimes over-react (typically, when information is "salient"), and sometimes under-react (typically to small news that are not attention-grabbing). Understanding the conditions under which people over-react and under-react to news remains an open problem in social sciences.

Currency shocks offer an interesting laboratory to analyze (i) the extent to which markets deviate from the efficient market hypothesis and (ii) when investors tend to under-react to new information. Indeed, companies' earnings are, on average, affected by exchange rate movements in a predictable manner once the split of their international sales by country is taken into account. Furthermore, currency returns offer the econometrician a large spectrum of intensity that can be used to ascertain the reaction of market participants. Small currency returns might be too small to grab the attention of investors, thus leading to under-reaction. In contrast, large shocks could be highly visible in the news and might be integrated into prices efficiently.

The contributions of this paper are the following. First, we document that analysts fail to fully integrate currency shocks in their firm-level forecasts. Their forecast errors can therefore be predicted by currency shocks. We also develop a methodology to distinguish between small and large currency shocks. We show that analysts under-react systematically to all shocks, small or large. Second, we show that stock prices fail as well to respond immediately to currency movements: they take about two weeks to integrate past currency shocks. But markets **do not** under-react to larger shocks, in line with a bounded rationality interpretation. Finally, we look at a trading strategy that goes long (short) stocks that are subject to positive (negative) currency shocks. The strategy exhibits a positive and significant Sharpe ratio and has continued performing strongly since the first version of the paper was disseminated more than two years ago. We then try to detect whether capital allocated to such a strategy has increased in recent years. We do so by looking at the negative impact on strategy performance of trading information lagged by a few days. This impact has increased in the past few years, giving some evidence that more arbitrage capital is chasing this anomaly.

Our work is related to the large body of literature on behavioral finance, and in particular to under-reaction and inattention. In that respect, Barberis and Thaler (2003) and Hirshleifer (2015) provide detailed surveys on behavioral finance. It is also well documented that analysts forecasts exhibit biases (see e.g. Abarbanell (1991) and Kothari et al (2016)). On the more specific subject of inattention (which is often cited as one of the main causes for under-reaction), Gabaix (2018) provides an in-depth review. More recently, a few papers have contributed to the debate on under- versus over-reaction. One example is Bordalo et al (2020), who show that professional forecasters tend to over-react to their individual news, while consensus forecasts are sluggish and show signs of under-reaction. They reconcile these seemingly contradictory empirical findings by formulating a diagnostic expectations model.

This paper is also related to the litterature on the decay of trading strategies. McLean and Pontiff (2016) show that many market anomalies disappear as soon as research papers documenting them are disseminated to the public, suggesting that arbitrage capital moves in quickly and decays their performance.

Finally, this work is also connected to papers who look at the interaction between markets and analysts. In that vein, Chen et al (2018) show that when analyst coverage drops, sophisticated investors scale up information acquisition and mitigate the market efficiency impairment caused by that drop.

The remainder of this paper is organized as follows. Section 2 describes the data used. Section 3 documents the impact of currency movements on companies' futures sales. Section 4 establishes that analysts fail to properly take into account the past dynamic of currency prices when they issue their firm-level forecasts. In Section 5, we show that the market is much quicker than analysts at integrating currency movements in stock prices. However, this reaction is not instantaneous: we find that FX shocks predict future stock returns for around two weeks. Section 6 analyses a long-short trading strategy that benefits from stock prices' initial under-reaction to currency shocks. Section 7 offers our conclusions.

# 2 Data

We merge firm-level data from Datascope for currency and equity data, Factset Geographic Revenue Exposure for geographic sales splits, Worldscope for balance sheet data and I/B/E/S for analyst forecasts, as described in detail below. The study covers a more than 12-year period starting in January 2007 and ending in June 2020 and the last quarterly financial period covered by balance sheet and forecast data is the first quarter of 2020.

## 2.1 Stock Sample Selection

The sample of firms used in this paper consists of the top 1,000 U.S. and Canadian firms at any given time, based on market capitalization. We thus restrict our attention to stocks that have a certain size and liquidity. This results in a sample that averages approximately 1,000 stocks over the time horizon studied.

## 2.2 Geographic Revenue Exposure

This data comes from the Factset Geographic Revenue Exposure database. For each firm, it provides the split of sales by countries. To compile the data, Factset uses information publicly disclosed by firms via regulatory filings and investor reports. As companies geographic segment reporting is disparate (some report by regions, others by countries etc.) geographic revenues to regions and countries that companies did not explicitly disclose are allocated by algorithms built by the data provider.

## 2.3 Fundamental and Forecasts Data

We obtain firm-level net sales data from Worldscope. From this data, we compute the year-on-year growth rate of quarterly sales, $SalesGr_{\mathrm{i,t}}$, for company $i$ and quarter $t$.

We also use analysts' forecasts data from I/B/E/S. Here, we are interested in earnings surprises versus consensus. Specifically, for a given fiscal quarter $t$ and company $i$, we observe the "Standardized Unexpected Earnings" $SUE_{\mathrm{i,t}} = (E_{\mathrm{i,t}} - F_{\mathrm{i,t}})/SD_{\mathrm{i,t}}$, where $E_{\mathrm{i,t}}$ is quarter $t$ realized earnings per share reported by firm $i$, $F_{\mathrm{i,t}}$ is the latest consensus forecast regarding $E_{\mathrm{i,t}}$ and $SD_{\mathrm{i,t}}$ is the standard deviation of these forecasts across analysts. $SUE$ therefore measures the intensity and significance of the surprise at the time of earnings publication versus the latest analyst consensus. A positive $SUE$ means that analysts are positively surprised by the earnings announced by the company.

### 2.4 Summary Statistics

**Table 1** provides summary statistics for some of the stock-level variables used in this paper. $NumberofCountries$ provides, for each firm-year, the number of foreign countries for which a firm has non-zero geographical exposures. The mean is 55 and the median 45, reflecting the fact that firms in our sample are selling their products or services in many countries on average. $NonDomesticSales$ focuses on the sub-set of firms that have non-zero foreign sales. The number of firm-year observations is close to 30% lower than $NumberofCountries$, reflecting the fact that close to a third of the firm in the sample are purely domestic focused and have no foreign sales. On average 43% of the sales of exporting firms come from abroad. $SalesGr$ shows quarterly year-on-year sales growth. Our sample of firms have an average $SalesGr$ of 9.7% and a median of 6%. $SUE$ shows quarterly earning surprises (as defined above). On average during our sample, analysts have been positively surprised by 1.37 times the analyst forecasts standard deviation for a given firm-quarter. Finally, we show the market capitalization statistics (in billion USD)over our sample. We have more than 3 million firm-day observations, with a mean of 20.47 and a median of 7.86. The smallest firm has a market capitalization of slightly less than 300 million USD and the largest firm more than 1.5 trillion USD.

Note that for all data used in subsequent regressions are winzorized at the 1% and 99% level, to deal with possible outlyers.

## Table 1

**Summary Statistics**

| | N | Mean | Median | Min | Max | SD |
|---|---|---|---|---|---|---|
| $NumberofCountries$ | 15,244 | 55 | 45 | 0 | 195 | 55 |
| $Non-DomesticSales$ | 10,863 | 0.43 | 0.41 | 0.01 | 1.00 | 0.27 |
| $SalesGr$ | 49,936 | 0.097 | 0.060 | -0.509 | 1.457 | 0.260 |
| $SUE$ | 49,203 | 1.3668 | 0.964 | -8.303 | 14.697 | 3.205 |
| $MarketCapitalization$ | 3,378,219 | \$20.47B | \$7.86B | \$0.29B | \$1,588.66B | \$46.41B |

This table reports summary statistics for some of the stock-level variables used in this paper. Non Domestic Sales (expressed as a fraction of total sales) is the sum of all non-domestic geographical exposures for the sub-set of firms that have non-zero foreign sales. Number of Countries is the number of foreign countries for which a firm has non-zero geographical exposures. $SalesGr_{\mathrm{i,t}}$ is the year-on-year quarterly sales growth. $SUE_{\mathrm{i,t}}$ is the quarterly standardized unexpected earning. The table also shows Market Capitalization. The sample runs from January 2007 to June 2020 and contains approximately the largest 1,000 US and Canadian firm at any given time.

# 3 Impact of Currency Movements on Firm's Net Sales

Exporting firms generally benefit when their country's currency depreciate, for the following reasons.

First, firms are exposed to exchange rate movements through mismatches between the currency denomination of their assets and liabilities. For instance, a firm with significant foreign sales (an exporting firm) would generally have an important proportion of its expected cash flows denominated in foreign currencies, whereas most of its production costs would be in local currency. As a result, absent any currency hedging, the profitability and value of exporting firms increase (decrease) with the depreciation (appreciation) of its country's currency. Firms often try to reduce such exchange rate sensitivity, either through derivatives hedging transactions (such as FX forwards) or by directly reducing their currency mismatches, for example by moving production and costs to the countries where it generates foreign currency sales. Second, the depreciation of a country's currency also makes its exporting firms more competitive as they can offer lower prices in foreign currencies and can thereby increase their market share. Finally, an appreciating foreign currency might be correlated with a stronger economic environment in that foreign country, thereby increasing demand for the products of companies that export in that country.

Here is an illustration of the above. Apple Inc. derives the majority of its net sales from abroad (63% in 2017, according to the firm's 10-K for the fiscal year 2017), and is therefore expected to be impacted by exchange rate movements. In the risk factors of the company's filings, we find the following passage:

*The Company's primary exposure to movements in foreign currency exchange rates relates to non-U.S. dollar-denominated sales and operating expenses worldwide. Weakening of foreign currencies relative to the U.S. dollar adversely affects the U.S. dollar value of the Company's foreign currency-denominated sales and earnings, and generally leads to the Company to raise international pricing, potentially reducing demand for the Company's products. The use of [...] hedging activities may not offset any, or more than a portion, of the adverse financial effects of unfavorable movements in the foreign exchange rates.*

Further, in the business highlights of the same filing, Apple Inc. reports:

*The weakness of foreign currencies relative to the U.S. dollar had an unfavourable impact on net sales during 2017 compared to 2016.*

The aim of this section is to verify in the data the economic intuition presented above: the link between past currency movements and firms' net sales.

We start by constructing a measure of whether firms are under positive or negative currency pressure. We define $s_{\text{i,C,t}}$ as the fraction of sales that company $i$ generates in country $C$. This information is available at time $t$ in the Factset Geographic Exposure database. We then compute, for each firm, $FXShock_{\text{i,t}}$, computed as the geographic revenue-weighted exchange rate shock. This measure essentially aggregates shocks coming from currency movements in countries where the firm has foreign sales:

$$\mathbf{FXShock}_{\text{i,t}} = \sum_{C} \mathbf{s}_{\text{i,C,t-3m}} \mathbf{FX}_{\text{C,[t-3m, t]}}$$

Where $FX_{\text{C,[t-3m, t]}}$ is the 3-month currency return of country $C$ up to time $t$.

We then regress firms' year-on-year quarterly net sales growth on quarterly FX shocks at various lags, with controls such as firm size and fixed effects. Our baseline regression is as follows:

$$\mathbf{SalesGr}_{\mathbf{i,t}} = \alpha + \beta \mathbf{FXShock}_{\mathbf{i,t}} + controls + \epsilon_{\text{i,t}}$$

$SalesGr_{\text{i,t}}$ is the year-on-year quarterly sales growth rate as of quarter $t$. We therefore have one observation per firm-quarter in the regression. Results are reported in **Table 2** and confirm that there is a positive and statistically significant relationship between firms' year-on-year sales growth and contemporaneous quarterly FX shocks. Our results are robust to various controls. The most controlled specification includes both firm fixed effects (which control for heterogeneity in individual sales growth rate) and quarter-sector fixed effects (which control for sector-specific shocks). Note that the coefficients are relatively large, which seem to indicate that currency hedging is only partial and/or that the impact of currency moves on competitiveness is important. FX shocks lagged by one quarter also have effects on a firm's earnings, possibly reflecting the fact that some currency shocks are permanent rather than temporary. Further lagged FX shocks have no impact.

## Table 2

**Net Sales Year-on-Year Growth vs. Past Quarterly FX Shocks**

| | $SalesGr$ | $SalesGr$ | $SalesGr$ | $SalesGr$ |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $FXShock$ | 0.63*** | 0.65*** | 0.60*** | 0.53*** |
| | (7.60) | (7.94) | (7.30) | (6.32) |
| $FXShock_{\mathrm{lag1}}$ | | 0.22*** | 0.25*** | 0.26*** |
| | | (2.58) | (2.91) | (2.98) |
| $FXShock_{\mathrm{lag2}}$ | | | -0.13 | 0.03 |
| | | | (-1.60) | (0.40) |
| $FXShock_{\mathrm{lag3}}$ | | | -0.06 | 0.11 |
| | | | (-0.66) | (1.25) |
| $Log(MarketCap)$ | | 0.10*** | 0.10*** | 0.10*** |
| | | (32.39) | (33.53) | (30.51) |
| Stock Fixed Effect | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | - |
| Sector*Time Fixed Effects | - | - | - | Yes |
| N | 49,936 | 48,848 | 46,823 | 46,823 |
| $R^2$ | 0.26 | 0.27 | 0.25 | 0.35 |

This table reports results from regressing firm-level year-on-year quarterly sales growth $SalesGr$ on contemporaneous and lagged quarterly FX shocks. $FXShock$, $FXShock_{\mathrm{lag1}}$, $FXShock_{\mathrm{lag2}}$ and $FXShock_{\mathrm{lag3}}$ correspond respectively to contemporaneous and past quarterly FX shocks lagged by 1, 2 and 3 quarters. Time fixed effects correspond to year-quarter and Sector*Time fixed effects correspond to year-quarter-GICS2 (sector classification) dummies. The sample runs from January 2007 to June 2020 and contains approximately the largest 1,000 US and Canadian firm at any given time. For each explanatory variable, two numbers are reported: in the first row, the coefficient of the regression, and in the second row (in parentheses) the t-statistic. *, ** and *** next to the coefficients indicate respectively that these coefficients are significantly different from zero at the 10%, 5% and 1% significance levels.

## 4 Are Analysts Attentive to Currency Movements?

Financial analysts are professional forecasters who produce, inter alia, estimates of companies' future earnings per share (EPS) for different horizons. Various biases have been documented in the literature: in particular, analysts tend to be over-optimistic and to react too slowly to past information (see for example, Abarbanell and Bernard (1992)).

If analysts' forecasts were perfectly rational, they would integrate all information available at the time they are issued. Thus, the sign and magnitude of the standardized unexpected earnings $SUE$ (described in Section 2) should not depend on anything that has happened prior to the forecast issuance. Our goal is to test whether analysts integrate past currency movements in their forecasts. To do so, we regress $SUE_{\mathrm{i,t}}$ (the standardized unexpected earnings for stock $i$ and quarter $t$), on past quarterly FX shocks and various controls such as firm size and fixed effects:

$$\mathbf{SUE_{i,t}} = \alpha + \beta\mathbf{FXShock_{i,ct\text{-}1m}} + controls + \epsilon_{\mathrm{i,t}}$$

We use the quarterly $FXShock$ calculated one month before $ct$, the date at which the consensus used to compute the quarterly $SUE$ was taken by I/B/E/S. We do so because we do not want our results to be driven by the staleness in the forecasts of analysts. In our specification, analysts are given one month to react to the information contained in $FXShock_{\mathrm{i,ct\text{-}1m}}$.

The results show that analysts fail to integrate past currency movements in their forecasts. This can be seen in columns 1 to 3 of **Table 3**. Quantitatively, a FX shock of 10% leads to a $SUE$ which is higher by around 0.5, which represents about 15% of the standard deviation of $SUE$. The result is statistically significant at the 1% level.

We then investigate if, in line with bounded rationality, analysts pay more attention to FX shocks when they are relatively large (and thus possibly more visible and attention-grabbing). To do so, we split FX shocks into two disjoint sub-sets: small and large shocks. Specifically, we define a binary variable $LargeShock_{\mathrm{i,t}}$ that is equal to 1 if $FXShock_{\mathrm{i,t}}$ is in $L$, the sub-set of FX shocks that are in the bottom 5% or top 5% of the set of non-zero FX shocks:

$$\mathbf{LargeShock_{i,t}} = 1 \;\; if \;\; \mathbf{FXShock_{i,t}} \in L \;\; else \;\; \mathbf{LargeShock_{i,t}} = 0$$

$$\mathbf{SmallShock_{i,t}} = 1 - \mathbf{LargeShock_{i,t}}$$

The hypothesis would be that analysts should be more attentive to large shocks, whose causes (e.g. large currency movements) are more likely to be covered in the media. We test this by running the following regression:

$$\mathbf{SUE_{i,t}} = \alpha + \beta_1 \mathbf{FXShock_{i,ct\text{-}1m}} * \mathbf{SmallShock_{i,ct\text{-}1m}} + \beta_2 \mathbf{FXShock_{i,ct\text{-}1m}} * \mathbf{LargeShock_{i,ct\text{-}1m}} + controls + \epsilon_{\mathrm{i,t}}$$

The results show that analysts under-react to large shocks as well. We see this from columns 4 to 6 in **Table 3**. The coefficient $\beta_2$ in front of the large shock is still positive and significantly different from zero. Therefore, we can conclude that analysts generally over-look currency movements when making their forecasts.

## Table 3

**Past FX Shocks Predict Earnings Surprise**

| | $SUE$ | $SUE$ | $SUE$ | $SUE$ | $SUE$ | $SUE$ |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $FXShock$ | 4.38*** | 4.64*** | 5.08*** | | | |
| | (3.53) | (3.71) | (3.75) | | | |
| $FXShock * SmallShock$ | | | | 4.76*** | 5.09*** | 4.63*** |
| | | | | (2.57) | (2.74) | (2.32) |
| $FXShock * LargeShock$ | | | | 4.15*** | 4.36*** | 5.34*** |
| | | | | (2.76) | (2.87) | (3.36) |
| $FXShock_{\text{lag1}}$ | | 5.00*** | 4.61*** | | 5.02*** | 4.59*** |
| | | (3.97) | (3.39) | | (3.98) | (3.37) |
| $Log(MarketCap)$ | | 0.04 | -0.00 | | 0.04 | -0.00 |
| | | (1.04) | (-0.06) | | (1.04) | (-0.06) |
| Stock Fixed Effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | - | Yes | Yes | - |
| Sector*Time Fixed Effects | - | - | Yes | - | - | Yes |
| N | 49,203 | 48,129 | 48,129 | 49,203 | 48,129 | 48,129 |
| $R^2$ | 0.18 | 0.18 | 0.22 | 0.18 | 0.18 | 0.22 |

This table reports results from regressing firm-level quarterly sales $SUE$ on $FXShock$. $FXShock$ is the quarterly FX Shock taken one month before the date of the consensus used to compute $SUE$, to account for possible staleness in analysts' forecasts. *SmallShock* (*LargeShock*) is a binary variable equal to 1 if the corresponding FX Shock is large (small) as defined in the text above, 0 otherwise. Time fixed effects correspond to year-quarter dummies and sector*time fixed effects correspond to year-quarter-GICS2 (sector classification) dummies. The sample runs from January 2007 to June 2020 and contains approximately the largest 1,000 US and Canadian firm at any given time. For each explanatory variable, two numbers are reported: in the first row, the coefficient of the regression, and in the second row (in parentheses) the t-statistic. *, ** and *** next to the coefficients indicate respectively that these coefficients are significantly different from zero at the 10%, 5% and 1% significance levels.

# 5 Does the Market Under-react?

We now investigate whether the market efficiently integrates currency movements in stock prices.

## 5.1 No Under-Reaction at Earnings Announcement

In a first step, we run a similar test to the one used for analysts. This time, we look at the relationship between price surprises at time of earnings publication and past FX shocks. **Table 4** summarizes the results. The left hand side of the regressions is the Cumulative Abnormal Return ($CAR_{\mathrm{i,t}}$): the cumulative beta-adjusted stock return computed over a two days window starting at the day of earnings announcement for stock $i$ and quarter $t$. Betas are estimated through rolling 1-year regressions of stock returns on market returns. We define the market as a value weighted basket of the stocks in our universe at a given time. $FXShock$ is the quarterly FX shock contemporaneous with the financial quarter. The regression is as follows:

$$\mathbf{CAR_{i,t}} = \alpha + \beta_1 \mathbf{FXShock_{i,t}} * \mathbf{SmallShock_{i,t}} + \beta_2 \mathbf{FXShock_{i,t}} * \mathbf{LargeShock_{i,t}} + controls + \epsilon_{\mathrm{i,t}}$$

Beyond our usual controls, we add firm characteristics which are known to affect returns: $mtb$ is the market-to-book value of equity and $R212$ is Carhart's momentum, i.e. the cumulative stock return between month -12 and month -2.

In contrast with analysts, the market appears to have already integrated past currency movement information into prices by the time earnings are announced. The coefficient on $FXShock$ is indeed insignificant. This is true both for small and large shocks. Prices are therefore faster than analysts at integrating this information.

## Table 4

**Absence of Price Surprises at Earnings Announcements as Past FX Shocks**

| | $CAR$ | $CAR$ | $CAR$ | $CAR$ | $CAR$ | $CAR$ |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $FXShock$ | -0.03 | -0.03 | -0.01 | | | |
| | (-1.42) | (-1.16) | (-0.25) | | | |
| $FXShock * SmallShock$ | | | | -0.04 | -0.03 | 0.02 |
| | | | | (-1.07) | (-0.79) | (0.51) |
| $FXShock * LargeShock$ | | | | -0.03 | -0.03 | -0.02 |
| | | | | (-1.09) | (-0.96) | (-0.68) |
| $FXShock_{\text{lag1}}$ | | 0.01 | 0.03 | | 0.01 | 0.03 |
| | | (0.51) | (1.19) | | (0.51) | (1.17) |
| $Log(MarketCap)$ | | -0.01*** | -0.02*** | | -0.01*** | -0.02*** |
| | | (-17.54) | (-18.55) | | (-17.54) | (-18.55) |
| $mtb$ | | 0.00 | 0.00 | | 0.00 | 0.00 |
| | | (0.57) | (0.87) | | (0.57) | (0.87) |
| $R212$ | | 0.40 | 0.46 | | 0.40 | 0.46 |
| | | (1.44) | (1.53) | | (1.44) | (1.53) |
| Stock Fixed Effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | - | Yes | Yes | - |
| Sector*Time Fixed Effects | - | - | Yes | - | - | Yes |
| N | 48,259 | 47,117 | 47,117 | 48,259 | 41,117 | 41,117 |
| $R^2$ | 0.05 | 0.06 | 0.09 | 0.05 | 0.06 | 0.09 |

This table reports results from regressions on $FXShock$ of cumulative abnormal returns $CAR$, computed over a two-day window starting the day of quarterly earnings announcement. Thus, there is one observation by firm-quarter. $SmallShock$ ($LargeShock$) is a binary variable equal to 1 if the corresponding FX Shock is large (small) as defined in the text above, 0 otherwise. $mtb$ is the market-to-book value of equity and $R212$ is Carhart's momentum, i.e. the cumulative stock return between month -12 and month -2. Time fixed effects correspond to year-quarter dummies and sector*time fixed effects correspond to year-quarter-GICS2 (sector classification) dummies. The sample runs from January 2007 to June 2020 and contains approximately the largest 1,000 US and Canadian firm at any given time. For each explanatory variable, two numbers are reported: in the first row, the coefficient of the regression, and in the second row (in parentheses) the t-statistic. *, ** and *** next to the coefficients indicate respectively that these coefficients are significantly different from zero at the 10%, 5% and 1% significance levels.

### 5.2 Under-Reaction to Recent Currency Shocks

We then attempt to measure precisely the speed at which markets integrate past currency movements. In perfectly efficient markets, the reaction of prices to information should be immediate. However, a large body of behavioral literature has documented abnormally slow price reactions to public information (see, for example, Hong, Lee and Stein (2000)).

In **Table 5**, we regress weekly cumulative beta-adjusted stock returns $AdjR_{\text{i,t}}$ on past weekly FX shocks $FXShockWeekly_{\text{i,t}}$ with several lags. We use smaller windows to compute FX shocks as we have established that prices react faster than analysts. We use Fama and Macbeth's two step regression methodology to obtain standard errors that are adjusted for cross-sectional dependence.

$$\mathbf{AdjR_{i,t}} = \alpha + \beta \mathbf{FXShockWeekly_{i,t}} + controls + \epsilon_{\text{i,t}}$$

Where: $\mathbf{FXShockWeekly}_{\text{i,t}} = \sum_C \mathbf{s}_{\text{i,C,t-1w}} \mathbf{FX}_{\text{C,[t-1w, t]}}$

There is one observation per firm-week in this regression. We use a rich set of firm-level controls, including *mtb*, $R212$, firm size and a dummy *domestics* which is equal to 1 if 100% of the revenues of a particular firm come from domestic sales. In a perfectly efficient market, we expect the coefficient $\beta$ to be equal to zero as $FXShockWeekly_{\text{i,t}}$ captures information already available at time $t$.

The results, reported in **Table 5**, show a significantly positive coefficient $\beta$, indicating market under-reaction. The economic magnitude can be interpreted as follows: a 10% FX shock experienced by a firm implies roughly a 1.5% abnormal return for the stock of that firm the following week.

This market under-reaction is driven by small shocks. In columns 4, 5 and 6 of **Table 5**, we split shocks between small and large (defined as before as the bottom and top 5% of the set of non-zero FX shocks). We find a lesser and non-significant under-reaction to large shocks. This in line with a bounded rationality interpretation whereby the market pays more attention to effects that are large enough. The coefficient on a one-week lagged FX shock ($FXShockWeekly_{\text{lag1}}$) are also significant at 5%, and has a magnitude of about two third of that of the weekly FX shock. In further regressions not reported in this paper, we included further lags, which appear insignificant and economically negligible. This indicates that a couple of weeks is the order of magnitude of the time it takes for stock prices to fully integrate currency movements.

## Table 5

**Stock Returns vs. Past One Week FX Shocks**

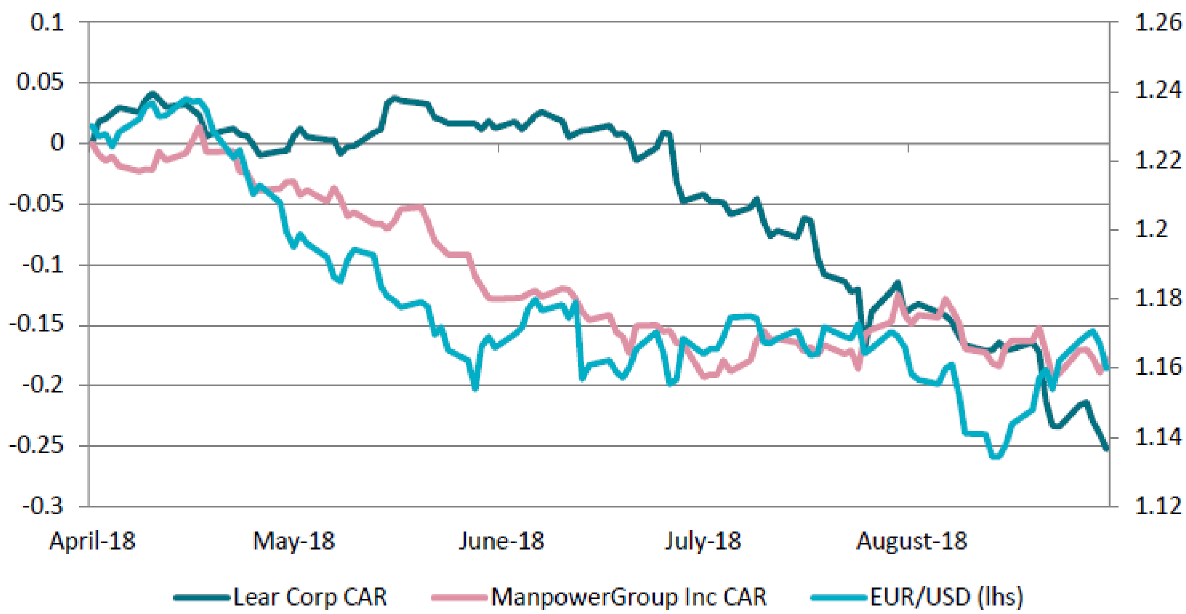
| | $AdjR$ | $AdjR$ | $AdjR$ | $AdjR$ | $AdjR$ | $AdjR$ |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $FXShockWeekly$ | 0.14*** | 0.12*** | 0.14*** | | | |
| | (2.72) | (2.79) | (2.75) | | | |
| $FXShockWeekly * SmallShock$ | | | | 0.15** | 0.14** | 0.13** |
| | | | | (2.37) | (2.43) | (2.13) |
| $FXShockWeekly * LargeShock$ | | | | 0.07 | 0.06 | 0.08 |
| | | | | (1.22) | (1.10) | (1.31) |
| $Log(MarketCap)$ | | 0.00 | 0.00 | | 0.00 | 0.00 |
| | | (0.38) | (0.37) | | (0.38) | (0.37) |
| $mtb$ | | 0.00*** | 0.00*** | | 0.00*** | 0.00*** |
| | | (2.96) | (3.04) | | (2.95) | (3.02) |
| $R212$ | | 0.14 | 0.14 | | 0.14 | 0.14 |
| | | (0.65) | (0.65) | | (0.65) | (0.66) |
| $domestics$ | | -0.00 | -0.00 | | -0.00 | -0.00 |
| | | (-0.34) | (-1.13) | | (-0.28) | (-0.98) |
| $FXShockWeekly_lag1$ | | | 0.099** | | | 0.10** |
| | | | (2.10) | | | (2.16) |
| Intercept | -0.00*** | -0.00 | -0.00 | -0.00*** | -0.00 | -0.00 |
| | (-4.47) | (-0.87) | (-0.81) | (-4.42) | (-0.88) | (-0.82) |
| N | 673,268 | 654,664 | 654,444 | 673,268 | 654,664 | 654,444 |
| $R^2$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

This table reports Fama-Macbeth regression results of cumulative beta-adjusted stock returns computed over a five-day window $AdjR$ on the preceding week FX shocks $FXShockWeekly$. $SmallShock$ ($LargeShock$) is a binary variable equal to 1 if the corresponding FX Shock is large (small) as defined in the text above, 0 otherwise. $mtb$ the market-to-book value of equity, $R212$ is Carhart's momentum, i.e. the cumulative stock return between month -12 and month -2 and $domestics$ is a dummy equal to 1 if 100% of the revenues of a particular firm come from domestic sales. The sample runs from January 2007 to June 2020 and contains approximately the largest 1,000 US and Canadian firm at any given time. For each explanatory variable, two numbers are reported: in the first row, the coefficient of the regression, and in the second row (in parentheses) the t-statistic. *, ** and *** next to the coefficients indicate respectively that these coefficients are significantly different from zero at the 10%, 5% and 1% significance levels.

**Figure 1** offers an illustration. Towards the end of April 2018, the EUR started to depreciate gradually against the USD. This information was quickly integrated in the stock price of ManpowerGroup Inc, a company with 46% of its revenues coming from the Eurozone (larger FX shock). In constrast, the stock price of Lear Corp, which has a smaller portion of its revenues coming from there (24%), under-reacted to the move in EUR/USD.

## Figure 1

**EUR/USD, Lear Corp and ManpowerGroup Inc**




This figure plots the EUR/USD (right hand scale) and the cumulative beta-adjusted returns of Lear Corp and ManpowerGroup Inc (left hand scale) between April and August 2018. Lear Corp and ManpowerGroup Inc have respectively 24% and 46% of their revenues coming from the Eurozone.

# 6 Long-Short Trading Strategy

We next turn to designing and analyzing a trading strategy that exploits the under-reaction of stock prices to past currency movements.

The trading strategy is daily re-balanced and buys stocks of companies that have experienced positive currency shocks and sells stocks of those who have been subject to negative shocks.

Every day $t$, each stock $i$ is ranked according to its past two-week FX shock. These ranks are then transformed into uniformly distributed values between -0.5 (for the stock with the most negative shock) and 0.5 (for the stock with the most positive shock). These resulting values $w_{\mathrm{i,t}}$ are the weights assigned to stock $i$ on day $t$.

The weights $w_{\mathrm{i,t}}$ can be computed by the close of markets in $t$ (currencies closing prices are all available, except for a few Latin American currencies). We assume that these weights are achievable via a re-balancing at the closing prices of that day $t$. The daily returns $r^{\mathrm{strategy}}{}_{\mathrm{t}}$ of the long-short trading strategy are then obtained by multiplying the subsequent returns of each stock $r_{\mathrm{i,t+1}}$ (the return computed between the closing prices at $t$ and those at $t+1$) by their weight $w_{\mathrm{i,t}}$ and summing across all stocks in the universe.

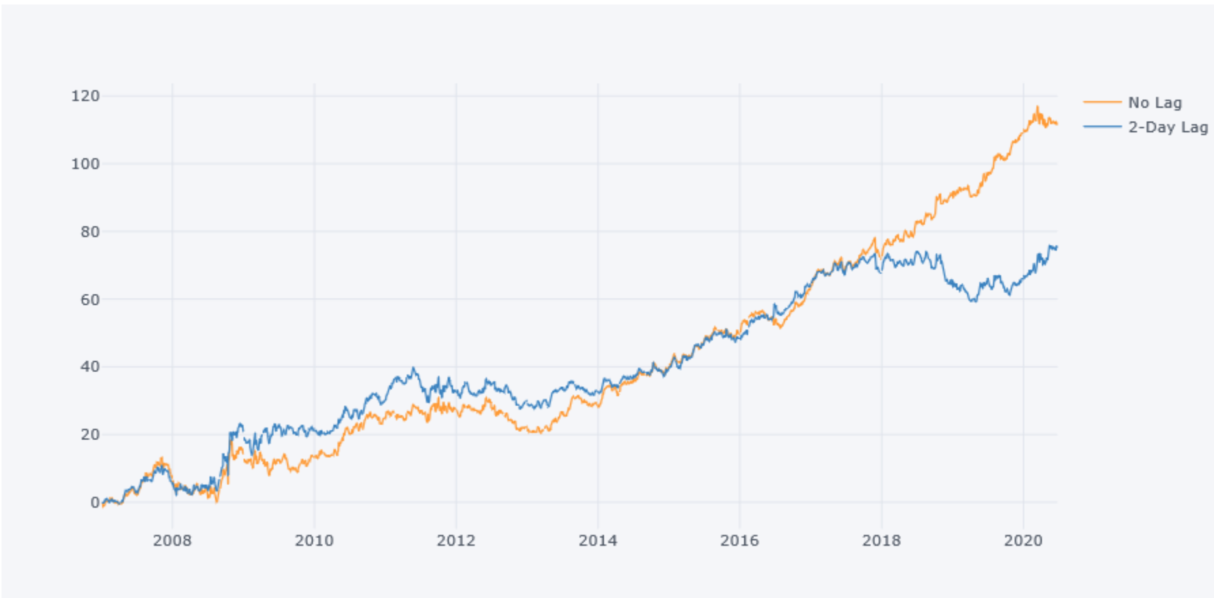
$$\mathbf{r}^{\mathrm{strategy}}{}_{\mathrm{t}} = \sum_i \mathbf{w}_{\mathrm{i,t}} \mathbf{r}_{\mathrm{i,\ t+1}}$$

**Figure 2** shows the cumulative return of the trading strategy on our sample (that goes from January 2007 to June 2020). The strategy performs strongly, exhibiting a Sharpe ratio of 1.04. The first version of this paper was made public on SSRN in 2018 and used a sample ending in October 2017. We therefore have close to three years of out of sample data for this market anomaly. As can be seen on the graph, the strategy continued performing out of sample, with a Sharpe ratio of 1.00 during the period from October 2017 to June 2020. This out of sample performance increases the likelihood that the anomaly we are documenting in this paper is not the result of data snooping.

**Figure 2** also plots the same trading strategy, but with weights lagged by two days. The idea here is to see what is the impact of trading with a 2-day lag. Both graphs are quite similar before 2017, after which the lagged version starts diverging and performing less. Why is that the case? One possible explanation is that more arbitrage capital has been devoted to trading this strategy, thereby impacting stock prices in the first few days after portfolio formation and making the lagged implementation less profitable.

## Figure 2

**Long/Short Trading Strategy, Cumulative Returns**

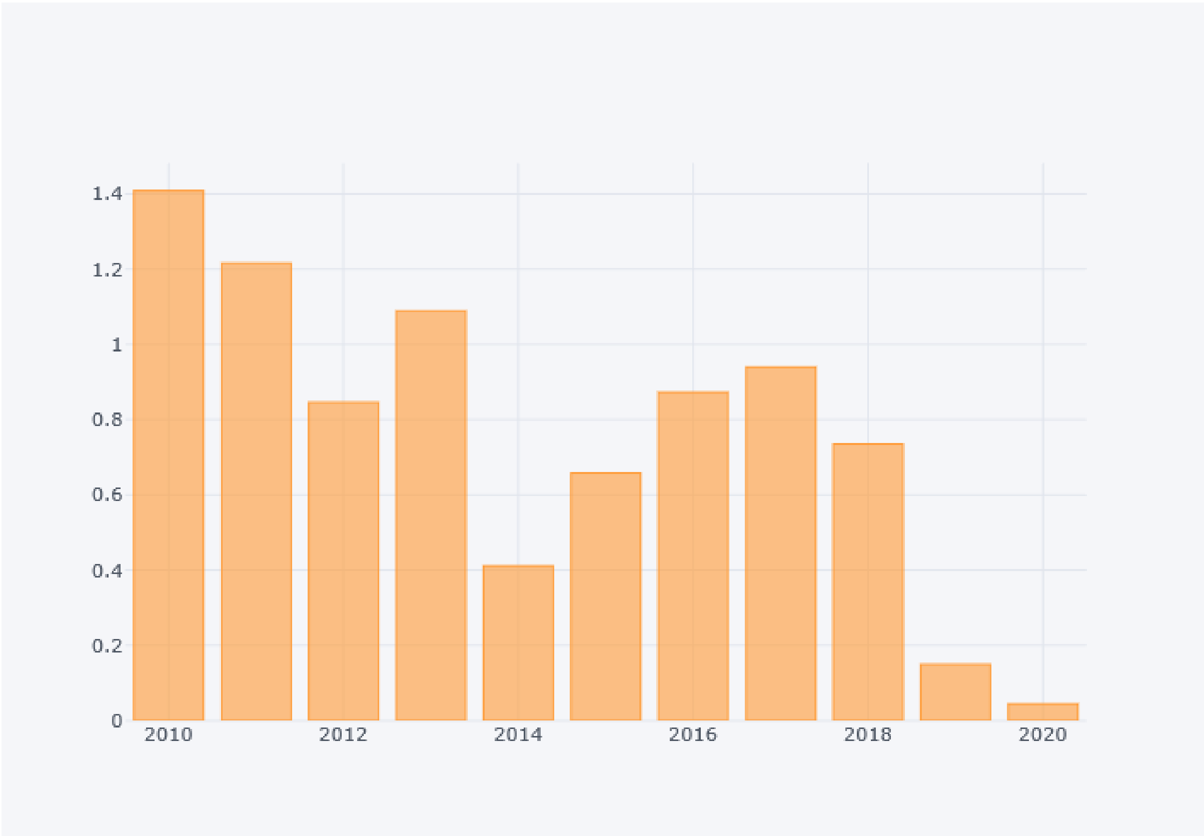



This figure plots the cumulative performance of a daily re-balanced trading strategy that goes long stocks with positive past 2-week FX shocks and short those with negative shocks. The weights of each stock in the portfolio are described in details in the paper. The figure also shows the same strategy with weights lagged by two days. The sample runs from January 2007 to June 2020 and contains approximately the largest 1,000 US and Canadian firm at any given time.

**Figure 3** illustrates this point further. It plots for each year, the 2-day lagged strategy's rolling 3-year Sharpe ratio normalized by the non-lagged strategy's rolling 3-year Sharpe ratio. This number becomes smaller as the lagged strategy's performance deteriorates versus the original (non-lagged) strategy. The graph shows that the decay has grown on average over the past years, consistent with an increase in arbitrage capital exploiting the under-reaction of stock prices to currency movements.

## Figure 3

**Increase in Sharpe Decay for the 2-Day Lagged Strategy**




This figure plots for each year the rolling 3-year Sharpe ratio of the 2-day lagged long/short strategy normalized by the rolling 3-year Sharpe ratio of the non-lagged strategy. The sample runs from January 2007 to June 2020 and contains approximately the top 1,000 liquid US and Canadian firm at any given time.

## 7 Conclusion

Exchange rate movements affect the value of firms, particularly those with significant foreign sales. This paper presents an empirical exploration of the integration of currency movements in firm-level financial analysts' estimates and stock prices.

Under the efficient market hypothesis, market prices should fully and immediately reflect all available information. In contrast, we report strong evidence that financial analysts generally **under-react** to FX shocks. The market is more efficient (quicker) at integrating FX shocks in stock prices, but still takes around two weeks to do so. Also, prices **do not under-react** to larger FX shocks, in line with bounded rationality.

A long-short trading strategy that benefits from the under-reaction of stock prices to currency movements is profitable (Sharpe ratio of 1.04). Further, such a strategy has continued performing out of sample (since the first version of this paper), showing that the under-reaction we are documenting is probably not the result of data snooping. Finally, we show that arbitrage capital exploiting this under-reaction has likely increased in the past few years.

These results shed light on market participants' behavior: a similar type of information, depending on its intensity, can either be over-looked or taken into account. Over-looked information leads to price under-reaction. Arbitrage capital moves in to exploit such under-reaction, helping prices integrate quicker the information.

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