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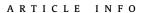
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# Foreign exchange exposure and analysts' earnings forecasts

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This study examines how movements in a firm's exposure to foreign exchange (forex) rates affect the properties of analysts' earnings forecasts. Our results suggest that analysts' forecast errors and dispersion increase with an increase in forex exposure within firms. These findings are robust to a wide range of robustness tests, including a quasi-experimental setting based on the sudden unpegging of the U.S. Dollar against the Chinese Yuan. Additional tests reveal that analysts spend more effort forecasting when firms experience an increase in forex exposure. Consistent with an increase in uncertainty of firm outcomes representing the primary channel through which forex exposure affects analysts' forecasts, we find that the effect of forex exposure is heightened in the presence of greater volatility in the U.S. Dollar. However, we also find that more readable annual reports and higher media coverage can help improve the quality of analysts' forecast properties for firms with increasing forex exposure. We also present evidence of some benefits analysts can realize from coverage of high forex exposure firms through generating greater stock trading and securing positions in more prestigious brokerage firms.

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#### 1. Introduction

This study considers how the foreign exchange (forex, hereafter) exposure of firms affects the accuracy and dispersion of analysts' earnings forecasts.<sup>1</sup> Recent times have seen significant growth in the globalization of trade. The number of foreign subsidiaries of U.S. firms grew exponentially from 1950 to 1970 (Kobrin, 1984), and U.S. firms continued to substantially internationalize between 1996 and 2010 (O'Hagan-Luff and Berrill, 2016). The relevance of foreign markets to U.S. firms is further underlined by significant increases in exports and imports of U.S. firms, raising concerns on the impact of foreign competition. Such concerns have contributed to firms such as Whirlpool Corporation (2017) filing safeguard peti-

tions against foreign competitors and President Trump introducing import tariffs in 2018 to reduce the threat of foreign competition (BBC, 2018).

The increasing trends in foreign investments, international trading, and global competition underline the importance of understanding how firms' exposure to forex movements affects the ability of analysts to forecast their earnings, even for purely domestic firms. The relevance of movements in forex rates to analysts for forecasting earnings is evident in practice from the questions posed to management by analysts during earnings conference calls. For example, the last quarter of 2014 witnessed 63% of North American companies fielding currency impact-related questions from analysts amidst a steep rise in the U.S. Dollar, signifying the difficulty analysts face in identifying and quantifying the effects of forex exposure (FiREapps, 2014).<sup>2</sup>

As alluded to above, forex exposure can affect firm performance through various avenues. While it is relatively easy to discern the forex exposure multinational firms face as a result of their foreign transactions and operations, it is important to note that



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<sup>&</sup>lt;sup>1</sup> Forex exposure is defined in the seminal work by Adler and Dumas (1984) as the effect of unpredictable changes in forex rates on cash flows and, by extension, firm value. Such exposure can arise through fluctuating exchange rates affecting not only the revenue and costs denominated in foreign currency, but the activities of competitors, customers that export, and suppliers that import.

<sup>&</sup>lt;sup>2</sup> Such questions are also faced by firms with predominantly U.S. Dollar-denominated sales. For example, Southwest Airlines' (2015) executives were asked about their strategy regarding leisure travelers given the strong Dollar, to which they replied that the Dollar could impact on demand.

even domestic firms can be significantly affected by forex exposure through competition from importers, possessing large domestic customers that export, heavily relying on local suppliers that import, and operating in industries (e.g., construction) that have significant relationships with other industries (e.g., steel) that are exposed to forex risks (Hodder, 1982; Levi, 1994; Marston, 2001; Bergbrant et al., 2014). In fact, some studies find that domestic and multinational firms have similar levels of exposure to forex risk (Aggarwal and Harper, 2010). We posit that the unpredictability of forex movements and their effects on earnings will likely result in larger analysts' forecast errors for firms with increasing forex exposure. While such uncertainty may also lead to greater forecast dispersion, the difficulty in forecasting earnings for firms with increasing forex exposure may induce analysts' to herd, resulting in lower forecast dispersion (Kim and Pantzalis, 2003).

Using a sample period that spans from 2001 to 2014 and an established proxy for the net exposure of firms to exchange rate risk (Bartram et al., 2010; Francis et al., 2008; Hutson and Laing, 2014), our results suggest an increase in analysts' earnings forecast errors and dispersion for firms with increasing forex exposure after controlling for various determinants of analyst forecast behavior, as well as the firm and year fixed effects. These effects are economically significant, with our results suggesting that an interquartile increase in forex exposure increases analysts' forecast errors (dispersion) by 6.26 percent (4.97 percent). The forecast dispersion findings suggest that analysts impound the effect of forex exposure on forecasts independently and imply a relatively weaker herding response by analysts. However, these independent efforts lead to lower forecast accuracy with increasing forex exposure in firms. Collectively, our analysts' dispersion and error results suggest that analysts' forecasts suffer from both reliability and validity problems when firms experience an increase in forex exposure.

To further establish causality, we exploit a quasi-natural experiment that generates an exogenous variation in forex exposure from the sudden unpegging of the U.S. Dollar against the Chinese Yuan in 2005 to show that firms that refer to business activities, opportunities, or risks stemming from China in their 10-K filings experience a significant increase in analysts' forecast errors and dispersion following the unpegging, compared to firms that do not refer to such activities, opportunities or risks. We augment these results with a placebo quasi-natural experiment test documenting insignificant changes in analysts' forecast errors and dispersion across a different period of our treatment firms that did not witness any exogenous shocks to the U.S. Dollar-Yuan exchange rate. Our main results are robust to a battery of sensitivity tests, including controlling for a large number of potential omitted variables using a significantly smaller sample with available data to measure these variables and employing the impact threshold for a confounding variable (ITCV) and entropy balancing procedures.

We conduct several additional analyses. Our first test provides some insights into how forex exposure is likely to affect analysts' effort and time constraints by showing that analysts issue more forecast revisions when a firm's forex exposure increases. Second, we show that our documented effects for forex exposure exist in both firms with and without any foreign sales and assets.<sup>4</sup> These

results are not surprising, given that prior studies highlight numerous ways domestic firms are also susceptible to risks from forex movements (Aggarwal and Harper, 2010; Bergbrant et al., 2014).

Our arguments imply that the primary channel through which forex exposure affects analysts' forecasts is via increasing the uncertainty of firm outcomes. Our third set of additional tests shed some support for this channel by documenting a more pronounced effect of an increase in a firm's forex exposure on forecast errors and dispersion in years with higher volatility in the U.S. Dollar that presents more significant uncertainty for firm outcomes. In our fourth set of tests, we show how certain factors may moderate the forex exposure effects. We argue that more relevant information may help analysts better understand the effects of forex exposure on firms' operations. Following prior studies that highlight the informational roles of more readable annual reports (Lehavy et al., 2011) and higher media coverage (Fang and Peress, 2009; Bradshaw et al., 2021), we find that the adverse effects of increasing forex exposure on analysts' forecast errors and dispersion are less pronounced when firms have more readable annual reports and have higher media coverage.

Our fifth set of additional tests considers the impact of analysts' experience (Mikhail et al., 1997). We find that analysts' forecast errors when firms experience an increase in forex exposure are lower for forecasts issued by analysts in the upper quartile of firm-specific experience, who are arguably better at assessing the impact of currency movements on the focal firm's earnings in their forecasts. However, this effect does not hold in relation to firms that are in the top quartile of readable annual reports. This implies that the disclosure of more readable information by firms allows less experienced analysts to perform to the levels of their more experienced counterparts.

While our main findings are symptomatic of the costs (e.g., larger errors) and the consequential career concerns that analysts face (e.g., Clement and Tse, 2005) when covering high forex exposure firms, it is also possible that analysts perceive career benefits from handling and generating greater trading from high forex exposure firms (Beyer and Guttman, 2011). Our final set of tests supports this viewpoint by showing that an increase in a firm's forex exposure attracts greater analyst coverage and generates higher stock trading volume. We also find that analysts that cover firms with increasing forex exposure are more likely to secure promotions to prestigious brokers.

Our findings on the adverse effects of forex exposure on analysts' forecast errors (dispersion) contribute to the streams of research on forex exposure and analysts' forecasts. In doing so, our study responds to calls for future research on whether analysts' forecasts are affected by the sensitivity of firms to forex rates (Muller and Verschoor, 2006) and novel firm-level factors that could affect the quality of analysts' forecasts (Gul et al., 2013). Our analyses also shed insights on moderating factors that can help less experienced analysts improve forecast accuracy for firms exposed to higher forex exposure. Further, our additional findings on how an increase in a firm's forex exposure attracts greater analyst coverage and stock trading volume, as well as a higher likelihood of analysts securing promotions to a prestigious brokerage house, suggest that analysts also perceive and realize benefits from handling high forex exposure firms to exceed the costs of covering these firms given analysts make more errors in forecasting high forex exposure firms.

It is important to note that our findings cannot be inferred from prior studies that have considered the relation between analysts' forecast properties and forex movements (Bartov and Bodnar, 1994), international diversification (Duru and Reeb, 2002; Platikanova and Mattei, 2016) and amendments to the accounting standard (SFAS No. 52) for translation of foreign currency transactions and financial statements (Ayres and Rodgers, 1994;

<sup>&</sup>lt;sup>3</sup> It is challenging to disentangle the specific effects of the many avenues through which forex exposure can affect earnings. For example, it would be difficult to isolate the impact of forex exposure arising from foreign transactions as firms are not required to provide disclosures on the extent to which they procure materials from overseas suppliers. Other channels of forex exposure, such as presence of customers and/or suppliers with considerable foreign transactions, can be equally difficult to measure. Therefore, using a measure of net exposure arguably provides the most feasible way of capturing the effects of exchange rates on a firm.

<sup>&</sup>lt;sup>4</sup> We do not refer to such firms as purely domestic firms as the unavailability of segmented data for purchases makes it difficult to discount the possibility of firms without foreign sales and assets purchasing foreign inputs.

Chen et al., 1990). This is because general exchange rate movements, international diversification, and new accounting standards represent broadly defined factors that do not capture the individualized net exposure of firms to forex rates. Further, while amendments to accounting standards such as SFAS No. 52 affect the accounting treatment of foreign currency translations, these amendments are unlikely to reflect the actual forex exposure of firms.<sup>5</sup>

## 2. Background and hypotheses development

The collapse of the Bretton Woods system of fixed exchange rates in 1971 increased the susceptibility of corporate performance to volatility in exchange rates. Numerous studies have since documented that exchange rate risk can explain the returns on the equity indices (e.g., Adler and Dumas, 1984; Francis et al., 2008). Bergbrant et al. (2016) show how forex exposure affects the interests of stakeholders other than shareholders by linking higher forex risk to bank loan spreads. Our study extends this line of research by considering the implications of exposure for financial analysts, who face the challenge of accounting for forex movements in their earnings forecasts.

While analysts' decision processes are commonly viewed as a "black box" in the literature, a few studies provide useful insights into the broad range of firm-specific, industry, and macroeconomic information that analysts consider when developing forecasts (Ramnath et al., 2008). Analysts often estimate future earnings by disaggregating the company into its constituent segments, developing forecasts of individual segments, and then reaggregating segment forecasts to form a firm-level earnings estimate. The prevalence of currency impact-related questions fielded by analysts during conference calls suggests that forex exposure is another important input to analysts' decisions.

However, predicting forex rate movements is an onerous task as it requires consideration of macroeconomic conditions such as purchasing power and interest rate parity conditions, balance of payments, and supply and demand of financial assets (Eiteman et al., 2016; Li et al., 2014). This process can also entail analyzing past forex rates using qualitative methods (e.g., recognition of patterns) and quantitative techniques (e.g., moving averages) (Menkhoff and Taylor, 2007). Not surprisingly, even prestigious forecasters struggle with predicting forex rates.<sup>6</sup>

Importantly, analysts are not only affected by such issues but are also required to understand the effects of forex rate movements on earnings. This is a challenging and tedious task because while the uncertainty of firm outcomes is the primary channel through which forex risk can affect analysts' forecasts, there are many ways through which forex risks can affect the uncertainty of firm outcomes. It is not that difficult to understand the forex risks that multinational firms face as a result of foreign transactions, cash flows, assets, and liability values. However, as mentioned earlier, even purely domestic firms can face similar foreign exchange exposures (Aggarwal and Harper, 2010). Such risks can again arise from many sources. For example, forex risks could arise from volatility and adverse movements in product prices and earnings of domestic (and multinational) firms if a strengthening domestic currency makes competing imports relatively cheaper (Hodder, 1982; Marston, 2001). The product prices, sales, and earnings of firms can also be adversely affected by forex movements if firms purchase goods from local wholesalers that deal with foreign manufacturers (e.g., the forex exposure costs incurred by wholesalers may be passed on to their customers) or sell goods to major customers that export to foreign markets (e.g., a strengthening domestic currency may decrease demand and sales).

Since determining the economic effects of forex movements from these different sources of exposure is a multifaceted and complex task, higher forex exposure can result in greater forecast errors. As discussed earlier, commentators and prior studies suggest that it is difficult for analysts to accurately predict movements in forex rates because exchange rates are random walks in the short run (Rossi, 2013). Figure 1 illustrates the wide swings in the trade-weighted exchange rates of the U.S. Dollar across our sample period. More importantly, analysts must determine how their forex rate forecasts affect the firm. This is challenging as the impact of exchange rate movements on firm earnings depends not only on the firm attributes discussed earlier (e.g., presence of large customers and suppliers that deal with foreign transactions), but also on the industry- and country-level parameters. Industry-level factors that can affect the forex exposure of firms include competitive factors (Allayannis and Ihrig, 2001) and membership in industries that have relationships with other industries that are affected by forex exposure (Bergbrant et al., 2014), while country-level factors such as the economic cycle (Chaieb and Mazzotta, 2013) and level of trade openness (Hutson and Stevenson, 2010) can also influence forex exposure through affecting the foreign trading levels. Figure 2 shows that, based on sample firms and our measure of forex exposure, forex risk is prominent across our entire sample period and is not a recent phenomenon. Interestingly, Figure 2 does not indicate an increase in forex exposure to match the increase in globalization witnessed during our sample period. However, this could be due to firms developing more effective financial and operational hedging strategies to neutralize the effects of the incremental forex exposure risks arising from increased globalization across time. Figure 3 illustrates the difficulty that analysts face in assessing the effects of forex exposure by showing that firms with larger forex exposure will have a greater ex-ante distribution of earnings.

The above arguments suggest two avenues through which greater forex exposure can adversely affect analysts' forecast errors. First, greater forex exposure increases the complexity of the earnings forecasting task by increasing the difficulty of identifying and processing all relevant information that could affect firms' earnings. Second, as illustrated in Figure 3, a given change in forex rates will naturally produce a greater ex-ante distribution of earnings for firms with higher forex exposure, which could impair the accuracy of analysts' earnings forecasts by increasing the uncertainty of firm outcomes and earnings. Collectively, these arguments suggest larger analysts' forecast errors for firms with greater forex exposure.

However, it is possible that the market penalty for missing analysts' forecasts incentivizes the management of firms with higher

<sup>&</sup>lt;sup>5</sup> In a related unpublished working paper, Guay et al. (2003) find that the accuracy of analysts' earnings forecasts is negatively affected by larger changes in exchange rates in the current quarter and that effect is more prominent in firms that are in the top decile of forex exposure. Our study differs from and extends Guay et al. (2003) in at least three ways. First, the fact that Guay et al. (2003) document weak results (p < 0.10) in a setting that is expected to exhibit the strongest effect (i.e., firms in the highest decile of forex exposure in conjunction with larger changes in forex rates) and without any robustness tests increases the difficulty of drawing strong causal inferences. Our study documents a direct and stronger effect of forex exposure across all firms after controlling for a wider range of control variables. We also demonstrate the robustness of our findings to a large number of tests including a quasi-natural experiment. Second, Guay et al. (2003) consider an interactive effect between forex exposure risk and changes in exchange rates without separately controlling for forex exposure risk in the analyses. Brambor et al. (2006) and Greene (2003) demonstrate that omitting constitutive terms in such interactional analyses can result in biased and inconsistent estimates. Our approach controls for the constitutive effects across all analyses. Finally, our study links forex exposure to a wider set of analysts' forecasting properties, and demonstrates how internal and external informational factors moderate forex exposure effects. Collectively, our findings from these tests allow us to provide a more holistic understanding of how analysts are affected by greater forex exposure.

 $<sup>^6</sup>$  Eiteman et al. (2016, p. 280) provide an illustration of this difficulty. In February 2004, JPMorgan Chase had forecast the spot rate to depreciate from the current rate of \$1.27/ $\epsilon$  to \$1.32/ $\epsilon$ , but the Dollar appreciated dramatically in the following threemonth period to close at \$1.19/ $\epsilon$ , producing a massive error in their forecast.

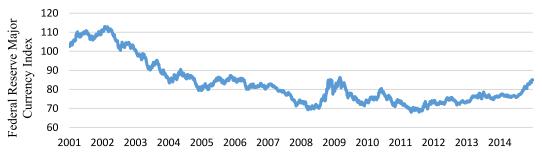


Fig. 1. Swings in U.S.trade-weighted exchange rates during the sample period.

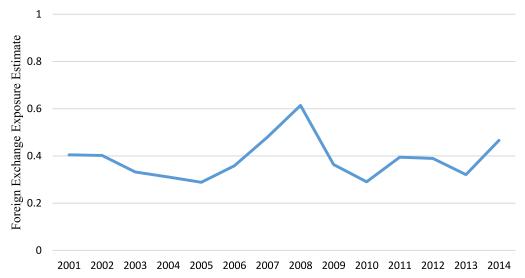
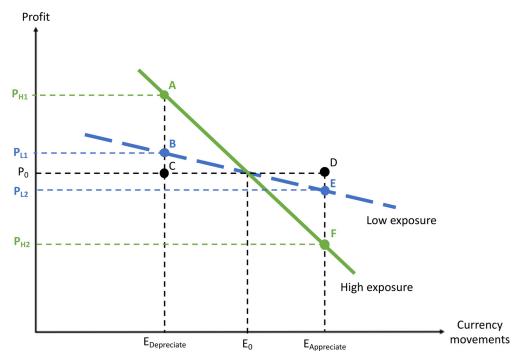


Fig. 2. Variability of foreign exchange exposure for the sample.



**Fig. 3.** Absolute forecast errors and foreign exchange exposure. This figure illustrates the profit function of two firms with negative foreign exchange exposure (that is, the firm's earnings will fall as their home currency appreciates): one with high exposure and the other with low exposure. The solid (Green) profit function assumes high foreign exchange exposure and the dashed (Blue) profit function assumes low foreign exchange exposure. Other things equal, compared to the firm with low negative exposure, the firm with a high negative exposure will have greater earnings when its home currency depreciates (point A is above point B) and lower earnings when its home currency appreciates (point F is below point E). It can be observed that the firm with a larger exposure to foreign exchange movements will have a greater ex-ante distribution of earnings (distance between  $P_{H1}$  and  $P_{H2}$  is greater that  $P_{L1}$  and  $P_{L2}$ ). This, in turn, increases the ex-ante volatility of reported earnings, which increases the potential error in analysts' consensus earnings forecasts (AC > BC when the home currency depreciates and FD > ED when the home currency appreciates).

forex exposure to provide greater disclosures and guidance, which can positively affect analysts' forecast accuracy for these firms. In line with this view, Cotter et al. (2006) show that optimistic initial earnings forecasts instigate firm management to provide public earnings guidance, which causes analysts to issue meetable or beatable forecasts. However, such responses by firms have not been widely documented, and it is likely the provision of more information by management will attenuate but not eliminate the negative effect of forex exposure on forecast accuracy. As such, our first hypothesis proposes that forex exposure will lead to less accurate forecasts:

**H**<sub>1</sub>: Analysts' consensus earnings forecast errors are larger when firms experience an increase in forex exposure.

The dispersion in analysts' earnings forecasts reflects the degree of uncertainty and the lack of consensus among market participants about firms' future economic performance (Barry and Jennings, 1992). Parkash et al. (1995) argue that the uncertainty analysts face regarding future earnings increases proportionally to the *ex-ante* volatility of reported earnings. As illustrated in Figure 3, firms with a larger exposure to forex movements are likely to have a greater *ex-ante* distribution of earnings. To the extent that analysts attempt to independently reflect expected exchange rate movements in their forecasts, the dispersion of earnings forecasts can be larger for firms with higher forex exposure because small errors and/or differences in assumptions in relation to the forex exposure can increase the variation in analysts' earnings estimates.

On the other hand, prior studies demonstrate herding behavior by analysts, whereby they release forecasts or recommendations similar to those previously announced by other analysts (Frijns and Huynh, 2018; Trueman, 1994). In line with this view, studies show that analysts demonstrate herding behavior by issuing less dispersed earnings forecasts when task difficulty increases, such as when issuing longer-term forecasts (De Bondt and Forbes, 1999) and forecasts for more diversified firms (Kim and Pantzalis, 2003). Hence, it is possible that the inherent difficulty in assessing the effects of foreign currency movements also causes analysts to herd in their earnings forecasts for such firms. As such, we examine the effect of forex exposure on analysts' forecast dispersion without predicting a sign. This leads to the second hypothesis specified in null form:

H<sub>2</sub>: Analysts' consensus earnings forecast dispersion is not affected when firms experience an increase in forex exposure.

# 3. Data and research design

# 3.1. Measure of foreign exchange exposure

Dumas (1978) and Adler and Dumas (1984) first suggested that forex exposure can be quantified as the sensitivity of stock returns to exchange rate movements, an approach that has been widely adopted in subsequent studies (e.g., Bartram et al., 2010; Francis et al., 2008; Hutson and Laing, 2014). Consistent with these studies, we use the following two-factor model to estimate the forex exposure of firms:

$$r_{i,t} = \alpha + \beta_1 s_t + \beta_2 R_t + \varepsilon_{i,t} \tag{1}$$

where,  $r_{i,t}$  is the logarithm of stock returns for firm i on day t,  $s_t$  is the logarithm of returns in the exchange rate on day t, and  $R_t$  is the value-weighted market portfolio returns on day t. We use the U.S. Dollar nominal trade-weighted index (Federal Reserve's Major Currencies Index) to determine movements in the exchange rate  $(s_t)$ , with an increase in the index's value representing an appreciating

U.S. Dollar relative to its trading partners' currencies.<sup>7</sup> We estimate Equation 1 based on daily data within a fiscal year to prevent possible averaging-out effects of monthly exchange rates (Glaum et al., 2000), capture a more fundamental relationship between exchange rates and firm value (Muller and Verschoor, 2006), and match the year time interval used to capture the control variables in the main analysis.<sup>8</sup>

Following prior studies, we use the absolute value of the coefficient estimates on  $s_t$  ( $\beta_1$ ) to measure the forex exposure of firms (*FXExposure*). This market-based measure of exchange exposure is expected to capture the net effect of forex exposure after accounting for financial and operational hedging activities (Bartram and Bodnar, 2007). Moreover, the inclusion of market portfolio returns ( $R_t$ ) in Equation (1) ensures that our forex exposure measure is derived after accounting for any confounding effects of other macroeconomic factors on stock prices (Hutson and Stevenson, 2010). In additional analyses, we estimate forex exposure by expanding the variables in Equation (1) to include other asset pricing and macroeconomic factors.

## 3.2. Analysts' forecast error and dispersion

We use the following ordinary least squares regression with robust standard errors clustered by firms to test the association between the within-firm forex exposure variations and analysts' consensus earnings forecast error  $(H_1)$  as well as the dispersion of analysts' forecasts  $(H_2)$ :

AbsFE/Dispersion

```
=\alpha+\gamma_{1}FXExposure+\gamma_{2}Size+\gamma_{3}Surprise+\gamma_{4}Loss+\gamma_{5}Auditor\\ +\gamma_{6}Horizon+\gamma_{7}StdROE+\gamma_{8}EPS+\gamma_{9}Meet+\gamma_{10}Growth+\gamma_{11}Segment\\ +\gamma_{12}Inst+\gamma_{13}Advert+\gamma_{14}MissAdvert+\gamma_{15}R\&D+\gamma_{16}MissR\&D\\ +\gamma_{17}TradVol+\gamma_{18}Beta+\gamma_{19}AnalystCov+\gamma_{20}MediaCov+\Sigma\ Firm\\ +\Sigma\ Year+\varepsilon
```

(2)

Following prior studies (e.g., Behn et al., 2008; Gul et al., 2013; Lang and Lundholm, 1996), we measure analysts' consensus forecast error (AbsFE) as the absolute value of the difference between the mean forecasted earnings in the two-month window before the annual earnings announcement and the actual annual earnings per share, divided by the price per share at the end of the previous fiscal year and multiplied by 100. Dispersion of the analysts' forecasts (Dispersion) is measured as the standard deviation of earnings forecasts issued by individual analysts scaled by stock price at the end of the previous fiscal year, multiplied by 100.<sup>10</sup> In relation to H<sub>1</sub>, we expect a positive coefficient on FXExposure because we expect larger forecast errors for firms with increasing forex exposure. For H<sub>2</sub>, a positive (negative) coefficient on FX-Exposure would suggest that analysts' earnings forecasts are more (less) dispersed for firms with increasing forex exposure. Consistent with the above-mentioned prior studies, our control variables in the forecast error and dispersion analyses include firm size (Size), earnings surprise (Surprise), loss indicator (Loss), Big N auditor (Auditor), analyst forecast horizon (Horizon), earnings volatility (StdROE), earnings level (EPS) and meet or beat analysts' earnings forecast indicator (Meet). We also follow other studies (e.g.,

 $<sup>^{7}</sup>$  The nominal trade-weighted index is a weighted average of the forex values of the U.S. Dollar against a broad subset of 21 currencies, including the Euro, Chinese Yuan, Japanese Yen, Canadian Dollar, and U.K. Pound.

<sup>&</sup>lt;sup>8</sup> Using a longer time horizon to capture forex exposure would produce rolling regression estimates of exposure, which will be serially correlated.

<sup>&</sup>lt;sup>9</sup> While our main analysis includes firm-year observations with both significant and insignificant forex exposure coefficients, our main findings are robust to controlling for observations with insignificant forex exposures.

 $<sup>^{10}\,</sup>$  We require at least two analysts' forecasts to calculate analysts' forecast dispersion.

Hope et al., 2006; Jiraporn et al., 2012; Lobo et al., 2012; Koh and Reeb, 2015) and control for growth options (*Growth*), business segments (*Segment*), institutional ownership (*Inst*), advertising spending (*Advert and Miss\_Advert*), research and development expense (*RD and Miss\_RD*), trading volume (*TradVol*), market beta (*Beta*), analyst coverage (*AnalystCov*) and media coverage (*MediaCov*). We expect positive (negative) coefficients for *Surprise*, *Loss*, *Horizon*, *StdRoe*, *Segment*, and *Beta* (*Size*, *Auditor*, *Meet*, *Growth*, *Inst*, *Advert*, *RD*, *StdRet*, *AnalystCov*, and *MediaCov*). We also include firm- and year-fixed effects to control for the potential impacts of firm- and time-varying factors. The inclusion of firm fixed effects allows us to capture how within-firm variation in the explanatory variables affects analysts' forecast errors and dispersion. Panel A of Appendix 1 provides definitions of variables. 12

#### 3.4. Sample and data

We use five data sets to construct our sample. Analyst forecast data are from *I/B/E/S*. U.S. exchange rate indices are collected from the *Federal Reserve Bank*. Financial, segment, and industry membership data are obtained from *COMPUSTAT*. Stock prices and the market index are from *CRSP*, and institutional ownership data are from *Thomson Reuters 13F*. Our original sample consists of 102,310 firmyear observations with sufficient data to estimate the forex exposure measure (FXExposure) over the 2001 to 2014 period.<sup>13</sup> Next, we exclude 76,629 firm-year observations without analyst forecast accuracy and dispersion data. Finally, we remove 7,653 firm-year observations without the data needed to construct the control variables for our analyses. The full sample consists of 18,028 observations, representing 3,876 unique firms.<sup>14</sup>

#### 4. Descriptive statistics

Table 1 Panel A reports descriptive statistics. The mean (median) value of our forex exposure proxy (FXExposure) is 0.389 (0.280). Untabulated summary statistics on the untransformed (signed) value of forex exposure reveal a mean value of 0.815, implying that a 1% increase in return for the trade-weighted U.S. Dollar increases firm stock returns by 0.815% (on average).

The mean value of *AbsFE* suggests that the absolute difference between the consensus earnings forecast and actual earnings is about 0.624% of the lagged stock price, while the mean value of *Dispersion* suggests that the standard deviation of individual analysts' forecasts equates to 0.498% of the lagged stock price. The descriptive statistics for the control variables are comparable to those reported in prior studies (e.g., Gul et al., 2013; Lehavy et al., 2011).<sup>15</sup>

Panel B of Table 1 demonstrates that the mean value of forecast errors and dispersion is higher for observations in the highest quintile of forex exposure relative to observations in the lowest exposure quintile. Wilcoxon two-sample tests indicate that these differences are significant (p < 0.01). Figure 4 illustrates that the mean value of forecast errors and dispersion increases monotonically, moving from the lowest quintile of forex exposure to the highest exposure quintile.

#### 5. Results

5.1. Foreign exchange exposure and analyst forecast error and dispersion

Table 2 reports our results on the effect of forex exposure on analyst forecast errors (H<sub>1</sub>) and dispersion (H<sub>2</sub>). The results from the forecast error analysis, reported in Column 1 of Table 2, reveal a positive and significant (p < 0.01) coefficient on FXExposure after controlling for various determinants of analyst forecast errors and firm and year fixed effects. This is consistent with our conjecture that the accuracy of analysts' earnings forecasts decreases with forex exposure. The comparative results from our forecast dispersion tests, reported in Column 2 of Table 2, also depict a positive and significant (p < 0.01) coefficient on FXExposure after controlling for other determinants of analyst forecast dispersion and firm and year fixed effects. This finding supports the view that analysts' earnings forecasts are more dispersed when firms experience an increase in forex exposure, implying that the effects of uncertainty in the forex exposure dominate the possible herding effect.<sup>16</sup> With regard to economic significance, we infer that an interquartile increase in FXExposure increases the predicted forecast error (dispersion) of firms by 6.26% (4.97%).<sup>17</sup>

The results for numerous control variables are significant at the 1% level with the expected signs in Columns (1) and (2). Specifically, we find that analysts' forecast errors and dispersion are positively associated with *Surprise, Loss, Segment,* and *Beta.* In contrast, analysts' forecast errors and dispersion are negatively related to *Size, EPS, Meet, Growth, Inst,* and *RD.* The explanatory power of the forecast error (dispersion) regression is 14.2 and 13.8 percent, respectively.

<sup>&</sup>lt;sup>11</sup> While we use contemporaneous controls, our results remain similar using lagged controls.

<sup>&</sup>lt;sup>12</sup> Continuous variables are winsorized at the 1<sup>st</sup> and 99<sup>th</sup> percentiles.

<sup>&</sup>lt;sup>13</sup> We set the year 2001 as our initial sample year to account for how analysts' errors and dispersion were affected by the restrictions introduced by the Regulation Fair Disclosure (Reg FD) in October 2000.

<sup>&</sup>lt;sup>14</sup> The intensive data requirements to measure the large set of control variables in our analysis results in our sample being generally made up of larger firms. For example, in untabulated tests, we find that the mean market capitalization of our sample firms (mean = \$8.83 billion) is significantly higher than the comparable mean value for firms not included in our sample (mean = \$1.12 billion). However, we find that repeating our analyses after interacting our test variable with an indicator for large firms (i.e., above median market capitalization) in our sample reveals an insignificant coefficient on the interaction term, suggesting that no significant differences in the magnitude of the effects of forex exposure across smaller and larger firms that are presented in our sample.

 $<sup>^{15}</sup>$  Untabulated correlation statistics reveal that the correlation between analyst forecast error and dispersion with exposure is positive and significant (0.175 and 0.178, respectively, p <0.01), suggesting that firms with larger exposure are correlated with higher forecast error and dispersion. The correlation coefficients between

the independent variables are relatively low, with the highest coefficient being - 0.54, between Loss and EPS. The largest VIF (untabulated) is 2.58 (RandD), which suggests that there are no unstable regression coefficients that are associated with large standard errors due to highly correlated independent variables. The correlation statistics also reveal several significant correlations suggesting that firms with greater forex exposure differ from those with lower exposure across many firm attributes. For example, we find that firms with greater forex exposure risk are generally smaller in size, loss-making firms, and clients of non-Big N auditors. This underlines the importance of controlling for these firm attributes in our main analysis.

However, this result does not suggest that herding effects of forex exposure do not take place at all. These results merely suggest an overall effect of uncertainty dominates, and a relatively weaker herding response by analysts.

<sup>&</sup>lt;sup>17</sup> Recall that our main results for forecast error are based on earnings forecasted in the two-month window before the actual annual earnings announcement. Consistent with the view that analysts may find it more challenging to predict movements in forex rates and how such movements affect firm earnings earlier in the year, untabulated analyses based on an expanded sample of analysts' forecast errors across all four quarters within the fiscal year and an interaction of forex exposure with a time trend variable that takes on values from 1 to 4 for each quarter in the fiscal year indicate that the positive effect of forex exposure on analysts' forecast errors is more pronounced for forecasts produced in the earlier quarters. These results are consistent with analysts facing greater uncertainty of firm outcomes in producing forecasts for higher forex exposure firms earlier in the year.

**Table 1**Summary statistics and univariate results

Panel A: Sum Variable	n	Mean	Median	P25	P75	SD.
AbsFE	18,028	0.624	0.173	0.056	0.533	1.157
Dispersion	18,028	0.498	0.134	0.047	0.430	0.922
FXExposure	18,028	0.389	0.280	0.132	0.519	0.385
Size	18,028	7.894	7.833	6.706	9.057	1.669
Growth	18,028	1.146	1.096	1.019	1.209	0.244
Segment	18,028	0.608	0.000	0.000	1.386	0.701
Inst	18,028	0.511	0.616	0.047	0.810	0.355
TradVol	18,028	0.206	0.163	0.094	0.271	0.162
Surprise	18,028	0.009	0.004	-0.018	0.023	0.163
Loss	18,028	0.190	0.000	0.000	0.000	0.393
Auditor	18,028	0.937	1.000	1.000	1.000	0.243
Horizon	18,028	3.297	3.356	3.068	3.593	0.413
StdROE	18,028	1.287	0.757	0.404	1.497	1.539
EPS	18,028	1.521	1.340	0.300	2.630	2.446
Meet	18,028	0.071	0.000	0.000	0.000	0.256
Advert	18,028	0.128	0.000	0.000	0.012	0.029
Miss_Advert	18,028	0.601	1.000	0.000	1.000	0.490
RD	18,028	0.056	0.000	0.000	0.034	0.129
Miss_RD	18,028	0.500	0.000	0.000	1.000	0.500
Beta	18,028	1.295	1.236	0.893	1.619	0.560
AnalystCov	18,028	1.719	1.099	1.099	1.609	0.582
MediaCov	18,028	2.120	2.773	0.000	3.497	1.686
Panel B: Univ	ariate resu	lts across	the lowest and hig	hest foreign exchange exposur	e quintiles	
		Lowest	Exposure Quintile	Highest Exposure Quintile	Difference	Wilcoxon p-value
AbsFE		0.413		0.972	-0.559	0.000***
Dispersion		0.322		0.766	-0.444	0.000***

This table provides descriptive statistics for the sample observations (Panel A) and univariate results across the lowest and highest foreign exchange exposure quintiles (Panel B). For every variable, the mean, median, lower quartile, upper quartile, and standard deviation are presented. Our main dependent variables are forecast error and dispersion: AbsFE is analysts' earnings forecasts error, measured as the percentage of the absolute difference between the consensus earnings forecast and actual earnings scaled by stock price at time t-1; Dispersion is the dispersion of analysts' forecasts, the percentage of the standard deviation of individual analysts' forecasts scaled by stock price at time t-1. The main test variable is forex exposure: EXExposure is the absolute foreign exchange exposure coefficient estimated using a regression of stock returns on the value-weighted market portfolio return and the return on the U.S. Dollar nominal trade-weighted index. Other variables are defined in Appendix 1. All continuous variables are winsorized at the 1st and the 99th percentiles. \*\*\*, \*\*, \* denote significance at the 1%, 5 %, and 10% levels, respectively.

#### 6. Robustness tests

## 6.1. Quasi-natural experiment

To strengthen the causal inferences that can be drawn from our main findings, we next use a quasi-natural experiment setting that generates an exogenous variation in forex exposure from the sudden revaluation of the Chinese Yuan (CNY) on 21<sup>st</sup> July 2005, from which point the Yuan was no longer pegged to the U.S. Dollar (USD) but managed floating exchange rate regime with reference to a basket of currencies. We conjecture that this change in the Yuan from a fixed exchange rate system to a managed float should affect analyst forecasts only through its exogenous effect on the forex exposure of U.S. firms through a change in exchange rate regime.

Accordingly, we employ a difference-in-differences (DiD) methodology to examine how analysts' forecast errors and dispersion change for a treatment sample of firms that are more susceptible to the unpegging of the Yuan. We report the analysis using a four-year window surrounding the unpegging date of 21st July 2005. We also include an indicator variable (*Post*) that is coded 1 for observations representing analysts' forecasts in the pre-unpegging period, consisting of analysts' forecasts for the

two years immediately preceding the unpegging date, and 0 for observations in the post-unpegging period (i.e., analysts' forecasts for the two years immediately after the unpegging date). To identify our treatment firms in our DiD analysis, we searched firm 10-K filings to identify firms that are likely to be more exposed to fluctuations in Yuan. Specifically, we classify firms mentioning the keywords China, Renminbi, Chinese Yuan, or any derivative words (e.g., Chinese) at least ten times or more in their 10K filings in the year immediately before and after the unpegging date as treatment firms (Treat=1) and firms that do not mention the above keywords at all in their 10K filings as the control firms (Treat=0).<sup>20</sup> Finally, we include the interaction of Treat and Post along with all the other control variables from our main analysis, including firm and year fixed effects. By including both year and firm fixed effects in the models, Treat and Post dummies have to be omitted to avoid the issue of multicollinearity, so the interaction variable ( $Post \times Treat$ ) is the variable of interest.

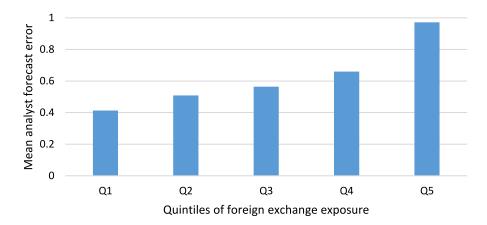
The results from our DiD analysis, reported in Panel A, Table 3, reveal that the interaction term  $Post\ x\ Treat$  is positive and significant (p < 0.10 or better) in the analyst forecast error and dispersion analyses, suggesting larger forecast errors for firms with increasing forex exposure and dispersion relative to control firms following the unpegging of the Yuan against the USD. In line with inferences from our main analyses, these findings show that firms likely to be more highly exposed to the unpegging of the Yuan ex-

<sup>&</sup>lt;sup>18</sup> Bloomberg (2005) reports that the timing of the unpegging of the Chinese Yuan was a shock for financial markets.

<sup>&</sup>lt;sup>19</sup> We do not consider a longer window for our DiD test to avoid the post-pegging period coinciding with the effects of the global financial crisis. Nonetheless, we find that our DiD results are unaffected when we repeat this analysis using a six-year window following the unpegging of the Yuan.

<sup>&</sup>lt;sup>20</sup> We manually checked references to the above-mentioned words for a random sample of 50 firms to ensure that the references to these words were being used to refer to business activities, opportunities or risks stemming from China.

# Panel A: Analyst forecast error



Panel B: Analyst forecast dispersion

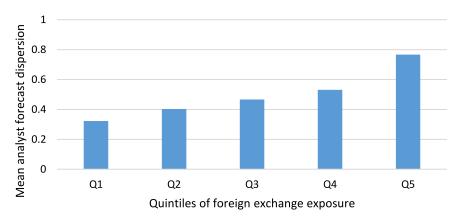


Fig 4. Mean forecast error and dispersion for quintiles of exposure.

perience a significant increase in analysts' forecast errors and dispersion in the post-unpegging periods.

The two panels in Figure 5 plot the predicted values of the forecast error and dispersion from the DiD model. We find that in the pre-unpegging period, the predicted forecast errors and dispersion for both the treatment and control firms have a similar downward trend, largely consistent with the parallel trend assumption. However, in the post-period, while both the treatment and control firms show an upward trend for forecast error and dispersion, the treatment firms experience a larger increase in forecast error and dispersion relative to years t-1 and t-2.<sup>21</sup> This is consistent with the exogenous shock from the unpegging event instigating changes in analyst forecast errors and dispersion.

To further ensure that our quasi-natural experiment analysis findings do not capture any time dynamics, we run a placebo test by reperforming our quasi-natural experiment analysis using 21st July 2012 (i.e., seven years after the actual unpegging date) as a placebo event date. The results from this analysis, reported in Panel B of Table 3, reveal an insignificant coefficient on the variable

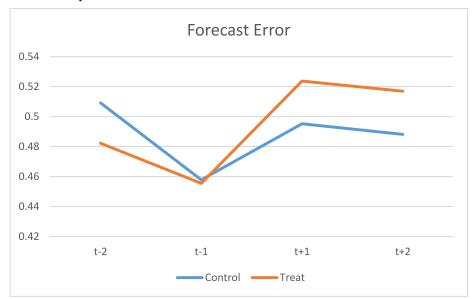
capturing the interaction between *Treat* and *PostPseudo*, the indicator variable differentiating between analysts' forecasts for the two years immediately preceding and following the placebo unpegging date. This finding supports our main results by showing insignificant differences between the changes in the analysts' forecast accuracy and dispersion of treatment and control firms across two periods that did not witness any exogenous shocks that strengthened or weakened the U.S. Dollar relative to the Chinese Yuan.

#### 6.2. Omitted variable bias

While we include many control variables as well as year- and firm-fixed effects in the empirical models to improve causal inferences, the list of control variables is not exhaustive. Hence, we next re-estimate our analyses after including other potentially omitted correlated variables that are not included in the main model to avoid significant sample attrition. To begin, international or geographic diversification can impair the quality of analysts' forecasts by increasing firm complexity (Duru and Reeb, 2002; Platikanova and Mattei, 2016). However, multinational firms are more likely to be naturally hedged by matching the currency denomination of their receipts and payments, which can lower their exposure to exchange rates (Hutson and Laing, 2014). We follow Duru and Reeb (2002) and control for international diversification using a factor analysis of three common measures of international

<sup>&</sup>lt;sup>21</sup> We explored various matching methods (propensity score matching and coarsened exact matching) to identify treatment and control observations with similar levels of analysts' forecast errors and dispersion in the pre-unpegging period. However, we could not balance our covariates using these methods, arguably due to the large number of control variables in our analysis.

# Panel A: Analyst forecast error



Panel B: Analyst forecast dispersion

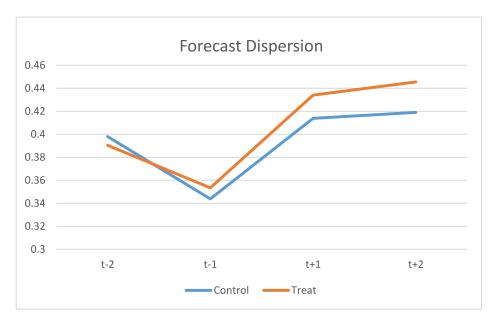


Fig 5. DiD graph. These figures show the predicted forecast error and dispersion during the pre- and post-period in Panels A and B, respectively.

diversification, namely, the ratio of foreign sales to total sales, the ratio of foreign assets to total assets, and the number of geographic segments. We also control for industry diversification (number of reported business segments) to account for the possibility of firms reducing their forex exposure through diversifying across multiple business lines (Pantzalis et al., 2001).

The next group of additional controls relates to corporate governance. Firms with better corporate governance can affect analyst forecasts by promoting the overall quality of information possessed by financial analysts (Byard et al., 2006). Effective board monitoring can also improve a firm's hedging policies, though evidence on this remains mixed (Adam et al., 2017; Kumar and Rabinovitch, 2013). We control for corporate governance using measures of board independence, board size, and CEO duality. Next, prior research shows that market competition can also affect analyst forecast properties (Datta et al., 2011; Haw et al., 2015; Zhang, 2018). Tangential to our setting, Bartram et al. (2010) ar-

gue that greater product market competition reduces the scope of firms passing on exchange rate movement costs to customers. We control for market competition using the product similarity index developed by Hoberg and Phillips (2010, 2016).

Finally, prior studies show that corporate social responsibility (CSR) can affect firm risk through product differentiation, which can improve the likelihood of firms passing through the costs from currency movements to consumers (Albuquerque et al., 2019; Miller and Reuer, 1998). There is also some evidence that CSR can impact analyst forecasts (Becchetti et al., 2013; Jo and Harjoto, 2014). As such, following Kim et al. (2014), we control for CSR performance using an aggregate CSR score rating that MSCI ESG assigns to each firm based on areas of strength and concern relating to CSR. While the inclusion of these additional controls significantly reduces our sample size by around 40 percent, untabulated results continue to reveal a positive and significant (p < 0.01) coef-

**Table 2**Regression results for analyst forecast error and dispersion

	AbsFE	Dispersion
Variable	(1)	(2)
FXExposure	0.101***	0.064***
	(3.62)	(3.00)
Size	-0.210***	-0.138***
	(-9.40)	(-7.80)
Surprise	0.512***	0.460***
-	(5.73)	(6.57)
Loss	0.347***	0.285***
	(8.93)	(9.63)
Auditor	0.213**	0.079
	(2.35)	(1.08)
Horizon	0.043**	0.007
	(2.23)	(0.45)
StdROE	-0.001	-0.002
	(-0.05)	(-0.22)
EPS	-0.068***	-0.055***
	(-8.55)	(-8.87)
Meet	-0.319***	-0.128***
	(-17.41)	(-9.03)
Growth	-0.096**	-0.185***
	(-1.79)	(-3.82)
Segment	0.059*	0.043*
	(1.86)	(1.77)
Inst	-0.255***	-0.210***
	(-3.32)	(-3.57)
Advert	0.566	-0.271
	(0.59)	(-0.38)
Miss_Advert	0.038	0.062
	(0.72)	(1.40)
RD	-0.436*	-0.452**
	(-1.92)	(-2.51)
Miss_RD	-0.025	-0.084
	(-0.33)	(-1.40)
TradVol	0.110	0.252***
	(0.94)	(2.64)
Beta	0.070**	0.044*
	(2.35)	(1.85)
AnalystCov	-0.068***	0.072***
	(-4.15)	(5.26)
MediaCov	-0.001	0.004
	(-0.05)	(0.41)
Constant	1.816***	1.302***
	(8.08)	(7.42)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
N	18,028	18,028
Adjusted R <sup>2</sup>	0.1422	0.1376

This table presents the results for the regression of analyst forecast error and dispersion. Our main dependent variables are analyst forecast error and dispersion: AbsFE is analysts' earnings forecasts error, measured as the percentage of the absolute difference between the consensus earnings forecast and actual earnings scaled by stock price at time t-1; Dispersion is the dispersion of analysts' forecasts, the percentage of the standard deviation of individual analysts' forecasts scaled by stock price at time t-1. The main test variable is forex exposure: FXExposure is the absolute foreign exchange exposure coefficient estimated using a regression of stock returns on the value-weighted market portfolio return and the return on the U.S. Dollar nominal trade-weighted index. Other variables are defined in Appendix 1. All t-statistics (in parentheses) are based on robust standard errors clustered by firm. \*\*\*, \*\* and \*\* denote statistical significance at the 1%, 5% and 10% levels, respectively.

ficient on FXExposure in our analysts' forecast error and dispersion analyses.<sup>22</sup>

 Table 3

 Results for the quasi-natural experiment difference-in-differences analysis

Panel A: Difference-in-differences analysis				
	AbsFE	Dispersion		
Variable	(1)	(2)		
$Post \times Treat$	0.109**	0.087*		
	(1.96)	(1.91)		
Control Variables	Yes	Yes		
Firm fixed effects	Yes	Yes		
Year fixed effects	Yes	Yes		
N	3,966	3,966		
Adjusted R <sup>2</sup>	0.0940	0.1111		
Panel B: Falsification test				
	AbsFE	Dispersion		
Variable	(1)	(2)		
$PostPseudo \times Treat$	-0.123	-0.022		
	(-0.91)	(-0.26)		
Control Variables	Yes	Yes		
Firm fixed effects	Yes	Yes		
Year fixed effects	Yes	Yes		
N	3,450	3,450		
Adjusted R <sup>2</sup>	0.0550	0.0298		

The table presents the results for the difference-in-differences (DiD) analysis using the unpegging of the Chinese Yuan on 21st July 2005 as an exogenous shock to forex exposure. Our main dependent variables are forecast error and dispersion: AbsFE is analysts' earnings forecasts error, measured as the percentage of the absolute difference between the consensus earnings forecast and actual earnings scaled by stock price at time t-1; Dispersion is the dispersion of analysts' forecasts, the percentage of the standard deviation of individual analysts' forecasts scaled by stock price at time t-1. In Panel A, we report the analysis using a four-year window surrounding the unpegging date of 21st July 2005. Analysts' forecasts in the pre-unpegging period consist of analysts' forecasts for the two years immediately preceding the unpegging date (Post coded as 0), while the post-unpegging period consists of analysts' forecasts for the two years immediately after the unpegging date (Post coded as 1). Treat is an indicator variable coded 1 for firms that mentioned China, Renminbi, Chinese Yuan, or any derivative words (e.g., Chinese) at least 10 times in their 10-K filings in year t-1 and year t+1, and 0 for the firms that do not mention any of these keywords at all in their 10-K filings. In Panel B, we report the DiD falsification test using 21st July 2012 as an event date. Analysts' forecasts in the pseudo pre-unpegging period consists of analysts' forecasts for the two years immediately preceding the unpegging date (PostPseudo coded as 0), while the pseudo post-unpegging period consists of analysts' forecasts for the two years immediately after the unpegging date (PostPseudo coded as 1). All t-statistics (in parentheses) are based on robust standard errors clustered by firm. \*\*\*, \*\* and \* denote significance at 1%, 5% and 10% levels, respectively.

We also follow Frank (2000) and conduct the impact threshold of a confounding variable (ITCV) analysis to assess how strongly correlated any other omitted variable needs to be with FXExposure and our outcome variables to invalidate our result for FXExposure (i.e., insignificant at the 5% level). This produces ICTV indices of 0.079 (Z-value = 2.56), and 0.040 (Z-value = 1.92) for error and dispersion analyses, respectively (untabulated). This implies that the correlation between a confounding variable and our two analysts' properties and the correlation between a confounding variable and FXExposure would both need to be higher than 0.281 ( $\sqrt{0.079}$ ) and 0.200 ( $\sqrt{0.040}$ ) to overturn our results for FXExposure in error and dispersion analyses, respectively. To put this in perspective, the highest ITCV index from all our control variables across our two analyses is 0.066. This suggests that our findings are unlikely to be driven by an omitted correlated variable.

We also repeat our main analyses after employing entropy balancing, a multivariate reweighting method for addressing issues related to functional form misspecification (Hainmueller, 2012). We execute this analysis after transforming our test variable into dichotomous measures (based on the median) to obtain treatment and control firms. We then balance the first three moments (i.e., mean, variance, and skewness) of the control variables across the two samples such that there are no significant post-weighting differences in the three moments across the two samples (untabulated). The untabulated results of this analysis indicate that the co-

<sup>&</sup>lt;sup>22</sup> Following the survey of analysts by Brown et al. (2015), our inferences remain unaffected when we include controls for other factors that may specifically affect analysts' decisions to cover firms. These include the firm's growth prospects (trailing price-to-earning's ratio), composition of investor base (transient, quasi-indexer, and dedicated classification), disclosure quality (Fog index of annual report), and profitability (return on assets).

efficient on our forex exposure test variable remains positive and significant (p<0.01) when the dependent variables are analysts' forecast error and dispersion.

#### 6.3. Other robustness tests

We perform a battery of other robustness tests. First, we rerun our main analyses in Table 2 after using the Federal Reserve's OITP and Broad currency indices as our exchange rate indices in Equation (1) to estimate forex exposure.<sup>23</sup> We also estimate exposure by expanding the explanatory variables in Equation (1) to include other asset pricing factors such as the Fama and French 3factor model, the Carhart 4-factor model, and the Fama and French 5-factor model. Second, we account for other macroeconomic factors by using month-level regressions to estimate firms' exposure to changes in interest rates and commodity risks and control for these additional types of macroeconomic exposure in our main analyses.<sup>24</sup> Third, to the extent that a firm's forex exposure is significantly influenced by its industry, we rerun our main tests using industry-adjusted FXExposure. Finally, we repeat our main regression analyses in Table 2 separately for each year and Fama and French 48 industry group. We then compute the mean of the coefficients on our forex exposure variable and assess significance using the Fama and Macbeth t-statistics on these coefficients. Our main results remain robust to these additional analyses.

#### 7. Supplemental analyses

#### 7.1. Analyst effort

Our results thus far suggest that analysts face greater difficulties in forecasting the earnings of firms with increasing forex exposure. Such challenges may manifest in greater analyst efforts in forecasting the earnings of these firms. We seek to shed some insights into this by examining the relation between forex exposure and two proxies of analysts' effort. The first measure, AvgFreq, is the average number of earnings forecasts issued by analysts for the focal firm during a fiscal year (Jacob et al., 1999; Keskek et al., 2017; Harford et al., 2019). Such an analysis can reveal whether the greater uncertainty that analysts face in relation to higher forex exposure firms results in more forecast revisions. To the extent that increased effort imposes time constraints on the ability to cover other firms, our second measure, AvgCov, allows us to assess whether analysts that follow firms that experience an increase in forex exposure cover fewer firms in total. AvgCov is the average number of other firms followed by analysts covering the focal firm in a particular year (Barth et al., 2001). The results from the regressions of AvgFreq and AvgCov on FXExposure and the controls are reported in Table 4. The significant (p < 0.05) coefficient on FXExposure in Column 1 suggests that analysts issue more forecast revisions when firms experience an increase in forex exposure. While we cannot observe analyst effort directly, this result is consistent with firms with increasing forex exposure demanding greater effort and time from analysts. However, we do not find analysts that cover firms with increasing forex risks cover fewer firms in Column 2, suggesting that analysts' coverage of firms with increasing forex

**Table 4**Regression results for analyst effort.

	AvgFreq	AvgCov
Variable	(1)	(2)
FXExposure	0.092**	0.089
	(2.14)	(0.93)
Size	0.029	0.032
	(0.86)	(0.41)
Surprise	-0.468***	-0.144
•	(-5.31)	(-0.65)
Loss	0.182***	-0.039
	(3.59)	(-0.36)
Auditor	0.076	0.782*
	(0.60)	(1.76)
Horizon	-0.082***	0.119
	(-2.71)	(1.57)
StdROE	-0.010	-0.024
StattoL	(-0.67)	(-0.71)
EPS	-0.007	0.012
LIJ	(-0.71)	(0.57)
Meet	-0.130***	0.062
Meet	(-3.05)	(0.60)
Growth	0.058	-0.269
GIOWLII		
Cagmant	(0.75) 0.071	(-1.35) -0.028
Segment		
To a t	(1.58)	(-0.22)
Inst	0.222*	0.082
	(1.86)	(0.27)
Advert	1.522	2.104
	(1.10)	(0.86)
Miss_Advert	-0.001	-0.149
	(-0.01)	(-0.78)
RD	0.058	0.217
	(0.22)	(0.28)
Miss_RD	0.131	-0.271
	(1.21)	(-0.77)
TradVol	1.135***	0.147
	(7.20)	(0.39)
Beta	0.051	-0.285**
	(1.33)	(-2.52)
AnalystCov	0.546***	-0.120*
	(18.76)	(-1.85)
MediaCov	-0.032	0.035
	(-1.36)	(0.65)
Constant	2.092***	13.996***
	(6.76)	(15.91)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
N	8,909	8,909
Adjusted R <sup>2</sup>	0.1974	0.1549

This table presents the results for the analysis of analyst effort. The dependent variables are the frequency of earnings forecast revisions and the number of other firms covered by the focal firm's analysts: AvgFreq is the average number of earnings forecasts issued by analysts for the focal firm during a fiscal year; AvgCov, is the average number of other firms followed analysts covering the focal firm in a particular year. The main test variable is forex exposure: FXExposure is the absolute foreign exchange exposure coefficient estimated using a regression of stock returns on the value-weighted market portfolio return and the return on the U.S. Dollar nominal trade-weighted index. Other variables are defined in Appendix 1. All t-statistics (in parentheses) are based on robust standard errors clustered by firm. \*\*\*, \*\* and \* denote statistical significance at the 1%, 5% and 10% levels, respectively.

exposure does not reduce the number of other firms they cover in their portfolio.

#### 7.2. Firms with and without foreign sales and assets

As discussed earlier, firms without foreign business activities are also heavily exposed to forex exposure to the extent that they can depict similar levels of overall exposure to forex risks compared to large multinational firms (Aggarwal and Harper, 2010). Consistent with this viewpoint, we find marginally higher forex exposure for firms with no foreign sales and assets (mean = 0.408) in

<sup>&</sup>lt;sup>23</sup> The OITP index is a weighted average of the forex values of the U.S. Dollar against a subset of 19 currencies in the broad index that does not circulate widely outside the country of issue (e.g., Singapore, Malaysia, Brazil, and Argentina). The broad index is a weighted average of the forex values of the U.S. Dollar against the currencies of a large group of major U.S. trading partners (40 countries).

<sup>&</sup>lt;sup>24</sup> To obtain interest rate and commodity exposures, we estimate Equation (1) based on a 36-month rolling regression using the monthly changes in the yield on three-month Treasury bills and the Goldman Sachs Commodity Index in place of the Federal Reserve's Major Currencies Index, respectively.

**Table 5**Analyses of firms with and without foreign sales and assets

Panel A: Univariate Ana	alysis			
Variable	(1) Without	(2) With Foreign	Difference	t-test
	Foreign	Sales/Assets		
	Sales/Assets			
FXExposure	0.408	0.380	-0.028	-4.37
N	5,634	12,394		
Panel B: Regression re	esults for firms with and v	without foreign sales and asse	ts	
	AbsFE	AbsFE	Dispersion	Dispersion
Variable	(1) Without	(2) With Foreign	(3) Without	(4) With Foreign
	Foreign	Sales/Assets	Foreign	Sales/Assets
	Sales/Assets		Sales/Assets	
FXExposure	0.103*	0.102***	0.096**	0.044*
	(1.90)	(3.09)	(2.18)	(1.84)
Control variables	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	5,634	12,394	5,634	12,394
Adjusted R <sup>2</sup>	0.2201	0.1134	0.2099	0.1075
z-score	(1)-(2)		(3)-(4)	
	0.002		1.025	

This table presents the analyses for forex exposure for firms with and without foreign sales and assets. Panel A provides the comparison of *FXExposure* means between firms with and without foreign sales and assets. Panel B reports the regression results for firms with and without foreign sales and assets. Our main dependent variables are forecast error and dispersion: *AbsFE* is analysts' earnings forecasts error, measured as the percentage of the absolute difference between the consensus earnings forecast and actual earnings scaled by stock price at time t-1; *Dispersion* is the dispersion of analysts' forecasts, the percentage of the standard deviation of individual analysts' forecasts scaled by stock price at time t-1; The main test variable is forex exposure: *FXExposure* is the absolute foreign exchange exposure coefficient estimated using a regression of stock returns on the value-weighted market portfolio return and the return on the U.S. Dollar nominal trade-weighted index. All t-statistics (in parentheses) are based on robust standard errors clustered by firm. \*\*\*, \*\* and \* denote statistical significance at the 1%, 5% and 10% levels, respectively.

comparison to firms with foreign sales and assets (mean = 0.380) in Panel A, Table 5. This implies that forex exposure can also impair analysts' earnings forecasts for firms without significant foreign business activities. While it is difficult to identify purely domestic firms due to the unavailability of refined data on the extent to which firms transact in foreign markets on particular aspects of the business (e.g., unavailability of segmented data for purchases), we explore whether our main findings hold for firms without significant foreign business by replicating our main analyses separately for firms with and without foreign sales and assets. $^{25}$ 

Results reported in Panel B, Table 5 show that the coefficient of forex exposure is positive and significant (p < 0.10) for both types of firms. Further, comparisons of coefficients between the two subsamples indicate the effect of forex exposure is not significantly different across firms with and without foreign sales and assets. These results are consistent with the view that the adverse effect of forex exposure on analysts' forecast error and dispersion prevails at similar levels for firms without significant foreign business activities.

# 7.3. Periods of pronounced uncertainty

As discussed earlier, we posit that the primary channel through which greater forex exposure impairs the quality of analysts' earnings forecasts is by increasing the uncertainty of firm outcomes. As such, we seek to augment our main findings by assessing whether the adverse effects of forex exposure on analyst forecast accuracy and dispersion are exacerbated in years that witness significant volatility in the U.S. Dollar. It is generally well accepted that the greater volatility in exchange rates can reduce the effectiveness of financial hedging (Hutson and Laing, 2014) and present more significant implications for earnings (Minaya, 2019). This suggests that greater volatility in the U.S. Dollar can increase the uncertainty of

firm outcomes and earnings, leading to greater analysts' forecast errors and dispersion. We assess this by repeating our main analyses in Table 2 after including an additional indicator variable (US-DVol) capturing years in the top quartile of volatility in the U.S. Dollar across our sample period and its interaction with our forex exposure proxy (FXExposure). The results from these analyses, reported in Table 6, reveal positive coefficients in our forecast error and dispersion tests (p < 0.05). Overall, the results in Table 6 suggest that the effects of forex exposure work through the uncertainty channel.

# 7.4. Moderating effects

While our findings suggest that forex exposure negatively impacts the quality of analysts' forecast properties, it is possible that the availability of more public information on firms with higher forex exposure can create a more transparent information environment that can lower the information-processing and private search costs of analysts. This can make it easier for analysts to identify more precise firm-, industry-, and macroeconomic-level information, which can help analysts better predict the impact of forex exposure on the future earnings and cash flows of firms under uncertain effects brought by forex exposure.

To shed insights into our conjecture the information environment may moderate the negative effects of forex exposure, we consider how our main results are moderated by three factors that represent sources of relevant information that may help analysts produce forecasts for firms with high forex exposure, namely more precise information on geographical segments, readability of annual reports, and media coverage. Specifically, given the challenges and complexity of accessing and processing information for higher forex exposure firms, the production and availability of information from other sources can complement analysts' information-gathering efforts to produce more accurate and less dispersed earnings forecasts. Prior studies show that analysts begin their earnings forecasts by developing estimates of individual segments (Ramnath et al., 2008). As such, the availability of more precise ge-

<sup>&</sup>lt;sup>25</sup> We follow Aggarwal and Harper (2010) and define firms without foreign sales/assets as those with zero values for foreign sales [Compustat segment item SALES] and foreign assets [Compustat segment item IAS].

**Table 6**Regression results for USD volatility

	AbsFE	Dispersion
Variable	(1)	(2)
FXExposure	0.065**	0.044**
	(2.46)	(2.11)
USDVol	0.630***	0.530***
	(14.97)	(15.29)
FXExposure × USDVol	0.223***	0.133**
-	(3.01)	(2.14)
Control variables	Yes	Yes
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
N	18,028	18,028
Adjusted R <sup>2</sup>	0.1439	0.1342

This table presents the results for the analysis based on the volatility of the U.S. Dollar. Our main dependent variables are analyst forecast error and dispersion: AbsFE is analysts' earnings forecasts error, measured as the percentage of the absolute difference between the consensus earnings forecast and actual earnings scaled by stock price at time t-1; Dispersion is the dispersion of analysts' forecasts, the percentage of the standard deviation of individual analysts' forecasts scaled by stock price at time t-1. The main test variable is forex exposure: FXExposure is the absolute foreign exchange exposure coefficient estimated using a regression of stock returns on the value-weighted market portfolio return and the return on the U.S. Dollar nominal trade-weighted index. The interaction term of interest is FXExposure × USDVol. USDVol is an indicator variable coded 1 if the yearly fluctuations of U.S. Dollar exchange are in the top quartile of the sample, and 0 otherwise. All tstatistics (in parentheses) are based on robust standard errors clustered by firm. \*\*\*, \*\* and \* denote statistical significance at the 1%, 5% and 10% levels, respectively.

ographic segment information could make it easier to predict future cash flows and how these are affected by forex exposure. Likewise, Lehavy et al. (2011) argue that analysts that follow firms with more readable annual reports bear lower information-processing and private search costs, resulting in smaller forecast errors and dispersion. Hence, it is possible that higher readability of annual reports will weaken the negative impacts of forex exposure on analysts' forecasts. Finally, prior research finds that greater media coverage is associated with a more transparent information environment (Bushee et al., 2010; Bradshaw et al., 2021). Consistent with the view that media coverage is a valuable external knowledge source for analysts that helps reduce information acquisition costs and improve forecasts, Fang and Peress (2009) find that stocks with no media coverage earn higher returns than stocks with high media coverage.

To evaluate the moderating effects of these three informational factors, we repeat our forecast accuracy and dispersion analyses after including three indicator variables representing firms in the top quartile of precise geographical disclosures (GeoDisc), readable annual reports (ReadAR), and media coverage (MediaCov), and the interactions of these variables with forex exposure (FXExposure). Following an approach similar to that of Chen et al. (2015), we start with firms that provide geographic segment disclosures on the Compustat segments file and measure the precision of geographic disclosures as the firm's proportion of non-missing financial items across all geographic segments (on the Compustat segments file) weighted by the sales of the segments. This provides us with a parsimonious way of capturing the comprehensiveness of disclosed geographic segment data. Likewise, we follow prior studies that have documented the usefulness of readable annual reports for analysts (e.g., Lehavy et al., 2011) and use the Fog Index to measure the readability of annual reports. Regarding media coverage, we use the firms covered on the Reuters Data Feed and count the number of news articles on a firm on the Reuters Data Feed after excluding any analyst-related news articles to measure media coverage.<sup>26</sup>

The results reported in Table 7 reveal negative and significant coefficients (p < 0.10 or better) on the interactions between FX-Exposure and ReadAR and MediaCov, but insignificant coefficients on the interaction between FXExposure and GeoDisc. The results for ReadAR and MediaCov support the view that the availability of information from other sources can help improve the quality of analysts' forecast properties for firms with increasing forex exposure.

#### 7.5. Analyst experience

Prior studies document that analysts improve their forecast accuracy as they gain firm-specific experience, suggesting the importance of firm-specific information (e.g., Mikhail et al., 1997). However, it is unclear whether such experience can improve forecast accuracy for firms with higher forex exposure. To evaluate this, we employ an analyst-level analysis that regresses the absolute value of an analyst's forecast error on forex exposure (*FXExposure*), a proxy of analyst experience, an interaction effect between *FXExposure* and analyst experience, and controls.<sup>27</sup> Our proxy of analyst experience is based on firm experience and is coded 1 if an analyst's forecasting experience with a firm is in the top quartile of our sample, and 0 otherwise. Following prior analyst-level studies (e.g., Hugon et al., 2016), we include analyst-, broker-, and firm-specific controls in these analyst-level regressions.<sup>28</sup>

The results from this analysis are presented in Column 1, Table 8. We find that while the *FXExposure* coefficients remain positive (p < 0.01), the interaction between *FXExposure* and analyst experience with the focal firm (*FirmExp*) is negative and significant (p < 0.01), supporting the view that analyst experience mitigates the adverse effect of forex exposure on analyst forecast errors. These findings suggest that the component of the forecast error that is induced by forex exposure is smaller for more experienced analysts

Columns (2) through (7) in Table 8 report the results from tests that replicate the Column (1) analysis within subsamples representing firms in the top and other three quartiles of precise geographical disclosures, readable annual reports, and media coverage. Interestingly, the results reveal that the positive impact of analyst experience on reducing forecast errors does not prevail in firms that are ranked in the top quartile of precise geographical disclosures, readable annual reports, and media coverage (Columns (2), (4), and (6)), but holds firms ranked in the other three quartiles of precise geographical disclosures, readable annual reports, and media coverage (Columns (3), (5), and (7)). However, untabulated tests of differences comparing coefficients on the variable of interest (FXE × FirmExp) across the related subsamples reveal significant results based on readable annual reports only. This finding implies that firms with higher forex exposure can assist less experienced analysts to produce more accurate forecasts relative to more experienced analysts by improving the readability of their annual reports.

 $<sup>^{26}</sup>$  For comparability of the three related factors, we remove observations with missing data in all three moderating factors.

<sup>&</sup>lt;sup>27</sup> Given that we employ an individual analyst-level regression in this part of the study, we only focus on the forecast error as tests on analysts' forecast dispersion are less applicable to this setting.

<sup>&</sup>lt;sup>28</sup> The analyst- and broker-specific variables, defined in Appendix 1, are *Horizo-nAna*, *NumInd*, *NumFirm*, *BrokerSize*, and *TopBroker*. Firm-specific controls are similar to those used in our main test.

**Table 7**Regression results for geographic disclosure, readability and media coverage

	AbsFE	Dispersion	AbsFE	Dispersion	AbsFE	Dispersion
Variable	(1) GeoDisc	(2) GeoDisc	(3) ReadAR	(4) ReadAR	(5) MediaCov	(6) MediaCov
FXExposure	0.123***	0.038	0.146***	0.084**	0.139***	0.073**
	(2.59)	(0.97)	(3.32)	(2.44)	(3.40)	(2.38)
GeoDisc	-0.041	-0.049*				
	(-1.22)	(-1.78)				
FXE × GeoDisc	-0.021	0.031				
	(-0.30)	(0.60)				
ReadAR			-0.071***	-0.042**		
			(-2.67)	(-2.07)		
$FXE \times ReadAR$			-0.120*	-0.111***		
			(-1.72)	(-2.23)		
MediaCov					0.029	0.016
					(0.83)	(0.64)
FXE × MediaCov					-0.143**	-0.103**
					(-2.12)	(-1.97)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	9,346	9,346	9,346	9,346	9,346	9,346
Adjusted R <sup>2</sup>	0.1349	0.1319	0.1359	0.1325	0.1354	0.1320

This table presents the results for the analysis based on the moderating effects of geographic disclosure, readability and media coverage. Our main dependent variables are analyst forecast error and dispersion: AbsFE is analysts' earnings forecasts error, measured as the percentage of the absolute difference between the consensus earnings forecast and actual earnings scaled by stock price at time t-1; Dispersion is the dispersion of analysts' forecasts, the percentage of the standard deviation of individual analysts' forecasts scaled by stock price at time t-1. The main test variable is forex exposure: FXExposure is the absolute foreign exchange exposure coefficient estimated using a regression of stock returns on the value-weighted market portfolio return and the return on the U.S. Dollar nominal trade-weighted index. The interaction terms of interest are FXExposure with geographic disclosure, readability, and media coverage. GeoDisc is an indicator variable coded 1 if the firm has high disclosure (lower quartile of missing geographic segment disclosures), and 0 otherwise. ReadAR is an indicator variable coded 1 if the firm high readability (lower quartile of Fog index), and 0 otherwise. MediaCov is an indicator variable coded 1 if the firm has high media coverage (upper quartile of news from the Thomson Reuters News Analytics database), and 0 otherwise. All t-statistics (in parentheses) are based on robust standard errors clustered by firm. \*\*\*, \*\* and \* denote statistical significance at the 1%, 5% and 10% levels, respectively.

**Table 8**Regression results for analyst experience

	AbsFEAna	AbsFEAna	AbsFEAna	AbsFEAna	AbsFEAna	AbsFEAna	AbsFEAna
Variable	(1) FirmExp	(2) Geo – High	(3) Geo - Other	(4) Read – High	(5) Read - Other	(6) Media – High	(7) Media – Other
FXExposure	0.347***	0.561***	0.200***	0.168	0.415***	0.270*	0.339***
	(4.61)	(3.70)	(2.69)	(1.56)	(4.29)	(1.69)	(3.98)
FirmExp	0.002	0.005	0.001	-0.001	0.004	-0.001	0.003
	(0.90)	(0.97)	(0.44)	(-0.46)	(1.31)	(-0.20)	(1.25)
$FXE \times FirmExp$	-0.015***	-0.014	-0.014*	-0.009	-0.018**	-0.015	-0.015**
-	(-2.61)	(-1.57)	(-1.87)	(-1.25)	(-2.28)	(-1.09)	(-2.29)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	149,885	38,003	111,882	42,668	107,217	37,808	112,077
Adjusted R <sup>2</sup>	0.4041	0.4517	0.3850	0.4414	0.4184	0.4229	0.4200

This table presents the results for the analysis on the impact of analyst experience overall (Column 1) and within sub-samples of firms in the top and other three quartiles of geographic disclosure, readability, and media coverage (Columns 2 to 7). The main dependent variable is analyst forecast error: AbsFEAna is analysts' earnings forecasts error, measured as the percentage of the absolute difference between the individual earnings forecast and actual earnings scaled by stock price at time t-1. The interaction term of interest is analyst firm experience, measured as an indicator variable coded 1 if the analyst is highly experienced (upper quartile of analyst experience), and 0 otherwise. All t-statistics (in parentheses) are based on robust standard errors clustered by firm. \*\*\*, \*\* and \* denote statistical significance at the 1%, 5% and 10% levels, respectively.

# 7.6. Forex exposure and analyst coverage, trading volume, and career progression

While our forecast error and dispersion findings present some evidence of the costs analysts face when covering firms with increasing forex exposure, the fact that firms with high forex exposure still attract some analyst coverage suggests that analysts also perceive benefits to arise from handling such firms. For example, while prior literature indicates forecast accuracy is an important indicator of analyst career success (e.g., Clement and Tse, 2005), the literature also suggests that analysts can enhance their careers by generating sufficient revenue by attracting clients to trade (Beyer and Guttman, 2011).

To shed some insights into this possibility, we commence by considering how forex exposure affects the level of analyst coverage firms attract. One view is that firms with increasing exposure to forex risks may depict more volatile stock prices, which may attract investors seeking to identify mispriced securities. If so, firms with increasing forex exposure may attract greater coverage by analysts seeking to cater to investors' interest in such firms. However, it is also possible that the reduced forecasting accuracy and higher costs (e.g., time and costs of acquiring and processing the information) associated with covering firms with greater forex exposure may ward off analysts from handling such firms.

We investigate this after repeating our main analysis using analyst coverage (AnalystCov), measured as the natural logarithm of the number of analysts who provide earnings forecasts announced in the two-month window before the annual earnings announcement, as the dependent variable. Table 9, Panel A, reports the regression results on the effect of forex exposure on analyst coverage. The results reveal that the coefficient for FXExposure is positive and significant (p < 0.05), supporting the view that firms with

**Table 9**Regression results for analyst coverage and trading volume

Panel A: Analyst coverage	
	AnalystCov
Variable	(1)
FXExposure	0.019**
-	(2.31)
Control Variables	Yes
Firm fixed effects	Yes
Year fixed effects	Yes
N	36,043
Adjusted R <sup>2</sup>	0.0624
Panel B: Trading volume	
_	TradVol
Variable	(1)
FXExposure	0.018***
•	(6.04)
Control variables	Yes
Firm fixed effects	Yes
Year fixed effects	Yes
N	18,028
Adjusted R <sup>2</sup>	0.2850

This table presents the results for the analysis of analyst coverage and trading volume. Panel A presents the results for analyst coverage. The dependent variable, *AnalystCov*, is the natural logarithm of the number of analysts who provide earnings forecasts announced in the two-month window before the annual earnings announcement. The main test variable, *FXExposure*, is the absolute foreign exchange exposure coefficient estimated using a regression of stock returns on the value-weighted market portfolio return and the return on the U.S. Dollar nominal trade-weighted index. Panel B presents the results for the analysis of trading volume. The dependent variable, *TradVol*, is the monthly average trading volume. All t-statistics (in parentheses) are based on robust standard errors clustered by firm. \*\*\*, \*\* and \* denote statistical significance at the 1%, 5% and 10% levels, respectively.

increasing forex exposure attract higher levels of analyst coverage, arguably due to catering to the increased information demands from the investors.

To further support the view that analysts follow firms with increasing forex exposure to cater to the increased demands of investors, we investigate the relationship between forex exposure and stock trading volume because generating revenue by attracting clients to trade can benefit analysts' career outcomes (Beyer and Guttman 2011). We investigate this by regressing trading volume (*TradVol*) on forex exposure (*FXExposure*) and the control variables from our main analyses. *TradVol* is defined as the monthly average stock trading volume scaled by the number of shares outstanding. The results presented in Table 9, Panel B, show that an increase in forex exposure of firms results in larger stock trading volume (p < 0.01).<sup>29</sup>

Given that producing more accurate earnings forecasts and generating greater investor trading represent two different ways through which analysts can enhance their career outcomes, we attempt to reconcile the above findings with our main findings on forex exposure reducing analysts' forecast accuracy by examining whether the past forecasting accuracy of analysts is associated with shorter coverage (i.e., tenure) of higher forex exposure firms. To investigate this, we first construct an analyst tenure variable (*Tenure*), which captures the total number of years an analyst follows a firm prior to the focal year. We then assess the re-

lation between *Tenure* and our measure of forex exposure within two samples of analysts that differ based on their forecasting accuracy across all years prior to the focal year. The untabulated results from this analysis indicate shorter coverage of firms with increasing forex exposure but only within the subsample of analysts with higher prior forecast accuracy. This result suggests that analysts that are less concerned about their forecasting accuracy and more interested in catering to the information demands of investors play a more prominent role in generating higher stock trading volume for firms with increasing forex exposure.

Given that career progression could be an important goal for analysts seeking to generate greater stock trading in higher forex exposure firms, we also consider the effect of covering firms with greater forex exposure on the career progression of analysts. Specifically, we investigate the relation between the coverage of firms with increasing forex exposure and the likelihood of analysts moving to better brokerage houses. This regression analysis employs an indicator outcome variable (*Promo*) that captures whether an analyst moves from a brokerage house outside the top 10 to a prestigious (top 10) brokerage house (Hilary and Hsu, 2013; Hong and Kubik, 2003).30 Our untabulated findings from this analysis reveal that, after controlling for other factors such as forecast accuracy, analysts who cover firms with increasing forex exposure are more likely to be recruited by a prestigious brokerage house. While the results from the analyst coverage effects and other effects of forex exposure in this section are not robust to all of the sensitivity tests we execute for our main analyses, taken together, the findings from tests discussed in this section shed some insights on the benefits analysts can realize from covering high forex exposure firms.

#### 8. Conclusion

Motivated by increasing globalization and analysts' interest in the forex exposure of firms, this study examines how analysts' forecasting properties are affected by the forex exposure of firms. Our findings, which are robust to a battery of sensitivity tests, suggest that as forex exposure increases within firms, analysts' forecast errors and dispersion also increase. Additional tests indicate that forex exposure can adversely affect analysts' forecast accuracy and dispersion for firms without significant foreign business activities, arguably because forex exposure influences the business activities of competitors, customers, and suppliers that transact in foreign markets. We find that the effects of increasing forex exposure are more prominent in years that witness greater volatility in the U.S. Dollar, which is consistent with the main channel through which forex risk can affect earnings forecasts (i.e., greater uncertainty of firm outcomes). However, we also find that the adverse effects of increasing forex exposure on analysts' forecast errors and dispersion are less pronounced when firms have more readable annual reports and have higher media coverage. Other tests reveal that while experienced analysts produce more accurate forecasts for firms with increasing forex exposure, less-experienced analysts appear to perform equally well when firms provide more readable annual reports. Finally, we present some evidence of the benefits that analysts can realize from covering firms with increasing forex exposure by documenting a positive relation between forex exposure and stock trading volume and showing that analysts with greater forex exposure expertise are more likely to secure promotions to prestigious brokers.

 $<sup>^{29}</sup>$  As prior research finds that analysts seek to generate trade from issuing optimistic forecasts, we also assess whether analysts issue optimistic forecasts for firms with increasing forex exposure, by regressing analyst forecast bias (signed difference between the consensus earnings forecast and actual earnings, scaled by stock price at time t-1) on our proxy for forex exposure (FXExposure) and controls that have been documented to explain analyst forecast bias (e.g., Duru and Reeb, 2002). The untabulated estimation results show a positive and significant (p < 0.05) coefficient on FXExposure, supporting the view that analyst tends to be more optimistic when the firm is more exposed to forex risks.

 $<sup>^{30}</sup>$  Our inferences remain unchanged if we define a promotion as when an analyst starts working for a larger brokerage house compared to his or her current brokerage house, or if an analyst leaves a small ( $\leq 25$  analysts) brokerage firm to join a large (>25 analysts) brokerage firm (Hilary and Hsu, 2013).

# **APPENDIX 1**Variable definitions

Panel A: Variable Variable	es used in the main analyses Definition
FXExposure	the absolute foreign exchange exposure coefficient estimated using a regression of stock returns on the value-weighted market portfolio return and the return on the U.S. Dollar nominal trade-weighted index;
AbsFE	analysts' earnings forecasts error, measured as the percentage of the absolute difference between the
	consensus earnings forecast and actual earnings scaled by stock price at time $t-1$ ;
Dispersion	dispersion of analysts' forecasts, the percentage of the standard deviation of individual analysts' forecasts scaled
Size	by stock price at time <i>t</i> –1; natural logarithm of market value of equity, calculated as the number of shares outstanding (Compustat item CSHO) times the share price (Compustat item PRCC_F);
Surprise	change in earnings per share (Compustat item EPSPX, EPSPX <sub>t</sub> – EPSPX <sub>t-1</sub> ) deflated by stock price at time $t$ -1
Loss	(Compustat item PRCC_F); an indicator variable coded 1 if the firm reports negative net income (Compustat item NI), and 0 otherwise;
Auditor	an indicator variable coded 1 if the firm is audited by a Big N auditor, and 0 otherwise;
Horizon	natural logarithm of the number of calendar days between forecast date and the actual earnings
	announcement date;
StdROE	earnings volatility, measured as the standard deviation of earnings per share before extraordinary items (Compustat item EPSPX) in the last 5 years $(t-1 \text{ through } t-6)$ ;
EPS	earnings per share before extraordinary items (Compustat item EPSPX);
Meet	an indicator variable coded 1 if earnings exactly meet or beat the consensus analysts' earnings forecast by one
Growth	cent per share, and 0 otherwise; compound average growth rate of firm sales (Compustation SALE) over the prior 2 years (codes   codes   1/3);
Segment	item SALE) over the prior 3 years [( $sales_t / sales_{t-3}$ ) <sup>1/3</sup> ]; natural logarithm of number of reported business segments in the Compustat segment file;
Inst	percentage of institutional ownership from the quarter prior to the 10-K filing;
Advert	advertising expense (Compustat item XAD) as a percentage of operating expense (Compustat item XOPR);
Miss_Advert	an indicator variable coded 1 if the firm has missing advertising expense (Compustat item XAD), and 0 otherwise:
RD	research and development expense (Compustat item XRD) as a percentage of operating expense (Compustat
Miss_RD	item XOPR); an indicator variable coded 1 if the firm has missing research and development expense (Compustat item
TradVol	XRD), and 0 otherwise; monthly average trading volume scaled by number of
Beta	shares outstanding; measure of a stock's systematic risk, captured by the coefficient of the value-weighted market portfolio return estimated using a regression of stock returns on the
	value-weighted market portfolio return and the return on the U.S. Dollar nominal trade-weighted index;
AnalystCov	the natural logarithm of the number of analysts who provide earnings forecasts announced in the two-month window before the annual earnings announcement;
MediaCov	the level of media coverage for the firm, an indicator variable coded 1 if the firm has high media coverage
	(upper quartile), and 0 otherwise. Our media data is from Thomson Reuters News Analytics (TRNA) which is a commercial database that incorporates all news items from the Reuters Data Feed as well as items released through business-related newswires. We use this database to determine the number of news items about a particular firm. TRNA's relevance score for a news story varies from 0 to 1 and equals 1 if a firm is mentioned in the headline of the story. We select news items with a relevance score equal to 1 to ensure that the client is the focus of a particular story. Further, we exclude any analyst-related news articles from our analysis;

## APPENDIX 1 (continued)

Variable	used in the main analyses Definition
Fi	Firm Good offeets
Firm	Firm fixed effect;
Industry	Fama and French (1997) 48 industry classification
	controls; and
Year	year fixed effects.
Panel B: Variables	used in additional tests
Variable	Definition
Post	an indicator variable coded as 1 for observations in the
1 031	post-unpegging period, and 0 in the pre-unpegging
<b>T</b>	period;
Treat	an indicator variable coded 1 for firms that mentioned
	China, Renminbi, Chinese Yuan, or any derivative words
	(e.g., Chinese) at least 10 times in their 10-K filings in
	the year immediately before $(t-1)$ and after $(t+1)$ the
	unpegging date and 0 for the firms that do not mention
	any of these key words at all in their 10-K filings.
Post × Treat	interaction between <i>Post</i> and <i>Treat</i> ;
PostPseudo	an indicator variable coded as 1 for observations in the
PostPseudo	
	pseudo post-unpegging period, and 0 in the pseudo
	pre-unpegging period;
	interaction between PostPseudo and Treat;
PostPseudo × Treat	
AvgFreq	the average number of earnings forecasts issued by
	analysts for the focal firm during a fiscal year;
AvgCov	the average number of other firms followed analysts
INSCOV	· ·
C. Die	covering the focal firm in a particular year;
GeoDisc	level of geographic segment disclosure, an indicator
	variable coded 1 if the firm has high disclosure (lower
	quartile of missing geographic segment disclosures), and
	0 otherwise. Compustat provides 33 financial items for
	segment disclosure on the historical segments file. These
	items include, among others, Net Sales, Operating Income
	Before Depreciation, Depreciation and Amortization,
	Operating Income After Depreciation, Capital
	Expenditures and Identifiable Total Assets. We first count
	the number of missing observations out of the 33
	financial items for each of the identified geographic
	segment and scaled it by its proportion of foreign sales
	to total sales. To provide an overall measure of disclosure
	granularity at the firm-level, we then take the sum of the
	sales weighted missing observations for all the
	geographic segments reported. Finally, we rank the firm
	in terms of the number of average non-missing segment
	financial items and code GeoDisc as 1 if the firm is in the
	upper quartile (i.e., high disclosure), and 0 otherwise;
FXE × GeoDisc	interaction between FXExposure and GeoDisc;
ReadAR	readability of the firm's annual report measured using
neuur in	the Fog index, an indicator variable coded 1 if the firm
	•
	high roadability and 0 othomsics. The data for the F-
	high readability, and 0 otherwise. The data for the Fog
	index of the 10-Ks are obtained from the WRDS SEC
	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per
	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with
	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per
	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher
	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more)
	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a
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	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a proxy for readability we code <i>Readability</i> as 1 if the firm is in the lower quartile (i.e., high readability), and 0 otherwise;
FXE × ReadAR	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a proxy for readability we code <i>Readability</i> as 1 if the firm is in the lower quartile (i.e., high readability), and 0
	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a proxy for readability we code <i>Readability</i> as 1 if the firm is in the lower quartile (i.e., high readability), and 0 otherwise;
FXE × Media-	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a proxy for readability we code <i>Readability</i> as 1 if the firm is in the lower quartile (i.e., high readability), and 0 otherwise; interaction between <i>FXExposure</i> and <i>ReadAR</i> ;
FXE × Media- Cov	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a proxy for readability we code <i>Readability</i> as 1 if the firm is in the lower quartile (i.e., high readability), and 0 otherwise; interaction between <i>FXExposure</i> and <i>ReadAR</i> ; interaction between <i>FXExposure</i> and <i>MediaCov</i> ;
FXE × Media- Cov	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a proxy for readability we code <i>Readability</i> as 1 if the firm is in the lower quartile (i.e., high readability), and 0 otherwise; interaction between <i>FXExposure</i> and <i>ReadAR</i> ; interaction between <i>FXExposure</i> and <i>MediaCov</i> ; the volatility of USD, an indicator variable coded 1 if the
FXE × Media- Cov	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a proxy for readability we code <i>Readability</i> as 1 if the firm is in the lower quartile (i.e., high readability), and 0 otherwise; interaction between <i>FXExposure</i> and <i>ReadAR</i> ; interaction between <i>FXExposure</i> and <i>MediaCov</i> ; the volatility of USD, an indicator variable coded 1 if the yearly fluctuations of U.S. Dollar exchange is in the top
FXE × Media- Cov USDVol	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a proxy for readability we code <i>Readability</i> as 1 if the firm is in the lower quartile (i.e., high readability), and 0 otherwise; interaction between <i>FXExposure</i> and <i>ReadAR</i> ; interaction between <i>FXExposure</i> and <i>MediaCov</i> ; the volatility of USD, an indicator variable coded 1 if the yearly fluctuations of U.S. Dollar exchange is in the top quartile of the sample,
FXE × Media- Cov USDVol FXE × USDVol	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a proxy for readability we code <i>Readability</i> as 1 if the firm is in the lower quartile (i.e., high readability), and 0 otherwise; interaction between <i>FXExposure</i> and <i>ReadAR</i> ; interaction between <i>FXExposure</i> and <i>MediaCov</i> ; the volatility of USD, an indicator variable coded 1 if the yearly fluctuations of U.S. Dollar exchange is in the top quartile of the sample, interaction between <i>FXExposure</i> and <i>USDVoI</i> ;
FXE × Media- Cov USDVol FXE × USDVol	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a proxy for readability we code <i>Readability</i> as 1 if the firm is in the lower quartile (i.e., high readability), and 0 otherwise; interaction between <i>FXExposure</i> and <i>ReadAR</i> ; interaction between <i>FXExposure</i> and <i>MediaCov</i> ; the volatility of USD, an indicator variable coded 1 if the yearly fluctuations of U.S. Dollar exchange is in the top quartile of the sample, interaction between <i>FXExposure</i> and <i>USDVoI</i> ; analysts' earnings forecasts error, measured as the
FXE × Media- Cov USDVol FXE × USDVol	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a proxy for readability we code <i>Readability</i> as 1 if the firm is in the lower quartile (i.e., high readability), and 0 otherwise; interaction between <i>FXExposure</i> and <i>ReadAR</i> ; interaction between <i>FXExposure</i> and <i>MediaCov</i> ; the volatility of USD, an indicator variable coded 1 if the yearly fluctuations of U.S. Dollar exchange is in the top quartile of the sample, interaction between <i>FXExposure</i> and <i>USDVoI</i> ;
FXE × Media- Cov USDVol FXE × USDVol	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a proxy for readability we code <i>Readability</i> as 1 if the firm is in the lower quartile (i.e., high readability), and 0 otherwise; interaction between <i>FXExposure</i> and <i>ReadAR</i> ; interaction between <i>FXExposure</i> and <i>MediaCov</i> ; the volatility of USD, an indicator variable coded 1 if the yearly fluctuations of U.S. Dollar exchange is in the top quartile of the sample, interaction between <i>FXExposure</i> and <i>USDVoI</i> ; analysts' earnings forecasts error, measured as the absolute difference between the analyst's individual
FXE × ReadAR FXE × Media- Cov USDVol FXE × USDVol AbsFEAna	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a proxy for readability we code Readability as 1 if the firm is in the lower quartile (i.e., high readability), and 0 otherwise; interaction between FXExposure and ReadAR; interaction between FXExposure and MediaCov; the volatility of USD, an indicator variable coded 1 if the yearly fluctuations of U.S. Dollar exchange is in the top quartile of the sample, interaction between FXExposure and USDVol; analysts' earnings forecasts error, measured as the absolute difference between the analyst's individual earnings forecast and actual earnings scaled by stock
FXE × Media- Cov USDVol FXE × USDVol AbsFEAna	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a proxy for readability we code $Readability$ as 1 if the firm is in the lower quartile (i.e., high readability), and 0 otherwise; interaction between $FXExposure$ and $ReadAR$ ; interaction between $FXExposure$ and $MediaCov$ ; the volatility of USD, an indicator variable coded 1 if the yearly fluctuations of U.S. Dollar exchange is in the top quartile of the sample, interaction between $FXExposure$ and $USDVol$ ; analysts' earnings forecasts error, measured as the absolute difference between the analyst's individual earnings forecast and actual earnings scaled by stock price at time $t-1$ ;
FXE × Media- Cov USDVol FXE × USDVol	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a proxy for readability we code <i>Readability</i> as 1 if the firm is in the lower quartile (i.e., high readability), and 0 otherwise; interaction between <i>FXExposure</i> and <i>ReadAR</i> ; interaction between <i>FXExposure</i> and <i>MediaCov</i> ; the volatility of USD, an indicator variable coded 1 if the yearly fluctuations of U.S. Dollar exchange is in the top quartile of the sample, interaction between <i>FXExposure</i> and <i>USDVol</i> ; analysts' earnings forecasts error, measured as the absolute difference between the analyst's individual earnings forecast and actual earnings scaled by stock price at time <i>t</i> —1; analyst experience, in terms of the number of previous
FXE × Media- Cov USDVol FXE × USDVol AbsFEAna	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a proxy for readability we code <i>Readability</i> as 1 if the firm is in the lower quartile (i.e., high readability), and 0 otherwise; interaction between <i>FXExposure</i> and <i>ReadAR</i> ; interaction between <i>FXExposure</i> and <i>MediaCov</i> ; the volatility of USD, an indicator variable coded 1 if the yearly fluctuations of U.S. Dollar exchange is in the top quartile of the sample, interaction between <i>FXExposure</i> and <i>USDVol</i> ; analysts' earnings forecasts error, measured as the absolute difference between the analyst's individual earnings forecast and actual earnings scaled by stock price at time <i>t</i> —1; analyst experience, in terms of the number of previous years an analyst issued a forecast for a specific firm,
FXE × Media- Cov USDVol FXE × USDVol AbsFEAna	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a proxy for readability we code Readability as 1 if the firm is in the lower quartile (i.e., high readability), and 0 otherwise; interaction between FXExposure and ReadAR; interaction between FXExposure and MediaCov; the volatility of USD, an indicator variable coded 1 if the yearly fluctuations of U.S. Dollar exchange is in the top quartile of the sample, interaction between FXExposure and USDVol; analysts' earnings forecasts error, measured as the absolute difference between the analyst's individual earnings forecast and actual earnings scaled by stock price at time t-1; analyst experience, in terms of the number of previous years an analyst issued a forecast for a specific firm, measured as an indicator variable coded 1 if the analyst
FXE × Media- Cov USDVol FXE × USDVol AbsFEAna	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a proxy for readability we code <i>Readability</i> as 1 if the firm is in the lower quartile (i.e., high readability), and 0 otherwise; interaction between <i>FXExposure</i> and <i>ReadAR</i> ; interaction between <i>FXExposure</i> and <i>MediaCov</i> ; the volatility of USD, an indicator variable coded 1 if the yearly fluctuations of U.S. Dollar exchange is in the top quartile of the sample, interaction between <i>FXExposure</i> and <i>USDVol</i> ; analysts' earnings forecasts error, measured as the absolute difference between the analyst's individual earnings forecast and actual earnings scaled by stock price at time <i>t</i> —1; analyst experience, in terms of the number of previous years an analyst issued a forecast for a specific firm,
FXE × Media- Cov USDVol FXE × USDVol AbsFEAna	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a proxy for readability we code <i>Readability</i> as 1 if the firm is in the lower quartile (i.e., high readability), and 0 otherwise; interaction between <i>FXExposure</i> and <i>ReadAR</i> ; interaction between <i>FXExposure</i> and <i>MediaCov</i> ; the volatility of USD, an indicator variable coded 1 if the yearly fluctuations of U.S. Dollar exchange is in the top quartile of the sample, interaction between <i>FXExposure</i> and <i>USDVol</i> ; analysts' earnings forecasts error, measured as the absolute difference between the analyst's individual earnings forecast and actual earnings scaled by stock price at time <i>t</i> —1; analyst experience, in terms of the number of previous years an analyst issued a forecast for a specific firm, measured as an indicator variable coded 1 if the analyst
FXE × Media- Cov USDVol FXE × USDVol AbsFEAna FirmExp	index of the 10-Ks are obtained from the WRDS SEC Analytics Suite and is calculated as the sum of words per sentence and percent of complex words (i.e. words with three or more syllables), multiplied by 0.4. A higher (lower) value of Fog suggests that the 10-K is less (more) readable. Hence, given the inverse measure of Fog as a proxy for readability we code Readability as 1 if the firm is in the lower quartile (i.e., high readability), and 0 otherwise; interaction between FXExposure and ReadAR; interaction between FXExposure and MediaCov; the volatility of USD, an indicator variable coded 1 if the yearly fluctuations of U.S. Dollar exchange is in the top quartile of the sample, interaction between FXExposure and USDVol; analysts' earnings forecasts error, measured as the absolute difference between the analyst's individual earnings forecast and actual earnings scaled by stock price at time t—1; analyst experience, in terms of the number of previous years an analyst issued a forecast for a specific firm, measured as an indicator variable coded 1 if the analyst is highly experienced (upper quartile of analyst

#### APPENDIX 1 (continued)

Panel A: Varial Variable	oles used in the main analyses Definition
HorizonAna	natural logarithm of the number of calendar days between analyst's individual forecast date and the actual earnings announcement date;
NumInd	number of Fama-French 48 industries that an analyst issues a forecast for in a particular fiscal year;
NumFirm	number of firms that an analyst issues a forecast for in a particular fiscal year;
BrokerSize	investment firm size, measured as the natural logarithm of the number of unique analysts employed by an analyst's investment firm in a particular fiscal year; and
TopBroker	an indicator variable coded 1 if the analyst's investment firm size is within the top 10 percent in a given fiscal year, and 0 otherwise.

Our analyses are subject to several caveats. First, while we closely follow prior studies in measuring forex exposure, our proxies may not perfectly capture such exposure and may partially reflect the effects of other correlated factors that are not controlled for in our analysis. Second, the inclusion of a large number of control variables naturally results in the representation of larger firms in our sample. We do not take a formal stance on whether our results can be generalized to smaller firms not included in our sample. However, we believe that the differences between our sample firms and those not included in our sample should not bias inferences on the relation between forex exposure and analyst forecasting properties within larger firms included within our sample. Third, while we attempt to provide insights regarding analyst effort based on forecast revisions, this analysis does not directly observe analyst effort. Fourth, while our study shows that media coverage levels improve the forecast errors and dispersion of firms with increasing forex exposure, we do not identify news that are likely to provide the greatest benefits for enhancing analysts' forecasts. Finally, while analysts' forecast errors and dispersion can be affected by different factors, there could also be a mechanical link between forecast errors and forecast dispersion. Without further tests to isolate the mechanical effect, we cannot conclude that the dispersion and forecast error results are disparate. These limitations serve as fruitful avenues for future research.

#### Appendix I

#### **Credit Author Statement**

This statement provides an accurate and detailed description of our co-authors' diverse contributions to the work entitled "Foreign exchange exposure and analysts' earnings forecasts". All the coauthors have confirmed their individual contributions as follows:

Chen Chen: Responsible for writing up the paper and research design.

Karen Lai: Responsible for writing up the paper and research design.

Vic Naiker: Responsible for writing up the paper, supervision of the research team and research design

lilyas Yusoff: Responsible for initiating the research question, research design and data analysis.

Jun Wang: Responsible for the research design, data analysis and execution of the research design.

# **Data Availability**

Data will be made available on request.

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