How Does Foreign Economic Policy Uncertainty Affect Domestic Analyst Earnings Forecasts?

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Abstract

In this study, we examine the impact of foreign economic policy uncertainty (EPU) on the performance of domestic analyst earnings forecasts. We analyze separately how U.S. EPU influences the accuracy of analyst earnings forecasts in other markets, as well as the reverse relationship. Our results show that the U.S. EPU (global EPU) negatively (positively) affects the accuracy of analyst earnings forecasts in other economies (the U.S.). The primary channel for this negative (positive) impact is the economic dependence of a given economy on the U.S. (capital flow to the U.S.). Our results remain robust even after controlling for a comprehensive set of variables.

Keywords: earnings forecasts, economic policy uncertainty, information dissemination, capital flow

JEL classification: G15, F36, D80

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1 Introduction

One important role of financial markets is to facilitate information dissemination. Financial analysts, together with the financial institutions they are working for, regulators, and investors, are an integral part of the market. Financial analysts provide valuable economy and firm-related information to other market participants and help to reduce information asymmetry in financial markets. Information revealed by analysts can not only provide advice for investors (e.g., retail and institutional), but also influence firms' information environments and financial policies (Hong and Kacperczyk, 2010 and Balakrishnan et al., 2014). Given the importance of their roles in financial markets, it is not surprising that prior studies consider various aspects of analysts' activities such as how they choose to cover particular firms (Jegadeesh et al., 2004 and Harford et al., 2019), what type of information (i.e., industry-level or firm-specific) they use to make their forecasts (Choi and Gupta-Mukherjee, 2022), and more importantly, why there is persistent upward bias in analysts earnings forecasts (Hong and Kubik, 2003 and Dong et al., 2021) and what could affect the performance of their earnings forecasts (e.g., Markov and Tamayo, 2006).

Although there is an extensive body of literature on the behaviors of financial analysts within a particular country, there are few studies providing international evidence on analysts' earnings forecasting activities, especially the international factor(s) that could affect their forecast bias and accuracy. More importantly, there is a lack of understanding about the channels through which such earnings forecasts bias/accuracy is affected. To fill this gap in the literature, our study attempts to investigate whether the Economic Policy Uncertainty (EPU; Baker et al., 2016) of foreign countries impacts the bias and accuracy of domestic analyst earnings forecasts. Furthermore, we also examine the potential channels through which foreign EPU could affect the performance of domestic analyst earnings forecasts.

Based upon a data sample comprising the U.S. and 29 non-U.S. markets, we initiate our analysis by conducting a univariate examination. Our findings demonstrate that higher U.S. EPU leads to a decline in the accuracy of analyst earnings forecasts for firms out of the U.S. This result remains consistent even after incorporating additional control variables into the model. Additionally, in line with previous studies such as Chahine et al. (2021) and Kim et al. (2022), our results indicate that elevated levels of local EPU also lead to less precise earnings forecasts by analysts. To further explore the relationship between U.S. EPU and the precision of earnings forecasts in non-U.S. markets, we investigate the channel of economic dependence. We measure this dependence by the ratio of a country's exports to the U.S. relative to its own GDP. Our findings affirm that this ratio, serving as a proxy for economic dependence on the U.S., constitutes a mechanism through which U.S. EPU exerts a negative impact on the performance of earnings forecasts for non-U.S. stocks. Finally, we conduct various robustness tests to confirm the adverse association between U.S. EPU and earnings forecast precision, as well as the proposed channel.

Next, we shift our focus to examine whether global EPU impacts the bias/accuracy of analyst earnings forecasts in the U.S. market. Interestingly, contrary to our previous findings that highlighted the negative influence of U.S. EPU on earnings forecasts precision in other countries, we discover that higher measures of global EPU in fact lead to a significant increase in analyst earnings forecasts precision for stocks listed in the U.S. market. Further, we observe an increase in capital inflow back to the U.S. market and this increase contributes to analyst financial reporting accuracy. Our results indicate that, apart from considering risk factors, the precision of earnings forecasts is also influenced by analyst attention, driven by uncertainly related capital inflow. The rationale is that when global uncertainty rises, investments such as refugee capital and U.S. overseas investments are more likely to return to the U.S. market, resulting in funds flow into the market. The increased availability of capital to invest requires analysts to provide a more comprehensive and precise analysis of the listed companies in the U.S. market. Based on our empirical findings, it appears that the impact of funds flow on earnings forecast precision outweighs that of uncertainty.

Our study makes a contribution to the vast body of literature on analysts' activities and the bias/accuracy of their forecasts (e.g., Markov and Tamayo, 2006, Dong et al., 2021, and Kumar et al., 2022). We consider our research as complementary to prior studies, as we provide new evidence with a dataset encompassing 30 international markets and identify distinctive channels for analysts' earnings forecasts bias/accuracy. Furthermore, our paper fits into the literature on EPU by exploring the impact of macro-level EPU on the micro-level analysts' information processing in an international context.

The rest of the paper is organized as follows: Section 2 presents the literature review and hypotheses development; Section 3 details the data and methodology; Section 4 discusses the impact of the U.S. EPU on the performance of analyst earnings forecasts in the other markets, and Section 5 presents the results of the impact of global EPU on the performance of analyst earnings forecasts of the U.S. market. Section 6 concludes the paper.

2 Literature Review and Hypotheses

2.1 Literature Review

Financial analysts contribute to financial information dissemination by publishing their forecasts and reports, which further exert a significant impact on stock price (e.g., Loh and Stulz, 2011). Several studies have highlighted the important role of earnings surprises, which are usually benchmarked to analyst earnings forecasts, as an important source of stock price fluctuations (e.g., Skinner and Sloan, 2002, Lopez and Rees, 2002, Kasznik and McNichols, 2002, Abarbanell and Park, 2017, Chiang et al., 2019). Furthermore, analyst earnings forecast is considered as an important guide for investment decisions of various types of investors, both for short-term and long-term (e.g., Kasznik and McNichols, 2002, Chang et al., 2009). Further, the economical and financial insights provided by analysts contribute significantly to the reduction of information asymmetry and the incorporation of information into stock prices (Loh and Stulz, 2018, Harford et al., 2019). Given the indispensable role analysts play in financial markets, it is important to understand the factors that influence analyst behaviors, particularly their earnings forecasts.

A large body of literature investigates factors that influence the performance of analyst earnings forecasts. Some studies delve into the characteristics of the analysts themselves as a focal point of investigation. For example, Bradley et al. (2017) find that analysts, who make forecasts on firms in the industries related to their pre-analyst experience, have better forecast accuracy. Similarly, Harford et al. (2019) find that an analyst makes more accurate, frequent, and informative earnings forecasts for firms that are more important to her affiliated institution. The study of Gibbons et al. (2021) shows that information acquisition via EDGAR is associated with a significant reduction in an analyst's forecasts error relative to his peers; Recently, Kumar et al. (2022) provide evidence of social learning benefits on analyst forecasts accuracy.

Another strand of research considers the entire analysts industry and investigates how external factors, such as the level of disclosure by firms and disagreement in macroeconomic condition, affect the performance of analyst earnings forecasts. For instance, Merkley et al. (2017) find that changes in the number of analysts covering a specific industry could impact analysts competition and have significant spillover effects on other analysts' forecast accuracy, bias, report informativeness, and effort; Hope (2003) document that firm-level disclosures are positively related to forecast accuracy, suggesting that such disclosures provide useful information to analysts; Gu and Wang (2005) show that high information complexity of intangible assets increases the difficulty for analysts to assimilate information and increases analyst forecasts error of intangibles-intensive firms; Using macroeconomic dispersion measures from the Survey of Professional Forecasters database as a proxy for macro disagreement, Sinha (2021) discovers that a higher disagreement leads to reduced accuracy in analyst earnings forecasts. Recently, Lin et al. (2022) find that regional GDP distortion leads to lower analyst forecasts accuracy in China.

It is widely recognized that macroeconomic conditions significantly influence earnings forecasts (e.g., Carabias, 2018 and Sinha, 2021). However, there has been limited research on how the uncertain nature of these macroeconomic factors affect earnings forecasts. In fact, uncertainty has been a primary concern in financial markets since its inception, however, it was not until the publication of "The Age of Uncertainty" (Galbraith, 1977) that uncertainty began to receive attention from academia, professionals, and the general public. In earlier studies, the focus primarily revolved around how uncertainty, such as unexpected changes in firms' demand and cost function, affects the behavior of a firm (e.g., Pindyck, 1982 and Abel, 1983). Recent papers, especially after the publication on Economic Policy Uncertainty (EPU) by Baker et al. (2016), study how uncertainty affects financial markets and various decision-making processes of investors and businesses (e.g., Nagar et al., 2019, Shen et al., 2021, Hoang et al., 2021, and López et al., 2022).

Regarding analyst earning forecasts, a few studies provide evidence on some particular markets. Using data from the U.S., Amiram et al. (2018) reveal that when uncertainty is high, analysts earnings forecasts tend to be more timely but less accurate. Chahine et al. (2021) find that the accuracy of analyst forecasts is compromised during periods of increased EPU in the U.S. market. In the same line, with Korean data, Kim et al. (2022) show that analyst forecasts accuracy are negatively associated with EPU and provide a labor-centric explanation of lower forecast quality in uncertain times.

However, as economies become increasingly globalized, countries are now more economically interconnected in present time. This greater interdependence makes domestic economies more sensitive to both domestic and foreign economic policies. As a result, there is a growing concern about the uncertainty in economic policies (Baker et al., 2016), especially in light of events such as the China-United States trade war and the escalating partisan policy disputes across the globe. Policy uncertainty is commonly considered an economic risk that arises from government policies and regulatory frameworks (e.g., monetary and fiscal policies). Such uncertainty can have a substantial impact on the investment choices of businesses and the spending behaviors of firms in both domestic and closely interconnected economies. Therefore, it is essential to investigate how EPU from foreign economies affects the dissemination of information within domestic financial markets.

Our paper is related to Boubakri et al. (2022), who find that analyst forecasts accuracy decreases in national election years compared to those in non-election years and argue that political or election uncertainty is a factor affecting earnings forecasts. However, our paper emphasizes the impact of economic policy uncertainty on the performance of analyst forecasts. Our paper is also connected to the study of Choi et al. (2022). They are the first study to explore the segregated herding behaviour of local, expatriate, and global analysts, and its impact on forecast accuracy among seven emerging Asian markets. In contrast, our paper focuses on examining the channels of economic dependence and funds flow, with evidence from 30 markets. In sum, our study attempts to provide insights into the impact of foreign EPU on information dissemination and analyst forecasts accuracy in domestic financial markets in a globalized financial landscape.

2.2 Hypotheses Development

As the largest and leading economy in the world, U.S. holds a dominant position in the global economy and financial markets. This is evident in various aspects, for instance, as highlighted in Ross (2020), U.S.-based companies carry significant weight in the S&P Global Broad Market Index, which tracks more than 11,000 stocks across 50 developed and emerging markets. The market capitalization of U.S.-based companies exceeds 50% of most industry totals. Given the U.S.'s prominent position, it is not surprising to observe a considerable body of literature documenting the influence of the U.S. on other economies and markets (e.g., Rapach et al., 2013, Berg and Vu, 2019, Balli et al., 2021, Cavaca and Meurer, 2021, and among others). In the same vein, Our paper analyzes separately how the U.S. EPU may influence the accuracy of analysts' earnings forecasts in the rest of the markets, as well as the reverse relationship.

2.2.1 U.S. EPU on the performance of other markets analyst forecasts

The world economy is linked among different markets even since a century ago. Accominotti (2019) finds that the U.S. and British banks were exposed to central European frozen credits in 1931. Now, considering the substantial interconnection between the U.S. economy and other economies (e.g., via supplier-customer relationships), analysts from other markets also pay attention to U.S. news to some extent. As a result, economic policy in the U.S. would impact the expectations regarding macroeconomic conditions and the earnings of firms in their respective markets. Given that the uncertainty of economical policy tends to amplify information asymmetry in the market (Nagar et al., 2019) and is likely to have a negative impact on the forecasts accuracy (Kim et al., 2022), we propose the following hypothesis:

Hypothesis 1.1: After controlling for the domestic EPU, the U.S. EPU has an additional effect on the accuracy of analyst earnings forecasts in other markets.

If hypothesis 1.1 can be confirmed empirically, we further conjecture that the magnitude of this effect could be influenced by the level of economic dependence of a given economy on the U.S.. However, we do not expect that the economic dependence alone would have a direct impact on analyst forecasts. Instead, it would serve as a moderator in the relationship between the U.S. EPU and the accuracy of analyst forecasts in non-U.S. markets.

Hypothesis 1.2: The greater the economic dependence on the U.S., the more pronounced the impact of the U.S. EPU on the accuracy of analyst forecasts in that economy.

2.2.2 Global EPU on the performance of U.S. market analyst forecasts

Despite the dominant position of the U.S. in the global economy and financial markets, it is crucial to acknowledge that some specific markets or the non-U.S. markets as a whole can still have an impact on the U.S.. For example, Lee et al. (2020) find that U.S. households reduce their exposure to the stock market in response to an increase in the China EPU. Furthermore, Lee et al. (2021) find that Chinese EPU shocks can explain 40% of the cross-sectional variation in bond returns in the U.S. market. Based on these findings, it is intriguing to determine whether global EPU, specifically the component unrelated to U.S. EPU, can affect the accuracy of analyst earnings forecasts in the U.S. market. Our hypothesis is as follows:

Hypothesis 2.1: Global EPU could impact the accuracy of analyst earnings forecasts in the U.S. market.

If hypothesis 2.1 can be confirmed empirically, we further explore potential channels through which this effect takes place. Two possible channels can be considered: real economy and capital market interconnection. Through the real economy channel, we expect a negative impact because increased uncertainty in other markets (e.g., consumer markets for U.S. firms) would likely lead to greater uncertainty in U.S. firm earnings. Consequently, the accuracy of analysts' earnings forecasts in the U.S. market is negatively affected. For the channel of the capital market, we anticipate a positive impact because more uncertainty in global markets drives funds to flow into the U.S. financial markets (i.e., flight-to-safety). This capital inflow in the U.S. requires more analyst attention, which further results in more accurate earnings forecasts from analysts.

Hypothesis 2.2: The greater the capital flow into the U.S. financial market, the higher the accuracy of analyst earnings forecasts in the U.S. market.

3 Data and Methodology

3.1 Data Sample

In this study, we utilize various datasets to conduct our analysis. Our country-level EPU index is obtained from the public website based on Baker et al. (2016).[1] The announced earnings per share (EPS) and consensus analyst forecasts data for listed companies are extracted from the summary files of Institutional Brokers' Estimate System (I/B/E/S) for the period of 1990 to 2021 at quarterly frequency. We take the EPS announcements as our target events. For firm-level financial information, we obtain the necessary data from the Compustat database. An economy's export to the U.S. data are from the United States Census Bureau while the GDP data for each economy is from World Bank and the U.S. flow of funds data are from Refinitiv.

Besides the need to have data for all the variables in our regressions, we only look at firms with fiscal quarter end in March, June, September and December.[2] Also, we need at least 5 observations for any firm and 500 firm-quarters for any market to be included in the data sample. Finally, a total of 30 markets and 413,722 firm-quarters are in our data sample.[3] The largest market in our sample is the U.S., accounting for 302,171 firm-quarters. The remaining 111,551 firm-quarters are distributed across the other 29 markets.

[Figure 1 about here]

Figure 1 illustrates the evolution of the number of quarterly earnings events during our sample period from 1990 to 2021. Overall speaking, the number of observations is increasing steadily through time. In 1990, there are slightly over 1,000 observations per

[1] https://www.policyuncertainty.com/index.html

[2] The main reason for this is to align the quarterly earnings data with other macroeconomic indicators. Overall, this accounts for roughly 90% of all the data available on I/B/E/S.

[3] Details about the 30 markets in the data sample and the number of firm-quarters for each market are shown in Appendix A.

quarter, which gradually grows over the years. By 2021, the number of quarterly earnings events exceeds 5,000 observations per quarter. However, there are two notable periods where the number of observations decreases. The first period is around 2000-2003, which corresponds to the dot-com crash. The second period is around 2008-2009, coinciding with the subprime mortgage crisis.

[Figure 2 about here]

Figure 2 presents the market-level number of observations (excluding the U.S., as we treat U.S. separately from other markets in this research) for the research period. They are not so evenly distributed as those through time in Figure 1. Overall, Canada and Taiwan carry much more weights than other non-U.S. markets in the data sample. We will address a bit more about this in section 4.3.2.

3.2 Methodology

3.2.1 Dependent Variables

The dependent variables in this research are different forecasts precision measures. To check the performance of analysts' earnings forecasts, we mainly look at 3 measures that are widely used in the literature:[4] forecast bias (*Bias* as defined in the variable definition in Appendix B), absolute forecast errors (*AbsErr*) and squared forecast errors (*SqrErr*). They are computed as following:

$$Bias = \frac{Forecasted\ EPS - Announced\ EPS}{Share\ price}$$

$$AbsErr = \frac{|Forecasted\ EPS - Announced\ EPS|}{Share\ price}$$

$$SqrErr = \left(\frac{Forecasted\ EPS - Announced\ EPS}{Share\ price}\right)^2$$

[4] For example, see Rajan and Servaes (1997); Gu and Wang (2005); Linnainmaa et al. (2016); Merkley et al. (2017); Amiram et al. (2018); Ball and Ghysels (2018); Carabias (2018); Gibbons et al. (2021); Kumar et al. (2022) and Boubakri et al. (2022).

The *Forecasted EPS* is the census analysts forecasts (*MEANEST*, which is mean estimate in the I/B/E/S database) for a firm.[5] The *Announced EPS* is the actual EPS announced by a firm and the *Share price* is the stock price at the fiscal quarter end. To be noted that *AbsErr* and *SqrErr* are forecast errors, thus, the lower the errors, the more accurate the analysts' forecasts.

[Table 1 about here]

Table 1 reports the descriptive statistics of the variables used in this study. Considering we will check the effect of U.S. separately with other markets, Panel A and Panel B show the statistics for the non-U.S. and U.S. market, respectively. If we look at the *Bias* data, it strongly confirms the well-documented upward bias in analysts' earnings forecasts (e.g., Lim, 2001, Hong and Kubik, 2003, Scherbina, 2008), either in the U.S. or the non-U.S. markets.

3.2.2 Independent Variables of Interest

We examine several EPU variables as our independent variables of interest, including the U.S., the local, and the global EPUs. It is important to note that in our dataset, the global EPU variable is adjusted to isolate the effect of U.S. EPU.[6] Specifically, the global EPU is calculated as the residuals obtained from regressing the original global EPU on the U.S. EPU. Also, we have variable *Exp2GDP*, which is the economy's export to U.S. scaled by the economy's GDP, as the moderator for the effect of U.S. EPU on other markets and variable *FundsFlow* as the mediator for the effect of global EPU on the U.S. market.

[5]For the census analyst forecasts, we only take the most updated *MEANEST* in I/B/E/S before the earnings announcement, which is usually believed to contain the most updated information.

[6]The original global EPU is the GDP weighted average of 21 markets EPUs and the U.S. takes roughtly 25% weight in it. The 21 markets are Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the United Kingdom, and the United States. More details can be found at https://www.policyuncertainty.com/global_monthly.html.

3.2.3 Control Variables

In addition to the main independent variables, our regressions include several common control variables, which have been widely used in previous studies (e.g., Lys and Soo, 1995, Merkley et al., 2017, Boubakri et al., 2022) These control variables help to account for various factors that may influence the performance of analysts' earnings forecasts. The control variables included in our analysis are: the number of analysts following a specific firm (*NumEst*), market-to-book ratio of the firm (M/B), return on assets (ROA) and the natural logarithm of firm size (*Size*). Detailed variable definitions can be found in Appendix B.

4 U.S. EPU on Other Markets Forecast Errors

4.1 Baseline Model

4.1.1 Univariate Analysis

We start with the baseline (univariate) model that examines how U.S. EPU affects the performance of analyst earnings forecasts in the rest of world, as discussed in Hypothesis 1.1 in section 2.

$$Pres_{i,t} = \alpha + \beta_1 \cdot Loc\_EPU_t + \beta_2 \cdot US\_EPU_t + \beta_3 \cdot Control_t + FirmFE + \epsilon_{i,t}, \quad (1)$$

where $Pres_{i,t}$ is the earnings forecasts precision measures of firm i for quarter t. Loc_EPU_t is the EPU index of quarter t for the country where firm i is listed in. US_EPU_t relates to the U.S. EPU index for quarter t. $Control_t$ are control variables such as the number of analysts for firm i. $FirmFE$ is the firm fixed effect. [7]

[7] We do not include time fixed effect in our regressions, because doing so would eliminate the variations in the U.S. EPU which is what we want to check on. In particular, time-fixed effects would subsume U.S. EPU, which varies over time but not in the cross-section.

[Table 2 about here]

Columns (1) to (3) of Table 2 report the baseline model results with U.S. EPU as the only independent variable. The univariate results show that higher U.S. EPU leads to a decrease in the performance of analyst forecasts for firms out of the U.S. This result is statistically significant for all three forecast precision measures. When control variables are included in the regressions (columns (4) to (6)), results still hold for absolute forecast errors and squared forecast errors, but not any more for forecast biases.

In addition, consistent with previous studies (e.g. Chahine et al., 2021 and Kim et al., 2022), our results also show that higher local EPU can also result in less precise analyst forecasts. Finally, the results suggest that analyst forecasts precision increases with the number of analysts, confirming the important role analysts play in information dissemination.

4.2 Channel Analysis

Now we turn our attention to the channel by which the U.S. EPU could affect the performance of analyst earnings forecasts of the other countries. As discussed in Hypothesis 1.2, how external uncertainty affects local economic forecasts should be related to how the local economy depends on the economy of the rest of the world. We measure this dependence on the rest of the world using an economy's export to the U.S. scaled by the economy's GDP (*Exp2GDP*). The rationale is that if the economic dependence of a given country on the U.S. is high, the uncertainty transmission effect should also be pronounced.

$$\begin{aligned} Pres_{i,t} = \alpha + \beta_1 \cdot Loc\_EPU_t + \beta_2 \cdot US\_EPU_t + \beta_3 \cdot Exp2GDP_t + \\ \beta_4 \cdot Exp2GDP_t \cdot US\_EPU_t + \beta_5 \cdot Control_t + FirmFE + \epsilon_{i,t} \end{aligned} \tag{2}$$

To test this moderation effect, we add *Exp2GDP* and the intersection of *Exp2GDP* and U.S. EPU in our baseline model. The results are presented in Table 3. Our results show that the coefficient of intersection is significantly positive for both absolute error and square error and that of bias is positive but not significant. At the same time, the variable *Exp2GDP* itself is not so significant. These results suggest that the importance of export to the U.S. is a moderator by which the U.S. EPU has an impact on the precise earnings forecasts for stocks out of the U.S. Another way to say, the more the economy depends on the U.S., the more the U.S. EPU has an impact on analyst earnings forecasts precision of the market.

[Table 3 about here]

4.3 Robustness

4.3.1 Squared Term

To further investigate whether the relationship between the U.S. EPU and other markets' analysts' forecasts precision is linear, we include a square term of the U.S. EPU. The results are presented columns (1) to (3) in Table 4. We find that overall the coefficients for the square term are not statistically significant, suggesting that the causal relationship between the U.S. EPU and local market analyst forecasts precision is likely to be linear.

[Table 4 about here]

4.3.2 Excluding Canada and Taiwan Data

As shown in Figure 2, the observations of firm-quarters in our data sample are not equally distributed across non-U.S. markets. Specifically, Canada and Taiwan obviously have the most observations in the developed markets and developing markets, respectively. To rule out the possibility that our previous results are mainly driven by the data of Canadian or Taiwan stock market, we re-estimate our models by excluding the data from Canada and Taiwan. The regression results, presented in columns (4) to (6) of Table 4, show that our main conclusions stay the same even discarding the markets with the most observations.[8]

4.3.3 Developed v.s. Developing Markets

Finally, we examine if our results are affected by the difference in market settings such as market participants and structures across exchanges. To do so, we divide the 29 non-U.S. economies into two groups: developed markets and developing markets, and then re-estimate our models. The results are reported in Table 5. The key conclusions remain the same, that is, the U.S. EPU is negatively associated with the analyst earnings forecast precision of other markets, and one important channel is economic dependence of the economy on that of the U.S..

[Table 5 about here]

5 Global EPU on U.S. Market Forecasts Performance

5.1 Baseline Model

Now, we turn to examine how the global EPU affects analyst earnings forecast precision of the U.S. market. To our best knowledge, there is no direct global EPU index without U.S. available in the data sample. To obtain a global EPU orthogonal to U.S. EPU, we run the regression of the original global EPU on the U.S. EPU, and then take

[8]We also have tested the models with data excluding Canada only or Taiwan only, and same conclusions hold.

the residuals from the regression as our global EPU measure. To double check the correlation between residual-based global EPU (*GlbEPU*) and the U.S. EPU, Table 6 presents the correlation between two EPUs and with several other key variables. The results show that *GlbEPU* and the U.S. EPU are basically not correlated, implying *GlbEPU* is a relatively clean measure in this research. In addition, the results suggest that *FundsFlow* is positively associated with global EPU. Finally, consistent with our expectation, all three forecasting precision measures are negatively correlated with funds flow. This result suggests that the capital inflow, which is most probably accompanied by an increase in investors' and analysts' attention, improves analyst earnings forecasts precision.

[Table 6 about here]

To establish the link between our residual-based global EPU and analyst earnings forecasts precision in the U.S. market, as discussed in Hypothesis 2.1, we estimate the following model:

$$Pres\_US_{i,t} = \alpha + \beta_1 \cdot US\_EPU_t + \beta_2 \cdot Glb\_EPU_t + \beta_3 \cdot Control_t + FirmFE + \epsilon_{i,t}, \quad (3)$$

The dependent variable is now changed to the precision measures for the U.S. market. The variable of interest β_2 will capture the effect of the EPU of the rest of the world on the performance of analyst earnings forecasts in the U.S. market.

[Table 7 about here]

The baseline results are reported in Table 7. Surprisingly, opposite to our previous results of the negative impact of the U.S. EPU on other countries' analyst forecasts precision, higher global EPU measure leads to a significant increase in analyst earnings forecasts precision for stocks listed in the U.S. market. This finding is supported by both the univariate analysis (columns (1) to (3)) and multivariate analysis with control variables (columns (4) to (6)). Our explanation for this result is that, apart from risk factors, analyst earnings forecasts precision is also determined by the attention of the market, especially, the attention of the financial analysts. When global uncertainty increases, the investments such as refugee capital and the U.S. overseas investment are more likely to flow back to the U.S. market, therefore there should be a larger funds flow in the U.S. market. The increase in the amount of capital to invest urges analysts to provide a deeper and more accurate analysis of listed companies in the U.S. market.

5.2 Channel Analysis

As discussed in Hypothesis 2.2, we expect the funds flow to be a mediator for the relationship between the global EPU and analyst earnings forecasts precision in the U.S. market. To do so, we conduct the following mediation test by estimating the models below,

$$F\_Flow_t = \alpha_1 + \alpha_2 \cdot Glb\_EPU_t + \alpha_3 \cdot Crl_t + \epsilon_{i,t} \tag{4}$$

$$Pres\_US_{i,t} = \beta_1 + \beta_2 \cdot US\_EPU_t + \beta_3 \cdot F\_Flow_t + \beta_4 \cdot Crl_t + \epsilon_{i,t} \tag{5}$$

$$Pres\_US_{i,t} = \gamma_1 + \gamma_2 \cdot US\_EPU_t + \gamma_3 \cdot F\_Flow_t + \gamma_4 \cdot Glb\_EPU_t + \gamma_5 \cdot Crl_t + \epsilon_{i,t} \tag{6}$$

The coefficient α_2 in equation (4) captures the effect of global EPU on the net capital flow to the U.S. market. The coefficient β_3 in equation (5) measures the effect of net capital flow to the U.S. market on analysts' earnings forecasts precision of the U.S. listed stocks. The coefficient γ_3 in equation (6) verifies the mediation effect of net capital flow on the relationship between global uncertainty and analyst earnings forecasts precision of the U.S. listed stocks. If net capital flow is a mediator, then coefficient γ_3 should be significantly negative.

[Table 8 about here]

The regression results are shown in Table 8. First, results in column (1) show that a higher global EPU can significantly increase the net capital flow to the U.S. market. Second, columns (2) to (4) show that an increase in the net capital inflow in the U.S. market leads to an increase in analyst earnings forecasts precision as the coefficients of all three precision measures are significantly negative. Finally, the coefficients of net capital flow in the regressions (5) to (7), which include both global EPU and net capital flow, are also significantly negative. Our findings suggest that global uncertainty drives capital flow back to the U.S. market, and the increase in net capital flow-based attention further requires more accurate financial reporting from analysts. Even though usually uncertainty leads to less precise forecasts, the effect of capital flow on analyst earnings forecasts precision dominates that of uncertainty.

5.3 Robustness

In the channel analysis above, we use the data from financial account of the U.S. balance of payments as proxy for funds flow to the U.S.. This may raise a question that whether the data is just a balance of payments artifact, as theoretically the financial account and current account are highly correlated. For example, for a country such as U.S. in this case, who tend to have current account deficits, such deficits tend to be covered by financing from other countries (thus, capital inflow in the financial account for this country). To solve this potential issue, in this section, we adjust the cash flow data from financial account by the cash flows from current account, to eliminate the effect from current account. With such difference as a measure of funds flow, the results are presented in Table 9 as robustness check.

[Table 9 about here]

Overall speaking, the results presented in Table 9 are quite similar to our main results presented in Table 8, which confirms that the funds flow is a mediator in our channel analysis. In fact, if we use other way to get the global EPU orthogonal to U.S. EPU, the results are also similar.[9]

6 Conclusion

In this paper, we examine the relationship between foreign economic policy uncertainty and domestic analyst earnings forecasts precision. Our findings reveal that an increase in the U.S. EPU is associated with a decrease in the accuracy of analyst earnings forecasts for firms out of the U.S. Furthermore, we explore the mechanism through which this relationship operates and find that the extent of economic dependence, as indicated by the economy's export to the U.S., serves as a channel through which U.S. EPU negatively impacts the precision of earnings forecasts for stocks in non-U.S. markets. Importantly, our results hold strong across various tests, confirming the robustness of our findings.

Subsequently, we delve into the impact of global EPU on the performance of analyst earnings forecasts in the U.S. market. Surprisingly, our findings demonstrate that higher global EPU leads to a significant increase in the precision of analyst earnings forecasts for stocks listed in the U.S. market. We further investigate the underlying drivers of this counter-intuitive result and reveal that the phenomenon is primarily driven by the flow of funds. Specifically, our results show that global uncertainty drives capital back to the U.S. market, and the increase in funds flow leads to more accurate reports from financial analysts. Our results suggest that, apart from uncertainty, analysts' attention is also an important determinant in the performance of analyst earnings forecasts. When global uncertainty increases, the investments such as refugee capital and U.S. overseas investment are more likely to flow back to the U.S. market, therefore there should be flow of funds to the U.S. market. The increase in the amount of capital to invest urges analysts to provide a deeper and more accurate analysis of listed companies in the U.S.

[9] To save space, the results are not presented here but available from the authors.

markets. Our empirical results seem to confirm that the effect of funds flow on earnings forecasts precision dominates that of uncertainty.

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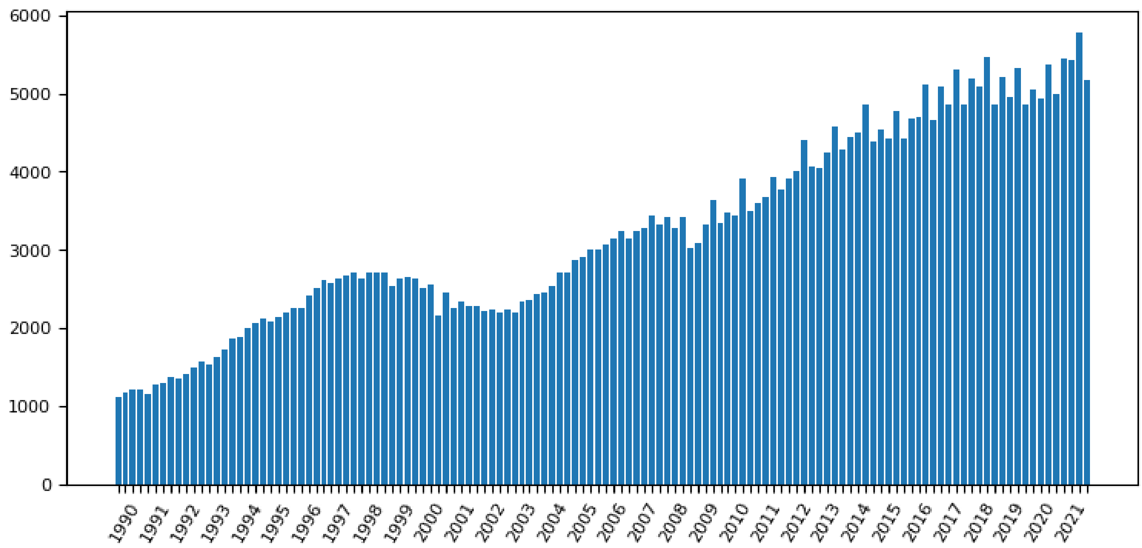
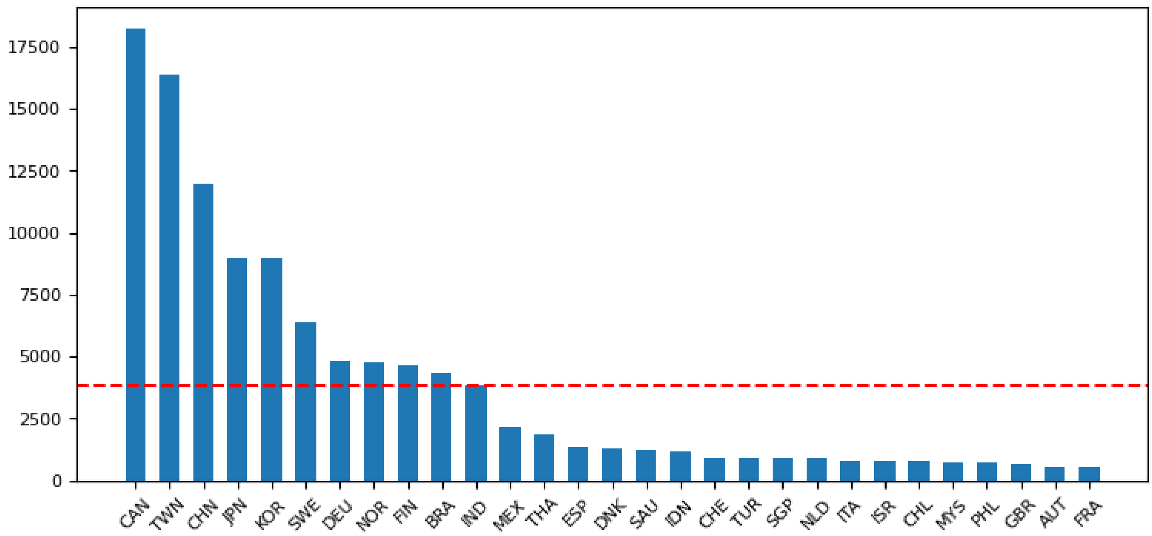
Figure 1: Obs Distribution in Time



The figure presents the number of observations from 1990 to 2021.

Figure 2: Obs Distribution in Non-U.S. Markets



The figure presents the number of observations per market in our sample from 1990 to 2021.

Table 1: Summary Statistics

This table presents the descriptive statistics of the variables used in this paper. Panel A contains statistics of the non-U.S. data and Panel B shows statistics of the U.S. data. 5%, 25%, 50%, 75% and 95% relate to the corresponding percentiles. All variable definitions are given in Appendix B.

Panel A: Non-U.S. data								
	N	Mean	Std	5%	25%	50%	75%	95%
Bias (*100)	111,551	0.46	3.95	-2.24	-0.24	0.03	0.47	4.03
AbsErr (*100)	111,551	1.44	3.37	0.01	0.11	0.34	1.01	7.30
SqrErr (*10000)	111,551	13.44	56.58	0.00	0.01	0.12	1.02	53.36
USEPU	111,551	159.79	68.43	82.59	114.47	151.55	187.10	300.24
LocEPU	111,551	189.65	132.34	61.30	107.59	152.42	238.73	428.07
Exp2GDP (*100)	111,551	6.97	6.69	1.34	2.21	4.29	8.32	20.59
NumEst	111,551	3.14	2.88	1.00	1.00	2.00	4.00	10.00
M/B	111,551	3.37	5.01	0.24	1.10	1.92	3.53	10.63
ROA (*100)	111,551	1.22	2.94	-2.09	0.27	1.04	2.13	5.18
Size	111,551	9.60	2.89	5.17	7.63	9.26	11.37	15.09
Panel B: the U.S. data								
	N	Mean	Std	5%	25%	50%	75%	95%
Bias (*100)	253,648	0.31	4.10	-1.92	-0.23	-0.03	0.12	2.97
AbsErr (*100)	253,648	1.27	3.60	0.00	0.05	0.19	0.63	6.57
SqrErr (*10000)	253,648	14.55	66.91	0.00	0.00	0.03	0.40	43.20
USEPU	253,648	134.68	60.23	61.75	86.34	116.62	169.04	252.59
GlbEPU	253,648	-2.20	33.79	-49.73	-23.54	-7.29	7.88	69.65
FundsFlow	253,648	120.39	73.39	12.09	53.22	116.06	168.59	258.04
NumEst	253,648	6.83	5.90	1.00	2.00	5.00	9.00	20.00
ROA (*100)	253,648	-4.61	30.82	-15.47	0.04	0.63	1.69	4.33
M/B	253,648	3.22	4.80	0.48	1.27	2.07	3.68	10.96
Size	253,648	6.87	1.97	3.75	5.42	6.82	8.17	10.32

Table 2: U.S. EPU on Other Markets - Baseline Model

This table presents the regression results of the baseline model when checking the U.S. EPU's effect on other markets analysts' earnings forecasts. Models (1) - (3) are the results for the univariate analysis while models (4) - (6) are the results for the multivariate analysis. The dependent variable for each model is shown in the table. All variable definitions are given in Appendix B. *t*-statistics are shown in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr
Intercept	0.0026***	0.0099***	0.0008***	0.0047	0.0038	-0.0002
	(7.6784)	(34.045)	(17.206)	(1.0816)	(0.8641)	(-0.2337)
USEPU	1.274e-05***	2.852e-05***	3.148e-06***	-1.504e-06	2.217e-05***	2.397e-06***
	(6.0297)	(15.710)	(10.293)	(-0.7080)	(11.637)	(7.3058)
LocEPU				1.392e-06	2.299e-06*	2.571e-08
				(1.0166)	(1.8787)	(0.1328)
NumEst				-7.126e-05	-0.0007***	-7.404e-05***
				(-0.6247)	(-6.9361)	(-4.4050)
M/B				0.0005***	-0.0005***	-3.704e-05***
				(5.1765)	(-6.2778)	(-3.3002)
ROA				-0.7055***	-0.1657***	-0.0280***
				(-28.754)	(-12.920)	(-11.875)
Size				0.0007	0.0013***	0.0002**
				(1.5241)	(2.6816)	(2.5401)
No. Obs.	111,551	111,551	111,551	111,551	111,551	111,551
R-squared	0.0005	0.0062	0.0025	0.1787	0.0390	0.0289
F-statistic	53.125	658.36	267.94	3854.8	718.56	527.48
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Clustered	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: U.S. EPU on Other Markets - Channel Analysis

This table presents the regression results of the channel analysis when checking the U.S. EPU's effect on other markets analysts' earnings forecasts. Models (1) - (3) are the results for without the interaction term while models (4) - (6) are the results with the interaction term. The dependent variable for each model is shown in the table. All variable definitions are given in Appendix B. *t*-statistics are shown in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr
Intercept	0.0007	0.0021	-0.0004	0.0006	0.0015	-0.0005
	(0.1471)	(0.4449)	(-0.4898)	(0.1229)	(0.3195)	(-0.6105)
USEPU	-1.781e-06	2.205e-05***	2.382e-06***	-1.555e-06	2.324e-05***	2.565e-06***
	(-0.8359)	(11.607)	(7.2890)	(-0.7240)	(11.960)	(7.6569)
Exp2GDP	0.0433***	0.0184	0.0023	0.0443***	0.0233*	0.0031
	(3.3000)	(1.3629)	(1.1405)	(3.3839)	(1.7063)	(1.4808)
USEPU*Exp2GDP				3.028e-05	0.0002***	2.456e-05***
				(0.8543)	(4.3283)	(3.8082)
LocEPU	2.167e-06	2.629e-06**	6.719e-08	2.028e-06	1.9e-06	-4.566e-08
	(1.6402)	(2.2139)	(0.3611)	(1.5434)	(1.5782)	(-0.2397)
NumEst	-5.015e-05	-0.0007***	-7.291e-05***	-5.034e-05	-0.0007***	-7.306e-05***
	(-0.4435)	(-6.8465)	(-4.3492)	(-0.4451)	(-6.8652)	(-4.3605)
M/B	0.0005***	-0.0005***	-3.692e-05***	0.0005***	-0.0005***	-3.669e-05***
	(5.2137)	(-6.2673)	(-3.2889)	(5.2192)	(-6.2666)	(-3.2778)
ROA	-0.7062***	-0.1660***	-0.0280***	-0.7062***	-0.1663***	-0.0281***
	(-28.794)	(-12.929)	(-11.883)	(-28.796)	(-12.969)	(-11.916)
Size	0.0008*	0.0013***	0.0002**	0.0008*	0.0014***	0.0002***
	(1.6825)	(2.7449)	(2.5620)	(1.6934)	(2.8067)	(2.6213)
No. Obs.	111,551	111,551	111,551	111,551	111,551	111,551
R-squared	0.1789	0.0391	0.0290	0.1789	0.0398	0.0296
F-statistic	3308.8	617.42	452.90	2895.4	550.87	404.66
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Clustered	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: U.S. EPU on Other Markets - Robustness 1

This table presents the regression results of the robustness checks when checking the U.S. EPU's effect on other markets analysts' earnings forecasts. Models (1) - (3) are the results when the squared term of USEPU (variable USEPU2 in the model) is included in the models. Models (4) - (6) are the results when the Canada and Taiwan data are excluded. The dependent variable for each model is shown in the table. All variable definitions are given in Appendix B. t-statistics are shown in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Squared Item			Exlcuding CAN and TWN		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr
Intercept	0.0014	0.0015	-0.0005	0.0031	-0.0088	-0.0017
	(0.2881)	(0.3071)	(-0.6066)	(0.5290)	(-1.3312)	(-1.5721)
USEPU	-1.379e-05**	2.42e-05***	2.517e-06***	-1.537e-06	2.947e-05***	3.422e-06***
	(-2.0574)	(4.6084)	(2.8118)	(-0.4200)	(7.4767)	(4.6844)
USEPU2	2.777e-08*	-2.185e-09	1.093e-10			
	(1.8476)	(-0.1984)	(0.0572)			
Exp2GDP	0.0441***	0.0233*	0.0031	0.0261	0.0534**	0.0077**
	(3.3718)	(1.7073)	(1.4804)	(1.2898)	(2.2775)	(1.9845)
USEPU*Exp2GDP	3.413e-05	0.0002***	2.458e-05***	6.309e-06	0.0002***	3.847e-05**
	(0.9568)	(4.3064)	(3.7977)	(0.0864)	(2.8950)	(2.3813)
LocEPU	2.343e-06*	1.875e-06	-4.441e-08	3.739e-06***	2.203e-06*	6.878e-08
	(1.8002)	(1.5673)	(-0.2355)	(2.7371)	(1.7166)	(0.3273)
M/B	0.0005***	-0.0005***	-3.669e-05***	0.0005***	-0.0004***	-2.884e-05**
	(5.2278)	(-6.2661)	(-3.2779)	(4.3827)	(-4.7831)	(-2.2910)
NumEst	-4.107e-05	-0.0007***	-7.303e-05***	-0.0003**	-0.0009***	-9.907e-05***
	(-0.3631)	(-6.8617)	(-4.3493)	(-2.0251)	(-6.3594)	(-4.1731)
ROA	-0.7062***	-0.1663***	-0.0281***	-0.6972***	-0.1659***	-0.0293***
	(-28.792)	(-12.969)	(-11.915)	(-23.884)	(-9.9993)	(-9.7768)
Size	0.0008*	0.0013***	0.0002***	0.0008	0.0022***	0.0003***
	(1.7463)	(2.7990)	(2.6192)	(1.4274)	(3.5135)	(2.9250)
No. Obs.	111,551	111,551	111,551	76,987	76,987	76,987
R-squared	0.1789	0.0398	0.0296	0.1564	0.0382	0.0292
F-statistic	2574.3	489.66	359.69	1699.6	363.65	275.26
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Clustered	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: U.S. EPU on Other Markets - Robustness 2

This table presents the regression results of the robustness checks when checking the U.S. EPU's effect on other markets analysts' earnings forecasts. Models (1) - (3) are the results for the developed markets while models (4) - (6) are the results for the developing markets. The dependent variable for each model is shown in the table. All variable definitions are given in Appendix B. *t*-statistics are shown in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Developed Markets			Developing Markets		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr
Intercept	-0.0076	0.0168**	0.0012	0.0054	-0.0215***	-0.0031***
	(-0.9933)	(2.5259)	(1.0714)	(0.8800)	(-3.3129)	(-3.1566)
USEPU	2.45e-06	2.779e-05***	2.989e-06***	-3.812e-06	1.674e-05***	1.93e-06***
	(0.7341)	(10.181)	(6.3993)	(-1.3274)	(6.1087)	(3.9814)
Exp2GDP	0.0703***	0.0088	0.0009	0.0112	0.0481**	0.0064*
	(3.4864)	(0.5831)	(0.3849)	(0.6085)	(2.1661)	(1.7509)
USEPU*Exp2GDP	9.223e-05**	0.0001***	2.175e-05***	-6.919e-06	0.0002**	2.731e-05*
	(2.1651)	(3.9122)	(3.4779)	(-0.0974)	(1.9691)	(1.7682)
LocEPU	-2.832e-06	5.371e-07	-2.64e-07	3.927e-06***	2.152e-06*	5.487e-08
	(-0.8460)	(0.1904)	(-0.5572)	(2.9000)	(1.7164)	(0.2902)
M/B	0.0003**	-0.0006***	-6.517e-05***	0.0008***	-0.0002**	2.907e-06
	(2.2380)	(-6.0783)	(-4.0384)	(6.0103)	(-2.2101)	(0.2078)
NumEst	-0.0002	-0.0007***	-7.712e-05***	0.0002	-0.0007***	-7.052e-05***
	(-1.5128)	(-5.5331)	(-3.5655)	(1.2642)	(-4.2223)	(-2.7144)
ROA	-0.7251***	-0.1702***	-0.0287***	-0.6592***	-0.1587***	-0.0270***
	(-23.379)	(-11.086)	(-10.161)	(-19.901)	(-7.0857)	(-6.4831)
Size	0.0016**	0.0001	8.207e-05	0.0004	0.0031***	0.0004***
	(2.1059)	(0.1951)	(0.7068)	(0.6383)	(5.2155)	(4.3801)
No. Obs.	65,617	65,617	65,617	45,934	45,934	45,934
R-squared	0.1891	0.0405	0.0305	0.1533	0.0427	0.0298
F-statistic	1827.2	330.30	246.48	987.32	243.45	167.55
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Clustered	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Global EPU on U.S. market - correlation

This table presents the correlations among several key variables when checking the Global EPU's effect on U.S. market analysts' earnings forecasts. All variable definitions are given in Appendix B. t-statistics are shown in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	USAEPU	GlbEPU	FundsFlow	Bias	AbsErr	SqrErr
USEPU	1.000	-0.026	0.105	-0.002	0.055	0.033
GlbEPU	-0.026	1.000	0.110	-0.013	0.008	0.007
FundsFlow	0.105	0.110	1.000	-0.015	-0.001	-0.006
Bias	-0.002	-0.013	-0.015	1.000	0.408	0.429
AbsErr	0.055	0.008	-0.001	0.408	1.000	0.964
SqrErr	0.033	0.007	-0.006	0.429	0.964	1.000

Table 7: Global EPU on U.S. Market - Baseline Model

This table presents the regression results of the baseline model when checking the Global EPU's effect on U.S. market analysts' earnings forecasts. Models (1) - (3) are the results for the univariate analysis while models (4) - (6) are the results for the multivariate analysis. The dependent variable for each model is shown in the table. All variable definitions are given in Appendix B. *t*-statistics are shown in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr
Intercept	0.0031***	0.0126***	0.0014***	-0.0145***	0.0024*	-0.0004*
	(454.12)	(1860.9)	(1139.1)	(-8.8134)	(1.7519)	(-1.6846)
GlbEPU	-2.274e-05***	-3.772e-05***	-5.693e-06***	-1.697e-05***	-1.604e-05***	-3.145e-06***
	(-7.3435)	(-12.209)	(-9.8885)	(-4.2583)	(-4.4901)	(-4.7582)
M/B				-4.425e-05	-0.0004***	-5.137e-05***
				(-1.5022)	(-18.104)	(-12.746)
NumEst				-0.0002***	-0.0006***	-8.482e-05***
				(-6.0610)	(-14.519)	(-11.289)
ROA				-0.0693***	-0.0456***	-0.0091***
				(-22.398)	(-23.187)	(-22.177)
Size				0.0023***	0.0015***	0.0003***
				(8.3781)	(6.4899)	(6.3250)
USEPU				3.962e-06*	2.7e-05***	2.45e-06***
				(1.8997)	(14.422)	(7.1452)
No. Obs.	253,648	253,648	253,648	253,648	253,648	253,648
R-squared	0.0003	0.0021	0.0013	0.0743	0.0888	0.0882
F-statistic	77.199	508.57	313.40	3278.2	3977.7	3950.5
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Clustered	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Global EPU on U.S. Market - Channel Analysis

This table presents the regression results of the channel analysis when checking the Global EPU's effect on U.S. market analysts' earnings forecasts. Model (1) shows the results about how GlbEPU affects FundsFlow. Models (2) - (4) are the results showing how FundsFlow affect analysts' earnings forecasts whithout controlling for GlbEPU, while models (5) - (7) are similar models but controlling for GlbEPU. The dependent variable for each model is shown in the table. All variable definitions are given in Appendix B. t-statistics are shown in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	FundsFlow	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr
Intercept	19.517***	-0.0126***	0.0042***	-7.459e-05	-0.0145***	0.0024*	-0.0004
	(4.9474)	(-8.6844)	(3.3513)	(-0.3203)	(-8.7741)	(1.8071)	(-1.6153)
GlbEPU	0.1459***				-1.639e-05***	-1.549e-05***	-3.01e-06***
	(25.660)				(-4.1147)	(-4.3152)	(-4.5337)
FundsFlow		-4.274e-06***	-4.104e-06***	-9.888e-07***	-3.915e-06***	-3.765e-06***	-9.228e-07***
		(-3.6371)	(-4.6594)	(-5.8924)	(-3.3337)	(-4.2346)	(-5.4557)
M/B	0.2735***	-4.781e-05	-0.0004***	-5.197e-05***	-4.318e-05	-0.0004***	-5.112e-05***
	(5.2018)	(-1.6251)	(-18.244)	(-12.886)	(-1.4658)	(-18.081)	(-12.701)
NumEst	-0.7294***	-0.0002***	-0.0006***	-8.406e-05***	-0.0002***	-0.0006***	-8.549e-05***
	(-6.9594)	(-5.9272)	(-14.416)	(-11.211)	(-6.1363)	(-14.572)	(-11.367)
ROA	12.331***	-0.0694***	-0.0456***	-0.0091***	-0.0693***	-0.0456***	-0.0091***
	(7.7194)	(-22.449)	(-23.147)	(-22.135)	(-22.389)	(-23.156)	(-22.147)
Size	14.716***	0.0020***	0.0012***	0.0002***	0.0023***	0.0015***	0.0003***
	(23.350)	(8.3717)	(5.8825)	(5.8189)	(8.4967)	(6.6771)	(6.5757)
USEPU	0.0356***	7.279e-06***	3.014e-05***	3.066e-06***	4.101e-06**	2.714e-05***	2.483e-06***
	(9.8005)	(4.0989)	(20.488)	(11.399)	(1.9690)	(14.478)	(7.2341)
No. Obs.	253,648	253,648	253,648	253,648	253,648	253,648	253,648
R-squared	0.0221	0.0743	0.0886	0.0881	0.0744	0.0889	0.0884
F-statistic	922.82	3274.3	3969.3	3945.2	2812.0	3414.1	3393.7
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Global EPU on U.S. Market - Robustness

This table presents the regression results of the channel analysis when checking the Global EPU's effect on U.S. market analysts' earnings forecasts. Model (1) shows the results about how GlbEPU affects FundsFlow. Models (2) - (4) are the results showing how FundsFlow affect analysts' earnings forecasts whithout controlling for GlbEPU, while models (5) - (7) are similar models but controlling for GlbEPU. The dependent variable for each model is shown in the table. All variable definitions are given in Appendix B. t-statistics are shown in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	FundsFlow	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr
Intercept	21.349***	-0.0127***	0.0041***	-8.333e-05	-0.0144***	0.0025*	-0.0004
	(18.284)	(-8.7239)	(3.3115)	(-0.3579)	(-8.7579)	(1.8283)	(-1.6248)
GlbEPU	0.2479***				-1.582e-05***	-1.479e-05***	-2.974e-06***
	(67.198)				(-3.9717)	(-4.0919)	(-4.4481)
FundsFlow		-5.568e-06***	-5.892e-06***	-8.668e-07***	-4.628e-06***	-5.013e-06***	-6.9e-07***
		(-4.2178)	(-7.3689)	(-5.5344)	(-3.5389)	(-6.0836)	(-4.2997)
M/B	0.1068***	-4.817e-05	-0.0004***	-5.213e-05***	-4.376e-05	-0.0004***	-5.13e-05***
	(4.2250)	(-1.6372)	(-18.239)	(-12.909)	(-1.4854)	(-18.085)	(-12.729)
NumEst	0.4164***	-0.0002***	-0.0006***	-8.301e-05***	-0.0002***	-0.0006***	-8.453e-05***
	(11.900)	(-5.7906)	(-14.314)	(-11.087)	(-6.0058)	(-14.472)	(-11.250)
ROA	0.6427	-0.0694***	-0.0457***	-0.0092***	-0.0693***	-0.0456***	-0.0091***
	(0.8904)	(-22.460)	(-23.174)	(-22.163)	(-22.403)	(-23.180)	(-22.173)
Size	-5.9191***	0.0019***	0.0011***	0.0002***	0.0022***	0.0014***	0.0003***
	(-30.038)	(8.1958)	(5.6001)	(5.4519)	(8.2826)	(6.3428)	(6.2141)
USEPU	0.1014***	7.545e-06***	3.042e-05***	3.105e-06***	4.431e-06**	2.751e-05***	2.52e-06***
	(85.119)	(4.2592)	(20.652)	(11.528)	(2.1293)	(14.562)	(7.2866)
No. Obs.	253,648	253,648	253,648	253,648	253,648	253,648	253,648
R-squared	0.0177	0.0743	0.0887	0.0880	0.0744	0.0889	0.0883
F-statistic	735.95	3274.5	3971.2	3939.9	2811.7	3414.6	3388.7
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix A Markets in the data sample

This table presents the markets in the data sample. ISO-3 Code is published by the International Organization for Standardization (ISO) to represent countries, dependent territories, and special areas of geographical interest. N is the number of firm-quarters for each market.

ISO-3 Code	Market	N	ISO-3 Code	Market	N
AUT	Austria	572	ITA	Italy	809
BRA	Brazil	4,301	JPN	Japan	8,988
CAN	Canada	18,215	KOR	Korea, Rep.	8,969
CHE	Switzerland	940	MEX	Mexico	2,135
CHL	Chile	766	MYS	Malaysia	750
CHN	China	11,941	NLD	Netherlands	922
DEU	Germany	4,842	NOR	Norway	4,745
DNK	Denmark	1,314	PHL	Philippins	714
ESP	Spain	1,332	SAU	Saudi Arabia	1,204
FIN	Finland	4,657	SGP	Singapore	924
FRA	France	537	SWE	Sweden	6,386
GBR	United Kingdom	669	THA	Thailand	1,853
IDN	Indonesia	1,156	TUR	Turkey	925
IND	India	3,840	TWN	Taiwan	16,349
ISR	Israel	796	USA	United States	302,171

Appendix B Variable deifnitions

Variable	Definition
Bias	Bias in earnings forecast, scaled by share price, computed as $\frac{Forecasted\ EPS - Announced\ EPS}{share\ price}$
AbsErr	Absolute earnings forecast error, scaled by share price, computed as $\frac{\lvert Forecasted\ EPS - Announced\ EPS)\rvert}{share\ price}$
SqrErr	Squared earnings forecast error, scaled by share price, computed as $\left(\frac{Forecasted\ EPS - Announced\ EPS}{share\ price}\right)^2$
USEPU	Economic Policy Uncertainty (EPU) data for the U.S.
LocEPU	Local EPU for a given market, if no EPU data exists for the given market, then regional EPU or global EPU is used.
GlbEPU	Global EPU, computed as residuals from the regression of USA EPU on the original Global EPU.
Exp2GDP	Export to GDP ratio, computed as an economy's export to the U.S. divided by the economy's GDP.
FundsFlow	Financial account of the U.S. balance of payments, converted to reflect cash flows to the U.S. and one quarter leaded.
NumEst	Number of estimates (analysts) for the earnings forecast in a given quarter for a given firm.
M/B	Market to book ratio, computed as market value divided by book value.
ROA	Return on assets, computed as earnings divided by total assets.
Size	Natural logarithm of firm size, measured by total assets.