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How does foreign economic policy uncertainty affect domestic analyst earnings forecasts?

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ABSTRACT

This study examines the impact of foreign economic policy uncertainty (EPU) on the performance of domestic analyst earnings forecasts. We separately analyze how U.S. EPU affects the accuracy of analyst earnings forecasts in other markets and the reverse relationship. Our findings indicate that the U.S. EPU (non-U.S. Global EPU) negatively (positively) affects the accuracy of analyst earnings forecasts in other economies (the U.S.). We find that the economic dependency of a given economy on the U.S. (capital flow to the U.S.) is a channel for this negative (positive) impact. Our results remain robust after controlling for a comprehensive set of variables.

1. Introduction

One important role of financial markets is to facilitate information dissemination. Financial analysts, together with the financial institutions they are working for, as well as regulators and investors, are an integral part of the market. By providing valuable insights on both the economy and individual firms, analysts not only guide investment decisions for investors (e.g., retail and institutional) but also influence firms' information environments and financial policies (Balakrishnan et al., 2014; Hong & Kacperczyk, 2010). Given the importance of their roles in financial markets, it is not surprising that prior studies explore various aspects of analyst activities, such as how they choose to cover particular firms (Harford et al., 2019; Jegadeesh et al., 2004), what type of information (i.e., industry-level or firm-specific) they use to make their earnings forecasts (Choi & Gupta-Mukherjee, 2022), the causes of the persistent upward bias in their earnings forecasts (Dong et al., 2021; Hong & Kubik, 2003) and the factors influencing their forecast accuracy (e.g., Markov & Tamayo, 2006).

Despite extensive research on analyst characteristics and the information environment in their home markets,[1] recent studies, driven by increasing globalization, have begun exploring how economic policy uncertainty (EPU, see Baker et al., 2016) in one country (the leading country) affects analyst earnings forecast accuracy in another (the affected country). In particular, as the world's largest

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[1] A more detailed literature review is provided in Section 2.

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and most influential economy, the U.S. plays a central role in shaping global markets.[2] Consequently, several studies have focused on examining the impact of the U.S. EPU on a particular market (Chen et al., 2022; Chourou et al., 2021 and Zhu et al., 2023). Following this line, our study examines how the U.S. EPU affects the accuracy of analyst earnings forecasts across a wide range of 29 non-U.S. markets and investigates the role of well-documented economic dependency in shaping this relationship.

While much of the existing research focuses on the impact of the U.S. EPU on non-U.S. markets, our study extends this analysis by investigating the reverse relationship, specifically, how non-U.S. Global EPU, as a source of risk, influences analyst earnings forecasts in the U.S. market. Additionally, recognizing that countries can be interconnected through economic, financial, or both channels, we examine the role of capital flows to explain our results. To the best of our knowledge, this issue has not been addressed in the literature.

Based upon a data sample comprising the U.S. and 29 non-U.S. markets, we start by conducting a univariate examination. Our findings demonstrate that higher U.S. EPU is associated with a decline in the accuracy of analyst earnings forecasts for firms out of the U.S. This result remains consistent after incorporating additional control variables into the model. We further investigate the role of economic dependency in the relationship between the U.S. EPU and the precision of earnings forecasts in non-U.S. markets. Our findings suggest that economic dependency on the U.S. channels the negative impact of the U.S. EPU on the accuracy of earnings forecasts for stocks outside the U.S. market. Specifically, the more an economy depends on the U.S., the more impact from the U.S. EPU for that market. Finally, we conduct various robustness tests to confirm the adverse association between the U.S. EPU and analyst earnings forecast accuracy as well as the important role played by economic dependency on the U.S.

We further turn our attention to examine whether non-U.S. Global EPU impacts the bias/accuracy of analyst earnings forecasts in the U.S. market. Contrary to our previous findings that heightened U.S. EPU is associated with lower analyst forecast accuracy in other markets, we find that heightened non-U.S. Global EPU in fact is associated with a significant increase in analyst earnings forecasts precision for stocks listed in the U.S. market. Our additional tests suggest that capital flows to the U.S. market is one driver of this phenomenon. For instance, during periods of heightened global uncertainty, speculative capital and U.S. overseas funds are more likely to return to the U.S. market, increasing capital availability. This capital inflow, driven by uncertainty, necessitates more comprehensive and precise analyses from analysts. Our empirical findings indicate that, in the context of non-U.S. Global EPU and U.S.-listed firms, the impact of capital flows on analyst earnings forecast precision outweighs the direct negative effect of global uncertainty.

This study makes a contribution to the extensive body of literature on analyst activities and the bias/accuracy of their earnings forecasts (e.g., Dong et al., 2021; Kumar et al., 2022 and Markov & Tamayo, 2006). Our research complements prior work by providing novel evidence from a dataset spanning 30 international markets and identifying distinct mechanisms through which foreign EPU affects domestic analyst earnings forecasts. We highlight the influential roles of economic dependency and capital flows, offering a nuanced perspective on the interaction between cross-country economic uncertainty and domestic earnings forecasts across varied contexts. Furthermore, this study enriches the EPU literature by examining the impact of macro-level EPU on micro-level analyst information processing within an international framework.

The rest of the paper is organized as follows: Section 2 presents the literature review and analytical framework; 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 other markets, and Section 5 presents the results of the impact of non-U.S. Global EPU on the performance of analyst earnings forecasts in the U.S. market. Section 6 concludes the paper.

2. Literature review and analytical framework

2.1. Analyst earnings forecast

Financial analysts play an important role in disseminating information through their forecasts and reports, which exert significant influence on stock prices (e.g., Loh & Stulz, 2011). Analyst earnings forecasts are especially valuable, considered as important guides for both short-term and long-term investment decisions by various types of investors (e.g., Chang et al., 2009; Kasznik & McNichols, 2002). The economic and financial insights provided by analysts significantly contribute to the reduction of information asymmetry and the incorporation of information into stock prices (Harford et al., 2019; Loh & Stulz, 2018). Many studies have highlighted the critical role of earnings surprises, which are measured against analyst earnings forecasts, as an important source of stock price fluctuations (e.g., Abarbanell & Park, 2017; Chiang et al., 2019; Kasznik & McNichols, 2002; Lopez & Rees, 2002; Skinner & Sloan, 2002). Given the indispensable role analysts play in financial markets, it is important to understand the factors that influence analyst behaviors, particularly the implications on analyst earnings forecasts. As a brief summary, Fig. 1 shows various factors that potentially can affect 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 the analysts, who make forecasts on firms in the industries related to their pre-analyst experience, usually 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 forecast accuracy. Another strand of research considers the entire

[2] 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.

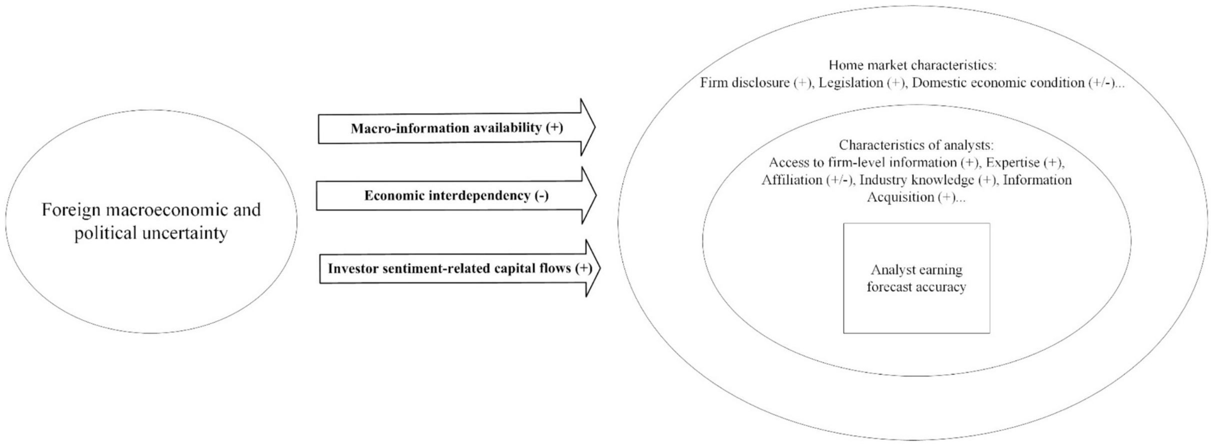

Fig. 1. Channels for the Impact of Foreign Uncertainty on Analyst Earnings Forecast Accuracy.
This diagram illustrates the factors influencing analyst earnings forecast accuracy. A "+" sign denotes a positive relationship, indicating that an increase or improvement in the factor enhances the accuracy of analyst earnings forecasts. Conversely, a "-" sign signifies a negative relationship, where a rise in the factor reduces forecast accuracy. The "+/-" sign represents a relationship that can vary, being either positive or negative, depending on specific circumstances or conditions.

analysts industry and investigates how the level of information disclosure and macroeconomic condition disagreement in home market affect the performance of analyst earnings forecasts (e.g., Gu & Wang, 2005; Hope, 2003; Lin et al., 2022; Merkley et al., 2017 and Sinha, 2021) (see Fig. 1).[3]

With the increasing trend of globalization, various foreign macroeconomic and political factors are influencing analyst earnings forecasts within domestic markets (see Fig. 1). Previous studies (e.g., Chen et al., 2022; Zhu et al., 2023) have examined the impact of EPU from key economies on specific affected markets. However, these studies typically focus on a limited number of closely linked markets, without capturing sufficient variation in economic dependency. Additionally, the role of capital flows is hardly discussed in existing literature. Our study aims to expand this analysis by investigating the relationship on a larger scale, incorporating a wider range of markets, and providing deeper insights into the role of economic dependency and capital flows in this dynamic.

As outlined in Fig. 1, A foreign country's EPU may influence domestic analyst earnings forecast accuracy through two mechanisms beyond the macro-information availability: economic dependency and capital flow. Economic dependency is particularly relevant for countries heavily reliant on trade with another, such as through exports. In such cases, heightened EPU in the foreign country may create uncertainty about future economic conditions, leading to less accurate forecasts. In contrast, capital flow becomes more relevant for safe-haven countries, as heightened foreign EPU may drive capital inflows, enhancing domestic information environment and shaping better analyst forecasts. The overall effect of foreign EPU on domestic analysts depends on which mechanism exerts a stronger influence. In this specific context - examining the impact of U.S. EPU on the earnings forecast accuracy of foreign markets versus the impact of non-U.S. Global EPU on the earnings forecast accuracy of the U.S. - the dominating mechanisms may differ due to the U.S.'s central role in the global economy. The effect of U.S. EPU on foreign markets is likely driven primarily by economic dependency, as many economies heavily rely on trade and financial ties with the U.S. In contrast, the influence of non-U.S. Global EPU on U.S. analyst forecast accuracy is expected to operate mainly through capital flows, reflecting the U.S.'s relatively lower economic dependence on individual foreign economies and its status as a global safe haven.

2.2. Economic policy uncertainty

It is widely recognized that macroeconomic conditions can significantly influence earnings forecasts (e.g., Carabias, 2018; 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

[3] 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 analyst 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 forecast accuracy in China.

function, affects the behavior of a firm (e.g., Abel, 1983; Pindyck, 1982). Recent studies, particularly following the influential work on EPU by Baker et al. (2016), have increasingly focused on how uncertainty affects financial markets and various decision-making processes of investors and businesses (e.g., Hoang et al., 2021; Lopez et al., 2023; Nagar et al., 2019 and Shen et al., 2021).

Regarding uncertainty's impact on analyst earnings 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, analyst 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 forecast accuracy is negatively associated with EPU and provide a labor-centric explanation of lower forecast quality in uncertain times.

Within a given market, previous studies have shown that the uncertainty of economic policy tends to amplify information asymmetry in the market (Nagar et al., 2019) and is likely to have a negative impact on analyst earnings forecast accuracy (Kim et al., 2022). These studies primarily focus on uncertainty while overlooking the effects of capital flows. By analyzing the impact of non-U.S. Global EPU on firms listed in the U.S. market, our study sheds light on how the capital flow channel affects the relationship between foreign EPU and domestic forecast accuracy.

2.3. Interconnection

2.3.1. Economic dependency

As economies become increasingly globalized, countries are more economically interconnected,[4] meaning that domestic economic outcomes are influenced by both local and foreign policies. Consequently, there is growing concern about the uncertainty surrounding economic policies in interconnected countries (Baker et al., 2016). One major consequence of this interconnection is the changing information environment within domestic financial markets.[5] Given the U.S.'s leading role in the global economy and financial markets, a substantial body of literature documents its influence on other economies (Rapach et al., 2013; Berg & Vu, 2019; Balli et al., 2021; Cavaca & Meurer, 2021; and among others). In the same vein, our study examines how the U.S. EPU may influence the accuracy of analyst earnings forecasts in other markets. Intuitively, as an economy's dependency on the U.S. increases, forecasting accuracy becomes more challenging for analysts, who must incorporate an expanding array of international factors.

To deepen our understanding of the economic dependency channel, we first examine whether economic dependency acts as a mediator in the relationship between U.S. EPU and analyst forecast accuracy in non-U.S. markets.[6] Drawing on the mediation framework outlined by Baron and Kenny (1986), we explore how changes in economic dependency transmit the effects of U.S. EPU to forecast accuracy in non-U.S. markets. Specifically, countries with higher trade dependency on the U.S. may experience greater exposure to U.S. economic shocks, which in turn influences the precision of analyst forecasts.

In addition to acting as a mediator, economic dependency may also serve as a moderator, shaping the extent to which U.S. EPU affects analyst forecast accuracy in non-U.S. markets. Building on the work of Gulen and Ion (2015), which finds that an industry's dependency on government spending significantly moderates the relationship between policy uncertainty and corporate investment, we apply a similar framework to explore the connection between the U.S. EPU and analyst earnings forecast accuracy in non-U.S. markets. We propose that economic dependency on the U.S. shapes the "sensitivity" of this relationship, with varying levels of dependency leading to differing degrees of forecast uncertainty. For instance, markets with higher economic reliance on the U.S. are likely to exhibit greater sensitivity to U.S. EPU, while less dependent markets may remain relatively insulated.[7]

Empirically, our findings confirm that both mediation and moderation are at play. Mediation captures how trade dependency channels the influence of U.S. EPU into forecast accuracy, while moderation explains the varying impact across countries with different levels of dependency. Together, these insights provide a comprehensive understanding of how U.S. EPU propagates its effects globally.

Our paper is related to Boubakri et al. (2022), who find that analyst earnings 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, which is different from election uncertainty, on the performance of analyst earnings forecasts. Our paper is also connected to the study of Choi et al. (2022). They are the first study to explore the segregated herding behavior 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 mechanisms about economic dependency and capital flows,

[4] Recent studies, often utilizing gravity models, suggest that the export of an economy can be linked to uncertainties (e.g., Nana et al., 2024; Tam, 2018; Yayi, 2024; Zhu & Ye, 2024).

[5] For instance, Wu (2000) shows that the amount of news coverage is highly related with trade volume between economies. Building on this, it is reasonable to assume that the more dependence of a country on the U.S., the more media coverage about news and policies from the U.S. This occurs may because media outlets in highly dependent economies are more responsive to news that may impact their economic or trade relationships with influential countries, particularly during periods of policy shifts or economic uncertainties. In addition, considering media coverage can have a significant impact on financial markets (e.g., Blankespoor et al., 2014; Fang & Peress, 2009 and Tetlock, 2007), those policy uncertainties from the U.S. reported in media may affect analyst perceptions of the domestic economy and focal firms, thus, affect the earnings forecast accuracy of those analysts.

[6] We thank an anonymous referee for suggesting this mediation channel.

[7] Consider two extreme cases: Economy A has a 100 % trade dependency on the U.S., while Economy B has no trade dependency on the U.S. at all. Intuitively, analysts in Market A would need to incorporate a wide range of U.S.-related external factors into their forecasts, as illustrated in Figure 1. Conversely, analysts in Market B could be relatively unaffected by these U.S.-related uncertainties, potentially simplifying their forecasting process.

with evidence from a total of 30 markets. In sum, our study attempts to provide insights into the impact of foreign EPU on analyst forecast accuracy in domestic financial markets in a globalized financial landscape.

2.3.2. *Capital flows*

Although the U.S. holds a dominant position 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. (Karolyi & Stulz, 2003). For example, Lee et al. (2020) find that the U.S. households reduce their exposure to the stock market in response to an increase in China EPU, suggesting that the U.S. investors actively respond to risks emerging from foreign economies. 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, highlighting the substantial influence of foreign uncertainty on U.S. asset prices. These findings raise an important question: can non-U.S. Global EPU influence the accuracy of analyst earnings forecasts in the U.S. market through financial mechanisms such as capital flows?

In the real economy channel, heightened non-U.S. Global EPU is likely to correlate with increased earnings volatility for U.S. firms, particularly those with substantial international exposure, reducing analyst forecast accuracy due to more unpredictable foreign demand. At the same time, in the capital market, uncertainty may also have a significant impact. For instance, Forbes and Warnock (2012) demonstrate that global factors, especially global risks, are significantly associated with extreme capital flow episodes. Given the widely accepted view of the U.S. dollar as a safe haven currency (e.g., Fatum & Yamamoto, 2016; Habib et al., 2020; Habib & Stracca, 2012; among others), this underscores the unique role of potential capital inflows to the U.S. during periods of heightened global uncertainty.

In fact, several recent studies have linked cross-border capital flows to EPU (Agoraki et al., 2024; Alok et al., 2022; Huang et al., 2024). Additionally, the "flight-to-safety" phenomenon in international finance (e.g., Ahmed, 2023; Aslanidis et al., 2020; Kekre & Lenel, 2024; among others) suggests that the capital market channel may have a positive impact of non-U.S. Global EPU on analyst earnings forecast accuracy in the U.S. market. Capital inflows, such as those driven by investor demand for safer assets, can increase the U.S. market visibility and liquidity (Brunnermeier & Pedersen, 2008), improving the information environment and increase price information efficiency (Chordia et al., 2008). Thus, capital inflows can be positively associated with both increased analyst coverage and greater forecast accuracy. Since analyst coverage and forecast accuracy can be recognized as proxies for a firm's information environment,[8] this suggests that capital flow may influence domestic analyst forecasts by improving the availability and quality of information through a strengthened information environment.[9]

Specifically, heightened global EPU can prompt capital flows into the U.S., leading to increased market activity and a stronger demand for reliable information from investors. Foreign investors, in particular, face higher levels of information asymmetry than domestic investors, as they often have less access to local market insights (e.g., Choe et al., 2005; Dvořák, 2005; Lang et al., 2003). This drives demand for analysts' expertise in interpreting and forecasting firm performance. To address this gap, analysts provide more frequent and detailed earnings forecasts, which become critical for informed decision-making by both foreign and domestic investors. Research consistently highlights the information value of analyst coverage (e.g., Corredor et al., 2019; Hou & Hu, 2023; Lee & So, 2017), as it disseminates information and reduces asymmetries. Moreover, a substantial body of literature (e.g., Lang et al., 2003; Lang & Lundholm, 1996) demonstrates that more analyst coverage is associated with more accurate earnings forecasts. The rationale is that increased coverage fosters competition and information sharing among analysts, resulting in more robust predictions. For example, a greater number of analysts introduces diverse perspectives, enhancing forecasts quality and motivating analysts to improve their performance through competitive pressure. Overall, foreign investor participation incentivizes the expansion of analyst coverage to meet the demand for detailed and localized financial information, thereby enhancing forecast quality and accuracy (Bae et al., 2008).

In summary, capital flows triggered by heightened non-U.S. Global EPU may lead to greater analyst coverage and more accurate earnings forecasts, as analysts respond to higher demand for U.S. market insights and leverage enhanced information from stock market (Clement et al., 2011). While the real economy channel in Section 2.3.1 suggests a negative relationship between non-U.S. Global EPU and analyst forecast accuracy in the U.S. market, the capital market channel implies a positive relationship, as summarized in Fig. 1. Thus, the overall effect remains ambiguous, making this an empirical question we aim to investigate in this study.

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).[10] 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 quarterly 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 is from the United States Census Bureau while the

[8] As Lang et al. (2003) note, "Analyst forecast accuracy is intended as a measure of how well the market understands the firm's economics. This may partially be a result of analyst activity, but it may also reflect disclosure by the firm or information gathering by other investors. Similarly, analyst following is intended to proxy for private information-acquisition activities."

[9] We thank an anonymous referee for suggesting this information environment channel.

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

GDP data for each economy is from World Bank and the U.S. capital flow data are from Refinitiv.

In addition to requiring data for all variables in our regressions, we focus exclusively on firms with fiscal quarter-ends in March, June, September, and December. 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. Also, we require at least 5 observations for any firm and 500 firm-quarters for any market to be included in the data sample. As a result, a total of 30 markets and 413,722 firm-quarters are included in our data sample.[11]

To check the breakdown of our data sample, the largest market is the U.S., accounting for 302,171 firm-quarters. The remaining 111,551 firm-quarters are distributed across the other 29 markets. Within these non-U.S. markets, 17 are developed markets, collectively contributing 65,617 firm-quarters, while 12 are emerging markets, adding a further 45,934 firm-quarters.[12]

Fig. 2 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 1000 observations per quarter, which gradually grows over the years. By 2021, the number of quarterly earnings events exceeds 5000 observations per quarter. This growth reflects an expanding global market presence in financial data sources like I/B/E/S, alongside an increase in analyst coverage over time as global markets evolve.

Notably, two periods deviate a bit from the growth trend, each marked by a decline in number of observations. The first period, roughly from 2000 to 2003, aligns with the dotcom crash, during which many technology and internet firms faced significant downturns and even bankruptcy, leading to fewer earnings announcements. Similarly, the 2008–2009 decrease corresponds with the global finance crisis, a time when financial turmoil reduced the number of publicly traded firms and temporarily decreased the frequency of earnings events, as some firms delisted from exchanges or merged by others.

Fig. 3 displays the market-level distribution of observations, excluding the U.S., which we treat separately from other markets in this study. Unlike the relatively even distribution over time shown in Fig. 2, observations across non-U.S. markets are more unevenly distributed. Notably, Canada and Taiwan have substantially higher weights in the data sample compared to other non-U.S. markets. Such disparities in market representation may introduce concern about weighting biases, potentially affecting cross-market comparability. We will address this issue in Section 4.

3.2. Methodology

3.2.1. Dependent variables

The dependent variables in this research assess the precision of analyst earnings forecasts for firm i in quarter t ($Pres_{i,t}$ in Eq. (1)) using three widely recognized measures[13]: the forecast bias ($Bias_{i,t}$), the absolute forecast error ($AbsErr_{i,t}$), and the squared forecast error ($SqrErr_{i,t}$). These measures, commonly utilized in literature, offer distinct perspectives on forecast accuracy and potential biases.

$$Pres_{i,t} = \begin{cases} Bias_{i,t} \\ AbsErr_{i,t} \\ SqrErr_{i,t} \end{cases} \tag{1}$$

The forecast bias ($Bias_{i,t}$) is computed as in Eq. (2). The $Forecasted\ EPS_{i,t}$ shown in the equations is the consensus analyst earnings forecasts (variable *MEANEST* in the I/B/E/S database, which is the mean estimate of analysts) for firm i 's EPS in quarter t.[14] The $Announced\ EPS_{i,t}$ is the announced EPS for firm i in quarter t, and the $Share\ Price_{i,t}$ is the stock price for firm i at the end of quarter t. This $Bias_{i,t}$ metric captures systematic deviations between analyst earnings forecasts and actual earnings. Positive or negative bias reflects analyst tendencies to overestimate or underestimate earnings.

$$Bias_{i,t} = \frac{Forcasted\ EPS_{i,t} - Announced\ EPS_{i,t}}{Share\ Price_{i,t}} \tag{2}$$

$$AbsErr_{i,t} = \left| \frac{Forecasted\ EPS_{i,t} - Announced\ EPS_{i,t}}{Share\ Price_{i,t}} \right| \tag{3}$$

$$SqrErr_{i,t} = \left(\frac{Forecasted\ EPS_{i,t} - Announced\ EPS_{i,t}}{Share\ Price_{i,t}} \right)^2 \tag{4}$$

The absolute forecast error ($AbsErr_{i,t}$) and the squared forecast error ($SqrErr_{i,t}$) are computed as shown in Eqs. (3) and (4), respectively. Both metrics capture the magnitude of forecast errors, regardless of direction. Thus, they indicate general accuracy in terms of forecast error magnitude, with the $SqrErr_{i,t}$ giving greater weight to larger errors. To be noted that $AbsErr_{i,t}$ and $SqrErr_{i,t}$

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

[12] The classification of markets as developed or emerging is based on the MSCI (Morgan Stanley Capital International) market classification. More details can be found at: https://www.msci.com/our-solutions/indexes/market-classification.

[13] 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), among others.

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

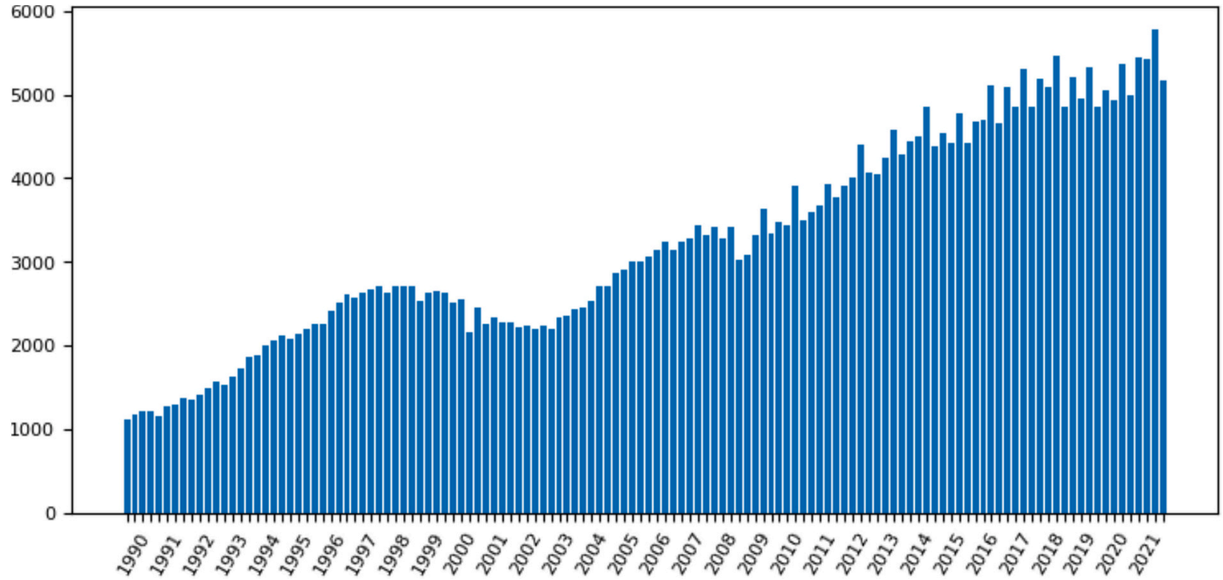

Fig. 2. Observations Distribution in Time.
This figure presents the number of observations in our data sample from 1990 to 2021.

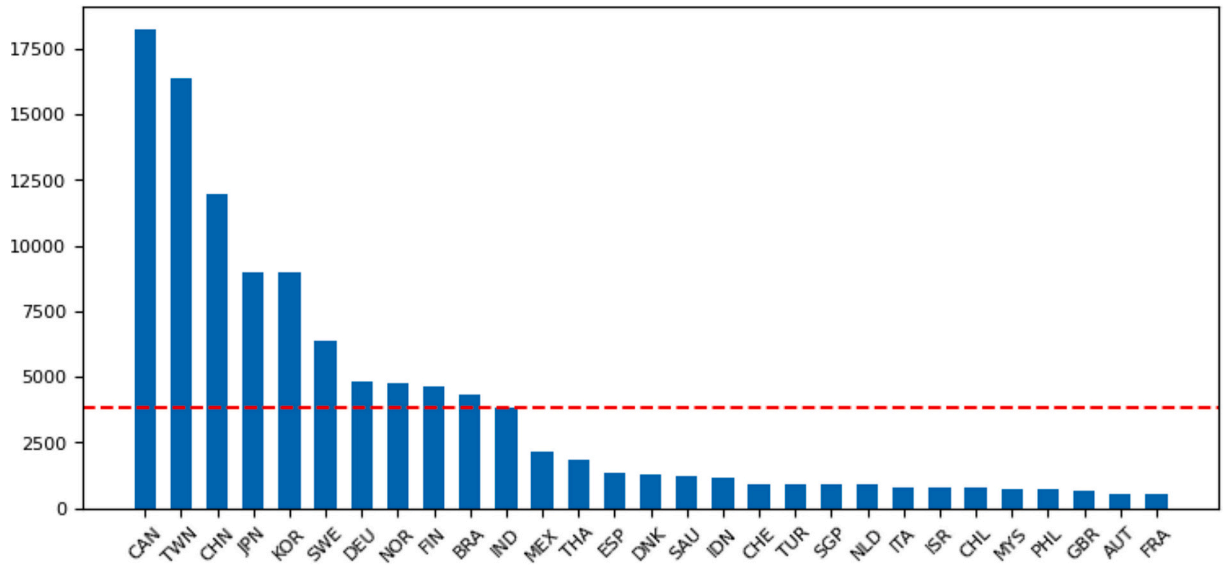

Fig. 3. Observations Distribution in Non-U.S. Markets.
This figure presents the number of observations for each market in our data sample from 1990 to 2021. The dashed line indicates the average.

represent analyst forecast errors. Thus, lower values in either measure indicate more precise analyst forecasts, as smaller error magnitudes indicate closer alignment with announced earnings.

Table 1 provides descriptive statistics for the variables used in this study, segmented to distinguish the U.S. from other markets. Panel A presents statistics for the non-U.S. markets, while Panel B covers the U.S. market. If we look at the *Bias* data, it strongly confirms the well-documented upward bias in analyst earnings forecasts (e.g., Hong & Kubik, 2003; Lim, 2001; Scherbina, 2008, among others), both in the U.S. and 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. EPU, the local EPU, and the non-U.S. Global EPU. These variables capture different dimensions of EPU across global and regional contexts, allowing us to assess their distinct impacts on analyst earnings forecast accuracy.

Table 1
Summary Statistics.

	N	Mean	Std	5 %	25 %	50 %	75 %	95 %
Panel A: Non-U.S. data sample								
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
ROA (*100)	111,551	1.22	2.94	−2.09	0.27	1.04	2.13	5.18
M/B	111,551	3.37	5.01	0.24	1.10	1.92	3.53	10.63
Size	111,551	9.60	2.89	5.17	7.63	9.26	11.37	15.09
Panel B: The U.S. data sample								
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
CapFlow	253,648	−3.04	54.54	−86.96	−43.73	−4.88	34.43	107.91
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

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

It is important to note that in our dataset, the non-U.S. Global EPU (*GlbEPU*) is derived by adjusting the original Global EPU (*OriGlbEPU*) to remove the influence of the U.S. EPU (*USEPU*).[15] Specifically, we regress *OriGlbEPU* on *USEPU* and then use the residuals (ϵ) derived from this regression as our *GlbEPU* measure, as shown in Eq. (5). This approach isolates the non-U.S. component of global economic uncertainty.

$$OriGlbEPU_t = \alpha + \beta \cdot USEPU_t + \epsilon_t \tag{5}$$

In addition, we have variable *Exp2GDP*, which is an economy's export to the U.S. scaled by the economy's GDP, as the channel for the effect of the U.S. EPU on other markets, and variable *CapFlow,* which is capital flow into the U.S., as the channel for the effect of non-U.S. Global EPU on the U.S. market.

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., Boubakri et al., 2022; Lys & Soo, 1995; Merkley et al., 2017). These control variables help to account for various factors that may influence the performance of analyst 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*), the natural logarithm of firm size (*Size*) and the world GDP growth rate (*GlbGDP*). Detailed definitions of these variables are provided in Appendix B.

4. The U.S. EPU on other market forecast performance

4.1. Baseline model

We start with the baseline model which examines how the U.S. EPU affects the performance of analyst earnings forecasts in the other 29 markets in our data sample, as discussed in Section 2.

$$Pres_{i,t} = \alpha + \beta_1 \cdot USEPU_t + \beta_2 \cdot LocEPU_{j,t} + \beta_3 \cdot Ctrl_{i,t} + FirmFE + \epsilon_{i,t} \tag{6}$$

where $Pres_{i,t}$ represents one of the three analyst earnings forecast precision measures for firm *i* in quarter *t*, as defined in Eq. (1) of

[15] The original Global EPU is the GDP weighted average of 21 market EPUs and the U.S. takes roughly 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/globalmonthly.html.

Section 3.2.1. $USEPU_t$ is the U.S. EPU index for quarter t. $LocEPU_{j,t}$ is the local EPU index of quarter t for the country j where firm i is listed.[16] $Ctrl_{i,t}$ are control variables, such as the number of analysts for firm i in quarter t ($NumEst_{i,t}$), included to account for additional influences on analyst earnings forecast precision. More control variables are introduced in Section 3.2.3. Additionally, firm fixed effects (*FirmFE*) are included to account for time-invariant firm characteristics that potentially could impact analyst earnings forecast accuracy. The error term covariance is clustered at the firm level to correct for potential within-firm correlations over time, which helps to ensure robust standard errors (Petersen, 2008).

Following previous literature, such as in Gulen and Ion (2015), Amiram et al. (2018), and Chourou et al. (2021), we do not include the time fixed effects 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 mechanically subsume the U.S. EPU, which varies over time but not in the cross-section. To partially mitigate the concerns from other confounding economic forces that may have impact on analyst earnings forecasts, we utilize the world GDP growth rate (variable *GlbGDP*) as a control variable in the regressions to work as a proxy for the summary of those economic forces.[17]

Columns (1) to (3) of Table 2 report the baseline model results with the U.S. EPU as the sole independent variable. The univariate results show that higher U.S. EPU is associated with 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, indicating that heightened U.S. EPU may contribute to greater earnings forecast errors internationally.

When control variables are added to the regressions (shown in columns (4) to (6) of Table 2), the effect of U.S. EPU remains significant for absolute forecast errors and squared forecast errors, suggesting that forecast accuracy is influenced by the U.S. EPU even when accounting for other relevant factors. However, the effect on forecast bias is no longer significant, implying that while the magnitude of forecast errors is affected, directional biases may be resilient as the errors from different directions (i.e., positive bias and negative bias) may offset each other in the aggregate. Overall, these results indicate that the U.S. EPU has a notable impact on forecast accuracy (as measured by absolute and squared forecast errors) for local firms outside the U.S., though it does not significantly affect forecast bias.

Examining the control variables in the models, our results suggest that forecast precision increases with the number of analysts (*NumEst*), which is consistent with prior literature (e.g., Lang & Lundholm, 1996). This in fact underscores the critical role of analyst coverage in reducing information asymmetry. With more analysts tracking the same firm, the diversity of expertise and greater scrutiny applied to earnings predictions likely improve forecast reliability, thus making analyst contribute to efficient information dissemination on the market.

4.2. The role of economic dependency

Now we turn our attention to the mechanism through which the U.S. EPU could affect the accuracy of analyst earnings forecasts in the non-U.S. markets. As discussed in Section 2, external uncertainty's influence on domestic analyst earnings forecasts might be linked to the extent of the domestic economy's dependency on the U.S. economy. We use *Exp2GDP*, an economy's exports to the U.S. as a percentage of its own GDP, as a proxy to capture this economic dependency.

4.2.1. The mediating effect

To explore whether economic dependency mediates the relationship between U.S. EPU and analyst forecast accuracy in non-U.S. markets, we estimate the following models:

$$Exp2GDP_{j,t} = \alpha_1 + \alpha_2 \cdot USEPU_t + \alpha_3 \cdot Ctrl_{i,t} + FirmFE + \epsilon_{i,t} \tag{7}$$

$$Pres_{i,t} = \beta_1 + \beta_2 \cdot Exp2GDP_{j,t} + \beta_3 \cdot LocEPU_{j,t} + \beta_4 \cdot Ctrl_{i,t} + FirmFE + \varepsilon_{i,t} \tag{8}$$

$$Pres_{i,t} = \gamma_1 + \gamma_2 \cdot USEPU_t + \gamma_3 \cdot Exp2GDP_{j,t} + \gamma_4 \cdot LocEPU_{j,t} + \gamma_5 \cdot Ctrl_{i,t} + FirmFE + \nu_{i,t} \tag{9}$$

where $Exp2GDP_{j,t}$ represents the export-to-GDP ratio for market j (the market where firm i is listed) in quarter t. In Eq. (7), we aim to test whether U.S. EPU (*USEPU*) is associated with the *Exp2GDP* in non-U.S. markets, with the coefficient α_2 capturing this effect. Eq. (8) examines the association between *Exp2GDP* and analyst earnings forecast precisions in non-U.S. markets, where the coefficient β_2 reflects this relationship. Finally, in Eq. (9), we verify the mediating role of economic dependency in the relationship between U.S. EPU and the precision of analyst earnings forecasts for non-U.S. markets. If economic dependency indeed serves as a mediator, as hypothesized, we expect the coefficient γ_3 to be statistically significant.

The regression results are presented in columns (1) to (7) of Table 3. First, column (1) demonstrates that *USEPU* is significantly associated with a market's *Exp2GDP*. Second, columns (2) to (4) indicate that increased *Exp2GDP* is associated with larger bias/errors in analyst earnings forecasts in non-U.S. markets, as evidenced by the significantly positive coefficients across all three measures. Lastly, in columns (5) to (7), which include both *USEPU* and *Exp2GDP*, the coefficients for *Exp2GDP* remain significantly positive, though its effect weakens slightly. These results provide evidence for a mediating role of *Exp2GDP*, suggesting that trade dependency

[16] In fact, it controls for the potential spillover effect from the U.S. EPU to local EPU.

[17] We thank an anonymous referee for suggesting this approach.

Table 2
The U.S. EPU on Earnings Forecast Accuracy in Other Markets - Baseline Model.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr
Intercept	0.0030***	0.0109***	0.0013***	0.0040	0.0024	−0.0006
	(7.3619)	(30.550)	(15.660)	(0.7330)	(0.4419)	(−0.5346)
USEPU	1.415e-05***	3.183e-05***	4.572e-06***	7.804e-07	1.703e-05***	2.029e-06***
	(5.4594)	(14.225)	(8.8472)	(0.2551)	(6.3963)	(3.2366)
LocEPU				9.758e-07	2.600e-06*	1.258e-08
				(0.5760)	(1.7752)	(0.0395)
NumEst				−0.0001	−0.0008***	−0.0001***
				(−0.9957)	(−6.1867)	(−3.7930)
M/B				0.0005***	−0.0004***	−3.253e-05*
				(4.4618)	(−4.5965)	(−1.9592)
ROA				−0.7366***	−0.1818***	−0.0427***
				(−24.568)	(−11.798)	(−10.942)
Size				0.0009	0.0018***	0.0004***
				(1.4089)	(3.0333)	(2.8526)
GlbGDP				0.0106	−0.0389***	−0.0069***
				(1.3075)	(−6.4721)	(−4.9686)
No. Obs.	111,551	111,551	111,551	111,551	111,551	111,551
R-squared	0.0004	0.0050	0.0018	0.1720	0.0380	0.0294
F-statistic	43.1	538.8	194.0	3153.9	599.1	460.2
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Clustered	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the regression results of the baseline model when checking the U.S. EPU's effect on other market analyst earnings forecasts. Columns (1)–(3) are the results for the univariate analysis, while columns (4)–(6) are the results for the multivariate analysis. The dependent variable for each column 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.

on the U.S. channels the effects of U.S. uncertainty into domestic analyst forecast performance.

4.2.2. The moderating effect

We further assess whether *Exp2GDP* moderates the relationship between the U.S. EPU and analyst forecast accuracy in non-U.S. markets. Specifically, we include an interaction term between *Exp2GDP* and *USEPU* in the following model:

$$\begin{aligned} Pres_{i,t} = \alpha + \beta_1 \cdot USEPU_t + \beta_2 \cdot Exp2GDP_{j,t} \cdot USEPU_t + \beta_3 \cdot Exp2GDP_{j,t} \\ + \beta_4 \cdot LocEPU_{j,t} + \beta_5 \cdot Ctrl_{i,t} + FirmFE + \epsilon_{i,t} \end{aligned} \tag{10}$$

This specification allows the effect of *USEPU* on analyst forecast accuracy to vary with levels of *Exp2GDP*. Rearranging terms reveals that the coefficient for *USEPU* is given by ($\beta_1 + \beta_2 \cdot Exp2GDP$), meaning that countries with higher economic dependency on the U.S. experience greater analyst forecast errors in response to U.S. uncertainty. This interaction suggests that *Exp2GDP* is crucial in shaping the "sensitivity" of the relationship between the U.S. EPU and domestic analyst earnings forecast errors. Put differently, while the *Exp2GDP* itself may not have a direct effect on analyst forecast errors (if β_3 is insignificant), it can nonetheless influence the strength of the U.S. EPU - forecast error relationship (if β_2 is significant) via the moderating role. In this context, a higher *Exp2GDP* would amplify the impact of the U.S. EPU on analyst earnings forecast errors in non-U.S. markets, indicating that markets more economically dependent on the U.S. are more sensitive to U.S. EPU.

The regression results for the proposed moderating effect are presented in columns (8) to (10) of Table 3. Our results show that the coefficient of the intersection term *Exp2GDP·USEPU* is significantly positive for both absolute forecast errors and squared forecast errors, while the effect on forecast bias is not significant. This finding suggests that the extent of an economy's exports to the U.S. serves as a moderating factor, influencing the precision of earnings forecasts in response to U.S. EPU for stocks outside the U.S. In other words, the greater an economy's dependency on the U.S. (as measured by *Exp2GDP*), the more pronounced the impact of U.S. EPU on the accuracy of analyst earnings forecasts within that market. This aligns with the hypothesis that stronger economic ties to the U.S. amplify the transmission of U.S. uncertainty to other markets.

4.2.3. The coexistence of mediation and moderation

Our empirical results reveal that *Exp2GDP* acts as both a mediator and a moderator in the relationship between the U.S. EPU and analyst forecast accuracy in non-U.S. markets. As a mediator, it explains how economic dependency transmits U.S. uncertainty into forecast errors, while as a moderator, it explains the heterogeneity in this relationship across markets with varying levels of trade dependency. These dual roles highlight how economic dependency shapes the global transmission of U.S. uncertainty. It is important to note that the mediating and moderating effects are not mutually exclusive. While mediation highlights the pathway through which economic dependency links U.S. uncertainty to domestic forecast errors, moderation emphasizes how the strength of this relationship depends on the level of economic dependency. Together, they provide a comprehensive understanding of how U.S. policy uncertainty spreads globally, underscoring the importance of considering both mechanisms when assessing the international impact of U.S.

Table 3
The U.S. EPU on Earnings Forecast Accuracy in Other Markets - Channel Analysis.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. Variable	Exp2GDP	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr
Intercept	0.0908***	−0.0002	−0.0009	−0.0012	−0.0002	−0.0003	−0.0011	−0.0003	−0.0011	−0.0013
	(6.1087)	(−0.0379)	(−0.1517)	(−0.9293)	(−0.0403)	(−0.0581)	(−0.8813)	(−0.0573)	(−0.1754)	(−0.9842)
USEPU	2.611e-05***				−4.397e-07	1.624e-05***	1.880e-06***	−2.591e-07	1.747e-05***	2.132e-06***
	(11.551)				(−0.1412)	(6.1086)	(3.0225)	(−0.0829)	(6.5057)	(3.3726)
Exp2GDP		0.0466***	0.0365**	0.0064*	0.0467***	0.0304*	0.0057	0.0476***	0.0361**	0.0069*
		(2.8763)	(2.1836)	(1.8294)	(2.8546)	(1.8351)	(1.6408)	(2.9185)	(2.1470)	(1.9070)
USEPU*Exp2GDP								2.775e-05	0.0002***	3.742e-05***
								(0.6303)	(4.1457)	(3.4127)
LocEPU	−1.914e-05***	1.762e-6	7.170e-6***	5.84-e-07*	1.87e-06	3.183e-06**	1.224e-07	1.744e-06	2.321e-06	−4.739e-08
	(−8.1573)	(1.0727)	(5.0076)	(1.8735)	(1.1569)	(2.2622)	(0.4011)	(1.0864)	(1.6254)	(−0.1518)
NumEst	−0.0005***	−0.0001	−0.0007***	−0.0001*	−0.0001	−0.0007***	−0.0001***	−0.0001	−0.0007***	−0.0001***
	(−4.0212)	(−0.8426)	(−5.9989)	(−3.6611)	(−0.8427)	(−6.0654)	(−3.6947)	(−0.8443)	(−6.0840)	(−3.7064)
M/B	−7.454e-05	0.0005***	−0.0004***	−3.127e-05*	0.0005***	−0.0004***	−3.210e-05*	0.0005***	−0.0004***	−3.174e-05*
	(−1.2011)	(4.4923)	(−4.4778)	(−1.8823)	(4.4996)	(−4.5703)	(−1.9330)	(4.5032)	(−4.5618)	(−1.9168)
ROA	0.0086**	−0.7370***	−0.1824***	−0.0427***	−0.7370***	−0.1821***	−0.0427***	−0.7370***	−0.1824***	−0.0428***
	(2.4813)	(−24.593)	(−11.829)	(−10.961)	(−24.595)	(−11.802)	(−10.947)	(−24.597)	(−11.835)	(−10.971)
Size	−0.0023	0.0010	0.0022***	0.0004***	0.0010	0.0019***	0.0004***	0.0010	0.0019***	0.0004***
	(−1.4378)	(1.5733)	(3.5842)	(3.1682)	(1.5563)	(3.1244)	(2.9018)	(1.5653)	(3.1878)	(2.9575)
GlbGDP	0.0961***	0.0067	−0.0656***	−0.0102***	0.0061	−0.0419***	−0.0075***	0.0060	−0.0427***	−0.0077***
	(19.347)	(0.9524)	(−11.787)	(−7.9135)	(0.7271)	(−6.7458)	(−5.2154)	(0.7107)	(−6.8670)	(−5.3149)
No. Obs.	111,551	111,551	111,551	111,551	111,551	111,551	111,551	111,551	111,551	111,551
R-squared	0.0493	0.1721	0.0374	0.0294	0.1721	0.0381	0.0295	0.1721	0.0388	0.0300
F-statistic	787.6	3157.4	590.7	459.3	2762.7	526.6	404.2	2455.9	477.1	365.2
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the regression results of the channel analysis when checking the U.S. EPU's effect on other market analyst earnings forecasts. Columns (1)–(7) are the results for the mediation effect, while columns (8)–(10) are the results for the moderation effect. The dependent variable for each column 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.

economic shocks.

In fact, a closer examination of model (10) reveals that it can capture both effects, given the relationships in models (7) and (8) are both confirmed. Specifically, with some rearrangements, the coefficient for *Exp2GDP* in model (10) can be expressed as ($\beta_3 + \beta_2 \cdot USEPU$), where β_3 captures the direct impact (mediating effect) from *Exp2GDP* and $\beta_2 \cdot USEPU$ captures the indirect impact (moderating effect) from *Exp2GDP*. A natural question arises: which effect predominates in this case? To explore this, we evaluate $\beta_2 \cdot USEPU$ using the mean value of *USEPU*, which is approximately 160. Multiplying β_2 by 160 and comparing it with β_3 reveals that both effects are of similar magnitude for absolute and squared forecast errors, suggesting that, on average, they are equally important. However, this relationship is not static and it varies with the actual level of *USEPU*: the moderating effect may be stronger when *USEPU* is high; while the mediating effect may be stronger when *USEPU* is low.

Taken together, the evidence suggests that analyst forecast errors in non-U.S. markets are not uniformly affected by U.S. EPU. An assessment of the influence of the U.S. EPU on analyst earnings forecast errors should take into account the cross-sectional differences in one economy's trade dependency on the U.S. However, we do not claim that the trade dependency is the only factor that channels the effects of the U.S. EPU on other market analyst earnings forecast accuracy. Rather, our findings highlight that average estimates may obscure significant cross-sectional variations in how U.S. EPU influences non-U.S. market analyst forecast accuracy.

4.3. Robustness

4.3.1. Developed vs. developing markets

As discussed in Section 4.2.3, given the relationships in models (7) and (8) are confirmed, model (10) inherently incorporates tests for both mediating and moderating effects. For the sake of brevity, we present the explicit tests for models (7) to (9) in Appendix C, while focusing primarily on model (10) in the following robustness tests.

We start by examining if our results are affected by the difference in market settings such as the variation in market participants and structural characteristics across exchanges. To assess this, we categorize the 29 non-U.S. economies into two groups based on economic development following the MSCI classification: 17 developed markets and 12 emerging markets. We then re-estimate our models for each group, with results presented in Table 4.

Overall, the key conclusions remain the same, that is, the U.S. EPU is negatively associated with the analyst earnings forecast precision in other markets, and one important channel is the economic dependency of the economy on the U.S. Notably, while the moderating effect is significant for both developed and developing markets, the mediating effect appears significant only for developing markets. Overall, this robustness across diverse markets reinforces our findings, underscoring the pervasive influence of the U.S.

Table 4
The U.S. EPU on Earnings Forecast Accuracy in Other Markets - Developed vs. Developing.

	Developed Markets			Developing Markets		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr
Intercept	−0.0127	0.0161*	0.0009	0.0064	−0.0188***	−0.0020***
	(−1.2882)	(1.9105)	(0.4820)	(1.2918)	(−3.5460)	(−3.5599)
USEPU	2.950e-06	1.978e-05***	2.610e-06***	1.611e-06	1.126e-05***	7.712e-07***
	(0.6024)	(5.1201)	(2.8366)	(0.6652)	(5.2654)	(3.2361)
Exp2GDP	0.0820***	0.0218	0.0039	−0.0018	0.0416**	0.0042*
	(3.1949)	(1.2158)	(1.0661)	(−0.1241)	(2.4010)	(2.1815)
USEPU*Exp2GDP	0.0001**	0.0002***	3.324e-05***	4.546e-06	0.0001**	1.300e-05*
	(2.1030)	(3.7706)	(3.1491)	(0.0868)	(1.9708)	(1.8099)
LocEPU	−4.567e-06	2.100e-06	−2.881e-07	3.403e-06***	2.303e-06**	6.158e-08
	(−1.0471)	(0.5895)	(−0.3465)	(3.1036)	(2.2307)	(0.5867)
NumEst	−0.0004*	−0.0008***	0.0001***	0.0001	−0.0006***	−4.828e-05***
	(−1.8757)	(−4.9662)	(−3.0998)	(1.1705)	(−4.9206)	(−3.6211)
M/B	0.0003*	−0.0008***	−0.0001***	0.0005***	−0.0002***	−8.468e-06
	(1.7916)	(−5.7641)	(−3.6399)	(5.5688)	(−2.9620)	(−1.2804)
ROA	−0.7574***	−0.1830***	−0.0426***	−0.5359***	−0.0764***	−0.0075***
	(−20.144)	(−10.065)	(−9.3231)	(−20.925)	(−5.0688)	(−4.2464)
Size	0.0023**	0.0007	0.0003	0.0001	0.0028***	0.0002***
	(2.2819)	(0.7828)	(1.2644)	(0.2018)	(5.4518)	(4.7355)
GlbGDP	−0.0053	−0.0574***	−0.0089***	0.0214***	−0.0122**	−0.0018***
	(−0.4171)	(−6.4031)	(−4.2767)	(3.2038)	(−2.4540)	(−3.1717)
No. Obs.	65,617	65,617	65,617	45,934	45,934	45,934
R-squared	0.1826	0.0405	0.0306	0.1311	0.0321	0.0175
F-statistic	1555.5	293.6	219.8	731.3	161.0	86.3
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Clustered	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the regression results for the robustness checks when checking the U.S. EPU's effect on other market analyst earnings forecasts. Columns (1)–(3) are the results for the developed markets, while columns (4)–(6) are the results for the developing markets. The dependent variable for each column 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.

EPU on global financial forecasts.

4.3.2. Excluding Canada and Taiwan firms

As shown in Fig. 3, 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 emerging markets, respectively. To rule out the possibility that our previous results are mainly driven by the data from these two markets, we re-estimate our models by excluding Canadian and Taiwanese firms from the sample, which helps control for potential biases introduced by those over- represented markets.

The regression results, presented in columns (1) to (3) of Table 5, demonstrate that our main conclusions remain robust even after removing data from the markets with the highest observations.[18] This consistency suggests that the observed relationships are not merely artifacts of particular markets but rather reflect a broader pattern across diverse markets.

4.3.3. Subsamples based on economic dependency

The difference in the trade dependency on the U.S. can be large across different non-U.S. markets. Fig. 4 shows the average *Exp2GDP* ratios for different economies examined in this study. Indeed, this figure has reflected the gravity theory of trade (e.g., Anderson & van Wincoop, 2003; Shepherd, 2016; Tinbergen, 1962), which posits that trade between countries is proportional to their economic size and inversely proportional to the distance between them. For example, in terms of distance, as Canada and Mexico are closest to the U.S., they have the largest *Exp2GDP* ratios. Meanwhile, China shows a moderate-to-large *Exp2GDP* ratio, influenced by its substantial economic size, among other factors.

Based on our discussion in Section 2, if the trade dependency (*Exp2GDP*) factor is important, we should also observe similar results with small subsamples. Additionally, for the moderating effect to be relevant, the subsample should exhibit cross-sectional variation in trade dependency. To confirm this, we conduct two subsample tests.[19]

Our first subsample consists of two economies (Mexico and Canada) with the highest trade dependency on the U.S. and other two economies (Turkey and Spain) with the lowest trade dependency on the U.S. This subsample includes a total of 22,627 firm-quarters, representing approximately 20 % of the entire non-U.S. sample. The results for this subsample are presented in columns (4) to (6) of Table 5 and generally align with findings from the full sample. Notably, the coefficients for *USEPU, Exp2GDP* and $Exp2GDP \cdot USEPU$ are all considerably larger than those in the full sample results, suggesting a stronger effect within this subsample, possibly due to the substantial cross-sectional variation across those four markets.

To further investigate, we conduct an additional subsample test on two large economies with varying levels of dependency on the U.S. Specifically, we examine China, an influential emerging market with recent trade tensions with the U.S., and Canada, a developed market with consistently strong trade ties to the U.S. This allows us to assess whether the trade dependency channel observed in our full sample holds in this targeted subsample, which includes variation in trade relationships with the U.S. The results, presented in columns (7) to (9) of Table 5, closely align with those from the full sample, though the mediating effect does not appear significant for those two forecast errors. Overall, these findings further support the role of economic dependency as a channel linking the U.S. EPU to analyst forecast accuracy in other markets.

5. Non-U.S. Global EPU on U.S. market forecasts performance

5.1. Baseline model

Now, we turn to examine whether and how the non-U.S. Global EPU affects analyst earnings forecast precision in the U.S. market. To our best knowledge, there is no direct Global EPU index excluding the U.S. within the available data. The original Global EPU is a GDP-weighted average of 21 market EPUs, with the U.S. alone comprising roughly 25 % of this weight, which is a significant proportion for a single market. To construct a Global EPU measure orthogonal to the U.S. EPU, we regress the original Global EPU on the U.S. EPU and use the residuals from this regression as our non-U.S. Global EPU measure, as shown in Eq. (5).

To verify the correlation between the non-U.S. Global EPU (*GlbEPU*) and the U.S. EPU, Table 6 presents their correlation along with correlations with several other key variables. The results indicate that *GlbEPU* and the U.S. EPU are essentially uncorrelated, suggesting that *GlbEPU* is a relatively clean measure in this study. In addition, the results show that capital flow into the U.S. (*CapFlow*) is positively correlated with non-U.S. Global EPU.

To establish the relationship between the non-U.S. Global EPU and analyst earnings forecast precision in the U.S. market, as discussed in Section 2, we estimate the following model:

$$PresUS_{i,t} = \alpha + \beta_1 \cdot GlbEPU_t + \beta_2 \cdot USEPU_t + \beta_3 \cdot Ctrl_{i,t} + FirmFE + \epsilon_{i,t} \tag{11}$$

The dependent variable ($PresUS_{i,t}$) is refer to those three analyst forecast precision measures ($Bias_{i,t}$, $AbsErr_{i,t}$, and $SqrErr_{i,t}$) for firm i in quarter t in the U.S. market. We anticipate β_1 to reflect the direction and magnitude of the impact of non-U.S. Global EPU on the performance of analyst earnings forecast in the U.S. market.

The baseline model results, presented in Table 7, reveal an interesting contrast with previous findings on the U.S. EPU. While a

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

[19] We thank an anonymous referee for suggesting such a subsample test, which helps us make the results more plausible in this study.

Table 5
The U.S. EPU on Earnings Forecast Accuracy in Other Markets - Subsamples.

	Excluding CAN and TWN			4 Markets: MEX, CAN, TUR, and ESP			2 Markets: CAN and CHN		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Variable	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr
Intercept	0.0050	−0.0113	−0.0027	−0.0190	−0.0109	−0.0033	−0.0340***	0.0071	0.0007
	(0.6723)	(−1.3674)	(−1.4789)	(−1.4058)	(−0.9049)	(−1.2516)	(−4.0789)	(1.3885)	(0.8689)
USEPU	−2.832e-06	1.482e-05***	1.431e-06*	1.060e-05	4.230e-05***	7.200e-06***	6.573e-06*	2.139e-05***	2.525e-06***
	(−0.7380)	(4.4684)	(1.8127)	(1.2806)	(5.1860)	(3.6533)	(1.8674)	(6.6405)	(5.3544)
Exp2GDP	0.0324	0.0718**	0.0139**	0.0526**	0.0625**	0.0146**	0.0717***	0.0022	0.0019
	(1.2765)	(2.4266)	(2.0180)	(1.9635)	(2.1753)	(2.1476)	3.4636	(0.1403)	(0.7475)
USEPU*Exp2GDP	−1.923e-05	0.0003***	5.894e-05**	7.669e-05	0.0003***	6.330e-05***	6.773e-05*	0.0002***	2.878e-05***
	(−0.2125)	(2.6942)	(2.0886)	(0.9937)	(3.6229)	(3.4993)	(1.7872)	(6.7461)	(6.0734)
LocEPU	4.084e-06**	2.859e-06*	1.759e-07	−6.008e-06	−2.496e-06	−7.689e-07	9.001e-07	3.229e-06***	2.742e-07**
	(2.4264)	(1.8275)	(0.4984)	(−0.8468)	(−0.5578)	(−0.8170)	(0.5824)	(3.1677)	(2.0292)
NumEst	−0.0005**	−0.0010***	−0.0002***	2.759e-05	−0.0005**	−5.373e-05	4.017e-06	−0.0004***	−1.814e-05
	(−2.1787)	(−5.6508)	(−3.5077)	(0.0880)	(−2.4732)	(−1.0763)	(0.0177)	(−2.6809)	(−0.7470)
M/B	0.0005***	−0.0003***	−2.366e-05	0.0010***	−0.0015***	−0.0002***	0.0007***	−0.0009***	−7.23e-05***
	(4.1167)	(−3.4531)	(−1.2972)	(3.0670)	(−5.2681)	(−3.3506)	(5.0165)	(−7.3599)	(−4.0328)
ROA	−0.7450***	−0.1706***	−0.0412***	−0.8289***	−0.1756***	−0.0394***	−0.6513***	−0.1662***	−0.0247***
	(−20.190)	(−8.3455)	(−8.1105)	(−12.325)	(−6.5289)	(−5.5133)	(−14.232)	(−8.7300)	(−7.3869)
Size	0.0008	0.0029***	0.0005***	0.0021	0.0029**	0.0005*	0.0036***	0.0008*	1.638e-05
	(1.0940)	(3.6659)	(3.0034)	(1.3330)	(2.4074)	(1.8244)	(4.1830)	(1.6696)	(0.2279)
World	−0.0034	−0.0482***	−0.0090***	−0.0029	−0.0878***	−0.0152***	0.0077	−0.0269***	−0.0033**
	(−0.3301)	(−6.5706)	(−5.2382)	(−0.1515)	(−5.1301)	(−3.7080)	(0.7811)	(−3.1864)	(−2.4610)
No. Obs.	76,987	76,987	76,987	22,607	22,607	22,607	30,156	30,156	30,156
R-squared	0.1409	0.0321	0.0239	0.2500	0.0560	0.0386	0.2648	0.0675	0.0512
F-statistic	1336.0	270.6	199.8	799.1	142.1	96.3	1142.3	229.4	171.1
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the regression results for the robustness checks when checking the U.S. EPU's effect on other market analyst earnings forecasts. Columns (1)–(3) are the results when the Canada and Taiwan data are excluded from the data sample. Columns (4)–(6) are the results for the 4 markets (MEX, CAN, TUR, and ESP) subsample, while columns (7)–(9) are the results for the 2 markets (CAN and CHN) subsample. The dependent variable for each column 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.

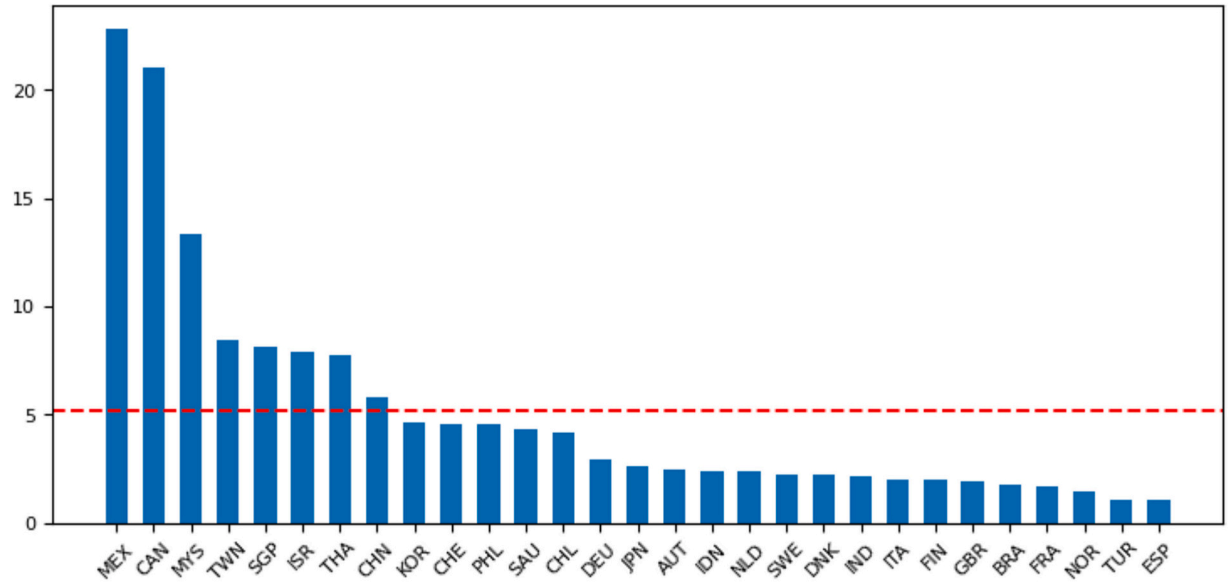

Fig. 4. *Exp2GDP* in Non-U.S. Markets.
This figure presents the average *Exp2GDP* (in percentage) for each non-U.S. market in our sample from 1990 to 2021. The dashed line indicates the average.

Table 6
EPU and U.S. Earnings Forecast Accuracy – Correlations.

	USEPU	GlbEPU	CapFlow	Bias	AbsErr	SqrErr
USEPU	1.000	−0.047	0.088	−0.000	0.047	0.027
GlbEPU	−0.047	1.000	0.109	−0.011	0.009	0.009
CapFlow	0.088	0.109	1.000	−0.013	−0.003	−0.006
Bias	−0.000	−0.011	−0.013	1.000	0.412	0.429
AbsErr	0.047	0.009	−0.003	0.412	1.000	0.965
SqrErr	0.027	0.009	−0.006	0.429	0.965	1.000

This table presents the correlations among several key variables when checking the non-U.S. Global EPU's effect on U.S. market analyst 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.

higher U.S. EPU has been associated with increased forecast errors for analysts in other markets, our results here indicate that an increase in non-U.S. Global EPU is associated with a significant decrease in analyst forecast errors for stocks listed in the U.S. market. This relationship is evident in both the univariate analysis (columns (1) to (3)) and the multivariate analysis that incorporates control variables (columns (4) to (6)).

Furthermore, the increase in non-U.S. Global EPU is also linked to a reduction in analyst forecast bias. Analysts are known to often provide overly optimistic earnings forecasts (positive bias), as highlighted in studies such as Hong and Kubik (2003) and Dong et al. (2021). This observed reduction in bias when uncertainty out of the U.S. heightened indicates that analysts may become more cautious and less overly optimistic in their predictions. We believe this shift in bias can be interpreted as an improvement in their forecast precision. This conclusion is particularly compelling when considering the concurrent decrease in forecast errors, which collectively suggest enhanced forecast accuracy under higher non-U.S. Global EPU.

5.2. The role of capital flows

As discussed in Section 2, the real economy channel suggests a negative relationship between non-U.S. EPU and analyst forecast accuracy in the U.S., while the capital market channel probably indicates a positive effect. Since the results from the baseline model reveal a net positive relationship, it suggests that the capital market channel dominates the real economy channel. In line with our expectations from Section 2, we propose that capital flows into the U.S. serve as a mediator in the relationship between non-U.S. Global EPU and analyst earnings forecast accuracy within the U.S. market. To verify this, we conduct the following mediation test by estimating the models below:

$$CapFlow_t = \alpha_1 + \alpha_2 \cdot GlbEPU_t + \alpha_3 \cdot Ctrl_{i,t} + FirmFE + \epsilon_{i,t} \tag{12}$$

Table 7
Non-U.S. Global EPU on Earnings Forecast Accuracy in the U.S. Market - Baseline Model.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr
Intercept	0.0038***	0.0147***	0.0024***	−0.0157***	0.0059***	−0.0003
	(492.57)	(1868.9)	(1138.1)	(−7.3611)	(3.3550)	(−0.6533)
GlbEPU	−2.546e-05***	−4.470e-05***	−9.456e-06***	−1.569e-05***	−1.802e-05***	−5.171e-06***
	(−6.5202)	(−11.269)	(−8.7884)	(−3.0789)	(−3.9420)	(−4.2547)
USEPU				3.560e-06	1.03e-05***	−7.576e-08
				(1.2584)	(4.0947)	(−0.1116)
NumEst				−0.0003***	−0.0007***	−0.0001***
				(−6.2875)	(−13.682)	(−10.416)
M/B				−5.302e-05	−0.0004***	−6.868e-05***
				(−1.5735)	(−15.346)	(−10.500)
ROA				−0.0633***	−0.0441***	−0.0128***
				(−18.698)	(−22.333)	(−21.422)
Size				0.0026***	0.0021***	0.0006***
				(7.3855)	(6.9401)	(6.6952)
GlbGDP				−0.0204***	−0.1079***	−0.0202***
				(−2.6314)	(−18.074)	(−12.324)
No. Obs.	253,648	253,648	253,648	253,648	253,648	253,648
R-squared	0.0002	0.0018	0.0010	0.0715	0.0944	0.0942
F-statistic	59.9	440.2	252.4	2692.3	3646.3	3640.3
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Clustered	Yes	Yes	Yes	Yes	Yes	Yes

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

$$PresUS_{i,t} = \beta_1 + \beta_2 \cdot CapFlow_t + \beta_3 \cdot USEPU_t + \beta_4 \cdot Ctrl_{i,t} + FirmFE + \varepsilon_{i,t} \tag{13}$$

$$PresUS_{i,t} = \gamma_1 + \gamma_2 \cdot CapFlow_t + \gamma_3 \cdot GlbEPU_t + \gamma_4 \cdot USEPU_t + \gamma_5 \cdot Ctrl_{i,t} + FirmFE + \nu_{i,t} \tag{14}$$

In Eq. (12), we aim to test whether non-U.S. Global EPU (*GlbEPU*) affects capital flows into the U.S. (*CapFlow*), with the coefficient α_2 capturing this effect. Eq. (13) examines the association between capital flows and analyst earnings forecasts precision in the U.S., where the coefficient β_2 reflects this relationship. Finally, in Eq. (14), we verify the mediating role of capital flows in the relationship between non-U.S. Global EPU and the precision of analyst earnings forecasts for U.S.-listed stocks. If capital flows indeed serves as a mediator, as hypothesized, we expect the coefficient γ_2 to be significantly negative. In this study, *CapFlow* (capital flows into the U.S.) is measured by cash flows from the financial account of the U.S. balance of payments, adjusted by cash flows from the current account.[20]

The regression results are presented in Table 8. First, column (1) demonstrates that a higher non-U.S. Global EPU significantly increases capital flows into the U.S. market. Second, columns (2) to (4) indicate that increased capital inflows are associated with higher precision in analyst earnings forecasts, as evidenced by the significantly negative coefficients across all three precision measures. Lastly, in regressions (5) to (7), which include both non-U.S. Global EPU and capital flow, the coefficients for capital flow remain significantly negative. These findings suggest that non-U.S. Global EPU prompts capital flows into the U.S. market, likely due to an improved information environment and enhanced price efficiency from which analysts can extract information, ultimately enhancing the precision of analyst earnings forecasts.

In this context, a natural question arises: beyond its role as a mediator, could capital flows also serve as a moderator in the relationship between non-U.S. Global EPU and analyst forecast accuracy in the U.S. market? To explore this, we conduct regression analyses for a moderating effect. The results presented in Appendix D show that the coefficients for the interaction term ($GlbEPU \cdot CapFlow$), which captures the moderating effect, are statistically insignificant across regressions using the three precision measures as dependent variables.

Given our empirical results, it seems that capital flows do not act as a moderator in the relationship between non-U.S. Global EPU and analyst forecast accuracy in the U.S. market. A moderator, by definition, reflects varying responses across firms or markets, implying that capital flow data should exhibit cross-sectional differences at time *t* to validate such an effect, if present. However, in the context of non-U.S. Global EPU and the earnings forecast accuracy in the U.S. market, we only have a country-level capital flow data point for the U.S., which remains constant across U.S. firms at time *t*. This absence of cross-sectional variation prevents us from distinguishing firm-specific responses. Instead, a unified response, as suggested by the mediating effect, seems more appropriate in this case.

[20] This adjustment addresses the concern that financial account cash flows might simply reflect balance of payments artifacts, given the high theoretical correlation between financial and current accounts. For instance, the U.S., which often runs a current account deficit, typically finances these deficits through capital inflows recorded in the financial account. This adjustment helps ensure that the *CapFlow* measure more accurately captures the net capital movement into the U.S., independent of influences from the current account.

Table 8
Non-U.S. Global EPU on Earnings Forecast Accuracy in the U.S. Market - Channel Analysis.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	CapFlow	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr
Intercept	15.439***	−0.0139***	0.0079***	0.0003	−0.0156***	0.0059***	−0.0003
	(13.160)	(−7.4638)	(4.9121)	(0.6440)	(−7.3246)	(3.3885)	(−0.6242)
GlbEPU	0.2227***				−1.447e-05***	−1.708e-05***	−4.977e-06***
	(63.841)				(−2.8459)	(−3.6996)	(−4.0592)
CapFlow		−6.269e-06***	−5.150e-06***	−1.139e-06***	−5.493e-06***	−4.234e-06***	−8.717e-07***
		(−3.6909)	(−5.0165)	(−3.8700)	(−3.2742)	(−4.0297)	(−2.9131)
USEPU	0.0832***	6.782e-06***	1.392e-05***	9.478e-07*	4.017e-06	1.066e-05***	−3.238e-09
	(68.331)	(2.7579)	(7.1128)	(1.7745)	(1.4261)	(4.2172)	(−0.0048)
NumEst	0.4045***	−0.0003***	−0.0007***	−0.0001***	−0.0003***	−0.0007***	−0.0001***
	(11.826)	(−6.0931)	(−13.520)	(−10.250)	(−6.2358)	(−13.649)	(−10.386)
M/B	0.0666***	−5.572e-05*	−0.0004***	−6.968e-05***	−5.265e-05	−0.0004***	−6.683e-05***
	(2.9246)	(−1.6545)	(−15.451)	(−10.628)	(−1.5628)	(−15.337)	(−10.492)
ROA	0.2404	−0.0634***	−0.0441***	−0.0129***	−0.0633***	−0.0441***	−0.0128***
	(0.4514)	(−18.735)	(−22.324)	(−21.410)	(−18.701)	(−22.329)	(−21.419)
Size	−5.2056***	0.0023***	0.0017***	0.0004***	0.0026***	0.0021***	0.0005***
	(−27.996)	(7.4817)	(6.3939)	(6.1402)	(7.3121)	(6.8526)	(6.6255)
GlbGDP	107.17***	−0.0203***	−0.1080***	−0.0203***	−0.0198**	−0.1074***	−0.0201***
	(21.597)	(−2.6196)	(−18.011)	(−12.307)	(−2.5587)	(−18.027)	(−12.287)
No. Obs.	253,648	253,648	253,648	253,648	253,648	253,648	253,648
R-squared	0.0139	0.0714	0.0942	0.0941	0.0715	0.0944	0.0943
F-statistic	491.9	2691.3	3639.8	3632.0	2357.1	3192.5	3186.3
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the regression results of the channel analysis when checking the non-U.S. Global EPU's effect on U.S. market analyst earnings forecasts. Column (1) shows the results of how *GlbEPU* affects *CapFlow*. Columns (2)–(4) are the results showing how *CapFlow* affect analyst earnings forecasts without controlling for *GlbEPU*, while columns (5)–(7) are similar regressions but controlling for *GlbEPU*. The dependent variable for each column 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.

5.3. Robustness

As a robustness check, we now use the total cash flows from the financial account balance of payments (unadjusted by cash flows from current account) as an alternative measure for *CapFlow*, representing the total actual capital flows into the U.S. The robustness check results are presented in Table 9. In summary, the results presented in Table 9 are similar to our main results presented in Table 8, which confirms that capital flow is a mediator in our channel analysis.

In the results presented so far, we derive the non-U.S. Global EPU (*GlbEPU*) by regressing the original Global EPU (*OriGlbEPU*) on the U.S. EPU (*USEPU*) with an intercept, as shown in Eq. (5). One may argue that the intercept (α) may present a consistent bias in the relationship between *OriGlbEPU* and *USEPU*. We address this concern by estimating an alternative model without an intercept, as shown in Eq. (15):

$$OriGlbEPU_t = \gamma \cdot USEPU_t + \nu_t \tag{15}$$

where ν_t serves as an alternative measure for non-U.S. Global EPU. We obtain similar results. For brevity, detailed results are not presented here.

6. Conclusion

In this study, we investigate the relationship between foreign EPU and domestic analyst earnings forecasts. Our findings indicate that an increase in the U.S. EPU is associated with decreased accuracy in analyst earnings forecasts for non-U.S. firms. Furthermore, we examine the mechanism about this relationship and identify economic dependency as a significant channel. Notably, our results remain robust across a series of tests.

Next, we examine the effect of non-U.S. Global EPU on the precision of analyst earnings forecasts for the U.S.-listed stocks. Our findings demonstrate that higher non-U.S. Global EPU is associated with a significant increase in analyst earnings forecasts precisions. Further analysis suggests that this effect is linked to capital flows, where increased non-U.S. Global EPU appears to drive capital back to the U.S. market, which in turn supports greater forecast accuracy among financial analysts. Our empirical results suggest that the influence of capital flows through financial markets outweighs the opposing effect from the real economy channel.

Table 9
Non-U.S. Global EPU on Earnings Forecast Accuracy in the U.S. Market - Robustness.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	CapFlow	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr
Intercept	−13.029***	−0.0140***	0.0079***	0.0003	−0.0157***	0.0058***	−0.0003
	(−3.4104)	(−7.4606)	(4.9094)	(0.6076)	(−7.3721)	(3.3451)	(−0.6777)
GlbEPU	0.1117***				−1.525e-05***	−1.792e-05***	−5.067e-06***
	(21.090)				(−2.9917)	(−3.9015)	(−4.1504)
CapFlow		−4.248e-06***	−1.227e-06	−1.019e-06***	−3.978e-06***	−9.904e-07	−9.294e-07**
		(−2.8482)	(−1.0802)	(−3.2490)	(−2.6689)	(−0.7927)	(−2.9365)
USEPU	0.1367***	7.015e-06***	1.385e-05***	1.019e-06*	4.104e-06	1.043e-05***	5.129e-08
	(42.224)	(2.8661)	(7.1046)	(1.9152)	(1.4601)	(4.1369)	(0.0755)
NumEst	−0.7075***	−0.0003***	−0.0007***	−0.0001***	−0.0003***	−0.0007***	−0.0001***
	(−6.9851)	(−6.2035)	(−13.559)	(−10.324)	(−6.3474)	(−13.689)	(−10.458)
M/B	0.1335***	−5.577e-05*	−0.0004***	−6.965e-05***	−5.249e-05	−0.0004***	−6.856e-05***
	(3.0700)	(−1.6558)	(−15.465)	(−10.625)	(−1.5577)	(−15.344)	(−10.484)
ROA	7.3195***	−0.0634***	−0.0441***	−0.0128***	−0.0633***	−0.0441***	−0.0128***
	(6.3849)	(−18.731)	(−22.313)	(−21.393)	(−18.695)	(−22.320)	(−21.403)
Size	13.879***	0.0023***	0.0017***	0.0005***	0.0027***	0.0021***	0.0006***
	(22.520)	(7.5906)	(6.3903)	(6.2778)	(7.4688)	(6.9387)	(6.8009)
GlbGDP	809.67***	−0.0176**	−0.1076***	−0.0196***	−0.0172**	−0.1071***	−0.0195***
	(154.96)	(−2.2715)	(−17.981)	(−11.942)	(−2.2237)	(−17.998)	(−11.930)
No. Obs.	253,648	253,648	253,648	253,648	253,648	253,648	253,648
R-squared	0.0542	0.0714	0.0942	0.0941	0.0715	0.0944	0.0943
F-statistic	2004.9	2690.7	3636.7	3632.5	2356.8	3190.7	3187.1
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the regression results of the channel analysis when checking the non-U.S. Global EPU's effect on U.S. market analyst earnings forecasts. Column (1) shows the results of how *GlbEPU* affects *CapFlow*. Columns (2)–(4) are the results showing how *CapFlow* affect analyst earnings forecasts without controlling for *GlbEPU*, while columns (5)–(7) are similar regressions but controlling for *GlbEPU*. The dependent variable for each column 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.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve readability and writing quality, including grammar, rephrasing, and clarity. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

CRediT authorship contribution statement

Jian Song: Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Xiaozhou Zhou:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

All authors declare that they have no conflicts of interest.

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Appendix A

Table A1
Markets in the data sample.

ISO-3 Code	Market	N	ISO-3 Code	Market	N
Panel A: Developed Markets					
AUT	Austria	572	ISR	Israel	796
CAN	Canada	18,215	ITA	Italy	809
CHE	Switzerland	940	JPN	Japan	8988
DEU	Germany	4842	KOR	Korea, Rep.	8969
DNK	Denmark	1314	NLD	Netherlands	922
ESP	Spain	1332	NOR	Norway	4745
FIN	Finland	4657	SGP	Singapore	924
FRA	France	537	SWE	Sweden	6386
GBR	United Kingdom	669	USA	United States	302,171
Panel B: Developing Markets.					
BRA	Brazil	4301	MYS	Malaysia	750
CHL	Chile	766	PHL	Philippines	714
CHN	China	11,941	SAU	Saudi Arabia	1204
IDN	Indonesia	1156	THA	Thailand	1853
IND	India	3840	TUR	Turkey	925
MEX	Mexico	2135	TWN	Taiwan	16,349

This table presents the markets used in the data sample of this study. *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. The classification of markets as developed (Panel A) or developing (Panel B) is based on the MSCI market classification.

Appendix B

Table B1
Variable definitions.

Variable	Definition
Bias	Bias in earnings forecast, scaled by share price, computed as shown in Eq. (2) in the main text.
AbsErr	Absolute earnings forecast error, scaled by share price, computed as shown in Eq. (3) in the main text.
SqrErr	Squared earnings forecast error, scaled by share price, computed as shown in Eq. (4) in the main text.
USEPU	Economic Policy Uncertainty (EPU) data for the U.S.
LocEPU	Local EPU for a given non-U.S. market, if no local EPU data exists for a particular given market, regional EPU or global EPU is used.
GlbEPU	Non-U.S. Global EPU, computed as residuals from the regression of the U.S. 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.
CapFlow	Cash flows from financial account of the U.S. balance of payments, adjusted by those from current account, sign is converted to reflect cash flows to the U.S. (i.e., "+" denotes capital inflow), with 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.
GlbGDP	The world GDP growth rate.

Appendix C

C.1. Additional tests for the mediating role of Exp2GDP
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Table C1
Mediation Analysis - U.S. EPU on Earnings Forecast Accuracy in Other Developed Markets.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	Exp2GDP	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr
Intercept	0.1192***	−0.0117	0.0169**	0.0011	−0.0117	0.0177**	0.0012
	(5.0068)	(−1.2075)	(2.0151)	(0.5934)	(−1.2005)	(2.1085)	(0.6410)
USEPU	2.004e-05***				6.8e-07	1.629e-05***	1.933e-06**
	(5.8161)				(0.1393)	(4.2182)	(2.1033)
Exp2GDP		0.0737***	0.0127	0.0018	0.0735***	0.0088	0.0014
		(2.9562)	(0.7263)	(0.5216)	(2.9399)	(0.4994)	(0.3900)
LocEPU	−2.792e-05***	−2.026e-06	1.245e-05***	1.2e-06*	−2.314e-06	5.561e-06*	3.831e-07
	(−5.1297)	(−0.5370)	(3.9027)	(1.6546)	(−0.5507)	(1.6601)	(0.5020)
NumEst	−0.0005***	−0.0004*	−0.0008***	−0.0001***	−0.0004*	−0.0008***	−0.0001***
	(−3.0262)	(−1.9224)	(−5.0939)	(−3.1936)	(−1.9172)	(−5.0382)	(−3.1637)
M/B	−0.0001	0.0003*	−0.0008***	−0.0001***	0.0003*	−0.0008***	−0.0001***
	(−1.1535)	(1.7672)	(−5.7794)	(−3.6567)	(1.7671)	(−5.7630)	(−3.6540)
ROA	0.0062	−0.7570***	−0.1825***	−0.0425***	−0.7570***	−0.1825***	−0.0425***
	(1.4337)	(−20.136)	(−10.039)	(−9.3042)	(−20.136)	(−10.033)	(−9.3018)
Size	−0.0046*	0.0022**	0.0009	0.0003	0.0022**	0.0006	0.0002
	(−1.7248)	(2.2955)	(1.0232)	(1.3784)	(2.2508)	(0.7036)	(1.2008)
GlbGDP	0.1071***	−0.0058	−0.0791***	−0.0115***	−0.0049	−0.0569***	−0.0088***
	(17.982)	(−0.5508)	(−10.187)	(−6.3973)	(−0.3917)	(−6.3565)	(−4.2376)
No. Obs.	65,617	65,617	65,617	65,617	65,617	65,617	65,617
R-squared	0.0759	0.1825	0.0395	0.0302	0.1825	0.0400	0.0303
F-statistic	735.6	1998.9	368.1	278.4	1749.0	326.2	244.6
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the regression results of mediation analysis when checking the U.S. EPU's effect on non-U.S. markets analyst earnings forecasts. The results are based on the subsample of developed markets. Column (1) shows the results of how USEPU affects Exp2GDP. Columns (2)–(4) are the results showing how Exp2GDP affects analyst earnings forecasts without controlling for USEPU, while columns (5)–(7) are similar regressions but controlling for USEPU. The dependent variable for each column 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.

Table C2
Mediation Analysis - U.S. EPU on Earnings Forecast Accuracy in Developing Markets.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	Exp2GDP	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr
Intercept	0.0618***	0.0063	−0.0201***	−0.0021***	0.0064	−0.0194***	−0.0020***
	(8.2291)	(1.2795)	(−3.7060)	(−3.6902)	(1.2913)	(−3.5884)	(−3.6080)
USEPU	4.513e-05***				1.606e-06	1.115e-05***	7.579e-07***
	(18.241)				(0.6652)	(5.2324)	(3.2034)
Exp2GDP		−0.0002	0.0580***	0.0056***	−0.0015	0.0488***	0.0050**
		(−0.0124)	(3.1352)	(2.7328)	(−0.1045)	(2.6227)	(2.4209)
LocEPU	−2.025e-05***	3.668e-06***	4.078e-06***	1.777e-07*	3.399e-06***	2.209e-06**	5.068e-08
	(−15.782)	(3.3974)	(4.0091)	(1.7487)	(3.1047)	(2.1215)	(0.4775)
NumEst	−0.0002*	0.0001	−0.0006***	−4.796e-05***	0.0001	−0.0006***	−4.829e-05***
	(−1.7312)	(1.1753)	(−4.8818)	(−3.6013)	(1.1706)	(−4.9293)	(−3.6290)
M/B	−4.198e-05	0.0005***	−0.0002***	−7.727e-06	0.0005***	−0.0002***	−8.399e-06
	(−0.8716)	(5.5831)	(−2.7738)	(−1.1571)	(5.5686)	(−2.9503)	(−1.2695)
ROA	0.0228***	−0.5361***	−0.0779***	−0.0077***	−0.5359***	−0.0767***	−0.0076***
	(2.8874)	(−20.919)	(−5.1704)	(−4.3206)	(−20.936)	(−5.0910)	(−4.2690)
Size	−0.0005	0.0001	0.0030***	0.0003***	0.0001	0.0028***	0.0002***
	(−0.6224)	(0.2679)	(5.8279)	(5.0129)	(0.2033)	(5.4504)	(4.7452)
GlbGDP	0.0872***	0.0189***	−0.0300***	−0.0030***	0.0213***	−0.0129**	−0.0018***
	(21.993)	(3.2492)	(−6.4927)	(−5.5619)	(3.1991)	(−2.5620)	(−3.2729)
No. Obs.	45,934	45,934	45,934	45,934	45,934	45,934	45,934
R-squared	0.0609	0.1311	0.0303	0.0164	0.1311	0.0315	0.0168
F-statistic	404.2	940.2	194.9	103.7	822.8	177.6	93.3
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the regression results of mediation analysis when checking the U.S. EPU's effect on non-U.S. markets analyst earnings forecasts. The results are based on the subsample of developing markets. Column (1) shows the results of how USEPU affects Exp2GDP. Columns (2)–(4) are the results showing how Exp2GDP affects analyst earnings forecasts without controlling for USEPU, while columns (5)–(7) are similar regressions but controlling for USEPU. The dependent variable for each column 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.

Table C3
Mediation Analysis - U.S. EPU on Earnings Forecast Accuracy in Non-U.S. Markets Subsample - excluding Canada and Taiwan.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	Exp2GDP	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr
Intercept	0.0459***	0.0052	−0.0132	−0.0030	0.0050	−0.0121	−0.0029
	(9.6321)	(0.7111)	(−1.5700)	(−1.6030)	(0.6792)	(−1.4412)	(−1.5431)
USEPU	1.579e-05***				−2.816e-06	1.457e-05***	1.381e-06*
	(11.870)				(−0.7348)	(4.4048)	(1.7595)
Exp2GDP		0.0303	0.0904***	0.0167**	0.0318	0.0826***	0.0160**
		(1.1882)	(2.8150)	(2.2276)	(1.2419)	(2.5864)	(2.1426)
LocEPU	−1.836e-05***	3.546e-06**	5.693e-06***	4.524e-07	4.079e-06**	2.935e-06*	1.908e-07
	(−21.252)	(2.0230)	(3.3914)	(1.1813)	(2.4239)	(1.8731)	(0.5399)
NumEst	−9.365e-05	−0.0005**	−0.0010***	−0.0002***	−0.0005**	−0.0010***	−0.0002***
	(−1.3551)	(−2.1915)	(−5.4933)	(−3.4273)	(−2.1816)	(−5.6095)	(−3.4736)
M/B	2.352e-06	0.0005***	−0.0003***	−2.302e-05	0.0005***	−0.0003***	−2.381e-05
	(0.0735)	(4.0959)	(−3.3590)	(−1.2581)	(4.1172)	(−3.4568)	(−1.3020)
ROA	0.0062**	−0.7449***	−0.1716***	−0.0413***	−0.7450***	−0.1710***	−0.0412***
	(2.4779)	(−20.188)	(−8.3987)	(−8.1414)	(−20.196)	(−8.3561)	(−8.1211)
Size	−0.0008*	0.0008	0.0033***	0.0006***	0.0008	0.0030***	0.0005***
	(−1.7359)	(1.0368)	(4.1282)	(3.2529)	(1.0911)	(3.6847)	(3.0281)
GlbGDP	0.0501***	0.0008	−0.0706***	−0.0112***	−0.0034	−0.0488***	−0.0091***
	(25.304)	(0.0943)	(−10.569)	(−7.0978)	(−0.3266)	(−6.6078)	(−5.2704)
No. Obs.	76,987	76,987	76,987	76,987	76,987	76,987	76,987
R-squared	0.0560	0.1409	0.0309	0.0234	0.1409	0.0315	0.0235
F-statistic	621.5	1717.6	3343.0	251.0	1503.0	297.6	220.4
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the regression results of mediation analysis when checking the U.S. EPU's effect on non-U.S. markets analyst earnings forecasts. The results are based on the subsample excluding Canada and Taiwan. Column (1) shows the results of how *USEPU* affects *Exp2GDP*. Columns (2)–(4) are the results showing how *Exp2GDP* affects analyst earnings forecasts without controlling for *USEPU*, while columns (5)–(7) are similar regressions but controlling for *USEPU*. The dependent variable for each column 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.

Table C4
Mediation Analysis - U.S. EPU on Earnings Forecast Accuracy in Mexico, Canda, Turkey and Spain.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	Exp2GDP	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr
Intercept	0.1865***	−0.0188	−0.0105	−0.0033	−0.0189	−0.0105	−0.0033
	(14.315)	(−1.4038)	(−0.8561)	(−1.2055)	(−1.4012)	(−0.8725)	(−1.2183)
USEPU	6.112e-05***				1.043e-05	4.167e-05***	7.055e-06***
	(7.3304)				(1.2731)	(5.1202)	(3.6107)
Exp2GDP		0.0546**	0.0707**	0.0158**	0.0517*	0.0593**	0.0138**
		(2.0359)	(2.3843)	(2.2695)	(1.9307)	(2.0731)	(2.0573)
LocEPU	−7.921e-05***	−1.927e-06	1.387e-05***	1.975e-06***	−6.128e-06	−2.926e-06	−8.682e-07
	(−13.100)	(−0.3138)	(3.7276)	(2.5832)	(−0.8636)	(−0.6405)	(−0.9009)
NumEst	−0.0014***	2.679e-05	−0.0006**	−5.317e-05	3.497e-05	−0.0005**	−4.764e-05
	(−5.1574)	(0.0851)	(−2.5171)	(−1.0742)	(0.1112)	(−2.3514)	(−0.9536)
M/B	−0.0004*	0.0010***	−0.0015***	−0.0002***	0.0010***	−0.0015***	−0.0002***
	(−1.8406)	(3.0710)	(−5.2364)	(−3.3263)	(3.0677)	(−5.2408)	(−3.3290)
ROA	−0.0004	−0.8288***	−0.1751***	−0.0393***	−0.8289***	−0.1756***	−0.0394***
	(−0.0556)	(−12.318)	(−6.5108)	(−5.5000)	(−12.326)	(−6.5285)	(−5.5122)
Size	0.0001	0.0022	0.0032***	0.0005**	0.0021	0.0029**	0.0005*
	(0.0882)	(1.3837)	(2.5956)	(1.9864)	(1.3332)	(2.3939)	(1.8120)
GlbGDP	0.2171***	−0.0137	−0.1313***	−0.0222***	−0.0016	−0.0831***	−0.0141***
	(22.723)	(−0.7121)	(−7.3792)	(−5.2785)	(−0.0838)	(−4.8840)	(−3.4649)
No. Obs.	22,607	22,607	22,607	22,607	22,607	22,607	22,607
R-squared	0.1484	0.2499	0.0522	0.0361	0.2499	0.0547	0.0375
F-statistic	537.4	1026.9	169.8	115.6	898.8	156.3	105.0
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the regression results of mediation analysis when checking the U.S. EPU's effect on non-U.S. markets analyst earnings forecasts. The results are based on the subsample of Mexico, Canada, Turkey and Spain. Column (1) shows the results of how *USEPU* affects *Exp2GDP*. Columns (2)–(4) are the results showing how *Exp2GDP* affects analyst earnings forecasts without controlling for *USEPU*, while columns (5)–(7) are similar regressions but controlling for *USEPU*. The dependent variable for each column 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.

Table C5
Mediation Analysis - U.S. EPU on Earnings Forecast Accuracy in Canada and China.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	Exp2GDP	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr
Intercept	0.2194***	−0.0322***	0.0130**	0.0014*	−0.0333***	0.0095*	0.0010
	(29.163)	(−3.8176)	(2.5734)	(1.8295)	(−3.9644)	(1.8776)	(1.2893)
USEPU	−2.445e-05***				6.739e-06*	2.192e-05***	2.596e-06***
	(−11.887)				(1.8834)	(6.7280)	(5.4188)
Exp2GDP		0.0659***	−0.0167	−0.0005	0.0674***	−0.0118	7.349e-05
		(3.1202)	(−1.0553)	(−0.1982)	(3.1944)	(−0.7457)	(0.0289)
LocEPU	−1.14e-05***	1.531e-06	5.298e-06***	4.978e-07***	4.136e-07	1.664e-06	6.741e-08
	(−8.8065)	(1.0090)	(5.2778)	(3.7128)	(0.2753)	(1.6074)	(0.4889)
NumEst	−0.0013***	1.017e-05	−0.0004**	−1.553e-05	1.006e-05	−0.0004**	−1.557e-05
	(−5.0191)	(0.0448)	(−2.5570)	(−0.6413)	(0.0443)	(−2.5552)	(−0.6415)
M/B	−0.0002*	0.0006***	−0.0009***	−7.475e-05***	0.0006***	−0.0009***	−7.519e-05***
	(−1.7113)	(4.9903)	(−7.5527)	(−4.1905)	(4.9824)	(−7.5707)	(−4.2094)
ROA	0.0103	−0.6513***	−0.1662***	−0.0247***	−0.6513***	−0.1662***	−0.0247***
	(1.2904)	(−14.227)	(−8.7120)	(−7.3723)	(−14.232)	(−8.7206)	(−7.3774)
Size	−0.0095***	0.0036***	0.0008	1.164e-05	0.0036***	0.0008	6.526e-06
	(−9.9552)	(4.1694)	(1.6053)	(0.1617)	(4.1488)	(1.5265)	(0.0910)
GlbGDP	0.1189***	0.0016	−0.0468***	−0.0056***	0.0097	−0.0205**	−0.0025*
	(15.097)	(0.1667)	(−5.6156)	(−4.2439)	(0.9859)	(−2.4652)	(−1.8611)
No. Obs.	30,156	30,156	30,156	30,156	30,156	30,156	30,156
R-squared	0.2170	0.2647	0.0626	0.0479	0.2648	0.0650	0.0494
F-statistic	1129.7	1467.3	272.3	205.3	1284.5	248.1	185.3
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Clustered	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the regression results of mediation analysis when checking the U.S. EPU's effect on non-U.S. markets analyst earnings forecasts. The results are based on the subsample of Canada and China. Column (1) shows the results of how *USEPU* affects *Exp2GDP*. Columns (2)–(4) are the results showing how *Exp2GDP* affects analyst earnings forecasts without controlling for *USEPU*, while columns (5)–(7) are similar regressions but controlling for *USEPU*. The dependent variable for each column 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.

Appendix D
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Table D1
The Non-U.S. Global EPU on Earnings Forecast Accuracy in the U.S. Market – Capital Flow as a Mediator.

	Primary Proxy for CapFlow			Alternative Proxy for CapFlow		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Bias	AbsErr	SqrErr	Bias	AbsErr	SqrErr
Intercept	−0.0156***	0.0060***	−0.0003	−0.0158***	0.0059***	−0.0003
	(−7.3276)	(3.4054)	(−0.6058)	(−7.4069)	(3.3868)	(−0.7015)
GlbEPU	−1.463e-05***	−1.657e-05***	−4.846e-06***	−1.450e-05***	−1.864e-05***	−4.958e-06***
	(−2.8385)	(−3.5206)	(−3.8843)	(−2.7860)	(−4.0000)	(−4.0099)
CapFlow*GlbEPU	1.039e-08	−3.376e-08	−8.594e-09	−5.722e-08	5.47e-08*	−8.339e-09
	(0.1829)	(−0.9759)	(−0.8830)	(−1.1673)	(1.6807)	(−0.9384)
CapFlow	5.515e-06***	−4.162e-06***	−8.535e-07***	−3.756e-06**	−1.122e-06	−8.969e-07**
	(−3.2716)	(−3.9407)	(−2.8357)	(−2.4834)	(−0.9772)	(−2.8288)
USEPU	3.949e-06	1.087e-05***	5.254e-08	4.797e-06*	9.765e-06***	1.523e-07
	(1.3963)	(4.2347)	(0.0759)	(1.6476)	(3.8011)	(0.2194)
NumEst	−0.0003***	−0.0007***	−0.0001***	−0.0003***	−0.0007***	−0.0001***
	(−6.2239)	(−13.641)	(−10.381)	(−6.3698)	(−13.607)	(−10.437)
M/B	−5.265e-05	−0.0004***	−6.863e-05***	−5.229e-05	−0.0004***	−6.855e-05***
	(−1.5627)	(−15.338)	(−10.492)	(−1.5517)	(−15.352)	(−10.481)
ROA	−0.0633***	−0.0441***	−0.0128***	−0.0633***	−0.0441***	−0.0128***
	(−18.701)	(−22.328)	(−21.419)	(−18.689)	(−22.315)	(−21.395)
Size	0.0026***	0.0021***	0.0005***	0.0027***	0.0021***	0.0006***
	(7.3192)	(6.8289)	(6.6047)	(7.4541)	(6.9539)	(6.7942)
GlbGDP	−0.0197**	−0.1079***	−0.0202***	−0.0166**	−0.1076***	−0.0194***
	(−2.5151)	(−18.168)	(−12.398)	(−2.1371)	(−17.929)	(−11.771)
No. Obs.	253,648	253,648	253,648	253,648	253,648	253,648
R-squared	0.0715	0.0944	0.0943	0.0715	0.0944	0.0943
F-statistic	2095.2	2837.9	2832.4	2095.1	2836.6	2833.1
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cov. Clustered	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the regression results of the channel analysis (capital flow as a moderator) when checking the non-U.S. Global EPU's effect on U.S. market analyst earnings forecasts. Columns (1)–(3) are the results for models with the primary proxy for capital flow (as shown in Section 5.2), while columns (4)–(6) are the results for regressions with the alternative proxy for capital flow (as shown in Section 5.3). The dependent variable for each regression 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.

Data availability

Data will be made available on request.

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