J. Account. Public Policy 40 (2021) 106775

Contents lists available at ScienceDirect

J. Account. Public Policy

journal homepage: www.elsevier.com/locate/jaccpubpol

Full length article

# Economic policy uncertainty and analysts' forecast characteristics

Lamia Chourou [a,*], Lynnette Purda [b], Samir Saadi [a,c]

[a] Telfer School of Management, University of Ottawa, 55 Laurier Avenue East, Ottawa, ON K1N 6N5, Canada
[b] Smith School of Business, Queen's University, 143 Union Street West, Kingston, ON K7L 3N6, Canada
[c] IPAG Business School, 184 Boulevard Saint-Germain, 75006 Paris, France

ARTICLE INFO

*Article history:*
Available online 29 August 2020

*JEL Classifications:*
G14
G18
G24
P16

*Keywords:*
Economic policy uncertainty
Analyst forecast
Information environment

ABSTRACT

We examine the influence of economic policy uncertainty (EPU) on the characteristics of analysts' earnings forecasts over a thirty-year period, spanning a wide variety of political and economic conditions. Motivated by both theory and empirical evidence that suggest a decline in the quality of the information environment for firms as EPU increases, we establish that analysts' forecast errors increase with EPU, as does the degree of forecast dispersion. Increased error and dispersion persist after controlling for several competing sources of economy-wide uncertainty. Cross sectional analysis exploring heterogeneity in forecast quality across both analyst and firm characteristics establishes that forecast error and dispersion increase with EPU across a broad spectrum of firms and levels of analyst expertise. We control for analysts' experience overall and the years spent covering a particular industry and firm. Five alternative methods for classifying firms as policy sensitive versus policy neutral provide consistent evidence that analyst forecast errors and dispersion increase with EPU, even for firms not deemed to be particularly sensitive to policy.


## 1. Introduction

Investors are bombarded with information on a daily basis. The sheer volume of news related to market-wide and firm-specific events is overwhelming and its interpretation requires the help of information intermediaries such as securities analysts. These analysts assist in translating information into meaningful implications for investors. During times of uncertainty, when information production is high, demands for analysts' services increase (Lehavey et al., 2011; Loh and Stulz, 2018). In this paper, we examine analysts' response to a particular source of uncertainty surrounding government's economic policy. Motivated by the increasing importance of economic policy uncertainty (EPU) in the minds of managers[1] and financial market participants (Bradley et al., 2016; Kaviani et al., 2020) we examine how analysts' forecast accuracy changes in response to EPU. We are careful to distinguish policy uncertainty from variation in the political and economic cycles and examine how heterogeneity in both analyst characteristics and firms' policy sensitivity influences earnings forecasts.

Uncertainty surrounding government policies exacerbates the information asymmetries that already exist between investors and firms (Brogaard and Detzel, 2015; Kelly et al., 2016). Policy ambiguity influences the real decisions of firms,

* Corresponding author.
*E-mail addresses:* lamia.chourou@telfer.uottawa.ca (L. Chourou), lpurda@business.queensu.ca (L. Purda), samir.saadi@telfer.uottawa.ca (S. Saadi).

[1] PriceWaterhouseCoopers 19th Annual Global CEO Survey, January 2016, available at https://www.pwc.com/gx/en/ceo-survey/2016/landing-page/pwc-19th-annual-global-ceo-survey.pdf

https://doi.org/10.1016/j.jaccpubpol.2020.106775
0278-4254/

causing them to alter previous plans for investment, hiring, or expansion (Baker et al., 2016; Gulen and Ion, 2016; Xu, 2016). In addition, EPU influences the information that firms choose to reveal, thereby further complicating an assessment of policies' potential implications (Arif et al., 2016; Chen et al., 2018b; Nagar et al., 2019). Unfortunately, we know little about the consequences of this economy-wide source of uncertainty for financial market participants. While previous research indicates that analysts' forecast accuracy declines in response to market-wide uncertainty and that macro factors are not fully incorporated into analysts' estimates (Amiram et al., 2018; Basu et al., 2010; Hugon et al., 2016) it is unclear whether this is the case for EPU as well.

We examine both the error and dispersion of security analysts' earnings forecasts as indicators of EPU's influence on a firm's information environment. Using analysts' forecasts has several advantages. First, the long history of data on earnings forecasts allows us to cover a 30-year period rich in a variety of economic and political conditions. While others have examined analyst performance in heightened periods of uncertainty during weak economic periods (Loh and Mian, 2003), or surrounding local or national elections (Baloria and Mamo, 2014; Chen et al., 2018a), we find that policy uncertainty is not always in sync with political and economic cycles.[2]

A second advantage of using analyst forecasts is that their coverage across a wide-spectrum of firms allows us to explore heterogeneity in firm-level information quality resulting from EPU. We explore this heterogeneity across two dimensions: potential differences in firms' exposure to policy uncertainty and the characteristics of the analysts that follow them. Previous work suggests that policy uncertainty has a greater influence on industries that are heavily regulated (Kaviani et al., 2020) or with high levels of exposure to energy prices, monetary policy, labor policies, or contract enforcement, such as defense, healthcare, and infrastructure (Baloria and Mamo, 2014; Baker et al., 2016). Given the variety of approaches to gauging the importance of policy to individual firms, we explore how analysts' forecast quality varies across five measures of policy sensitivity alternatively derived from stock returns, government sales, industry, and the proportion of time that a firm's executives devote to the discussion of political risk (Hassan et al., 2019).

With respect to analyst characteristics, we are motivated by Pastor and Veronesi's (2012) observation that individuals learn. We proxy for learning by incorporating measures of analyst experience into our analysis and explore whether analysts with greater experience overall, within a specific industry, or for a particular firm, are able to provide improved forecasts despite high levels of EPU. In addition, we ask whether analysts from larger brokerage houses with presumably better resources and support (Clement, 1999; Amiram et al., 2018) are better able to assess the consequences of EPU for the firms that they follow.

Intuitively, policy uncertainty may make forecasting a firm's upcoming earnings a more difficult task for analysts. Investment may decline or accelerate due to uncertainty (Gulen and Ion, 2016; Xu, 2016; Auerbach and Hines, 1988; Bloom, 2009) and changes to tax policy may have non-uniform consequences for firms (Guenther, 1994; Poterba et al., 2011) particularly those who foster relations with tax policy makers (Brown et al., 2015). Analysts may also be encumbered by changes in policies governing how accounting information is presented (Bailey et al., 2003; Dinh et al., 2015; Maaloul et al., 2016). All of these possibilities may increase forecast error.

As uncertainty increases, so too may forecast dispersion as analysts respond differently to ambiguous information. Market participants may formulate different opinions when faced with identical information (Varian, 1985; Harris and Raviv, 1993; Kandel and Pearson, 1995) and some may have unique access to political or policy information, that they use to their benefit (Bradley et al., 2018; Christensen et al., 2017; Jagolinzer et al., 2020).

We find that analysts' forecasts are influenced considerably by policy uncertainty. Forecast error increases significantly with EPU as does the level of disagreement among analysts. Our results show that EPU's influence on the firm-level information environment is pervasive. We control for uncertainty driven by macroeconomic factors, elections, recessions, and firm characteristics but none remove the influence of policy uncertainty. Analysts find it difficult, or too costly, to embed the consequences of EPU into their estimates. We find no distinction in error or dispersion for firms covered by highly experienced analysts versus those followed by more novice forecasters. In robustness tests, we refine our sample to firms in the healthcare industry and include measures of overall economic policy uncertainty and health-specific policy uncertainty. Even in this specialized context, forecast error and dispersion increase in response to higher levels of EPU, however industry-specific policy uncertainty shows no significant influence on forecast accuracy. Finally, as an additional indication of the pervasiveness of EPU's influence, we find that increases in forecast error and dispersion are not confined to firms deemed to be particularly policy-sensitive; rather these forecast characteristics span all firms.

Our work provides several contributions. We add to well-established findings on analysts' ability to forecast earnings. While there exists several examples of how firm-specific information causes analysts to revise their forecasts (Donelson and Resutek, 2012; Maaloul et al., 2016), we know far less about how analysts incorporate economy-wide news into their evaluations despite important linkages between the macroeconomy and firm-level earnings (Konchitchki and Patatoukas, 2014a, 2014b).[3] We also contribute to the quickly expanding work examining the interaction between political activity and

[2] As Nguyen and Phan (2017, p. 616) note, political uncertainty is different from policy uncertainty in a number of ways. First, election indicators do not tell how policy uncertainty changes during elections. Second, they do not capture the variation in policy uncertainty between elections. Furthermore, policy uncertainty is broader and includes different types of uncertainty that are directly tied to policies. We expand on these differences in more detail in the section on hypotheses development.

[3] Amiram et al. (2018) examine how analyst forecast characteristics change in response to market, industry, and firm level uncertainty. They measure market uncertainty as the standard deviation of the value-weighted daily market return over the 30 days prior to the forecast.

businesses (Akey and Lewellen, 2017; Kang et al., 2014). Unlike most of the work in this area, our emphasis is not on the relation between politics and the individual actions of firms but rather on policy's influence on the information environment for these firms and the predictability of earnings.

We formalize our hypotheses on the relation between policy uncertainty and analysts' forecast characteristics in the next section of the paper, drawing heavily on the models of Pastor and Veronesi (2012, 2013) as motivation. In Section 3, we discuss our methodology and data. We present the results of our empirical analysis in Section 4, beginning with overall findings on the pervasiveness of EPU's influence on analyst accuracy followed by cross-sectional analysis on the heterogeneity of analyst characteristics and firm policy sensitivity. The section ends with robustness tests including detailed analysis of the healthcare sector and policy uncertainty specific to this industry. Section 5 concludes with implications for policy makers and market participants.

## 2. Hypothesis development

Our examination of EPU's influence on analysts' forecast characteristics is motivated by the asset pricing models of Pastor and Veronesi (2012, 2013). In these models, uncertainty influences asset prices through its impact on firm profits, which is precisely the variable that stock analysts predict. Pastor and Veronesi are clear to distinguish between *political* uncertainty and *impact* uncertainty.[4] Political uncertainty is uncertainty with respect to whether or not a policy will change, while impact uncertainty relates to the unknown impact of a particular policy once it is in place.

In our empirical tests, we measure EPU by the Baker, Bloom, and Davis (2016) index which is broad enough to cover both political and impact uncertainty without necessarily distinguishing between the two. The index is derived from three components: (1) news coverage about policy-related economic uncertainty measured by the volume of related news articles,[5] (2) upcoming tax code provisions scheduled to expire, and (3) the general level of disagreement among professional economic forecasters. The expiration of tax provisions aligns more clearly with impact uncertainty, given that policy expiration is fully anticipated but its implications are unknown. In contrast, the remaining two index components, news coverage and disagreement among forecasters, can relate to either uncertainty regarding the adoption or withdrawal of polices (political uncertainty) or their consequences (impact uncertainty). Important for our context is that both political and impact uncertainty have unknown implications for firm profitability and can plausibly complicate analysts' task.[6]

Viewing EPU comprehensively to encompass political and impact uncertainty suggests that analysts' forecast accuracy and dispersion may be influenced in a wide variety of economic and political contexts. This perspective distinguishes our work from the large number of studies that use elections as the primary source of policy risk (e.g., Bernhard and Leblang, 2006; Campello, 2007; Goodell and Vähämaa, 2013). Though economic policy uncertainty and elections are related, they differ in several important respects. First, uncertainty about an election outcome is only one dimension of policy risk. Even if the result of an election is known with certainty, ambiguity remains about the policy to be implemented by the winning party (Brogaard and Detzel, 2015; Füss and Bechtel, 2008). Second, as noted by Brogaard and Detzel (2015), "the passing of legislation or an election does not necessarily indicate the complete resolution of uncertainty surrounding the government policy." Governments frequently reverse or adjust their economic policy to respond to shifts in popular support even outside election periods (Bechtel, 2009; Sattler et al., 2010).

The combined influence of political and impact uncertainty suggests that less reliable information may be available to predict firm earnings when EPU is high. Supporting this intuition is the finding of Chen et al. (2018a) that political uncertainty worsens the information environment by reducing the availability of firm-specific information. They find that firms react to political uncertainty by reducing the amount and quality of information disclosed, while both analysts and media increase the production of information.[7] This result is in direct contrast to findings by Nagar et al. (2019) that U.S. managers increase firm disclosures during periods of heightened EPU but this increase cannot compensate for the increased uncertainty brought on by EPU.

An additional strain of literature argues that changes in information flow may result endogenously from reduced trading or investment when uncertainty is high (Faigelbaum et al., 2017; Van Nieuwerburgh and Veldkamp, 2006). Specifically, if traders hesitate due to economic or political conditions, security prices may become less informative (more uncertain) since information is slow to be incorporated into prices when trades are scarce. Certain policies may also relate directly to disclosure requirements, thereby influencing the quantity or quality of information at analysts' disposal market-wide (Bagnoli et al., 2008; Hahn and Song, 2013). EPU may also influence an individual company's accounting decisions, such as the level

[4] Strictly speaking, the terminology used by Pastor and Veronesi changes slightly from one paper to the other. The 2012 paper first makes use of the terms political and policy uncertainty. Political uncertainty referred to uncertainty surrounding whether a policy would change while policy uncertainty referred to the uncertain impact of a policy once in place. The 2013 paper changed terminology slightly, replacing the term policy uncertainty with impact uncertainty. For our purposes, we follow the 2013 paper in separately identifying political and impact uncertainty. We use the term "policy" uncertainty to refer to the combined uncertainty related to both the probability of change in policy (political uncertainty) and the impact of any policy in place (impact uncertainty).

[5] In particular, the authors search for articles containing the term 'uncertainty' or 'uncertain', the terms 'economic' or 'economy' and one or more of the following terms: 'congress', 'legislation', 'white house', 'regulation', 'federal reserve', or 'deficit'.

[6] Baker et al. (2016) conduct extensive analysis to validate their index and it has achieved widespread use by major commercial data providers, academics, medial outlets, and policy makers. Information on research making use of the index in addition to links for media outlets, congressional testimony, and central bank speeches is available at http://www.policyuncertainty.com/research.html

[7] They did not, however, examine the effect of policy uncertainty on the quality of the information provided by analysts.

of accruals (Arif et al., 2016; Chen et al., 2018a) or the propensity for a firm to engage in earnings management (Stein and Wang, 2016).[8]

Drawing on these theoretical and empirical observations, we formalize our first hypothesis on the relation between EPU and analyst forecast error. Presented in null form, we have Hypothesis 1:

**H.1.** *Security analysts' forecast error is not associated with EPU.*

The second characteristic of analysts' forecasts that may be influenced by EPU is the degree of dispersion surrounding analysts' predictions. We suggest several possible channels through which dispersion may increase with EPU. First, analysts may assign different probabilities to different policy outcomes even when faced with the same information (Harris and Raviv, 1993; Kandel and Pearson, 1995; Varian, 1985). Second, analysts may have different levels of expertise in interpreting or predicting the consequences of government policies. For instance, Bradley et al. (2018) suggest that analysts working for investment firms that employ specialized *Washington Analysts*—whose task is to study and interpret policy—provide superior stock recommendations. This finding complements the already extensive literature suggesting that individual analyst characteristics, such as experience or compensation, influence forecast performance (Brown et al., 2015; Cao et al., 2020; Kumar, 2010) in addition to characteristics of the firm at which they are employed (Clement, 1999; Ljungqvist et al., 2006). Third, market participants may not share the same information set. Uncertainty may prompt some analysts to seek out additional information (Kim and Verrecchia, 1991) or the private information individual analysts have access to may vary (Diamond and Verrecchia, 1981). With respect to policy knowledge specifically, Gao and Huang (2016) demonstrate that hedge fund managers with ties to lobbyists earn abnormal returns in policy sensitive stocks while Christensen et al. (2017) suggest that analysts issue more profitable stock recommendations when their firms maintain political connections. The combination of these observations leads us to Hypothesis 2, presented in null form:

**H.2.** *Analyst forecast dispersion is not influenced by EPU.*

In empirical tests, we elaborate on our two primary hypotheses by controlling for competing sources of uncertainty such as macroeconomic uncertainty, national elections, and recessions. In addition, we examine cross-sectional heterogeneity in forecast error and dispersion for firms with varying levels of analyst expertise and policy sensitivity. We include robustness tests focused on the healthcare sector and its own unique policy uncertainty measure to enable us to distinguish between economy-wide versus industry-specific policies and analyst expertise.

We turn next to a discussion of our methodology and the dataset we use to explore the relation between EPU and analysts' forecast characteristics.

## 3. Relating EPU to forecast characteristics

### 3.1. Empirical methodology

We examine all individual one-year-ahead analyst forecasts for firms with data available on both I/B/E/S and COMPUSTAT for fiscal years ending between January 1985 and December 2015. To avoid potential staleness of the I/B/E/S consensus forecasts, following Abarbanell and Bernard (1992) we calculate consensus forecasts ourselves using individual analysts' predictions for year-end earnings. We drop observations for which the I/B/E/S ticker, the analyst code, the forecasted EPS, or the actual EPS is missing (125,669 observations deleted). Anonymous analysts are also excluded (2,054 observations deleted). Additionally, we restrict the sample to forecasts for annual earnings made before the end of the accounting period and no earlier than a full year prior to fiscal year-end. As a result, the maximum forecast horizon is 365 calendar days (294,260 observations deleted). Since the influence of EPU on analysts' ability to predict earnings may depend on how far in the future the fiscal year-end lies, we distinguish between forecasts with long and short horizons. We define long horizon forecasts as those corresponding to forecast periods equal to or greater than the sample median of five months, while short horizon forecasts are for fiscal year-ends occurring within four months.

Our main variables of interest are absolute forecast error (*abs_FE*) and forecast dispersion (*DISP*). Formally, *abs_FE* is defined as the absolute value of the difference between the actual annual earnings per share (*EPS*) and the consensus forecast, where consensus is represented by the median of individual analyst forecasts for the company within a calendar month. A new error is calculated each month and the value deflated by stock price at the beginning of the firm's fiscal year. *DISP* is defined as the standard deviation of earnings forecasts issued by individual analysts during a calendar month and is also deflated by the stock price at the beginning of the fiscal year. Both *abs_FE* and *DISP* are expressed as percentages.

After merging I/B/E/S data with Compustat we have a total of 464,942 observations relating to 7,143 unique firms for the forecast error sample and 247,935 observations relating to 5,762 unique firms for the forecast dispersion sample when a minimum of three forecasts is used to calculate dispersion.

Our approach to establishing the potential influence of EPU is similar—regardless of whether our focus is on forecast error or dispersion—and follows the framework of Eq. (1) in which either *abs_FE* or *DISP* are the dependent variables. Regressions are pooled across monthly observations spanning both companies and time.

[8] To some extent, accounting quality may help to mitigate the information effects of EPU on individual firms. Consistent with this idea, Chen, Hope, Li, and Wang (2018) document a shift in mutual fund holdings towards firms with higher quality earnings during periods of policy uncertainty such as national elections.

$$Forecast\ \ Characteristic_{j,t,i} = \alpha + \beta Ln\_EPU_{j,t} + \gamma_1 Forecast\ \ Controls_{i,t} + \gamma_2 Firm\ \ Controls_{i,t} + \gamma_3 Aggregate\ \ Influences_{j,t} + \varepsilon_{j,t,i} \quad (1)$$

Eq. (1) outlines that forecast characteristic (*abs_FE* or *DISP*) at month *j* of year *t* for firm *i*, is a function of: the EPU value during month *j* of year *t*; forecast and firm controls corresponding to company *i* at year *t*; aggregate influences occurring at month *j* of year *t*; and a residual term ($\varepsilon$). Following Gulen and Ion (2016), our analyses do not include time (monthly) fixed effects since doing so would mechanically absorb all the explanatory power of the policy uncertainty variable.[9] We include firm fixed effects to capture the time invariant characteristics of the firm including its industry. Standard errors are clustered at the firm level or, for robustness, across both firm and time. Regressions take the form of ordinary least squares.

### 3.2. Data description and summary statistics

Our regression analysis controls for features of analyst forecasts, individual firm characteristics, and four alternative economy-wide sources of uncertainty that may impede analysts' ability to make accurate forecasts. These sources of uncertainty are listed in Table 1 and include: two proxies for economic uncertainty in general, a measure reflecting equity market uncertainty specifically, and an indicator variable for election periods. Economic uncertainty measures include an indicator variable for recessions based on the NBER definition of recessions classifying July 1990–March 1991, March–November 2001, and December 2007–June 2009 as recessionary periods. To control for time-varying U.S. macroeconomic uncertainty, we include the Jurado et al. (2015) index of macroeconomic uncertainty which is based on the uncertainties of 132 broad categories of macroeconomic series. Stock market uncertainty is measured by the Baker et al. (2016) equity market uncertainty index (EU) which is compiled from textual searches of newspaper articles. To construct the index, the authors first obtain daily counts of articles containing the term 'uncertainty' or 'uncertain', the terms 'economic' or 'economy' and one or more of the following terms: 'equity market', 'equity price', 'stock market', or 'stock price'. In other words, the article must include terms in all three categories pertaining to uncertainty, the economy, and the stock market. We take the average during a calendar month as our proxy for EU. In identifying election years, we code the months from January to October as one, indicating unresolved election outcomes. November and December in election years, and all calendar months in non-election years, are coded with the indicator variable as zero.

Panel A of Table 1 provides the mean, standard deviation, and other distributional characteristics for all economy-wide uncertainty measures while Panel B presents their correlation matrix. While policy changes are potentially more likely with transfers of power or weak economies—that is, at times when governments feel pressure to provide policy responses to economic difficulties (Pastor and Veronesi, 2012) —the table clearly shows the merit in taking a broader perspective of policy uncertainty. Economic policy uncertainty behaves in a manner distinct from economic and election uncertainty, with the highest degree of correlation being between EU and EPU at 0.67. National elections show little relation to EPU or any of the other uncertainty measures. All correlations are below 0.02, suggesting that the use of national elections as a proxy for policy uncertainty is not well supported by the data. Panel C of Table 1 confirms this interpretation by providing the average EPU value for months in election versus non-election periods. We see that the *Ln_EPU* averages of 4.64 and 4.63 are not significantly different from one another. Fig. 1, Panel A, further supports the distinction between uncertainty due to elections versus EPU by plotting the monthly EPU measure between 1985 and 2015, highlighting years with elections. The figure shows both significantly elevated values of EPU outside of election years and elections with relatively low levels of EPU.

The greatest EPU correlation is with our proxies for equity market uncertainty, macro uncertainty, and recessions. The *t*-test of difference in means confirms that the *Ln_EPU*'s average value of 4.82 during recessionary months is significantly greater than its mean of 4.61 in non-recessionary periods (Panel C, Table 1) confirming a tendency for more extensive policy reform when the economy is in crisis (Bloom, 2014; Geithner, 2014). Panel B of Fig. 1 further examines this relation by plotting the time series of EPU with both recessionary and financial crisis periods indicated.[10] While it is true that recessionary periods frequently coincide with peaks in EPU, more recent years have seen persistently elevated levels of EPU that do not appear to be associated with either weak economic periods or national elections. These observations inform us that EPU is a unique source of uncertainty distinct from elections, equity markets, and general economic conditions.

Table 2 provides descriptive statistics for the dependent variables (*abs_FE* and *DISP)* and firm-level and forecast control variables. Control variables related to analysts' forecasts include the logarithm of the number of analysts following the firm (*Ln_N_Analyst*) and the time horizon associated with the forecast using the logarithm of the number of months between the forecast date and the fiscal year end (*Ln_Horizon*). Note that we count the number of analysts as the aggregate number of analysts that provide a forecast for the firm in the twelve months leading up to its fiscal year-end, as greater analyst coverage may be associated with an enhanced information environment for the firm. Altering this definition to control for the number

[9] We explore the use of year fixed effects to allow for within-year variation in EPU while controlling for time fixed effects but find that during some periods of our sample, the yearly variation in EPU is relatively small so that concerns regarding the absorption of EPU by time fixed effects remain. Nevertheless, when we do include year fixed effects, our primary results persist and higher levels of EPU are associated with increased forecast error and dispersion. We do not report these results in the paper due to the increased risk of multicollinearity in these regressions and the consistent results that they provide.

[10] Financial crisis periods are defined to incorporate September – November 1987 (1987 crisis), August – December 1998 (LTCM crisis), and July 2007 – March 2009 (credit crisis).

**Table 1**
Descriptive statistics and correlation matrix of uncertainty measures.

*Panel A. Descriptive statistics*

| Variable | Mean | sd | p1 | p50 | p99 |
|---|---|---|---|---|---|
| *ln_EPU* | 4.5265 | 0.3930 | 3.6469 | 4.4912 | 5.3813 |
| *ln_EU* | 4.2398 | 0.6984 | 2.8096 | 4.1915 | 6.2344 |
| *ln_macro* | −0.4178 | 0.1119 | −0.57745 | −0.42316 | 0.0456 |
| *Election* | 0.1887 | 0.3918 | 0 | 0 | 1 |
| *Recession* | 0.1240 | 0.3300 | 0 | 0 | 1 |

*Panel B. Correlations between uncertainty variables*

| | ln_EPU | ln_EU | ln_macro | Election | Recession |
|---|---|---|---|---|---|
| ln_EPU | 1.0000 | | | | |
| ln_EU | 0.6721 | 1.0000 | | | |
| | (0.0000) | | | | |
| ln_macro | 0.2106 | 0.1148 | 1.0000 | | |
| | (0.0000) | (0.0270) | | | |
| Election | −0.0025 | 0.0131 | −0.0089 | 1.0000 | |
| | (0.9621) | (0.8011) | (0.8649) | | |
| Recession | 0.2934 | 0.2019 | 0.6042 | 0.0276 | 1.0000 |
| | (0.0000) | (0.0001) | (0.0000) | (0.5961) | |

*Panel C. Mean Ln EPU during different sub-periods*

| | Mean | Observations | *t*-test for Difference |
|---|---|---|---|
| Election years | 4.6419 | 70 | |
| | | | *t* = 0.8711 |
| Non-election years | 4.6359 | 301 | |
| Recession | 4.8161 | 46 | |
| | | | *t* = −4.6886 |
| Non-recession | 4.6122 | 325 | |

This table presents summary statistics (Panel A), correlation matrix among uncertainty variables (Panel B), a comparison of EPU (in logarithm) across various sub-periods (Panel C). All variables are defined in the appendix. P-values are reported in parenthesis below the correlation coefficients.

of forecasts provided in the month of observation does not change our results on the influence of EPU on forecast accuracy and dispersion.

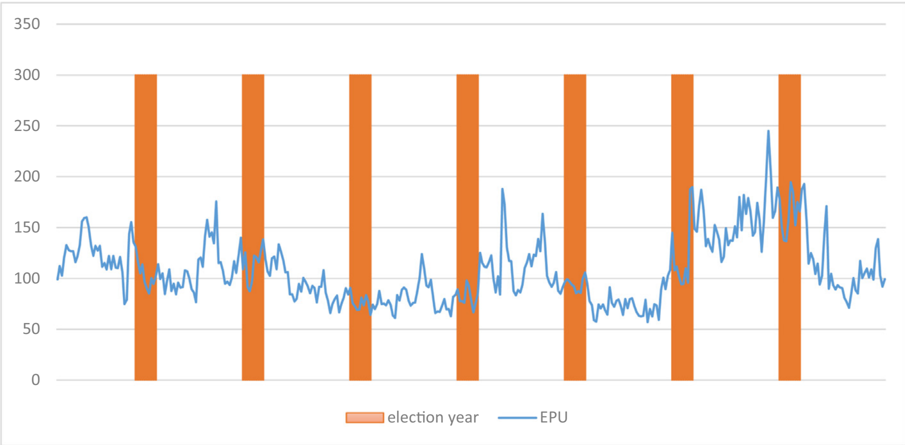
The specific firm-level controls we use follow Behn et al. (2008) and include firm size (measured as the logarithm of assets), Zmijewski's (1984) financial distress score (for which higher values relate to greater chance of default (*ZMIJ*)), historical standard deviation of return on equity (*Sd_ROE*), and variables related to earnings. These earnings-related variables include an indicator variable for negative earnings (*Loss*), the actual earnings per share (*Actual*), and the absolute value of the difference between this year's and last year's earnings, scaled by share price (*abs_surprise*). Details for the calculation and source of all variables are in the appendix.

In general, we expect larger firms will have lower levels of analyst forecast error and dispersion consistent with both Lang and Lundholm (1996) and Behn et al. (2008). We expect this to be the case, even during periods of elevated policy uncertainty, given the findings of Kang et al. (2014) that uncertainty has significantly less influence on the investment patterns of large firms. Firms with losses, that are in financial distress, or that have more significant changes in earnings from year to year, are expected to have earnings that are more difficult to forecast. Similarly, forecasts that refer to earnings that are farther away, or that are more volatile (measured by the standard deviation of return on equity over the past five years (*Sd_ROE*)), are expected to have greater forecast error and dispersion.

Panel A of Table 2 shows that analysts generate an average forecast error of −0.58%, which confirms the tendency for analysts to be overly optimistic in their forecasts. Absolute forecast error is on average 1.90%, however, this value is skewed upward—far beyond the median value of 0.44%—due to the presence of some very large errors. Forecast dispersion is similarly skewed upwards with a mean of 0.83% and a median of 0.21%. Panel B of Table 2 shows that, on average, 14 analysts follow a firm during the year and the average (median) forecast horizon is 5.2 (5) months. About 15.8% of the sample observations report a loss for the year. These statistics and others from Table 2 are comparable to those reported by Behn et al. (2008) who make use of a similar sample.

We proxy for differential ability and expertise across analysts by measuring their experience across three dimensions, with summary statistics provided in Panel C of Table 2. We calculate the analyst's overall experience (*Genexp*), measured by the number of years for which they have provided forecasts for any firm within the I/B/E/S database. Using a company's two digit SIC code, we identify the number of years for which an analyst has covered firms in that same industry (*Indexp*) and, finally, the number of years for which an analyst has covered a specific firm (*Firmexp*). As our forecast characteristics are calculated monthly, we include the average experience level for all analysts making forecasts for the firm in a particular month. Panel C shows that, on average, a sample analyst has over seven years of experience, almost six of which are for firms in the same industry and over 3.7 years for an individual firm.

*Panel A: EPU and National Elections*




*Panel B: EPU, Financial Crisis and Recessions*

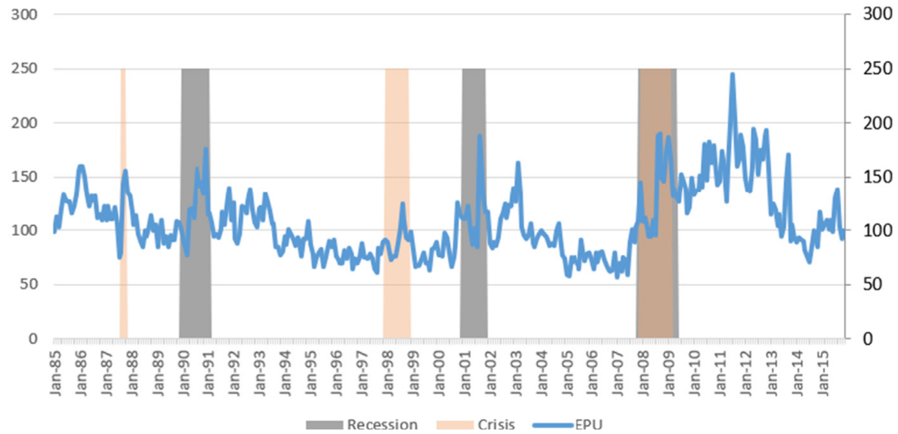



**Fig. 1.** Panel A plots the time series of economic policy uncertainty highlighting years with national elections. Panel B plots the same series with recessionary periods and financial crisis. Recession periods are: July 1990–March 1991, March–November 2001, and December 2007–June 2009. Crisis periods are September–November 1987 (1987 crisis), August–December 1998 (LTCM crisis), and July 2007–March 2009 (credit crisis).

As a final measure of potential expertise or resources that an analyst has at his or her disposal, we include a measure of brokerage house size based on the total number of analysts that it employs during a particular year. As is the case for analyst experience, in our regressions we average this value across all analysts providing forecasts for the firm in a given month. We motivate this variable by the general findings of Clement (1999) and Jacob et al. (1999) that forecast accuracy improves with brokerage house size, presumably due to environmental factors supporting analysts at these firms. Forecast accuracy may also improve due to the significant correlation between political connections and brokerage firm size, documented by Christensen et al. (2017) which may provide analysts with additional information on policy plans.

## 4. Results

### 4.1. Baseline results

In this section, we provide empirical results on the association between EPU and analyst forecast characteristics, focusing on the aggregate sample across the 30-year period. Table 3, Panel A examines forecast error in relation to EPU while Panel B reports regression results when forecast dispersion is the dependent variable. In both panels, we control for the number of analysts covering the firm, the forecast horizon, properties of the actual earnings reported, and firm characteristics. In Columns 1 and 2 of both panels we include the EPU index and two competing sources of uncertainty, one related to political environment and one related to equity market uncertainty. Specifically, we include the indicator for national elections and follow the recommendations of Baker et al. (2016) to control for equity uncertainty using the EU index, given the

**Table 2**
Descriptive statistics for dependent, firm level, and analyst variables.

| Variable | N | Mean | St-dev | P5 | Median | P95 |
|---|---|---|---|---|---|---|
| *Panel A. Dependent variables* | | | | | | |
| *FE* | 464,942 | −0.583 | 4.608 | −6.380 | −0.010 | 2.818 |
| *abs_FE* | 464,942 | 1.898 | 4.239 | 0.011 | 0.439 | 9.296 |
| *Dispersion* | 247,935 | 0.825 | 2.754 | 0.016 | 0.209 | 2.826 |
| *Panel B. Firm and forecast level control variables* | | | | | | |
| *Horizon* | 464,942 | 5.199 | 3.233 | 0.000 | 5.000 | 10.000 |
| *N_Analyst* | 99,619 | 13.883 | 10.499 | 1.000 | 11.000 | 35.000 |
| *Loss* | 99,619 | 0.158 | 0.364 | 0.000 | 0.000 | 1.000 |
| *ZMIJ* | 99,619 | −1.496 | 1.611 | −3.814 | −1.544 | 0.944 |
| *Total Assets* | 99,619 | 6,039.798 | 14112.982 | 48.658 | 1,085.310 | 30,891.000 |
| *Actual ($ per share)* | 99,619 | 1.122 | 2.134 | −1.100 | 0.870 | 4.270 |
| *Sd_ROE* | 99,619 | 0.210 | 0.410 | 0.012 | 0.069 | 1.161 |
| *Abs_Surprise (% share price)* | 99,619 | 6.343 | 42.521 | 0.074 | 1.143 | 18.797 |
| *Panel C. Analyst characteristics* | | | | | | |
| *Genexp* | 464,942 | 7.341 | 3.936 | 2 | 7 | 14.192 |
| *Indexp* | 464,942 | 5.969 | 3.528 | 1 | 5.500 | 12.304 |
| *Firmexp* | 464,942 | 3.781 | 2.307 | 1 | 3.250 | 8 |
| *Brokerage_size* | 464,942 | 54.692 | 39.857 | 8 | 47.500 | 127 |

This table presents summary statistics of the dependent variables, firm and forecast level control variables as well as analyst characteristics used in the regression analysis. All variables are defined in the appendix.

potential for a strong relation between EPU and general market uncertainty.[11] All columns control for firm fixed effects and clustering of standard errors by firm. In addition, Columns 2, 4, and 6 of the table double cluster the standard errors by firm and time for robustness.

Table 3 provides initial support for our hypotheses by showing a significant positive relation between EPU and both forecast error and dispersion. This relation exists despite controlling for national elections and equity market uncertainty. In terms of economic significance, our estimates from the first column indicate that a 10% increase in EPU is associated with 0.06 units increase in forecast error and 0.05 units increase in forecast dispersion. These figures are nontrivial given that median forecast error and dispersion are 0.43 and 0.21 respectively. While both EU and election years are associated with forecast error, elections have no meaningful relation with forecast dispersion.

The remaining columns of Table 3 introduce alternative sources of uncertainty to examine whether the relation between EPU and analyst forecast characteristics remains. Columns 3 and 4 add the Jurado et al. (2015) macro uncertainty index to both Panels A and B while Columns 5 and 6 replace this index with the recession indicator. Since the correlation between the measures of macroeconomic uncertainty and recessions exceeds 0.60, we refrain from including both in the same model specification. In all columns, we continue to include the indicator variable for national elections and the EU index.

Regardless of model specification, we see that the positive association between EPU and analyst forecast characteristics remains. This association is significant at the one percent level or better for all columns of the table for both forecast error and dispersion. The inclusion of competing measures of uncertainty does not influence EPU's effect on analyst forecast characteristics. The macro uncertainty index maintains a positive association with forecast error and dispersion, but the indicator for recessionary periods does not. Analysts' forecast error and dispersion increase significantly in response to multiple market-wide sources of uncertainty, however EPU appears to be distinct from macroeconomic conditions, elections, recessions and equity market uncertainty.

Control variables related to forecasts, earnings, and firm characteristics behave as expected. Earnings forecasts are more accurate and less dispersed when the firm is followed by more analysts, suggesting an improvement in the firm-level information environment. Increasing levels of financial distress, indicated by greater values of *ZMIJ* appear to complicate analysts' task and are associated with higher levels of forecast error and dispersion. Error and dispersion also increase with longer forecast horizons.

We examine the importance of forecast horizon for the relation between EPU and analyst forecast characteristics in more detail in Table 4. Table 4 separates the sample into short (less than five months) and long horizon forecasts and asks whether policy uncertainty continues to contribute to greater forecast error and dispersion. Columns 1 and 2 of the table present results when forecast error is the dependent variable while Columns 3 and 4 examine forecast dispersion. We again control for additional sources of uncertainty, specifically EU, election years, and macroeconomic uncertainty, and find that for both long and short term forecasts, policy uncertainty remains positively associated with increased forecast error and dispersion.[12] Long horizon forecasts show slightly larger coefficient estimates relating EPU to analyst forecast characteristics however

[11] We thank an anonymous referee for this suggestion.

[12] From this point in the paper onwards, we abstain from including an indicator variable for recession as the measure is highly correlated with the macroeconomic index. In addition, regressions in the tables are reported using firm fixed effects and have standard errors clustered by firm. We have repeated all analysis with standard errors double clustered by time and firm and results do not change.

**Table 3**
EPU and analyst forecast error and dispersion.

*Panel A. Forecast error*

| VARIABLES | abs_FE | abs_FE | abs_FE | abs_FE | abs_FE | abs_FE |
|---|---|---|---|---|---|---|
| *Ln_EPU* | 0.6185*** | 0.6185*** | 0.4697*** | 0.4697*** | 0.5595*** | 0.5595*** |
| | (12.5456) | (7.3021) | (9.4973) | (6.6538) | (11.3045) | (7.3147) |
| *Ln_EU* | −0.1180*** | −0.1180*** | −0.1641*** | −0.1641*** | −0.1556*** | −0.1556*** |
| | (−5.4207) | (−2.7123) | (−7.4658) | (−4.1690) | (−7.1407) | (−3.7627) |
| *Election_year* | 0.0425* | 0.0425 | 0.0421* | 0.0421 | 0.0308 | 0.0308 |
| | (1.9176) | (0.9774) | (1.9043) | (1.1070) | (1.3980) | (0.7764) |
| *Ln_macro* | | | 1.6118*** | 1.6118*** | | |
| | | | (14.7926) | (8.2008) | | |
| *Recession* | | | | | 0.3440*** | 0.3440*** |
| | | | | | (11.2510) | (4.8457) |
| *Ln_N_Analyst* | −0.4243*** | −0.4243*** | −0.3919*** | −0.3919*** | −0.4136*** | −0.4136*** |
| | (−11.6385) | (−10.0632) | (−10.7561) | (−9.6710) | (−11.3629) | (−9.9761) |
| *Ln_Horizon* | 0.7528*** | 0.7528*** | 0.7510*** | 0.7510*** | 0.7451*** | 0.7451*** |
| | (52.5422) | (26.8975) | (52.4419) | (28.3157) | (52.4221) | (27.9689) |
| *Loss* | 3.0733*** | 3.0733*** | 3.0633*** | 3.0633*** | 3.0707*** | 3.0707*** |
| | (32.4472) | (26.6478) | (32.4212) | (26.6328) | (32.4593) | (26.6298) |
| *ZMIJ* | 0.2631*** | 0.2631*** | 0.2606*** | 0.2606*** | 0.2584*** | 0.2584*** |
| | (12.0094) | (11.7445) | (11.9401) | (11.6909) | (11.8142) | (11.5543) |
| *Size* | 0.2355*** | 0.2355*** | 0.1837*** | 0.1837*** | 0.2256*** | 0.2256*** |
| | (7.4480) | (6.5813) | (5.7513) | (5.2840) | (7.1391) | (6.4143) |
| *Actual* | −0.2290*** | −0.2290*** | −0.2256*** | −0.2256*** | −0.2278*** | −0.2278*** |
| | (−7.5694) | (−7.2301) | (−7.4997) | (−7.1342) | (−7.5511) | (−7.2120) |
| *Sd_ROE* | 0.4522*** | 0.4522*** | 0.4355*** | 0.4355*** | 0.4561*** | 0.4561*** |
| | (5.9520) | (5.7731) | (5.7474) | (5.6057) | (6.0062) | (5.8204) |
| *abs_surprise* | 0.0157*** | 0.0157*** | 0.0155*** | 0.0155*** | 0.0157*** | 0.0157*** |
| | (6.3668) | (6.4359) | (6.3309) | (6.3834) | (6.3447) | (6.4047) |
| *Constant* | −2.3742*** | −2.3742*** | −0.5352* | −0.5352 | −1.9371*** | −1.9371*** |
| | (−8.9124) | (−5.8874) | (−1.8327) | (−1.3802) | (−7.2190) | (−5.3452) |
| Observations | 464,942 | 464,942 | 464,942 | 464,942 | 464,942 | 464,942 |
| R-squared | 0.5253 | 0.5253 | 0.5267 | 0.5267 | 0.5259 | 0.5259 |
| Firm FE | YES | YES | YES | YES | YES | YES |
| Firm clustering | YES | YES | YES | YES | YES | YES |
| Time clustering | NO | YES | NO | YES | NO | YES |

*Panel B. Forecast dispersion*

| VARIABLES | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion |
|---|---|---|---|---|---|---|
| *Ln_EPU* | 0.5077*** | 0.5077*** | 0.4447*** | 0.4447*** | 0.5004*** | 0.5004*** |
| | (11.9191) | (7.6431) | (10.3754) | (7.9185) | (11.7180) | (7.9263) |
| *Ln_EU* | −0.1502*** | −0.1502*** | −0.1731*** | −0.1731*** | −0.1563*** | −0.1563*** |
| | (−8.0238) | (−5.6684) | (−9.2757) | (−6.5817) | (−8.3433) | (−5.7205) |
| *Election_year* | −0.0503*** | −0.0503** | −0.0493*** | −0.0493** | −0.0526*** | −0.0526** |
| | (−4.5489) | (−2.3002) | (−4.4518) | (−1.9822) | (−4.7193) | (−2.2664) |
| *Ln_macro* | | | 0.6884*** | 0.6884*** | | |
| | | | (8.4461) | (4.0049) | | |
| *Recession* | | | | | 0.0486*** | 0.0486 |
| | | | | | (2.6117) | (0.8978) |
| *Ln_N_Analyst* | −0.1467*** | −0.1467*** | −0.1186*** | −0.1186*** | −0.1431*** | −0.1431*** |
| | (−3.7985) | (−3.3995) | (−3.0699) | (−2.8655) | (−3.7076) | (−3.3818) |
| *Ln_Horizon* | 0.1578*** | 0.1578*** | 0.1559*** | 0.1559*** | 0.1564*** | 0.1564*** |
| | (16.9230) | (9.7154) | (16.8510) | (10.4045) | (16.9379) | (10.1637) |
| *Loss* | 0.4870*** | 0.4870*** | 0.4834*** | 0.4834*** | 0.4865*** | 0.4865*** |
| | (7.6090) | (7.3870) | (7.5762) | (7.3719) | (7.6029) | (7.3863) |
| *ZMIJ* | 0.1382*** | 0.1382*** | 0.1379*** | 0.1379*** | 0.1375*** | 0.1375*** |
| | (6.4999) | (6.1145) | (6.4905) | (6.0994) | (6.4713) | (6.1032) |
| *Size* | 0.0870** | 0.0870** | 0.0651* | 0.0651* | 0.0854** | 0.0854** |
| | (2.3971) | (2.3059) | (1.7752) | (1.7232) | (2.3489) | (2.2647) |
| *Actual* | −0.1454*** | −0.1454*** | −0.1445*** | −0.1445*** | −0.1453*** | −0.1453*** |
| | (−4.1402) | (−4.1150) | (−4.1114) | (−4.0926) | (−4.1373) | (−4.1139) |
| *Sd_ROE* | 0.3275*** | 0.3275*** | 0.3207*** | 0.3207*** | 0.3281*** | 0.3281*** |
| | (4.2566) | (4.1621) | (4.1860) | (4.1119) | (4.2649) | (4.1656) |
| *abs_surprise* | 0.0236*** | 0.0236*** | 0.0235*** | 0.0235*** | 0.0236*** | 0.0236*** |
| | (5.2514) | (5.3642) | (5.2382) | (5.3417) | (5.2492) | (5.3600) |
| *Constant* | −1.2571*** | −1.2571*** | −0.4922 | −0.4922 | −1.1992*** | −1.1992*** |
| | (−4.1735) | (−3.5209) | (−1.5536) | (−1.4133) | (−3.9663) | (−3.5056) |
| Observations | 247,935 | 247,935 | 247,935 | 247,935 | 247,935 | 247,935 |
| R-squared | 0.6278 | 0.6278 | 0.6284 | 0.6284 | 0.6278 | 0.6278 |

(*continued on next page*)

**Table 3** (*continued*)

| *Panel B. Forecast dispersion* | | | | | | |
|---|---|---|---|---|---|---|
| VARIABLES | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion |
| Firm FE | YES | YES | YES | YES | YES | YES |
| Firm clustering | YES | YES | YES | YES | YES | YES |
| Time clustering | NO | YES | NO | YES | NO | YES |

This table reports the effect of EPU on forecast error (Panel A) and forecast dispersion (Panel B) after adding additional controls. All variables are defined in the appendix. T-statistics are reported below the coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 4**
Long and short forecast horizon.

| | abs_FE | | Dispersion | |
|---|---|---|---|---|
| VARIABLES | Long Horizon | Short Horizon | Long Horizon | Short Horizon |
| *Ln_EPU* | 0.5012*** | 0.4048*** | 0.4668*** | 0.4029*** |
| | (7.3780) | (9.0676) | (8.6732) | (9.8395) |
| *Ln_EU* | −0.0679** | −0.1672*** | −0.1142*** | −0.1897*** |
| | (-2.0306) | (-8.3205) | (-4.8614) | (-9.6610) |
| *Election_year* | 2.2589*** | 0.9901*** | 1.0228*** | 0.3744*** |
| | (14.9108) | (9.7073) | (9.1828) | (4.8218) |
| *Ln_macro* | 0.1098*** | 0.0307 | −0.0367*** | −0.0435*** |
| | (3.8641) | (1.4350) | (-2.6279) | (-3.7371) |
| *Ln_N_Analyst* | −0.4656*** | −0.3424*** | −0.2177*** | −0.0370 |
| | (-10.4104) | (-9.6198) | (-5.2884) | (-0.8957) |
| *Ln_Horizon* | 1.1796*** | 0.4522*** | 0.2140*** | 0.0989*** |
| | (30.2097) | (38.6027) | (8.5543) | (10.0425) |
| *Loss* | 3.9395*** | 2.2552*** | 0.4640*** | 0.4974*** |
| | (33.4841) | (25.9235) | (6.4396) | (7.4484) |
| *ZMIJ* | 0.3144*** | 0.2163*** | 0.1247*** | 0.1471*** |
| | (11.4343) | (10.1410) | (5.8998) | (5.8606) |
| *Size* | 0.3367*** | 0.1062*** | 0.0914** | 0.0547 |
| | (8.3739) | (3.5003) | (2.3381) | (1.4258) |
| *Actual* | −0.2790*** | −0.2036*** | −0.1438*** | −0.1388*** |
| | (-7.2556) | (-7.0768) | (-3.8958) | (-3.7565) |
| *Sd_ROE* | 0.5484*** | 0.3589*** | 0.3834*** | 0.2600*** |
| | (5.5026) | (5.2131) | (4.0420) | (3.5419) |
| *abs_surprise* | 0.0171*** | 0.0151*** | 0.0271*** | 0.0240*** |
| | (4.4871) | (8.2895) | (3.9440) | (6.1784) |
| *Constant* | −2.6191*** | 0.2930 | −0.8089** | −0.4026 |
| | (-6.5425) | (1.0834) | (-2.2447) | (-1.2443) |
| Observations | 216,209 | 248,733 | 115,345 | 132,590 |
| R-squared | 0.2002 | 0.1378 | 0.1516 | 0.1232 |
| Number of firms | 6,973 | 7,013 | 5,363 | 5,534 |
| Firm FE | YES | YES | YES | YES |
| Firm clustering | YES | YES | YES | YES |

This table reports the effect of EPU on forecast error and forecast dispersion for long and short-term forecasts. Long (short) horizon forecasts are those corresponding to earnings that will be reported in more (less) than five months. All the variables are defined in the appendix. T-statistics are reported below the coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

even short horizon forecasts show that the relation is statistically significant at the one percent level. In comparing these subsample results to the full sample of observations, we see few differences. The election year indicator continues to have less consistent results between forecast error and dispersion however EU and macro uncertainty persistently influence the short and long horizon forecasts in ways similar to the full sample. We turn next to examining whether analyst expertise moderates the influence of EPU on forecast characteristics.

### 4.2. Heterogeneity in analyst experience

We explore whether the influence of EPU on forecast characteristics differs according to the level of analysts' experience. Presumably, experience may proxy for learning or developed skill in correctly assessing the implications of EPU on firm profit levels. Firms that are on average covered by more experienced analysts may benefit from lower levels of forecast error and dispersion. We examine whether this is the case in Table 5. The regressions in this table take the same form as Eq. (1) where *abs_FE* and *DISP* are dependent variables measured monthly for each firm. To continue to control for competing sources of uncertainty, we include the election year indicator and indices reflecting equity market and macroeconomic uncertainty in all regressions. As in previous tables, we control for firm and earnings characteristics in addition to firm fixed effects. We add

**Table 5**
Effect of analyst experience and brokerage house size.

*Panel A. Forecast error*

| VARIABLES | abs_FE | abs_FE | abs_FE | abs_FE | abs_FE | abs_FE | abs_FE | abs_FE |
|---|---|---|---|---|---|---|---|---|
| *Ln_EPU* | 0.4711*** | 0.5337*** | 0.4743*** | 0.5202*** | 0.4651*** | 0.5081*** | 0.4607*** | 0.5073*** |
| | (9.5237) | (5.8095) | (9.5940) | (6.6554) | (9.4033) | (7.8004) | (9.3205) | (3.8926) |
| *Ln_genexp* | −0.0911*** | 0.0608 | | | | | | |
| | (−5.6029) | (0.3206) | | | | | | |
| *Ln_genexp*ln_EPU* | | −0.0327 | | | | | | |
| | | (−0.7957) | | | | | | |
| *Ln_indexp* | | | −0.0624*** | 0.0638 | | | | |
| | | | (−4.2281) | (0.3631) | | | | |
| *Ln_indexp*ln_EPU* | | | | −0.0272 | | | | |
| | | | | (−0.7135) | | | | |
| *Ln_firmexp* | | | | | 0.0267* | 0.1868 | | |
| | | | | | (1.7845) | (1.1869) | | |
| *Ln_firmexp*Ln_EPU* | | | | | | −0.0344 | | |
| | | | | | | (−1.0201) | | |
| *Ln_brokerage_size* | | | | | | | −0.0588*** | −0.0021 |
| | | | | | | | (−5.4538) | (−0.0141) |
| *Ln_brokerage_size*Ln_EPU* | | | | | | | | −0.0123 |
| | | | | | | | | (−0.3881) |
| *Ln_EU* | −0.1715*** | −0.1718*** | −0.1698*** | −0.1701*** | −0.1611*** | −0.1620*** | −0.1591*** | −0.1589*** |
| | (−7.8718) | (−7.8984) | (−7.7777) | (−7.8129) | (−7.3756) | (−7.4408) | (−7.2371) | (−7.2166) |
| *Ln_macro* | 1.5811*** | 1.5799*** | 1.5900*** | 1.5888*** | 1.6224*** | 1.6215*** | 1.6326*** | 1.6320*** |
| | (14.5094) | (14.4932) | (14.5996) | (14.5855) | (14.8695) | (14.8538) | (14.9291) | (14.9398) |
| *Election_year* | 0.0453** | 0.0459** | 0.0442** | 0.0447** | 0.0414* | 0.0418* | 0.0403* | 0.0404* |
| | (2.0485) | (2.0729) | (1.9979) | (2.0166) | (1.8702) | (1.8862) | (1.8184) | (1.8220) |
| *Ln_N_Analyst* | −0.4130*** | −0.4134*** | −0.4059*** | −0.4063*** | −0.3859*** | −0.3867*** | −0.3898*** | −0.3900*** |
| | (−11.3179) | (−11.3290) | (−11.1046) | (−11.1219) | (−10.5415) | (−10.5723) | (−10.7097) | (−10.7158) |
| *Ln_Horizon* | 0.7536*** | 0.7536*** | 0.7534*** | 0.7534*** | 0.7495*** | 0.7494*** | 0.7530*** | 0.7529*** |
| | (52.4875) | (52.4850) | (52.4674) | (52.4658) | (52.2781) | (52.2714) | (52.4777) | (52.4812) |
| *Loss* | 3.0654*** | 3.0655*** | 3.0655*** | 3.0655*** | 3.0617*** | 3.0619*** | 3.0660*** | 3.0661*** |
| | (32.4365) | (32.4370) | (32.4332) | (32.4335) | (32.4228) | (32.4238) | (32.4563) | (32.4543) |
| *ZMIJ* | 0.2630*** | 0.2630*** | 0.2623*** | 0.2623*** | 0.2598*** | 0.2598*** | 0.2610*** | 0.2610*** |
| | (12.0222) | (12.0222) | (11.9954) | (11.9952) | (11.9005) | (11.9003) | (11.9587) | (11.9587) |
| *Size* | 0.2109*** | 0.2115*** | 0.2016*** | 0.2021*** | 0.1771*** | 0.1776*** | 0.1972*** | 0.1974*** |
| | (6.4848) | (6.5130) | (6.1976) | (6.2294) | (5.4384) | (5.4586) | (6.1601) | (6.1769) |
| *Actual* | −0.2252*** | −0.2251*** | −0.2255*** | −0.2254*** | −0.2258*** | −0.2257*** | −0.2260*** | −0.2259*** |
| | (−7.4879) | (−7.4841) | (−7.4963) | (−7.4931) | (−7.5046) | (−7.4994) | (−7.5076) | (−7.5054) |
| *Sd_ROE* | 0.4397*** | 0.4402*** | 0.4370*** | 0.4373*** | 0.4358*** | 0.4362*** | 0.4384*** | 0.4385*** |
| | (5.8040) | (5.8117) | (5.7668) | (5.7728) | (5.7518) | (5.7575) | (5.7941) | (5.7952) |
| *abs_surprise* | 0.0155*** | 0.0155*** | 0.0155*** | 0.0155*** | 0.0155*** | 0.0155*** | 0.0155*** | 0.0155*** |
| | (6.3301) | (6.3305) | (6.3309) | (6.3311) | (6.3306) | (6.3309) | (6.3306) | (6.3302) |
| *Constant* | −0.5003* | −0.7943* | −0.5358* | −0.7506* | −0.5160* | −0.7135** | −0.3867 | −0.6029 |
| | (−1.7143) | (−1.7117) | (−1.8346) | (−1.8713) | (−1.7610) | (−2.0306) | (−1.3144) | (−0.9712) |
| Observations | 464,942 | 464,942 | 464,942 | 464,942 | 464,942 | 464,942 | 464,942 | 464,942 |
| R-squared | 0.1729 | 0.1729 | 0.1727 | 0.1728 | 0.1727 | 0.1727 | 0.1728 | 0.1728 |
| Number of firms | 7,143 | 7,143 | 7,143 | 7,143 | 7,143 | 7,143 | 7,143 | 7,143 |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm clustering | YES | YES | YES | YES | YES | YES | YES | YES |

*Panel B. Forecast dispersion*

| VARIABLES | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion |
|---|---|---|---|---|---|---|---|---|
| *Ln_EPU* | 0.4481*** | 0.4323*** | 0.4494*** | 0.4525*** | 0.4345*** | 0.4747*** | 0.4265*** | 0.8462*** |
| | (10.4568) | (4.0522) | (10.4982) | (4.7173) | (10.1284) | (6.0661) | (10.0124) | (4.8576) |
| *Ln_genexp* | −0.0920*** | −0.1286 | | | | | | |
| | (−3.6401) | (−0.5794) | | | | | | |
| *Ln_genexp*ln_EPU* | | 0.0078 | | | | | | |
| | | (0.1630) | | | | | | |
| *Ln_indexp* | | | −0.0592** | −0.0513 | | | | |
| | | | (−2.5421) | (−0.2346) | | | | |
| *Ln_indexp*ln_EPU* | | | | −0.0017 | | | | |
| | | | | (−0.0358) | | | | |
| *Ln_firmexp* | | | | | 0.0599*** | 0.1940 | | |
| | | | | | (2.6480) | (0.9350) | | |
| *Ln_firmexp*Ln_EPU* | | | | | | −0.0289 | | |
| | | | | | | (−0.6456) | | |
| *Ln_brokerage_size* | | | | | | | −0.0710*** | 0.4160** |
| | | | | | | | (−4.3839) | (2.1041) |

(*continued on next page*)

**Table 5** (*continued*)

*Panel B. Forecast dispersion*

| VARIABLES | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion |
|---|---|---|---|---|---|---|---|---|
| *Ln_brokerage_size*Ln_EPU* | | | | | | | | −0.1057** |
| | | | | | | | | (−2.4303) |
| *Ln_EU* | −0.1810*** | −0.1809*** | −0.1787*** | −0.1787*** | −0.1659*** | −0.1665*** | −0.1656*** | −0.1636*** |
| | (−9.7866) | (−9.7901) | (−9.6218) | (−9.6344) | (−8.8546) | (−8.9024) | (−8.9182) | (−8.7586) |
| *Ln_macro* | 0.6574*** | 0.6577*** | 0.6666*** | 0.6665*** | 0.7144*** | 0.7125*** | 0.7130*** | 0.7080*** |
| | (8.1111) | (8.1197) | (8.2678) | (8.2649) | (8.8402) | (8.8079) | (8.5754) | (8.5747) |
| *Election_year* | −0.0470*** | −0.0472*** | −0.0479*** | −0.0479*** | −0.0504*** | −0.0500*** | −0.0514*** | −0.0509*** |
| | (−4.2435) | (−4.2497) | (−4.3208) | (−4.3089) | (−4.5583) | (−4.5162) | (−4.6243) | (−4.5773) |
| *Ln_N_Analyst* | −0.1514*** | −0.1514*** | −0.1388*** | −0.1388*** | −0.1011** | −0.1019** | −0.1277*** | −0.1290*** |
| | (−3.7471) | (−3.7468) | (−3.4191) | (−3.4232) | (−2.5073) | (−2.5212) | (−3.2827) | (−3.3165) |
| *Ln_Horizon* | 0.1575*** | 0.1575*** | 0.1573*** | 0.1573*** | 0.1534*** | 0.1534*** | 0.1571*** | 0.1569*** |
| | (16.8513) | (16.9139) | (16.8396) | (16.8858) | (16.6124) | (16.6112) | (16.9033) | (16.9268) |
| *Loss* | 0.4846*** | 0.4845*** | 0.4845*** | 0.4845*** | 0.4805*** | 0.4807*** | 0.4847*** | 0.4853*** |
| | (7.5857) | (7.5839) | (7.5882) | (7.5879) | (7.5567) | (7.5551) | (7.5946) | (7.5993) |
| *ZMIJ* | 0.1404*** | 0.1404*** | 0.1395*** | 0.1395*** | 0.1359*** | 0.1359*** | 0.1387*** | 0.1388*** |
| | (6.6119) | (6.6188) | (6.5742) | (6.5768) | (6.4430) | (6.4430) | (6.5322) | (6.5351) |
| *Size* | 0.0941** | 0.0941** | 0.0830** | 0.0831** | 0.0489 | 0.0492 | 0.0814** | 0.0830** |
| | (2.4768) | (2.4789) | (2.1817) | (2.1882) | (1.2710) | (1.2804) | (2.1921) | (2.2460) |
| *Actual* | −0.1440*** | −0.1440*** | −0.1443*** | −0.1443*** | −0.1447*** | −0.1447*** | −0.1446*** | −0.1444*** |
| | (−4.0984) | (−4.0970) | (−4.1077) | (−4.1065) | (−4.1215) | (−4.1177) | (−4.1123) | (−4.1066) |
| *Sd_ROE* | 0.3273*** | 0.3272*** | 0.3239*** | 0.3240*** | 0.3191*** | 0.3194*** | 0.3247*** | 0.3251*** |
| | (4.2639) | (4.2658) | (4.2240) | (4.2285) | (4.1613) | (4.1668) | (4.2352) | (4.2446) |
| *abs_surprise* | 0.0235*** | 0.0235*** | 0.0235*** | 0.0235*** | 0.0235*** | 0.0235*** | 0.0235*** | 0.0235*** |
| | (5.2355) | (5.2356) | (5.2367) | (5.2367) | (5.2384) | (5.2381) | (5.2363) | (5.2354) |
| *Constant* | −0.4409 | −0.3663 | −0.4777 | −0.4922 | −0.4602 | −0.6451 | −0.2461 | −2.1993*** |
| | (−1.3908) | (−0.7048) | (−1.5074) | (−1.0246) | (−1.4471) | (−1.5670) | (−0.7733) | (−2.8376) |
| Observations | 247,935 | 247,935 | 247,935 | 247,935 | 247,935 | 247,935 | 247,935 | 247,935 |
| R-squared | 0.1271 | 0.1271 | 0.1269 | 0.1269 | 0.1269 | 0.1269 | 0.1271 | 0.1271 |
| Number of firms | 5,762 | 5,762 | 5,762 | 5,762 | 5,762 | 5,762 | 5,762 | 5,762 |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm clustering | YES | YES | YES | YES | YES | YES | YES | YES |

This table reports the effect of analyst characteristics on the association between EPU and forecast error (Panel A) and between EPU and forecast dispersion (Panel B). All variables are defined in the appendix. T-statistics are reported below the coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

measures of analyst experience overall, within an industry, and for each specific firm. We are motivated to distinguish expertise in this way given previous work on the demands and capabilities of analysts. Kadan et al. (2012) suggest that investors value analysts' industry expertise as the most important attribute contributing to their forecasts while Amiram et al. (2018) specifically examine how analysts' forecasts respond to market, industry, and firm level uncertainty. Similarly, Hutton et al. (2012) examine the accuracy of analyst versus management forecasts when earnings are influenced by macroeconomic, industry, and firm-level events.

We introduce each measure of analyst experience into our analysis in a consistent way. First, the measure is introduced into our regression independently to gauge the influence of the average level of analyst experience on forecast error and dispersion. Next, the expertise measure is interacted with the concurrent value of *Ln_EPU* to establish whether forecasts made by more experienced analysts have smaller error and dispersion in times of heightened policy uncertainty.

Beginning with forecast error in Panel A of Table 5 we see that, in general, analyst experience behaves as we would expect: more experienced analysts are capable of producing earnings forecasts with less error. Analysts' overall years of experience and their industry-specific expertise are strongly associated with more accurate earnings forecasts. However, we see only a weak, and in fact positive association for firm-specific experience and forecast error consistent with the findings of Hutton et al. (2012) that earnings can be difficult for analysts to predict if they are driven primarily by managerial decisions rather than macro or industry trends.

Including these alternative measures of analyst experience does not reduce the influence of economy-wide sources of uncertainty on analyst forecast error. Our measures for elections, equity market uncertainty, and macroeconomic uncertainty continue to be positively associated with earnings forecast error. The influence of EPU in particular remains strong. Across all columns of Panel A, EPU remains positively and significantly associated with an increase in forecast error at the one percent level. After controlling for average years of analyst experience, a 10 percent increase in EPU remains associated with 0.5 units increase in forecast error.

Moving to include the interaction terms to establish if analyst expertise enhances analysts' capability of providing accurate estimates even in the face of policy uncertainty, we find insignificant results. There is no distinction in forecast errors for more experienced analysts in the face of EPU. Similar results hold when examining the average brokerage house size for analysts providing forecasts in a given month. While it is true that analysts from larger brokerage houses (defined as those employing more analysts) produce forecasts with smaller error, they show no demonstrative difference in forecast ability as it relates to incorporating the influence of EPU.

Panel B shows similar results for forecast dispersion. When forecasts are made by analysts with more overall and industry specific experience, they are less dispersed; however, the reduction in dispersion is not associated with the concurrent level of EPU. Similarly, analysts from larger firms show less dispersion, again unrelated to EPU. Our results suggest that even experienced analysts, capable of making more accurate forecasts with greater consensus, show no significant advantage in predicting the consequences of EPU on firm profitability. This finding suggests that EPU remains a significant influence on a firm's information environment.

### 4.3. Analyst experience and industry-specific uncertainty

As an additional examination of analysts' expertise on forecast characteristics in the face of policy uncertainty we make use of an industry-specific policy index for the healthcare industry. Baker et al. (2016) create this index by requiring that additional terms such as "healthcare", "hospital", and "health insurance" are present in newspaper articles that also express general sentiments of uncertainty surrounding government policy. Similar to the EPU index, the healthcare policy index is measured monthly. We add this industry-specific variable to the models presented in Table 6 but retain other sources of market-wide uncertainty including EPU, elections, and macroeconomic uncertainty in our regressions. As in Table 5 we introduce measures of analyst experience and brokerage house size one-by-one and then interact each expertise proxy with the healthcare EPU to establish whether more experienced analysts, or those from larger firms, generate forecast predictions with different properties during times of high healthcare policy uncertainty. We continue to control for properties of the forecasts, earnings, and firms and include firm fixed effects. The sample is now restricted to 719 firms with four-digit SICs consistent with healthcare.[13]

Panel A of Table 6 presents results when *abs_FE* is the dependent variable while Panel B provides results for *DISP*. Only in this specialized context do we begin to see an indication that some heterogeneity exists in how analysts respond to policy uncertainty. While the overall EPU index continues to be associated with less accurate and more dispersed earnings forecasts, for this group of firms, the healthcare uncertainty index shows no significant relation to *abs_FE* or *DISP*. We interpret this insignificance to suggest that analysts focused on healthcare firms are able to incorporate policy uncertainty specific to the healthcare industry into their earnings estimates in a way that does not result in greater forecast error or disagreement among analysts. These findings are consistent with the results of Amiram et al. (2018) that analysts respond to heightened industry uncertainty (measured by the standard deviation of industry stock returns) by producing earnings estimates that are more timely but do not sacrifice accuracy.

The insignificant relation between healthcare policy uncertainty and forecast characteristics remains regardless of whether we control for analyst expertise using years of overall, industry, or firm-specific experience. Analysts with more overall and industry-specific experience continue to produce forecasts with smaller forecast errors in general but this experience does not interact with the healthcare uncertainty index in any meaningful way. While this subsample analysis suggests that an analyst's specialization may equip him or her to correctly predict the consequences of industry-specific policy, our fundamental results for the EPU index remain. Regressions in both Panels A and B continue to show the pervasive influence of overall economic policy uncertainty on analyst forecast characteristics. EPU remains significantly and positively related to both forecast error and dispersion suggesting that very general, market-wide uncertainty has consequences for earnings predictability.

In unreported robustness tests we restructure our regression models to be at the analyst rather than firm-level. Given the large number of analysts across our entire 30-year sample and the monthly structure of our data, we previously averaged analyst characteristics for each firm-month observation. In the smaller, healthcare sample, we alter this setup to allow for expertise at the individual analyst level and introduce analyst fixed effects as a potential control for time invariant expertise. Although this approach works well for individual analyst forecast error, it cannot be employed for forecast dispersion across multiple analysts.

Even in this setup, consistent findings occur. Individual analysts incorporate healthcare policy uncertainty into their forecasts without an increase in forecast error, however higher levels of economy-wide EPU continue to be associated with higher forecast error regardless of individual analyst expertise. More years being an analyst, a longer time-period of covering the healthcare industry, and working for a larger brokerage house continue to improve the accuracy of an analyst's earnings forecast but do not remove the association between EPU and greater forecast error.

### 4.4. Heterogeneity in policy sensitivity

We next ask whether the association between EPU and less accurate and more dispersed earnings forecasts are driven by a subset of firms, namely those that are particularly sensitive to government policy. There appears to be little consensus in the literature as to precisely how to categorize firms into policy sensitive versus policy neutral, therefore we present a variety of approaches following past work. A disadvantage of several of these approaches is that they are time-invariant for a

[13] The precise SIC codes that we include are 2830, 2831, 2833–2836, 6300, 6310–6329, 6370–6379, 8000–8099.

**Table 6**
Effect of healthcare EPU and analyst characteristics for healthcare firms.

*Panel A. Forecast error*

| VARIABLES | abs_FE | abs_FE | abs_FE | abs_FE | abs_FE | abs_FE | abs_FE | abs_FE |
|---|---|---|---|---|---|---|---|---|
| *Ln_EPU* | 0.8492*** | 0.8442*** | 0.8562*** | 0.8489*** | 0.8464*** | 0.8395*** | 0.8519*** | 0.8478*** |
| | (4.1972) | (4.1808) | (4.2410) | (4.2383) | (4.2113) | (4.1347) | (4.2306) | (4.1849) |
| *Ln_healthcare_EPU* | −0.0232 | −0.0453 | −0.0270 | −0.0574 | −0.0527 | −0.0859 | −0.0427 | −0.1357 |
| | (−0.3432) | (−0.3025) | (−0.4017) | (−0.4187) | (−0.7895) | (−0.7311) | (−0.6485) | (−0.5651) |
| *Ln_genexp* | −0.1442** | −0.2032 | | | | | | |
| | (−2.5179) | (−0.6523) | | | | | | |
| *Ln_genexp*Ln_healthcare_EPU* | | 0.0130 | | | | | | |
| | | (0.1937) | | | | | | |
| *Ln_indexp* | | | −0.1217** | −0.2076 | | | | |
| | | | (−2.1795) | (−0.6931) | | | | |
| *Ln_indexp*Ln_healthcare_EPU* | | | | 0.0190 | | | | |
| | | | | (0.2954) | | | | |
| *Ln_firmexp* | | | | | 0.1374** | −0.0108 | | |
| | | | | | (2.3521) | (−0.0287) | | |
| *Ln_firmexp*Ln_healthcare_EPU* | | | | | | 0.0322 | | |
| | | | | | | (0.4030) | | |
| *Ln_brokerage_size* | | | | | | | −0.0607 | −0.1771 |
| | | | | | | | (−1.3768) | (−0.6433) |
| *Ln_brokerage_size*Ln_healthcare_EPU* | | | | | | | | 0.0256 |
| | | | | | | | | (0.4307) |
| *Ln_EU* | −0.2850*** | −0.2846*** | −0.2854*** | −0.2848*** | −0.2599*** | −0.2587*** | −0.2700*** | −0.2710*** |
| | (−4.0394) | (−4.0305) | (−4.0547) | (−4.0477) | (−3.6695) | (−3.6574) | (−3.8357) | (−3.8471) |
| *Ln_macro* | 1.1622*** | 1.1649*** | 1.1688*** | 1.1734*** | 1.2521*** | 1.2560*** | 1.2229*** | 1.2267*** |
| | (3.0964) | (3.1128) | (3.1108) | (3.1300) | (3.3230) | (3.3229) | (3.2543) | (3.2599) |
| *Election_year* | −0.2347*** | −0.2346*** | −0.2354*** | −0.2353*** | −0.2357*** | −0.2354*** | −0.2388*** | −0.2384*** |
| | (−3.3065) | (−3.3064) | (−3.3157) | (−3.3149) | (−3.3278) | (−3.3250) | (−3.3626) | (−3.3621) |
| *Ln_N_Analyst* | −0.9108*** | −0.9113*** | −0.9058*** | −0.9064*** | −0.8624*** | −0.8616*** | −0.8876*** | −0.8874*** |
| | (−7.3168) | (−7.3227) | (−7.2922) | (−7.2989) | (−7.0382) | (−7.0391) | (−7.1542) | (−7.1525) |
| *Ln_Horizon* | 0.7852*** | 0.7850*** | 0.7843*** | 0.7841*** | 0.7650*** | 0.7644*** | 0.7800*** | 0.7799*** |
| | (16.0509) | (16.0482) | (16.0644) | (16.0585) | (15.8652) | (15.8631) | (16.0491) | (16.0492) |
| *Loss* | 0.0725 | 0.0722 | 0.0713 | 0.0713 | 0.0602 | 0.0592 | 0.0714 | 0.0707 |
| | (0.2534) | (0.2526) | (0.2491) | (0.2492) | (0.2108) | (0.2074) | (0.2501) | (0.2478) |
| *ZMIJ* | 0.1358*** | 0.1357*** | 0.1353*** | 0.1352*** | 0.1287*** | 0.1287*** | 0.1330*** | 0.1328*** |
| | (3.6514) | (3.6526) | (3.6429) | (3.6429) | (3.4561) | (3.4571) | (3.6136) | (3.6069) |
| *Size* | 0.2371*** | 0.2376*** | 0.2320** | 0.2326** | 0.1832** | 0.1834** | 0.2236** | 0.2229** |
| | (2.6304) | (2.6160) | (2.5824) | (2.5739) | (2.0399) | (2.0410) | (2.5159) | (2.5137) |
| *Actual* | −0.2948*** | −0.2949*** | −0.2953*** | −0.2954*** | −0.2990*** | −0.2993*** | −0.2989*** | −0.2993*** |
| | (−4.1021) | (−4.0931) | (−4.1090) | (−4.1023) | (−4.1642) | (−4.1607) | (−4.1520) | (−4.1473) |
| *Sd_ROE* | 0.3717** | 0.3720** | 0.3704** | 0.3707** | 0.3652** | 0.3662** | 0.3669** | 0.3671** |
| | (2.1708) | (2.1745) | (2.1626) | (2.1668) | (2.1203) | (2.1266) | (2.1386) | (2.1407) |
| *abs_surprise* | 0.0087** | 0.0087** | 0.0087** | 0.0087** | 0.0087** | 0.0087** | 0.0087** | 0.0087** |
| | (2.1320) | (2.1318) | (2.1322) | (2.1319) | (2.1334) | (2.1333) | (2.1342) | (2.1349) |
| *Constant* | −0.2040 | −0.0842 | −0.2428 | −0.0764 | −0.2537 | −0.0761 | −0.1527 | 0.2981 |
| | (−0.1915) | (−0.0727) | (−0.2279) | (−0.0678) | (−0.2388) | (−0.0640) | (−0.1414) | (0.1867) |
| Observations | 38,267 | 38,267 | 38,267 | 38,267 | 38,267 | 38,267 | 38,267 | 38,267 |
| R−squared | 0.0755 | 0.0755 | 0.0754 | 0.0754 | 0.0754 | 0.0755 | 0.0752 | 0.0752 |
| Number of firms | 719 | 719 | 719 | 719 | 719 | 719 | 719 | 719 |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm clustering | YES | YES | YES | YES | YES | YES | YES | YES |

*Panel B. Forecast dispersion*

| VARIABLES | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion |
|---|---|---|---|---|---|---|---|---|
| *Ln_EPU* | 0.7141*** | 0.7542*** | 0.7163*** | 0.7397*** | 0.7151*** | 0.7065*** | 0.6897*** | 0.7360*** |
| | (4.2587) | (4.4673) | (4.3073) | (4.4236) | (4.4436) | (4.2731) | (4.1674) | (4.3383) |
| *Ln_healthcare_EPU* | 0.0790 | 0.2393 | 0.0789 | 0.1677 | 0.0433 | 0.0083 | 0.0645 | 1.0060** |
| | (1.6168) | (1.4162) | (1.6183) | (1.0930) | (0.9348) | (0.0632) | (1.3789) | (2.4993) |
| *Ln_genexp* | −0.0889 | 0.3041 | | | | | | |
| | (−0.9844) | (0.8158) | | | | | | |
| *Ln_genexp*Ln_healthcare_EPU* | | −0.0891 | | | | | | |
| | | (−1.0296) | | | | | | |
| *Ln_indexp* | | | −0.0921 | 0.1372 | | | | |
| | | | (−1.0800) | (0.3808) | | | | |
| *Ln_indexp*Ln_healthcare_EPU* | | | | −0.0518 | | | | |
| | | | | (−0.6252) | | | | |
| *Ln_firmexp* | | | | | 0.2394*** | 0.1046 | | |
| | | | | | (2.9578) | (0.2318) | | |

**Table 6** (*continued*)

*Panel B. Forecast dispersion*

| VARIABLES | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion |
|---|---|---|---|---|---|---|---|---|
| *Ln_firmexp*Ln_healthcare_EPU* | | | | | | 0.0296 | | |
| | | | | | | (0.2946) | | |
| *Ln_brokerage_size* | | | | | | | −0.1868*** | 0.9157** |
| | | | | | | | (−3.1420) | (1.9806) |
| *Ln_brokerage_size*Ln_healthcare_EPU* | | | | | | | | −0.2431** |
| | | | | | | | | (−2.3883) |
| *Ln_EU* | −0.3059*** | −0.3102*** | −0.3066*** | −0.3091*** | −0.2720*** | −0.2703*** | −0.2819*** | −0.2695*** |
| | (−4.5428) | (−4.6149) | (−4.5508) | (−4.6103) | (−4.0643) | (−4.0698) | (−3.9339) | (−3.7108) |
| *Ln_macro* | 0.8622*** | 0.8422*** | 0.8592*** | 0.8464*** | 0.9594*** | 0.9649*** | 0.9282*** | 0.8861*** |
| | (3.0214) | (2.9380) | (3.0096) | (2.9420) | (3.3644) | (3.3428) | (3.2962) | (3.1208) |
| *Election_year* | 0.0289 | 0.0280 | 0.0289 | 0.0284 | 0.0286 | 0.0290 | 0.0241 | 0.0237 |
| | (0.4689) | (0.4535) | (0.4677) | (0.4605) | (0.4651) | (0.4702) | (0.3895) | (0.3836) |
| *Ln_N_Analyst* | −0.4544*** | −0.4513*** | −0.4534*** | −0.4514*** | −0.3829*** | −0.3821*** | −0.4646*** | −0.4604*** |
| | (−4.2168) | (−4.1842) | (−4.2242) | (−4.1961) | (−3.7237) | (−3.7057) | (−4.3915) | (−4.4121) |
| *Ln_Horizon* | 0.2835*** | 0.2850*** | 0.2841*** | 0.2849*** | 0.2602*** | 0.2595*** | 0.2837*** | 0.2854*** |
| | (7.2645) | (7.2425) | (7.2568) | (7.2285) | (6.9486) | (6.9519) | (7.4113) | (7.4374) |
| *Loss* | −0.4902** | −0.4863** | −0.4908** | −0.4894** | −0.4922** | −0.4932** | −0.4827** | −0.4802** |
| | (−2.1608) | (−2.1350) | (−2.1621) | (−2.1499) | (−2.1749) | (−2.1743) | (−2.1231) | (−2.1101) |
| *ZMIJ* | 0.0928** | 0.0927** | 0.0928** | 0.0927** | 0.0850** | 0.0850** | 0.0931*** | 0.0936*** |
| | (2.5539) | (2.5535) | (2.5579) | (2.5576) | (2.3566) | (2.3571) | (2.5868) | (2.6016) |
| *Size* | 0.0689 | 0.0665 | 0.0690 | 0.0676 | 0.0047 | 0.0053 | 0.0947 | 0.0986 |
| | (0.8409) | (0.8052) | (0.8451) | (0.8224) | (0.0617) | (0.0692) | (1.1920) | (1.2450) |
| *Actual* | −0.2159*** | −0.2149*** | −0.2159*** | −0.2153*** | −0.2207*** | −0.2210*** | −0.2207*** | −0.2178*** |
| | (−2.6650) | (−2.6403) | (−2.6666) | (−2.6514) | (−2.7206) | (−2.7149) | (−2.7144) | (−2.6659) |
| *Sd_ROE* | 0.1370 | 0.1360 | 0.1374 | 0.1371 | 0.1211 | 0.1219 | 0.1362 | 0.1303 |
| | (0.8886) | (0.8818) | (0.8921) | (0.8897) | (0.7807) | (0.7867) | (0.8734) | (0.8308) |
| *abs_surprise* | 0.0093* | 0.0093* | 0.0093* | 0.0093* | 0.0094* | 0.0094* | 0.0094* | 0.0093* |
| | (1.6617) | (1.6594) | (1.6617) | (1.6604) | (1.6690) | (1.6690) | (1.6652) | (1.6616) |
| *Constant* | 0.0370 | −0.8330 | 0.0230 | −0.4659 | −0.0553 | 0.1332 | 0.5622 | −4.0247* |
| | (0.0428) | (−0.7376) | (0.0268) | (−0.4190) | (−0.0654) | (0.1253) | (0.6431) | (−1.8893) |
| Observations | 19,909 | 19,909 | 19,909 | 19,909 | 19,909 | 19,909 | 19,909 | 19,909 |
| R−squared | 0.0522 | 0.0523 | 0.0522 | 0.0522 | 0.0532 | 0.0532 | 0.0530 | 0.0543 |
| Number of firms | 602 | 602 | 602 | 602 | 602 | 602 | 602 | 602 |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Firm clustering | YES | YES | YES | YES | YES | YES | YES | YES |

This table reports the effect of analyst characteristics on the association between healthcare EPU and forecast error (Panel A) and between healthcare EPU and forecast dispersion (Panel B). Healthcare firms are those with the following SIC codes: 2830, 2831, 2833–2836, 6300, 6310–6329, 6370–6379, 8000–8099. All variables are defined in the appendix. T−statistics are reported below the coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

firm. We rely on measures based on stock returns, government spending, and the text of executive conference calls. We interact time-invariant measures immediately with *Ln_EPU* in our regressions to examine their association with analyst forecast characteristics as their main effect will be subsumed by firm fixed effects.

Our first measures of a firm's policy sensitivity, included in Columns 1 and 2 of Table 6, follow Nagar et al. (2019). We label these measures as *Beta1* and *Beta2* and describe their calculation, and the calculation of all other measures, in the appendix. In essence, *Beta1* and *Beta2* are derived by regressing monthly excess stock return on the monthly EPU index and the Fama and French (1993) three factors of MKT, SMB, and HML. *Beta1* simply takes the coefficient resulting from the estimated relation between EPU and excess stock return after controlling for the other three factors. *Beta2* accounts for the possibility of non-synchronous trading by including EPU and the Fama French three factors at the month of observation and lagged by a month. An individual firm's sensitivity to EPU is calculated as the aggregated beta by summing the coefficient on EPU and its value lagged by one month. When *Beta1* and *Beta2* are used in regressions, they enter into the estimation in their absolute value form.

Our second approach to measuring a firm's exposure to policy uncertainty follows Baker et al. (2016) and uses government spending as an indicator of firm sensitivity to government actions. We make use of two of their firm-level measures with the first being a function of the firm's own sales to the federal government. This proxy calculates an average of the firm's government sales during the period 1985–2014. The second proxy uses firm-level exposure calculated by Baker et al.'s (2016) two-step method. As a first step, they aggregate revenues and contract awards to obtain the ratio of federal purchases to revenues in each 3-digit industry by year. These ratios are then averaged across years to obtain an exposure measure for each 3-digit SIC. In a second step, they measure each firm's exposure to government purchases as its revenue-weighted mean of the industry-level exposure measures calculated in the first step.

Our third approach to establishing the extent to which a firm may be sensitive to economic policy makes use of Hassan et al.'s (2019) political risk (*PRisk*) measure, which, unlike the other measures, does vary over time. Using textual analysis of

**Table 7**
EPU and forecast characteristics for policy neutral versus policy sensitive firms.

*Panel A. Forecast error*

| VARIABLES | abs_FE | abs_FE | abs_FE | abs_FE | abs_FE |
|---|---|---|---|---|---|
| *Ln_EPU* | 0.4702*** | 0.4850*** | 0.4279*** | 0.4234*** | 0.6256*** |
| | (8.8621) | (9.5347) | (8.2445) | (8.0607) | (8.8389) |
| *abs_Beta1* Ln_EPU* | −0.0264 | | | | |
| | (−0.0148) | | | | |
| *abs_Beta2* Ln_EPU* | | −0.7197 | | | |
| | | (−0.5059) | | | |
| *firm_intens* Ln_EPU* | | | 0.8123 | | |
| | | | (1.1206) | | |
| *firm_sic_intens* Ln_EPU* | | | | 1.3283 | |
| | | | | (1.3972) | |
| *prisk* | | | | | 0.0007 |
| | | | | | (0.5646) |
| *prisk* Ln_EPU* | | | | | −0.0001 |
| | | | | | (−0.3689) |
| *Ln_EU* | −0.1641*** | −0.1632*** | −0.1650*** | −0.1656*** | −0.2486*** |
| | (−7.4037) | (−7.3565) | (−7.2522) | (−7.2824) | (−8.8147) |
| *Ln_macro* | 1.6118*** | 1.6112*** | 1.7150*** | 1.7178*** | 1.7932*** |
| | (14.7902) | (14.7847) | (15.6062) | (15.6369) | (13.5179) |
| *Election_year* | 0.0421* | 0.0420* | 0.0395* | 0.0385* | 0.0643* |
| | (1.9038) | (1.8968) | (1.7370) | (1.6937) | (1.7650) |
| *Ln_N_Analyst* | −0.3919*** | −0.3922*** | −0.4030*** | −0.3996*** | −0.6438*** |
| | (−10.7585) | (−10.7664) | (−10.5921) | (−10.4457) | (−10.0093) |
| *Ln_Horizon* | 0.7510*** | 0.7510*** | 0.7650*** | 0.7659*** | 0.7507*** |
| | (52.4435) | (52.4433) | (50.9049) | (51.0081) | (40.1923) |
| *Loss* | 3.0633*** | 3.0633*** | 3.0011*** | 2.9967*** | 2.1240*** |
| | (32.4211) | (32.4244) | (31.5244) | (31.4694) | (17.7367) |
| *ZMIJ* | 0.2606*** | 0.2606*** | 0.2586*** | 0.2622*** | 0.2581*** |
| | (11.9397) | (11.9413) | (11.8218) | (11.9306) | (8.2352) |
| *Size* | 0.1837*** | 0.1837*** | 0.1867*** | 0.1843*** | 0.3252*** |
| | (5.7485) | (5.7487) | (5.7028) | (5.6190) | (5.3046) |
| *Actual* | −0.2257*** | −0.2257*** | −0.2415*** | −0.2416*** | −0.1749*** |
| | (−7.5031) | (−7.5052) | (−7.8405) | (−7.8600) | (−5.3477) |
| *Sd_ROE* | 0.4355*** | 0.4360*** | 0.4534*** | 0.4503*** | 0.4061*** |
| | (5.7458) | (5.7521) | (5.8207) | (5.8009) | (4.3395) |
| *abs_surprise* | 0.0155*** | 0.0156*** | 0.0154*** | 0.0154*** | 0.0190*** |
| | (6.3288) | (6.3295) | (6.2730) | (6.3227) | (8.2531) |
| *Constant* | −0.5320* | −0.5166* | −0.3127 | −0.3004 | −1.5763*** |
| | (−1.7659) | (−1.7142) | (−1.0431) | (−1.0022) | (−3.4830) |
| Observations | 464,942 | 464,942 | 437,981 | 438,763 | 197,172 |
| R−squared | 0.1726 | 0.1726 | 0.1765 | 0.1762 | 0.1449 |
| Number of firms | 7,143 | 7,143 | 6,544 | 6,596 | 3,608 |
| Firm FE | YES | YES | YES | YES | YES |
| Firm clustering | YES | YES | YES | YES | YES |

*Panel B: Forecast dispersion*

| VARIABLES | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion |
|---|---|---|---|---|---|
| *Ln_EPU* | 0.3782*** | 0.3861*** | 0.4220*** | 0.4254*** | 0.5505*** |
| | (8.8425) | (9.4792) | (9.2114) | (9.1824) | (9.8900) |
| *abs_Beta1* Ln_EPU* | 3.5949* | | | | |
| | (1.8283) | | | | |
| *abs_Beta2* Ln_EPU* | | 2.9197* | | | |
| | | (1.9069) | | | |
| *firm_intens* Ln_EPU* | | | 0.2151 | | |
| | | | (0.4621) | | |
| *firm_sic_intens* Ln_EPU* | | | | 0.0482 | |
| | | | | (0.0841) | |
| *prisk* | | | | | 0.0012 |
| | | | | | (0.8353) |
| *prisk* Ln_EPU* | | | | | −0.0002 |
| | | | | | (−0.7942) |
| *Ln_EU* | −0.1760*** | −0.1762*** | −0.1731*** | −0.1737*** | −0.2173*** |
| | (−9.2019) | (−9.2207) | (−8.7545) | (−8.7900) | (−10.5476) |
| *Ln_macro* | 0.6919*** | 0.6920*** | 0.7649*** | 0.7693*** | 0.7191*** |
| | (8.4680) | (8.4697) | (9.2248) | (9.2705) | (6.6953) |
| *Election_year* | −0.0491*** | −0.0491*** | −0.0508*** | −0.0497*** | −0.1211*** |
| | (−4.4288) | (−4.4333) | (−4.5151) | (−4.3737) | (−6.2959) |

**Table 7** (*continued*)

*Panel B: Forecast dispersion*

| VARIABLES | Dispersion | Dispersion | Dispersion | Dispersion | Dispersion |
|---|---|---|---|---|---|
| *Ln_N_Analyst* | −0.1176*** | −0.1172*** | −0.1142*** | −0.1138*** | −0.3348*** |
| | (−3.0490) | (−3.0404) | (−2.8114) | (−2.8041) | (−5.5605) |
| *Ln_Horizon* | 0.1559*** | 0.1560*** | 0.1586*** | 0.1604*** | 0.1968*** |
| | (16.8519) | (16.8607) | (16.7288) | (16.8249) | (13.4702) |
| *Loss* | 0.4829*** | 0.4833*** | 0.4522*** | 0.4513*** | 0.3796*** |
| | (7.5575) | (7.5654) | (6.9653) | (6.9500) | (4.5210) |
| *ZMIJ* | 0.1380*** | 0.1380*** | 0.1351*** | 0.1353*** | 0.1820*** |
| | (6.4929) | (6.4964) | (6.2151) | (6.2452) | (6.3548) |
| *Size* | 0.0653* | 0.0652* | 0.0629* | 0.0629* | 0.1186** |
| | (1.7781) | (1.7770) | (1.6689) | (1.6704) | (1.9811) |
| *Actual* | −0.1442*** | −0.1442*** | −0.1530*** | −0.1533*** | −0.1412*** |
| | (−4.1052) | (−4.1048) | (−4.1475) | (−4.1613) | (−3.3065) |
| *Sd_ROE* | 0.3193*** | 0.3187*** | 0.3359*** | 0.3369*** | 0.4051*** |
| | (4.1712) | (4.1622) | (4.2941) | (4.3125) | (4.0594) |
| *abs_surprise* | 0.0235*** | 0.0235*** | 0.0239*** | 0.0239*** | 0.0285*** |
| | (5.2298) | (5.2329) | (5.1951) | (5.2318) | (7.0636) |
| *Constant* | −0.5417* | −0.5419* | −0.3678 | −0.3753 | −0.6836 |
| | (−1.6522) | (−1.6536) | (−1.1192) | (−1.1426) | (−1.4583) |
| Observations | 247,935 | 247,935 | 235,409 | 235,655 | 118,003 |
| R−squared | 0.1270 | 0.1269 | 0.1357 | 0.1346 | 0.1463 |
| Number of firms | 5,762 | 5,762 | 5,279 | 5,313 | 3,272 |
| Firm FE | YES | YES | YES | YES | YES |
| Firm clustering | YES | YES | YES | YES | YES |

This table reports the effect of firm policy sensitivity on the association between EPU, forecast error (Panel A) and forecast dispersion (Panel B). In columns 1 and 2, the policy sensitivity measure is based on stock returns. *abs_Beta1* (*abs_Beta2*) is the absolute value of *Beta1* (*Beta2*). In columns 3, 4 and 5, policy sensitivity is measured by the firm level intensity (*firm_intens*), the 2 step method firm level intensity (*firm_sic_intens*) and the political risk measure (*prisk*) compiled by Hassan et al. (2019), respectively. All policy sensitivity measures, except prisk, are time invariant. All variables are defined in the appendix. T-statistics are reported below the coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

quarterly conference calls held by company executives, the authors measure the proportion of the call that relates to political risks. While the measure is not provided for all of our sample observations, there is significant overlap so that the size of our tests remains sufficient.

Results are presented in Table 7. Following our previous convention, Panel A of the table provides estimated coefficients for regressions in which forecast error is the dependent variable while Panel B presents results for forecast dispersion. In both panels, Column 1 shows the interaction of *Beta1* with the concurrent level of *Ln_EPU* to examine whether firms with higher levels of policy sensitivity show larger forecast errors and dispersion in the face of EPU. Column 2 provides similar analysis using the policy sensitivity measure *Beta2*. Columns 3 and 4 make use of the Baker et al. measures while Column 5 relies on Hassan et al.'s (2019) text-based measure.

Panel A confirms our previous results that EPU has a pervasive influence across a broad spectrum of firms and a wide range of political and economic conditions. We see no significant difference in the size of analyst forecast errors for firms deemed more policy sensitive. Economic policy uncertainty continues to show strong positive influence on forecast error in these regressions, despite controlling for firm-level heterogeneity in policy sensitivity.

Panel B provides largely similar results. While there is some weak evidence (ie., at the ten percent level) that firms that are more policy sensitive as measured by the stock-based measures of *Beta1* and *Beta2* have greater earnings forecast dispersion, competing measures of policy sensitivity based on government sales or textual analysis do not support these results. Columns 3 through 5 show no significant association between these measures of policy sensitivity and analyst forecast dispersion during periods of heightened EPU. Moreover, the consistently strong relation between EPU and forecast dispersion remains, even after identifying varying levels of policy sensitivity among firms. We again conclude that the influence of EPU on analyst forecast characteristics is pervasive.

## 5. Conclusion

Motivated by the insight that EPU can significantly reduce the quality of information available about a firm, we gain a better understanding of the role EPU plays in contributing to the characteristics of analysts' forecasts. Political uncertainty around which policies may be implemented and impact uncertainty related to the potential influence of these policies on individual firms may both serve to make firm-level profits harder to forecast. Differences in opinion, specialized expertise, or access to private political or policy-related information may introduce more disperse forecasts as well.

Our results suggest that, across both time and firms, EPU has a significant and persistent influence on the information environment that is distinct from other sources of uncertainty. After controlling for competing sources of economy-wide uncertainty—such as national elections, recessions, equity market and macroeconomic uncertainty—we find that EPU is significantly and positively associated with higher absolute forecast error and forecast dispersion.

We also examine whether a particular subset of analysts is better able to provide more accurate and less disperse forecasts in the face of EPU. Drawing on the notion that learning may occur, we examine whether analyst experience overall, within a particular industry, or for a specific firm, influences their ability to make earnings forecasts with smaller errors, even in the face of EPU. We find no consistent evidence that forecasts made by more experienced analysts have fewer errors or less dispersion during periods of higher EPU. Similarly, forecasts made by analysts from larger brokerage houses, which are presumably better supported or more likely to maintain political connections, show no significant improvement in forecast characteristics. In subsample analysis based on the healthcare sector and a measure of healthcare policy uncertainty specifically, we do find some evidence that analysts are able to integrate this uncertainty into their estimates. The healthcare policy index shows no systematic association with less accurate or more dispersed earnings forecasts. However, the more general EPU measure of market-wide uncertainty across all sectors continues to be positively associated with forecast error and dispersion.

Using three alternative approaches and five distinct measures of firm sensitivity to policy uncertainty based on stock returns, government spending, and the text of quarterly executive conference calls, we see few differences. Forecast error and dispersion are positively associated with EPU across both policy sensitive and policy neutral firms. Furthermore, individual firm exposure seems to matter less than the overall level of EPU, leading to few cross-sectional differences in forecast characteristics.

The implications of our work are significant for users of analyst forecasts, suppliers of capital, analysts themselves, and the policy makers who contribute to EPU. Economic policy uncertainty makes earnings more difficult for analysts to predict, in that these predictions have greater error and are more disperse. These findings, however, should not be taken to suggest that the forecasts are of lower aggregate value to investors. A limitation of our work is that we do not evaluate the timeliness of analyst predictions. Analysts may respond quickly to policy uncertainty by updating their forecasts despite a potential decrease in precision however investors may prefer this quick response, despite potential errors.

For analysts, further research should be done to probe why forecast accuracy declines for both policy sensitive and policy neutral firms. Is it the case that analysts over-react to policy uncertainty, thereby unnecessarily adjusting their forecasts for firms less likely to be influenced by these policies? Or, is it that EPU augments uncertainty across all firms, leading to an overall increase in the complexity associated with forecasting earnings? If EPU has an overall influence on the information environment, the policy makers that contribute to its level should take care to provide clarity in their objectives and the means used to achieve them. Doing so may allow analysts and other market participants to more accurately anticipate the consequences of policy makers' actions for business. Additional clarity can enhance analyst forecast accuracy, thereby improving the information environment for firms and enhancing capital market operations.

## Acknowledgements

We thank Kose John, Sattar Mansi, Hongping Tan, Maurice McCourt, Xueping Wu, Imed Chkir, Sara Ding, Francois Eric-Racicot and participants of the 2017 Telfer Annual Conference in Accounting and Finance, the 2017 International Research Meeting in Business and Management, the 2017 Paris Financial Management Conference, the 2018 International Research Meeting in Business and Management, the 2018 International Conference of the African Federation of Operational Research Societies, the University of Ottawa, IPAG Business School, South Champagne Business School, and ESSCA Business School for their helpful comments and suggestions on previous versions of the paper. Previous versions of this work were titled Does Economic Policy Uncertainty Influence Analyst Behavior? Lamia Chourou gratefully acknowledges financial support from the CPA-Canada Accounting and Governance Research Center. We thank Rui Duan and Julia Thornley for excellent research assistance. All errors are our own responsibility.

## Appendix. Variable Definitions

| Variables | Definitions | Source |
|---|---|---|
| *Dependent variables* | | |
| *abs_FE* | The median of absolute value of individual forecast errors scaled by stock price at time *t*-1 in a given month for a given firm. | I/B/E/S, CRSP and authors' calculations |
| *Dispersion* | The standard deviation of EPS forecasts for a given firm in a given month scaled by stock price at time *t*-1. | I/B/E/S, CRSP and authors' calculations |
| *Independent variables* | | |
| *Ln_EPU* | The natural logarithm of the economic policy uncertainty index developed by Baker et al. (2016) | Available at www.policyuncertainty.com |
| *Ln_heatthcare_EPU* | The natural logarithm of the healthcare economic policy uncertainty index developed by Baker et al. (2016) | Available at www.policyuncertainty.com |

**Appendix** (*continued*)

| Variables | Definitions | Source |
|---|---|---|
| *Ln_EU* | The natural logarithm of the equity uncertainty (EU) index developed by Baker et al. (2016) | Available at http://www.policyuncertainty.com/equity_uncert.html. |
| *Ln_N_Analyst* | The natural logarithm of the number of analysts following the firm during the year. | I/B/E/S and authors' calculations |
| *Ln_Horizon* | The natural logarithm of the number of months between the forecast announcement date and the fiscal year end. | I/B/E/S and authors' calculations |
| *Loss* | Coded as 0 (1) for firm-year observations with positive (negative) earnings. | COMPUSTAT and authors' calculations |
| *ZMIJ* | Zmijewski's financial distress score (Zmijewski, 1984). | COMPUSTAT and authors' calculations |
| *Firm Size* | Logarithm of total assets. | COMPUSTAT and authors' calculations |
| *Actual* | Actual earnings per share. | I/B/E/S |
| *Sd_ROE* | Standard deviation of return on equity over the previous five years. | COMPUSTAT and authors' calculations |
| *abs_surprise* | Absolute value of this year's earnings minus last years' earnings deflated by stock price at time *t-1*. | COMPUSTAT and authors' calculations |
| *Election Year* | A dummy variable that equals one for every presidential-election year (January to October) and zero otherwise. | |
| *Macro-Uncertainty* | Jurado et al. (2015) index of macro-economic uncertainty. | Available at https://www.sydneyludvigson.com/data-and-appendixes/ |
| *Recession* | A dummy variable that take the value of one for the periods: July 1990-March 1991, March-November 2001, and December 2007-June 2009, and zero otherwise | NBER |
| *Beta1* | Firm-level EPU returns beta, which we compute by running firm-level regressions of monthly excess returns on the monthly EPU index and the three factors MKT, SMB and HML. | CRSP and authors' calculations |
| *Beta2* | Firm-level EPU returns beta (Policy Beta), which we compute by running firm-level regressions of monthly excess returns on the monthly EPU index and the three factors MKT, SMB and HML as well as their prior month's lagged (t-1) forms. We then sum the contemporaneous EPU beta and the lagged EPU beta to create an alternative beta. | CRSP and authors' calculations |
| *Firm_intens* | Firm level intensity calculated as the average of firm's own sales to the government over the period 1985–2014 derived by Baker et al. (2016). | Available at http://www.policyuncertainty.com/research.html. |
| *Firm_sic_intens* | 2 step method firm level intensity calculated by the two-step method derived by Baker et al. (2016). | Available at http://www.policyuncertainty.com/research.html. |
| *PRisk* | Proportion of quarterly conference calls that a firm's executives devote to discussions of political risk. It is compiled by Hassan et al. (2019). | Available at http://www.policyuncertainty.com/firm_pr.html |
| *Firmexp* | Analyst's firm-specific experience measured as the number of prior years he has issued annual earnings forecasts for a given firm. The variable is averaged across analysts following the firm during a particular month. | I/B/E/S and authors' calculations |
| *Genexp* | General experience measured as the number of prior firm years the analyst has issued annual forecasts for any firm on the I/B/E/S database. The variable is averaged across analysts following the firm during a particular month. | I/B/E/S and authors' calculations |
| *Indexp* | Industry experience measured as the number of prior firm years the analyst issued an annual forecast for any firm in the | I/B/E/S and authors' calculations |

(*continued on next page*)

**Appendix** (*continued*)

| Variables | Definitions | Source |
|---|---|---|
| | same two-digit SIC code as the forecasted firm. The variable is averaged across analysts following the firm during a particular month. | |
| *Brokerage size* | The number of analysts employed by the brokerage employing analyst i following firm j in year t. The variable is averaged across analysts issuing an annual forecast for a given firm during a given month. | I/B/E/S and authors' calculations |

## References


Abarbanell, J., Bernard, V., 1992. Tests of analysts' overreaction/ underreaction to earnings information as an explanation for anomalous stock price behavior. J. Finan. 47, 1181–1207.
Akey, P., Lewellen, S., 2017. Policy uncertainty, political capital, and firm risk-taking. University of Toronto, Working Paper.
Amiram, D., Landsman, W.R., Owens, E., Stubben, S.R., 2018. How are analysts' forecasts affected by high uncertainty? J. Bus. Finan. Acc. 45, 295–318.
Arif, S., Marshall, N.T., Yohn, T.L., 2016. Understanding the relation between accruals and volatility: A Real options-based investment approach. J. Acc. Econ. 62, 65–86.
Auerbach, A.J., Hines, J.R., 1988. Investment tax incentives and frequent tax reforms. Am. Econ. Rev. 78, 211–216.
Bailey, W., Li, H., Zhong, R., 2003. Regulation fair disclosure and earnings information: market, analyst, and corporate responses. J. Finan. 58, 2487–2514.
Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. Q. J. Econ. 131, 1593–1636.
Bagnoli, M., Watts, S.G., Zhang, Y., 2008. Reg-FD and the competitiveness of all-star analysts. J. Account. Pub. Pol. 27, 295–316.
Baloria, V.P., Mamo, K., 2014. Political uncertainty and analyst performance. Working Paper.
Basu, S., Markov, S., Shivakumar, L., 2010. Inflation, earnings forecasts, and post-earnings announcement drift. Rev. Acc. Stud. 15, 403–440.
Behn, B., Choi, J.-H., Kang, T., 2008. Audit quality and properties of analyst earnings forecasts. Acc. Rev. 83, 327–349.
Bernhard, W., Leblang, D., 2006. Polls and pounds: Public opinion and exchange rate behavior in Britain. Q. J. Politi. Scien. 1, 25–47.
Bechtel, M., 2009. The political sources of systematic investment risk: Lessons from a consensus democracy. J. Politi 71, 667–677.
Bloom, N., 2009. The impact of uncertainty shocks. Economet. 77, 623–685.
Bloom, N., 2014. Fluctuations in uncertainty. J. Econ. Perspect. 28, 153–176.
Bradley, D., Pantzalis, C., Yuan, X., 2016. The influence of political bias in state pension funds. J. Finan. Econ. 119, 69–91.
Brogaard, J., Detzel, A., 2015. The asset pricing implications of government economic policy uncertainty. Manag. Scien. 61, 3–18.
Brown, L., Call, A., Clement, M., Sharp, N., 2015. Inside the "black box" of sell-side financial analysts. J. Acc. Res. 53, 1–47.
Bradley, D., Gokkaya, S., Liu, X., Michaely, R., 2018. Is Washington Policy Research Valuable to Capital Markets? W. P.
Campello, D., 2007. Do markets vote? A systematic analysis of portfolio investors' response to national elections'. Princeton University. Unpublished manuscript.
Cao, Y., Guan, F., Li, Z., Yang, G.Y., 2020. Analysts' beauty and performance. Manage. Scien., forthcoming.
Chen, F., Hope, O., Li, Q., Wang, X., 2018a. Flight to quality in international markets: Investors' demand for financial reporting quality during political uncertainty events. Contemp. Acc. Res. 35, 156–163.
Chen, Y., Chen, D., Wang, W., Zheng, D., 2018b. Political uncertainty and firms' information environment: Evidence from China. J. Acc. Pub. Pol. 37, 39–64.
Christensen, D.M., Mikhail, M.B., Walther, B.R., Wellman, L.A., 2017. From K street to wall street: political connections and stock recommendations. Acc. Rev. 92, 87–112.
Clement, M., 1999. Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? J. Acc. Econ. 281 (51–82), 7–112.
Diamond, D., Verrecchia, R.E., 1981. Information aggregation in a noisy rational expectations economy. J. Finan. Econ. 9, 221–235.
Dinh, T., Eierle, B., Schultze, W., Steeger, L., 2015. Research and development, uncertainty, and analysts' forecasts: The case of IAS 38. J. Int. Finan. Manag. Acc. 26, 257–293.
Donelson, D.C., Resutek, R.J., 2012. The effect of R&D on future returns and earnings forecasts. Rev. Acc. Stud. 17, 848–876.
Faigelbaum, P., Schaal, E., Taschereau-Dumouchel, M., 2017. Uncertainty traps. Quar. J. Econ. 132 (4), 1641–1692.
Füss, R., Bechtel, M., 2008. Partisan politics and stock market performance: The effect of expected government partisanship on stock returns in the 2002 German federal election. Pub. Choi. 135, 131–150.
Fama, E.F., French, K.R., (1993). Common risk factors in the returns on stocks and bonds. J. Finan. Econ. 33, 3–56.
Gao, M., Huang, J., 2016. Capitalizing on Capitol Hill: Informed trading by hedge fund managers. J. Finan. Econ. 121, 521–554.
Geithner, T., 2014. Stress Test: Reflections on Financial Crises. Random House Business.
Goodell, J.W., Vähämaa, S., 2013. U.S. presidential elections and implied volatility: The role of political uncertainty. J. Bank. Finan. 37, 1108–1117.
Guenther, D., 1994. Measuring earnings management in response to corporate tax rate changes: evidence from the 1986 tax reform act. Acc. Rev. 69, 230–243.
Gulen, H., Ion, M., 2016. Policy uncertainty and corporate investment. Rev. Finan. Stud. 29, 523–564.
Hahn, T., Song, M., 2013. Regulation fair disclosure and analysts' reliance on earnings announcements. J. Account. Pub. Pol. 32, 26–43.
Hassan, T., Hollander, S., Laurence, V.L., Tahoun, A., 2019. Firm-level political risk: Measurement and effects. Q. J. Econ. 134, 2135–2202.
Harris, M., Raviv, A., 1993. Differences of opinion make a horse race. Rev. Finan. Stud. 6, 473–506.
Hugon, J., Kumar, A., Lin, A.P., 2016. Analysts, macroeconomic news, and the benefit of active in-house economists. Acc. Rev. 91, 513–534.
Hutton, A.P., Lee, L.F., Shu, S.Z., 2012. Do managers always know better? Relative accuracy of management and analyst forecasts. J. of Acc. Res. 50, 1217–1244.
Jacob, J., Lys, T.Z., Neale, M.N., 1999. Expertise in forecasting performance of security analysts. J. Acc. Econ. 28, 51–82.
Jagolinzer, A.D., Larcker, D.F., Ormazabal, G., Taylor, D., 2020. Political connections and the informativeness of insider trades. J. Finan., forthcoming.
Jurado, K., Ludvigson, S., Ng, S., 2015. Measuring uncertainty. Am. Econ. Rev. 105, 1177–1216.
Kadan, O., Madureira, L., Wang, R., Zach., 2012. Analysts' industry expertise. J. Acc. Econ., 54, 95–120.
Kang, W., Lee, K., Ratti, R.A., 2014. Economic policy uncertainty and firm-level investment. J. Macroecon 39, 42–53.
Kandel, E., Pearson, N., 1995. Differential interpretation of public signals and trade in speculative markets. J. Politi. Econ. 103, 831–872.
Kaviani, M.S., Kryzanowski, L., Maleki, H., Savor, P.G., 2020. Policy uncertainty and corporate credit spreads. J. Finan. Econ.
Kelly, B., Pastor, L., Veronesi, P., 2016. The price of political uncertainty: Theory and evidence from the option market. J. Finan. 71, 2417–2480.
Kim, O., Verrecchia, R.E., 1991. Trading volume and price reactions to public announcements. J. Acc. Res. 29, 302–321.
Konchitchki, Y., Patatoukas, P.N., 2014a. Accounting earnings and gross domestic product. J. Acc. Econ. 57, 76–88.

Konchitchki, Y., Patatoukas, P.N., 2014b. Taking the pulse of the real economy using financial statement analysis: Implications for macro forecasting and stock valuation. Acc. Rev. 89, 669–694.
Kumar, A., 2010. Self-selection and the forecasting abilities of female equity analysts. J. Acc. Res. 48, 393–435.
Lang, M., Lundholm, R., 1996. Corporate disclosure policy and analyst behavior. Acc. Rev. 71, 467–492.
Lehavey, R., Li, F., Merkley, K., 2011. The Effect of annual report readability on analyst following and the properties of their earnings forecasts. Acc. Rev. 86, 1087–1115.
Ljungqvist, A., Marston, F., William, W., 2006. Competing for securities underwriting mandates: Banking relationships and analyst recommendations. J. Finan. 61, 301–340.
Loh, R.K., Mian, M., 2003. The quality of analysts' earnings forecasts during the Asian crisis: Evidence from Singapore. J. Bus. Finan. Acc. 30, 749–769.
Loh, R., Stulz, R.M., 2018. Is sell-side research more valuable in bad times? J. Finan. 73, 959–1013.
Maaloul, A., Ben Amar, W., Zeghal, D., 2016. Voluntary disclosure of intangibles and analysts' earnings forecasts and recommendations. J. App. Acc. Res. 17, 421–439.
Nagar, V., Schoenfeld, J., Wellman, L., 2019. The effect of economic policy uncertainty on investor information asymmetry and management. J. Acc. Econ. 67, 36–57.
Nguyen, N.H., Phan, H.V., 2017. Policy uncertainty and mergers and acquisitions. J. Finan. Quantita. Analy. 52, 613–644.
Pastor, L., Veronesi, P., 2012. Uncertainty about government policy and stock prices. J. Finan. 67, 1219–1264.
Pastor, L., Veronesi, P., 2013. Political uncertainty and risk premia. J. Finan. Econ. 110, 520–545.
Poterba, J.M., Nirupama S., Rao, Seidman, J.K., 2011. Deferred tax positions and incentives for corporate behavior around corporate tax changes. Natio. Tax J., 64, 27–57.
Sattler, T., Brandt, P.T., Freeman, J.R., 2010. Democratic accountability in open economies. Q. J. Politi. Scien. 5, 71–97.
Stein, L.C.D., Wang, C.C.Y., 2016. Economic uncertainty and earnings management. Harvard Business School Accounting & Management Unit. Working Paper.
Van Nieuwerburgh, S., Veldkamp, L., 2006. Learning asymmetries in real business cycles. J. Mone. Econ. 53, 753–772.
Varian, H.R., 1985. Divergence of opinion in complete markets: A note. J. Finan. 40, 309–317.
Xu, H., 2016. Economic policy uncertainty and housing returns in Germany: Evidence from a bootstrap rolling window. J. Econ. Bus. 34, 43–61.
Zmijewski, M.E., 1984. Methodological issues related to the estimation of financial distress prediction models. J. Acc. Res. 22, 59–82.