Wall Street Watches Washington: Asset Pricing Implications of Policy Uncertainty*

Ralph C. Verhoeks[†]

Willem F.C. Verschoor[‡]

Remco C.J. Zwinkels[§]

January 2021

Abstract

We study the effect of economic policy uncertainty (EPU) on sell-side analyst forecasts, and how this uncertainty interacts with the stock-market response to firm's earnings news. We find that analysts tend to disagree more when faced with higher levels of EPU, and that their forecasts tend to be less precise and more conservative. We show that this lower forecast accuracy can be attributed at least partly to distraction: in periods of higher EPU, analyst attention tends to be drawn to the overall stock market, while being distracted from firm-specific earning news. On the relation between EPU and the stock market reaction to firm news, our results suggest that investors naively follow analysts' forecasts, independent of their accuracy and credibility. They do not seem to filter for the decreased forecast accuracy during high EPU regimes.

Keywords: *earnings announcements, economic policy uncertainty, analyst forecasts*

JEL Classification: G12, G14, G18, G41

*We are grateful to Jack Bekooij for excellent assistance in collecting the research data. We thank participants of the Australasian Finance and Banking Conference 2020 and seminar participants at DNB for their helpful comments and suggestions.

[†]De Nederlandsche Bank and Vrije Universiteit Amsterdam; r.c.verhoeks@dnb.nl.

[‡]Vrije Universiteit Amsterdam and Tinbergen Institute; w.f.c.verschoor@vu.nl.

[§]Vrije Universiteit Amsterdam and Tinbergen Institute; r.zwinkels@vu.nl.

1 Introduction

Since the 2008 financial crisis, economic policy uncertainty (EPU) has attracted higher attention among market participants, policymakers, and academic researchers (Stock and Watson, 2012). EPU reflects uncertainty in the minds of economic agents about the future course of the government and other relevant authorities concerned with public finance, budgetary issues and monetary policy. Policy reactions to the financial crisis were surrounded by this kind of uncertainty and unpredictability. The relevance of economic policy for firm value and growth prospects is obvious: governments determine the rules of the game played by the private sector. By imposing taxes, introducing climate policies, supervising competition, subsidizing certain activities, or setting new laws, economic policy choices can (in)directly influence firm value.

Over the sample period involved in this paper (2000-2018), we have witnessed several cases of comparable uncertainty surrounding the response of politicians and central banks. Examples in Europe include the European sovereign debt crisis and the Brexit, where political indecision resulted in a long period of increased uncertainty. In the United States, health care reforms of Obamacare, the monetary policy of the Federal Reserve, political disputes about fiscal and budgetary policy (resulting in several government shutdowns), and trade tensions with China have been surrounded by increased policy uncertainty.

Recent literature documents the negative consequences of uncertainty about government actions on the real economy. In their contribution, the IMF (2012) suggests that uncertainty about fiscal, regulatory and monetary policies has contributed to the depth of the 2008 crisis and the slow recovery afterwards. In line with this, Azzimonti (2018) shows that a high degree of partisan conflict in American politics depressed private investment, which slowed down the recovery. As noted by Bloom (2014), greater policy uncertainty reduces the willingness of firms to hire and invest, and consumers to spend. Baker, Bloom and Davis (2016) show that higher policy uncertainty, as measured by their index, is associated with reduced investment and employment in policy-sensitive sectors like defense, healthcare, finance and infrastructure construction. At the macro level, increases in policy uncertainty often function as a harbinger of declines in output, employment and investment. This corresponds with Fernandez-Villaverde et al. (2015), who find that uncertainty about fiscal policies has a negative impact on output.

In this paper, we shed light on the effect of EPU on sell-side analyst forecasts and how this uncertainty interacts with the the stock-market response to earnings news. Besides the literature on the real economic effects of policy uncertainty, there is a small but growing amount of research on the impact of government-induced uncertainty on asset pricing, showing that it also has financial effects. An important characteristic of policy uncertainty is that it cannot be influenced by firm managers or investors and that it is to a large extent non-diversifiable. For instance, Pastor and Veronesi (2012, 2013) show that political uncertainty commands a risk premium, because investors demand compensation for uncertainty about the outcomes of political events. Also, policy uncertainty reduces the value of the implicit put protection provided by the government to the market. Governments often intervene in times of economic downturn, causing investors to perceive that governments provide a put protection on equity prices. The value of this put option is reduced by uncertainty about future economic policies. Moreover, they also show that when future government policies are perceived as more heterogeneous ex ante, stock prices are more volatile and more correlated. In addition, Brogaard and Detzel (2015) conclude that economic policy uncertainty is an economically important risk factor for equity. They find that an increase in policy uncertainty is associated with a contemporaneous decrease in stock returns, but with an increase in future returns. Kelly, Pastor and Veronesi (2016) find that political uncertainty is also priced in the option market: options whose maturity span political events tend to be more expensive as such options provide protection against the risks associated with political events. Political uncertainty can also have consequences for the extent to which information about future earnings is reflected in stock prices, as suggested by Drake, Mayberry and Wilde (2018). They show that during years in which presidential elections take place in the US, stock prices respond less to information about future earnings expectations. Economic policy uncertainty also interacts with liquidity, as shown by Nagar, Schoenfeld and Wellman (2019), who find that higher policy uncertainty is associated with decreased stock liquidity, especially for firms that are more exposed to this source of uncertainty. They also find that firm managers respond to this uncertainty by increasing voluntary disclosure, but this only partly mitigates the drop in liquidity.

In this paper, we further reduce the gap between asset pricing and political economy by analyzing the effects of EPU on analyst's earnings forecasts, and how the market reaction to earnings news depends on (the lack of) a clear future economic policy path. This will contribute to our understanding of how analysts influence market prices. To this end, we apply a two-step approach. We first investigate how EPU affects the information that analysts convey to financial markets. Secondly, we examine to what extent market participants rely on the information provided by analysts and how this is influenced by policy uncertainty.

To test the effect of EPU, we use the index constructed by Baker, Bloom and Davis (2016). Their index serves as a proxy for policy related uncertainty and aims to capture this by applying textual analysis and quantifying the volume of newspaper articles dealing with policy-related uncertainty. The index offers an objective measure to quantify EPU on a continuous and country-specific basis.

We hypothesize that disagreement among analysts increases with higher levels of EPU: higher EPU increases the total amount of uncertainty faced by analysts and investors, adding up to firm specific and other market-wide sources of uncertainty and widening the distribution of future earnings. This implies that analysts are more likely to disagree about their (point) forecasts. Important to note is that uncertainty is more than disagreement, although the latter is often used as a proxy for the former. During times of high uncertainty, it is likely that analysts will disagree more strongly, but individual analysts will also be more uncertain about their own (point) forecasts. As shown by Ter Ellen, Verschoor and Zwinkels (2019), disagreement can be caused by both uncertainty as well as heterogeneity. Heterogeneity-driven disagreement does not necessarily mean that individual analysts are uncertain about their own (point) forecasts. In this paper, we limit our analysis to uncertainty-driven disagreement, and find that higher levels of EPU are associated with higher disagreement among analysts, also if we control for disagreement caused by firm-specific sources of uncertainty. Analysts tend to disagree more strongly when they are faced with an uncertain path of economic policy.

We also hypothesize that analyst forecast accuracy decreases with higher levels of EPU. Forecasts are often biased, because of analysts having career concerns, compensation incentives, and a desire to have good relationships with firm management (Kothari, So and Verdi, 2016). We find that forecast accuracy is not only influenced by firm characteristics and analysts' incentives, but also by EPU. Higher levels of EPU are associated with larger analyst forecast errors. Moreover, concerning the direction of forecast errors, we find that forecasts are on average more conservative during periods of high EPU, and higher EPU is associated with larger positive earnings surprises. We further demonstrate that limited investor attention, at least partially, explains the reduced forecast accuracy: a higher level of EPU attracts (institutional) investor attention to the overall stock market, while it has a distracting effect on investor attention to firm-specific earnings news.

Next, we investigate how economic policy uncertainty influences the stock-market response to a firm's earnings news. Do investors take into account the decline in analysts' forecast accuracy that we observe during periods of high EPU and, therefore, discount analysts' forecasts? The review of Kothari, So and Verdi (2016) suggests that investors more or less naively fixate on analysts' earnings forecasts and that they do not (fully) unravel biases in these forecasts. We hypothesize that investors do not correct earnings forecasts made during periods of high policy uncertainty or take into account their decline in accuracy. Our results suggest that higher EPU mutes the trading volume reaction to earnings surprises and that investors do indeed not manage to unravel the bias in analysts' forecasts and do not take into account the reduced accuracy during high EPU.

The remainder of this paper is organized as follows. In Section 2, we further motivate our hypotheses development. Section 3 describes the sample construction and our data and methodology. Our empirical results are provided and discussed in Section 4. Finally, Section 5 concludes the paper.

2 Hypotheses Development

2.1 EPU and analyst forecasts

Sell-side equity analysts have an important role on stock markets by providing information to investors. Their information is potentially useful in asset pricing, since it considers important parameters of security valuation, such as a firm's expected earnings. As both retail and institutional investors trade on earnings forecasts and analyst recommendations (see e.g. Mikhail, Walther, and Willis, 2007), analyst forecasts clearly influence investment decisions. Hence, analysts have the potential to bring prices in line with the expectations embedded in their forecasts.

At the same time, analysts' forecasts tend to exhibit several biases. Due to the significant influence of equity analysts on the stock market, there is a lot of research interest in 'analyzing the analysts' and investigating the drivers behind analysts' forecasts and their accuracy. The literature demonstrates that the level of bias and accuracy varies with firm characteristics and analysts' incentives. For instance, forecast accuracy decreases with firm-specific sources of uncertainty, such as volatility in earnings and stock returns (Kross, Ro and Schroeder (1990)). Also, the tasks and experience of the analyst matter. Clement (1999) finds that forecast accuracy decreases when the analyst is less experienced, works at a smaller broker firm and has to follow a large number of firms. Similarly, Hirshleifer et al. (2019) find that what they call decision fatigue also affects analysts' predictions. Forecast accuracy tends to decline with the number of forecasts already made by the analyst on the same day and the likelihood that an analyst resorts to more heuristic predictions increases. In addition, an extensive amount of literature shows that analysts' incentives and economic motivations play an important role in forecast accuracy and bias. Particularly important is the incentive to please management of firms followed by the analyst and the incentive to generate revenues for the employer for which the analyst works. For instance, Das et al. (1998) find that analysts on average issue more optimistic forecasts for low predictability firms than for high predictability firms, suggesting that analysts bias their earnings forecasts to gain access to private information. Similarly, Francis and Philbrick (1993) show that analysts optimistically adjust their forecasts after negative recommendations by others to distinguish themselves from other analysts and to gain information advantages. The affiliation with an investment banking firm provides a similar incentive for analysts (Michaely and Womack, 1999).

On the relation between EPU and analysts' forecasts, we hypothesize that forecasts become more dispersed and less accurate during times of high policy-related uncertainty. EPU is a source of uncertainty that adds up to other sources of uncertainty, such as firm complexity and volatile earnings. When analysts are faced with more uncertainty surrounding future earnings, they are more likely to disagree in their forecasts and they will also be less certain about their own point forecasts. Stated differently, analysts are more likely to issue different point (or mean) forecasts, but also tend to have broader confidence intervals around these forecasts. We only test the former by examining the link between EPU and disagreement.

Secondly, we hypothesize that analysts' forecasts also become less accurate when EPU is high. Forecast errors are likely to be inflated when analysts face a higher amount of uncertainty, because uncertainty widens the distribution of future earnings. Moreover, we envisage an additional channel that could lead to increased forecast errors during high EPU. We expect that higher levels of EPU attract the attention of analysts to the overall stock market and distract them from firm-specific news. During times of high policy uncertainty, analysts and market participants tend to allocate more of their scarce attention resources (see e.g. Kahneman, 1973) to following the news around government decisions, which could distract them from following firm-specific developments. We test for this attention channel by examining the link between EPU and attention allocated to the overall market and firm-specific news. According, this leads to our first hypothesis:

Hypothesis 1: Analyst forecasts become more dispersed and less accurate during periods of high economic policy uncertainty

2.2 EPU and the market reaction to earnings news

According to our first hypothesis, analysts' forecasts are on average more accurate when there is a well-established path of economic policy. As a second step, we examine to what extent stock market investors rely on the information provided by analysts, and how this interacts with policy uncertainty. Therefore, we investigate to what extent stock market investors distinguish between forecasts issued during different EPU regimes. We examine if market participants rationally correct for a decline in forecast accuracy (hypothesis 1) during high policy uncertainty. If stock market investors identify predictable variation in the accuracy of analysts' forecasts, stock prices would respond more strongly to more credible forecasts made during periods of low EPU and vice versa. Stated differently, if investors discount analysts' forecasts during times of higher EPU, they react more (less) strongly to earnings surprises in periods of low (high) policy related uncertainty. Based on findings in the literature on analysts' biases and how these are treated by investors, we hypothesize that investors do *not* correct or discount earnings forecasts made during high policy related uncertainty. Prior research shows that even though investors sometimes recognize certain biases in analysts' forecasts, they often fail to appropriately correct for these biases. For instance, So (2013) provides evidence of stock market participants that overweight analysts' predictions by demonstrating that stock prices do not fully incorporate predictable components of forecast errors. He shows that investors tend to naively follow analysts' forecasts. Also several studies in the literature on stock pricing anomalies point in the direction of investors that overweight analysts' forecasts. Anomalous stock returns can be attributed at least partly to investors following biased analyst predictions. Abarbanell and Bernard (1992) find that security analysts' behavior can partially explain the well-documented stock price underreaction to earnings news (see e.g. Bernard and Thomas, 1989). Dechow and Sloan (1997) find that stock prices tend to naively reflect analysts' biased forecasts of future earnings growth, which can explain the higher returns to contrarian investment strategies. In particular smaller and less sophisticated investors show a tendency to neglect analysts' biases (see e.g. Malmendier and Shanthikumar, 2007 and Hilary and Hsu, 2013). On the opposite side, Hirshleifer et al. (2019) find that investors understand the reduction in forecast accuracy due to decision fatigue and correct for it. Accordingly, our second hypothesis is as follows:

Hypothesis 2: Stock market investors naively follow analyst forecasts and do not discount for a decrease in forecast accuracy during periods with high levels of EPU.

3 Data

3.1 EPU-index

As a proxy for economic policy uncertainty, we use the data from Baker, Bloom and Davis (2016). They constructed different country-specific indices to measure policy-related economic uncertainty. As our analysis is restricted to the U.S. stock market, we primarily use the U.S. EPU index and its global variant. The daily version of the EPU index applies textual analysis and employs the frequency of newspaper articles dealing with the topic of economic policy uncertainty. The index is based on newspaper archives from Access World NewsBank, covering more than 1,000 American newspapers. The newspapers included in the textual analysis range from large national newspapers as USA Today to smaller local newspapers at the state or city level. The data goes back to 1985. The EPU index includes articles that contain terms on all three categories pertaining to (i) uncertainty, (ii) the economy and (iii) policy.[2] Based on word counts on these terms, they construct a normalized daily index of news articles discussing economic policy uncertainty.[3]

The monthly EPU index is constructed slightly differently from the daily index. The monthly index is constructed from three types of underlying components. The first component is comparable to the daily EPU index and is based on news coverage, but only including 10 large newspapers. The second component uses tax code expiration data from the Congressional

[2]More precisely, the index reflects the frequency of news paper articles containing the following triple: uncertainty or uncertain; economic or economy; and one or more of congress, deficit, Federal Reserve, legislation, regulation or White House.

[3]The number of newspapers covered by the NewsBank database has increased substantially over the sample period. Hence, the authors correct for the total number of newspaper articles by scaling the raw counts by the total number of articles.

Budget Office (CBO). Temporary tax measures are a source of uncertainty for households and corporates, since the U.S. Congress often extends them last minute. The third component measures disagreement among economic forecasters, using the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. The authors measure dispersion for three variables that are clearly influenced by government, fiscal or monetary policy: (i) consumer prices, (ii) purchases of goods and services by state and local governments, and (iii) purchases of goods and services by the federal government. For each variable, the dispersion is measured for the quarterly forecasts for one year in the future. The overall monthly EPU index is computed as an average of these underlying components.[4]

Figure 1 plots the different variants of the EPU index: the monthly index, the monthly index only including the news-based component and the daily index, for which we computed the monthly average for each month in the sample period. The figure shows that the different indices strongly comove. The index based on daily data has a correlation of 0.875 with the monthly index and 0.836 with the monthly news-based index. All indices increased during the financial crisis and in other particular periods. The average index value over the years 2007-2018 is 23.8% higher than for the pre-crisis period 2000-2006 (based on the daily variant). The index is also highly auto-correlated: 1$^{\text{st}}$, 2$^{\text{nd}}$ and 3$^{\text{rd}}$ order autocorrelations of the monthly index are 0.79, 0.66, and 0.61 respectively. This is conform intuition, since economic policy uncertainty often changes gradually. Exceptions are more disruptive events, where the EPU index increases quickly. An example are the three US government shutdowns that occurred during our sample period, when Democrats and Republicans could not agree on the government budget and US Congress failed to pass a funding legislation to finance the government. The daily EPU index increased on average by 30.2% on the first day of the shutdown.[5]

The construction of the EPU data has been subjected to several tests to assess issues about

[4]More precisely, to compute the overall EPU index, the authors first normalize each of the components by its own standard deviation before 2012. Secondly, they compute an average using weights of 1/2 for the news-based EPU index and 1/6 for each of the other three components: the tax expiration index, the CPI forecast disagreement index and the local, state and federal purchases forecast disagreement index.

[5]The three government shutdowns during the sample period started on 1 October 2013, 20 January 2018 and 22 December 2018.

accuracy and potential bias. For instance, the index is compared with other measures of uncertainty. Second, the authors show that the political slant of newspapers does not impact the index, as they find very similar index movements based on right- or left-leaning newspapers. Finally, a large manual audit study based on human readings of 12,000 articles shows that human-generated and textual analysis-based indices are highly correlated.

Next to the EPU data, several related proxies for economic policy uncertainty could be imagined. However, most of them lack the frequency that is desired in the context of this paper. For instance, a similar proxy could be build with textual analysis on the Federal Reserves Beige Book, an overview of the US economy published after each meeting of the Federal Reserve Open Market Committee. Since the FOMC only has eight meetings a year, this proxy is less useful. This also holds for other low frequency alternatives. The EPU data allows us to measure economic policy uncertainty on a more continuous basis.

3.2 Earnings announcements data and firm characteristics

3.2.1 I/B/E/S and analyst forecasts

We extract quarterly earnings announcement data from the detail tape of the the Institutional Brokers Estimate System (I/B/E/S) provided by Thomson Reuters. The I/B/E/S database is a historical earnings estimate database, recording analyst estimates for different forecasts measures. More than 3,000 brokers and 30,000 individual analysts deliver their forecasts to I/B/E/S. The data on actuals is collected by Thomson Reuters from, among others, company websites and public filings. Our sample includes all U.S. companies included in the I/B/E/S database for the years 2000-2018 and we only consider *quarterly* earnings announcements. Following Hirshleifer, Lim and Teoh (2009), we exclude forecasts issued more than 60 days before the actual earnings announcement. Likewise, in case an analyst made multiple forecasts, we only include the most recent one. To minimize data errors, we exclude forecasts after the announcement date and discard observations with a reporting lag (which is the time between the end of the fiscal quarter and the actual earnings announcement) of less than 10 days or more than 60 days. Furthermore, we require a minimum coverage by five different analysts having issued a forecast. The latter data cleaning step has the largest impact, since it reduces the number of announcement observations by 78% and the number of forecasts by 42% (after having already eliminated forecasts issued after the announcement or more than 60 days before the announcement).

Table 1 reports the distribution of our earnings announcements sample over days of the week and months of the year. In line with the literature (e.g. DellaVigna and Pollet, 2009), we find that announcements cluster by day of the week and exhibit a seasonal pattern. The vast majority of earnings announcements were on Tuesday, Wednesday, and Thursday (83.0% in total), while only 6.5% was on Friday. When the sample is separated by month, it appears that only 6.0% of the announcements was in March, June, September or December. These months are often the end of a fiscal quarter and, in our sample, it takes on average 30 days from the end of the fiscal quarter until the actual announcement.

To measure the earnings surprise, we follow the literature (e.g. Livnat and Mendenhall, 2006; Hirshleifer and Teoh, 2009; and Chen, Jiang and Zhu, 2018) and define the consensus forecast error for the quarterly earnings announcement for firm i in quarter q ($CFE_{i,q}$) as the difference between the actual announced earnings per share ($AE_{i,q}$) and the consensus forecast ($CF_{i,q}$). The latter is defined as the median of the individual analyst forecasts that remain after our data cleaning steps. We normalize this difference by the stock price at the moment of the actual announcement ($P_{i,q}$):

$$CFE_{i,q} = \frac{AE_{i,q} - CF_{i,q}}{P_{i,q}}. \tag{1}$$

3.2.2 Market reaction to earnings news

To examine the market response to earnings news, we measure both the abnormal trading volume as well as the abnormal market return. We define abnormal trading volume over the two day window around the announcement as follows:

$$ATV_i[0,1] = log\Big(\frac{1+\overline{TV}_{i[t,t+1]}}{1+\overline{TV}_{i[t-21,t-3]}}\Big), \tag{2}$$

where $\overline{TV}_{[t,t+1]}$ is the average trading volume over the day of and the day after the announcement and $\overline{TV}_{[t-21,t-3]}$ is average trading volume over the window [t-21, t-3].

We calculate cumulative abnormal buy-and-hold returns ($CAR_{i,t}$) for different windows around the announcement date based on the capital asset pricing model (CAPM). We define $CAR_{i,t}$ as the difference between the cumulative buy-and-hold return of the stock of the announcing firm and the cumulative return of the market multiplied by the firm's beta. In the sample of Michaely, Rubin and Vedrashko (2013), 43% of the earnings announcements are made after market close. Figure 2 shows the distribution of earnings announcements by the hour of the day and shows that our sample results in a similar picture: 45% of the earnings announcements in our sample are made after 4 p.m. Since we aim to calculate the $CAR_{i,t}$ over the announcement window as 'clean' as possible, reflecting the return as a reaction to the earnings announcement, we calculate CAR[0,1] depending on the timing of the announcement. We define CAR[0,1] as follows if the earnings announcement is made before 4 p.m.:

$$CAR[0,1]_{i,q} = \prod_{k=t}^{t+1}\Big((1+R_{i,k}) - \beta_t \times (1+R_{M,k})\Big). \tag{3}$$

Similarly, if the earnings announcement is made after 4 p.m., the reaction to the earnings announcement cannot be reflected in the stock price of the same day and we only take into account the return on the day after the earnings announcement:

$$CAR[0,1]_{i,q} = (1+R_{i,t+1}) - \beta_t \times (1+R_{M,t+1}). \tag{4}$$

The post-announcement return is measured over the window [2,a] for a=10 and 60, measured in trading days following the earnings announcement, and is defined as follows:

$$CAR[2,a]_{i,q} = \prod_{k=t+2}^{t+a} \Big((1 + R_{i,k}) - \beta_t \times (1 + R_{M,k}) \Big), \tag{5}$$

where $R_{i,k}$ is the return of firm i on day k, $R_{M,k}$ is the market return on day k and t is the earnings announcement date in quarter q. We choose a maximum a of 60 days, as Bernard and Thomas (1989) show that the largest part of the earnings announcement drift is within three months after the announcement. The market return is assumed to be equal to the S&P 500 return. In this equations, the firm's CAPM market beta β_t is estimated by a simple (rolling) regression of daily returns of firm i on the returns of the market over 300 trading days before the announcement:

$$R_{i,t} = \alpha - \beta_i \cdot R_{M,t} + \epsilon_t, \tag{6}$$

with t over the window [-305,-5] to exclude any possible impact of the earnings announcement in the preceding five trading days.

3.2.3 Firm and announcement characteristics

Next to the EPU data and analyst forecasts, we use several additional variables in our empirical analysis. We use data on firm characteristics from Datastream and calculate multiple characteristics for each announcement based on the I/B/E/S data. Table 2 presents the precise variable definitions. Our variables include the firm size (*Size*), the ratio of price to book value (*MtoB*), the industry in which the firm operates (*IndustryDummies*, using the Fama-French 10 industry classification), the number of analysts following the firm in a quarter (*Coverage*),[6] the dispersion in analysts' forecasts (*Dispersion*), the number of announcements on the same days (*#Announcements*), the percentage of shares owned by institutional investors (*InstOwnership*), the reporting lag (*RepLag*), the estimation lag (*EstLag*), the volatility of past earnings (*EarningsVol*), the stock price volatility (*StockVol*) and the firm's market beta (*Beta*). Table 3 reports the descriptive statistics for the firm character-

[6]Our data on *Coverage* are tilted upwards by construction, since we exclude announcement observations where less than five analysts stored a forecast in I/B/E/S.

istics and earnings announcement data.

4 Empirical results

4.1 EPU and analyst forecasts

In this section we examine the influence of economic policy uncertainty on the forecasting behavior of analysts, which is the first step of our two-step approach. To this end, we study how EPU affects two forecast characteristics of equity analysts following the announcing firms: (1) disagreement and (2) forecast accuracy.

4.1.1 EPU and analyst disagreement

Concerning the influence of EPU on the level of analyst disagreement, we test our hypothesis that disagreement increases with higher levels of EPU. We measure disagreement (or dispersion) by the standard deviation of individual earnings estimates divided by the median or consensus forecast ($CF_{i,t}$). We estimate a multivariate regression, in which we regress the disagreement coefficient on EPU and control for earnings volatility, stock volatility and analyst coverage. Here we use the monthly variant of the EPU data series, EPU_t^M. Using the daily EPU is not feasible, since forecasts are made at different days prior to the announcement. We measure earnings volatility by the standard deviation of the actual earnings in the preceding five quarters and standardize this by the actual earnings over the period involved. Likewise, stock volatility is measured by the volatility of the stock price during the 200 preceding days, divided by the stock price (P_t) on the day of the announcement. For variable definitions, see also Table 2. We control for earnings and stock volatility, because these firm specific sources of uncertainty are expected to increase analyst disagreement. This results in the following regression equation:

$$\frac{Dispersion_{i,q}}{CF_{i,q}} = \alpha + \beta^{EPU^M} EPU_t^M + \beta^{EV} \frac{EarningsVol}{AE_{i,q}} + \beta^{SV} \frac{StockVol}{P_t} + \beta^{Cov} Coverage + \epsilon_{i,q}. \tag{7}$$

Table 4 presents the outcomes. The coefficients on EPU and both volatility measures are positive and statistically significant. It shows that economic policy uncertainty significantly increases the disagreement among analysts, also if we control for disagreement caused by firm-specific sources of uncertainty. Consequently, analysts tend to disagree more strongly in their earnings forecasts when they are faced with an uncertain path of economic policy. This confirms our hypothesis that EPU increases uncertainty-driven disagreement. Theoretically, a higher economic policy uncertainty could widen the distribution of a firm's future earnings, in particular when a firm operates in a policy-sensitive sector and the government's economic policy is an important determinant of future earnings. The empirical results show that analysts still tend to disagree more strongly when economic policy uncertainty is high, despite the forecast horizon being relatively short.

4.1.2 EPU and forecast accuracy

Second, we look at how EPU affects forecast accuracy. We use two different definitions for forecast accuracy. First, we use the absolute forecast error or earnings surprise. In this case, we compare the actual with the median or consensus forecast, as defined in Equation (1). Moreover, we take the *decile rank* of the absolute forecast error ($ACFED$) instead of the forecast error itself, since the literature has shown several non-linear relations of earnings surprises, for example with stock market reactions (e.g. Kothari, 2001). The deciles are estimated by sorting the earnings announcements by their forecast error (a similar way of sorting is applied in, among others, Hirschleifer, Lim and Teoh, 2009).[7] In the second defi-

[7]We apply sorting over the entire sample period to calculate the decile of the earnings surprise, whereas e.g. Hirschleifer, Lim and Teoh (2009) apply a quarterly sorting. We do not apply sorting on a quarterly basis for the following reason. Because analyst forecasts are stored in I/B/E/S for a maximum of 60 days prior to the earnings announcement (as a result of our data cleaning), we use the monthly EPU index instead of the value of the daily EPU index at the day of the actual announcement. Since a quarter only includes three months, a quarterly sorting of earnings would not make sense, as there is very little variation in the value of EPU over this horizon. Also, we control for any seasonality or day of the week effect by means of

nition of forecast accuracy, we take the *average* absolute forecast error. The difference with the first definition is that is does not only take into account the deviation of the consensus forecast from the actual, but also the forecast errors of the other analysts. Again, we take the decile of this average absolute forecast error, which results in the variable $AAFED$. We include several control variables that are expected to influence forecast accuracy. Again, we control for recent earnings and stock volatility, since those are likely to decrease the predictability of earnings and thereby increase analyst's forecast errors. We also include the number of analysts, the reporting lag and the estimation lag. As a result, we estimate the following regression equations:

$$\begin{aligned} ACFED_{i,q} = \alpha + \beta^{EPU^M} EPU_t^M + \beta^{EV} \frac{EarningsVol}{AE_{i,q}} + \beta^{SV} \frac{StockVol}{P_t} + \beta^{Cov} Coverage \\ + \beta^{RL} RepLag + \beta^{EL} EstLag + \epsilon_{i,q} \quad (8) \end{aligned}$$

$$\begin{aligned} AAFED_{i,q} = \alpha + \beta^{EPU^M} EPU_t^M + \beta^{EV} \frac{EarningsVol}{AE_{i,q}} + \beta^{SV} \frac{StockVol}{P_t} + \beta^{Cov} Coverage \\ + \beta^{RL} RepLag + \beta^{EL} EstLag + \epsilon_{i,q}. \quad (9) \end{aligned}$$

We estimate these equations with an ordered logit model, since the dependent variable ($ACFED$ or $AAFED$) is ordered and always between 1 and 10 due to the decile transformation.[8] Table 5 reports the estimation results for both equations. The outcomes on the control variables are broadly in line with expectations. Both recent earnings volatility and stock price volatility have a positive and statistically significant regression coefficient, independent of the measure of forecast accuracy. Apparently, analysts have more difficulty with precisely forecasting the earnings if recent earnings or the stock price of the company

dummy variables. Moreover, earnings surprises are comparable over time and across firms, since we apply standardisation.

[8]In unreported analysis, we estimate a Tobit regression model with the surprise percentage (defined as the percentage deviation of the actual earnings from the consensus forecast) as dependent variable. We performed this alternative estimation to test the robustness of the outcomes to the chosen regression technique. A Tobit estimation is required here, since the dependent variable is left censored at zero. The outcomes of this estimation are broadly in line with the Logit estimation, with regression coefficients having the same sign.

were volatile. The earnings of companies with stable earnings and a stable stock price are easier to predict (in line with Kross, Ro and Schroeder, 1990). Also the reporting and estimation lag increase the size of forecast errors. For the estimation lag, the coefficient is only statistically significant with ($AAFED$) as dependent variable. Earnings that are announced relatively late after the end of the fiscal quarter are more difficult to forecast. The same holds for announcements for which analyst forecasts are made relatively early (on average) without later adjustment. The latter is intuitive, since the later a forecast is made, the more information that is relevant for a firms earnings becomes available. The effect of the number of analysts ($Coverage$) is undetermined, since the regressions of $ACFED$ and $AAFED$ give a different sign. However, we are predominantly interested in the effect of EPU. The coefficient on EPU is positive and statistically significant in both cases, which means that both the error of the consensus forecast and the average forecast error increase with economic policy uncertainty. Hence, in line with our hypothesis, analysts tend to become less precise in their forecasts when economic policy uncertainty increases.

Given that EPU leads to a reduction in the forecast accuracy of equity analysts, we want to test if EPU not only reduces accuracy, but also makes analysts less or more conservative. Stated differently, we examine if the larger forecast errors during times of higher EPU are on average on the positive (negative) side, with actual earnings more (less) often being above than below what has been predicted by analysts. Higher EPU could lead to analysts shifting more towards the conservative side in their forecasts, because of a perception that higher EPU leads to more downside risk in a firms earnings, without having much upward potential. To test if EPU also influences the direction of forecast errors, we adjust Equations (8) and (9) above by not longer taking the *absolute* forecast error. The dependent variables therefore become $CFED$ and $AFED$, respectively:

$$\begin{aligned} CFED_{i,q} = \alpha + \beta^{EPU^M} EPU_t^M + \beta^{EV} \frac{EarningsVol}{AE_{i,q}} + \beta^{SV} \frac{StockVol}{P_t} + \beta^{Cov} Coverage \\ + \beta^{RL} RepLag + \beta^{EL} EstLag + \epsilon_{i,q} \quad (10) \end{aligned}$$

$$AFED_{i,q} = \alpha + \beta^{EPU^M} EPU_t^M + \beta^{EV} \frac{EarningsVol}{AE_{i,q}} + \beta^{SV} \frac{StockVol}{P_t} + \beta^{Cov} Coverage + \beta^{RL} RepLag + \beta^{EL} EstLag + \epsilon_{i,q}. \quad (11)$$

Table 5 also reports the results of the logistic regression estimations. In both cases, EPU has a positive and statistically significant coefficient. This means that higher levels of EPU not only increase forecast errors, but also tend to inflate the earnings surprises in the upward direction. During periods of high EPU, it is more likely that the actual earnings announcement implies a surprise in one of the higher deciles, where the actual is higher than and further above the average or consensus forecast. EPU is therefore associated with more conservative and lower earnings forecasts.

4.1.3 Attention as explanation for decreased forecast accuracy

The decrease in forecast accuracy and increase in disagreement during high policy uncertainty can be attributed to the fact that high policy-related uncertainty could widen the distribution of future earnings, in particular for policy-sensitive firms. As a consequence of a more fat-tailed and wider distribution of future earnings, forecast errors increase. However, an additional channel that could explain the observed pattern in analysts' forecasts is limited attention. In this section, we examine if investor attention can explain the patterns observed in previous sections, where higher levels of EPU are associated with higher analyst disagreement and decreased forecast accuracy. We examine how economic policy uncertainty relates to the attention allocated by investors to the overall market on the one hand, and to firm-specific news on the other hand. Therefore, we empirically test the interaction between the EPU index and different proxies for attention.

First, we test if the level of investor attention to the overall market depends on the level of economic policy uncertainty. In the literature, several proxies for investor attention have been proposed. Among others, Barber and Odean (2008) proxy investor attention by trading volume and absolute market return, as these variables are clearly associated with investor attention. For instance, in the case of trading volume, the intuition is that when investors pay less attention to a certain stock, they are less likely to buy or sell it. We define the excess trading volume on day t as $ETV_t = ln(TV_t/\overline{TV}_{[t-21,t-3]})$, with TV_t as the total trading volume on day t and $\overline{TV}_{[t-21,t-3]}$ as the average trading volume over the window [t-21, t-3] or the past month. The market trading volume is proxied by the total dollar trading volume of the S&P 500. Similarly, the daily absolute market returns ($|r|$) are based on the S&P 500 index.

The upper panel of Table 6 shows the average trading volume, average ETV_t and average absolute market returns for the two most extreme deciles (the 1$^{\text{st}}$ and 10$^{\text{th}}$) of the (daily) EPU-index, together with the difference. The spread between the statistics in the $EPU1$ and $EPU10$ decile measures the extent to which investors pay more attention to the overall market if economic policy uncertainty is high. We show the same statistics based on a calculation of the deciles over the whole sample period as well as based on annual sorting.[9] The figures show that for all proxies of attention, the difference in means between days in $EPU10$ and $EPU1$ is statistically significant. This suggests that investors indeed pay more attention to the overall stock market in times of high economic policy uncertainty.

Next to this univariate analysis, we test the relation between our market wide attention proxies and EPU based on simple regression analysis. We estimate the following equations to control for possible day-of-the-week and seasonality effects:

$$TV_t = \alpha + \beta^{EPU} EPU_t + \sum_{i=1}^{n_1} \gamma_i^W d_{i,t}^W + \sum_{i=1}^{n_2} \gamma_i^M d_{i,t}^M + \epsilon_t \tag{12}$$

$$ETV_t = \alpha + \beta^{EPU} EPU_t + \sum_{i=1}^{n_1} \gamma_i^W d_{i,t}^W + \sum_{i=1}^{n_2} \gamma_i^M d_{i,t}^M + \epsilon_t \tag{13}$$

$$|r_t| = \alpha + \beta^{EPU} EPU_t + \sum_{i=1}^{n_1} \gamma_i^W d_{i,t}^W + \sum_{i=1}^{n_2} \gamma_i^M d_{i,t}^M + \epsilon_t, \tag{14}$$

where $d_{i,t}^W$ and $d_{i,t}^M$ represent day-of-the-week and month-of-the-year dummies. Panel B of Table 6 shows the estimated β^{EPU} coefficients and standard errors. The figures confirm the

[9] In each calendar year, we perform a sort of the time series for the attention proxies (TV_t, ETV_t and $|r|$) based on the value of the EPU index. The reason to also apply yearly sorting, next to calculating the deciles over the whole sample period, is that the level of economic policy uncertainty being considered as relatively high or low depends on the time frame taken into account.

relationship between our market wide attention proxies and economic policy uncertainty. For all three proxies, the β^{EPU} coefficient is statistically significant.

As a second step, we examine how policy-related uncertainty affects the attention for firm-specific news. Therefore, we use a direct measure of attention, based on the so-called $NewsHeat$ data provided by Bloomberg. Ben-Rephael, Da and Israelsen (2017) show that this measure captures the attention of institutional investors, using the news-searching and news-reading activity for specific stocks on Bloomberg terminals. Bloomberg records the number of readers of each news article covering a particular stock, as well as the number of times that users actively search for a certain stock. Subsequently, they benchmark these numbers against the average search behavior for the same stock during the previous 30 days.[10] We extract the $NewsHeat$ from Bloomberg for all S&P 500 firms for the period 2010-2018. Second, we follow Ben-Rephael, Da and Israelsen (2017) and construct a dummy variable for institutional investor attention (IIA), which equal to 1 if the $NewsHeat$ variable is equal to 2, 3 or 4 and 0 otherwise. By construction, a dummy value of 1 implies that attention is in the highest decile.[11] To examine the interaction between the attention for firm news and economic policy uncertainty, we estimate the following probit regression:

$$P(IIA_t = 1) = \Phi(\alpha + \beta_1 EPU_t + \beta_2 d^{EA}_{i,t} + \beta_3 EPU_t \times d^{EA}_{i,t} + \sum_{i=1}^{n_1} \gamma_i X_{i,t}) + \epsilon_t, \tag{15}$$

where $d^{EA}_{i,t}$ is a dummy variable, which is equal to 1 on the earnings announcement day and the day after and $X_{i,t}$ are control variables. Table 7 shows the results. Next to the regression of IIA on the original EPU-index, we also estimate the regression with the EPU decile rank ($EPUD_t$) as explanatory variable. As expected, the coefficient on $d^{EA}_{i,t}$

[10] To put more weight on active news searching for a certain stock, Bloomberg assigns a 10 if terminal users search for news on a particular stock and a 1 if users click on a news article on the same stock (in the latter case, users might read a news article without the intention to gather information about a specific firm). These figures are aggregated to hourly counts, for which Bloomberg constructs an attention score by comparing this hourly count to the average during the previous 30 days for the same stock. Subsequently, Bloomberg assigns a 0 if the score is in the lowest 80% of the counts over the previous 30 days, and a score of 1, 2, 3 or 4 if the count is between 80% and 90%, 90% and 94%, 94% and 96%, or greater than 96% of the counts over the previous 30 days, respectively. Bloomberg only publishes daily data, which is the average of the hourly scores during the day.

[11] This follows directly from the footnote above, since a score of 2 or higher is allocated if the score is greater than 90% of the scores over the preceding 30 days. In our sample, the *NewsHeat* variable is indeed equal to 0 or 1 in 89% and equal to 2,3 or 4 in 11% of the observations.

is significantly positive, independent of the chosen regression specification, indicating that institutional investor attention is significantly higher on a day with earnings news and the day after. However, the coefficient of interest is β_3, as it measures the effect of economic policy uncertainty on institutional investor attention to earnings news. This coefficient is negative, independent of the regression specification. For instance, if we estimate Equation (4) with the EPU decile rank, the coefficient is negative (-0.008) and significant at the 1% level (column 3 in Table 7). Since the coefficient estimate for $d_{i,t}^{EA}$ is 1.562, this means that the marginal effect of earnings announcements on investor attention is about 4.6% lower on days with high economic policy uncertainty (EPU-decile 10) compared to days with low economic policy uncertainty (EPU-decile 1).[12] The estimation based on the untransformed EPU data also results in a negative interaction coefficient, but this coefficient is only significant at the 10% level. Overall, these findings suggest that a high level of economic policy uncertainty attracts (institutional) investor attention to the overall stock market and has a statistically significant distracting effect on investor attention to firm-specific earnings news. Consequently, limited investor attention is at least a partial explanation for the decrease in forecast accuracy that we observe in the previous section.

4.2 EPU and the market response to earnings news

In this section we examine the link between EPU and the market response to earnings news, the second step of our two-step approach. To what extent do market participants rely on analysts' forecasts and to what extent does this depend on the EPU regime? We test if investors' reaction to earnings news is muted or strengthened by increases in economic policy uncertainty. Also, we investigate if and to what extent investors correct for the decreased accuracy in analysts' forecasts during high EPU that we found in the previous section. We thereby test our hypothesis that investors naively fixate on analysts' forecasts, independent on the level of policy uncertainty they face.

[12]The sensitivity is 1.562 - 0.008 x 10 = 1.482 for EPU decile=10 and 1.562 -0.008 x 1 = 1.554 for EPU decile=1.

4.2.1 EPU and the trading volume response to earnings news

In the literature, the market response to earnings news is often measured by looking at both the abnormal trading volume as well as the abnormal buy-and-hold return. We first look at the effect of EPU on the trading volume reaction. Also, we examine if investors correct and filter for the decrease in accuracy and the increase in conservatism during times of high EPU. If investors do so, they attach less value to analysts' predictions made during higher EPU and react less strongly to earnings surprises.

We perform regression analysis of $ATV[0,1]$, as specified in Equation (2), over the decile rank of *absolute* earnings surprises ($ACFED$), the EPU index, the interaction between $ACFED$ and EPU, the market's abnormal trading volume $ATV_M[0,1]$ and a set of control variables $X_{i,t}$, also interacted with $ACFED$:

$$\begin{aligned} ATV_{i,t}[0,1] = \alpha + \beta_1 ACFED_{i,t} + \beta_2 EPU_t + \beta_3 ACFED_{i,t} \times EPU_t + \beta_4 ATV_M[0,1] \\ + \sum_{i=1}^{n_1} \gamma_i X_{i,t} + \sum_{i=1}^{n_1} \delta_i (ACFED \times X_{i,t}) + \epsilon_t. \quad (16) \end{aligned}$$

We use the *absolute* earnings surprise decile as explanatory variable, since we expect positive and negative earnings surprises to have a symmetrical impact on trading volume. Moreover, we use the decile rank of the forecast error instead of the forecast error itself, since the literature has shown that the relation between stock market reactions and earnings surprises is often nonlinear (Kothari, 2001), with small negative surprises having relatively strong negative impacts. The deciles are estimated by sorting the earnings announcements by its forecast error, as described in Section 4.1.2. We control for size, price to book, industry, analyst coverage, disagreement, number of announcements, reporting lag, estimation lag, earnings volatility, stock price volatility and day of the week. We also include those control variables in interaction with $ACFED$ and control for the market's abnormal trading volume (based on the S&P 500 and defined similar as in Equation (12)), to control for variation in the trading volume of the overall stock market. We estimate the regression model with the daily variant of the EPU index as well as with its decile (constructed similar as in the case of surprise deciles).

The first column of Table 8 shows the results of the regression estimation if we use the daily EPU variant. The coefficient on $ACFED$ is positive and statistically significant: the higher the absolute surprise in earnings, the higher the abnormal trading volume. This is in line with expectations, since large earnings surprises (either positive or negative) are likely to trigger a trading volume response. Also the signs of some control variables are conform expectations. When the abnormal market trading volume is high, the stock's abnormal trading volume is also more likely to be high. The sign of the interaction between $ACFED$ and $Announcements$ is negative, in line with the results of Hirshleifer and Teoh (2009), who show that the higher the number of other announcements on the same day, the lower the market response to earnings news due to distraction effects. The coefficients of the interactions of $ReportingLag$ and $EstLag$ with $ACFED$ are negative and statistically significant, suggesting that the longer a firm waits with the earnings announcement, the smaller the market reaction. This is conform intuition, since the market might already be processing information about the next quarter. The coefficient of $Coverage \times ACFED$ is positive and statistically significant, which implies that the reaction to earnings surprises is stronger for firms that are followed by a larger number of analysts. The coefficients of our main interest are however on EPU (β_2) and its interaction with $ACFED$ (β_3). The coefficient on EPU is negative and statistically significant. This suggests that abnormal trading volume is lower when earnings are announced during times of high economic policy uncertainty compared to low uncertainty times, after controlling for earnings surprise, market trading volume, firm characteristics and other controls. This seems to be in line with Nagar, Schoenfeld and Wellman (2019), who show that higher levels of EPU reduce stock liquidity. The coefficient on the interaction term is negative, but statistically insignificant. This means that investors do not react differently to earnings surprises in a low or high EPU regime. Also, they do not seem to discount analysts' forecasts during times of high policy uncertainty, despite the decrease in accuracy of these forecasts that we found in the previous section. This confirms our hypothesis that investors tend to fixate on analysts' forecasts and naively follow these forecasts.

Table 8 also presents the estimation results with two alternatives for the original EPU series. The second column presents the results if we replace EPU by its decile ($EPUD$) to take into account any non-linearity in the relation between EPU and the reaction to earnings news.[13] The results are similar: the coefficient on EPU is negative and statistically significant, whereas the interaction term is insignificant. As a second alternative, the third column of table 8 presents the results if we use the newsbased monthly EPU-index, EPU^M (see section 3.1). Surprisingly, the coefficient on EPU^M becomes insignificant, whereas the coefficient on the interaction becomes significant and still has a negative sign. Based on this estimation, we could conclude that investors still seem to apply a discount on analysts' forecasts issued during times of high EPU and assess them as less credible. However, the economic significance of this effect is low: an upward change of one standard deviation in EPU results in a 3.5% lower effect of $ACFED$ on the trading volume reponse.[14] Hence, based on the estimations with different variants of the EPU data, it seems that stock market investors do not or only slightly correct for the decline in accuracy of analysts' forecasts.

4.2.2 EPU and price reactions to earnings announcements

The literature has shown several forms of underreaction to earnings news, followed by a post-earnings announcement drift. In this section we examine the effect of economic policy uncertainty on the price reaction to earnings announcements. To control for the effects of other variables that influence the investor reaction to earnings news, we perform multivariate regression analysis. We regress announcement abnormal returns (CAR[0,1]) and post-announcement abnormal returns (CAR[2,10] and CAR[2,60]) on the earnings forecast error decile rank (*CFED*), the interaction term *CFED * EPU* and several control variables. These control variables are also included in interaction with *CFED*:

[13] The decile of EPU is estimated by sorting over the sample period, similar with the decile definition of earnings surprises.

[14] The standard deviation of the newsbased monthly EPU is 45.07. The coefficient on the interaction term is -0.006. An upward change of one standard deviation in EPU means a reduction in the coefficient of $ACFED$ of -0.006 $\times$ 45.07 = -0.278, which is a reduction of 3.5% of the coefficient of 7.832.

$$CAR[t,t+a]_{i,q} = \alpha + \beta_1 CFED_{i,t} + \beta_2 EPU_t + \beta_3 CFED_{i,t} \times EPU_t + \sum_{i=1}^{n_1} \gamma_i X_{i,t} + \sum_{i=1}^{n_1} \delta_i (CFED \times X_{i,t}) + \epsilon_t. \quad (17)$$

Again, we use the decile rank of the forecast error instead of the forecast error itself. However, we do not use the absolute variant ($ACFED$) that we used in the previous section, since positive and negative earnings surprises obviously have an asymmetric impact on the price reaction. Equation (17) is estimated for CAR[0,1], CAR[2,10] and CAR[2,60]. The results are reported in Table 9. Again, we report the results with the EPU index as determinant as well as with its decile alternative ($EPUD$). The control variables are the same as in the previous section.

For the announcement return CAR[0,1], the coefficient on the forecast error decile is positive and statistically significant, as expected. The more positive the earnings surprise, the more likely that the stock will earn a positive return during the announcement window. The coefficients of most relevance are however β_2 and β_3, since they measure the interaction of economic policy uncertainty with the stock price reaction to earnings news and the influence on the announcement return. We do not observe a statistically significant effect for the interaction coefficient and neither for the coefficient on EPU. The results with the decile transformation ($EPUD$) are the same in terms of statistical significance. This confirms our hypothesis that investors do not unravel or correct for the bias and decline in accuracy of analysts' forecasts in times of high EPU.

For the post-announcement returns CAR[2,10] and CAR[2,60], we do not observe a significant interaction between $CFED$ and EPU or $EPUD$ either. The coefficient on $EPUD$ is positive and statistically significant for both windows and for CAR[2,60], also the coefficient on the (untransformed) EPU is positive and statistically significant. This suggests that EPU increases the post-earnings announcement return, but this does not have a clear economic interpretation. The insignificant interaction term implies that the post-earnings announcement drift, if present, does not depend on the level of EPU.

5 Conclusion

We examine whether economic policy uncertainty affects analysts earnings forecasts and how it interact with the stock-market response to a firms earnings news. We find that periods of higher economic policy uncertainty are associated with higher analyst disagreement and decreased forecast accuracy. Analyst tend to disagree more strongly in forecasting earnings when they are faced with an uncertain path of economic policy. Moreover, their forecast accuracy tend to be less precise and more conservative. In addition to the increased total uncertainty, which widens the distributions of future earnings, we find that investor attention could (partially) explain the decreased accuracy of analyst forecasts: a higher level of EPU attracts investor attention to the overall stock market, while it has a distracting effect on investor attention to firm-specific earnings news.

We further find that higher EPU mutes the trading volume reaction to earnings surprises and corroborate the findings of Kothari, So and Verdi (2016) that investors do not unravel biases in analysts' forecasts. Our results suggest that investors naively follow analysts' forecasts, also during high EPU regimes, and independent of their accuracy and credibility.

References

[1] Azzimonti, M. (2018), 'Partisan Conflict and Private Investment', *Journal of Monetary Economics*, 93, 114-131.

[2] Barber, B.M. and T. Odean (2008), 'All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors', *Review of Financial Studies*, 21 (2), 785-818.

[3] Baker, S.R., N. Bloom and S.J. Davis (2016), 'Measuring Economic Policy Uncertainty', Working paper, Stanford University and University of Chicago.

[4] Ben-Rephael, A., Z. Da and R.D. Israelsen (2017), 'It Depends on Where You Search: Institutional Investor Attention and Under-reaction to News', *Review of Financial Studies*, 30(9), 3009-3047.

[5] Abarbanell, J.s. and V.L. Bernard (1992), 'Tests of analysts' overreaction/underreaction to earnings information as an explanation for anomalous stock price behavior', *Journal of Finance* 47(3), 1181-1207.

[6] Bernard, V.L. and J.K. Thomas (1989), 'Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium?', *Journal of Accounting Research* 27, 1-36.

[7] Brennan, M.J., N. Jegadeesh, and B. Swaminathan (1993), 'Investment analysis and the adjustment of stock prices to common information', *Review of Financial Studies* 6, 799-824.

[8] Bloom, N. (2014), 'Fluctuations in Uncertainty', *Journal of Economic Perspectives*, 28 (2), 153-176.

[9] Brogaard, J. and A. Detzel (2015), 'The Asset-Pricing Implications of Government Economic Policy Uncertainty', *Management Science* 61(1), 3-18.

[10] Chen, L.H., G.J. Jiang and K.X. Zhu (2018), 'Total Attention: The Effect of Macroeconomic News on Market Reaction to Earnings News', *Journal of Banking and Finance*

97, 142-156.

[11] Dechow, P.M. and R.G. Sloan (1997), 'Returns to contrarian investment strategies: tests of naive expectations hypotheses', *Journal of Financial Economics* 43(1), 3-27.

[12] DellaVigna, S. and J.M. Pollet (2007), 'Demographics and industry returns', *American Economic Review* 97, 1167-1702.

[13] DellaVigna, S. and J.M. Pollet (2009), 'Investor inattention and Friday earnings announcements', *Journal of Finance* 64, 709-749.

[14] Drake, M.D., M.A. Mayberry and J.W. Wilde (2018), 'Pushing the Future Back: The Impact of Policy Uncertainty on the Market Pricing of Future Earnings', *Journal of Business, Finance and Accounting*, 45(7), 895-927.

[15] Fernández-Villaverde, J., P. Guerrón-Quintana, K. Kuester and J. Rubio-Ramírez (2015), 'Fiscal volatility shocks and economic activity', *American Economic Review 105* (11), 3352-3384.

[16] Francis, J., D. Pagach and J. Stephan (1992), 'The stock-market response to earnings announcements released during trading versus non-trading periods', *Journal of Accounting Research* 30 (2), 165-184.

[17] Hilary, G. and C. Hsu (2013), 'Analyst forecast consistency', *Journal of Finance* 68(1): 271-297.

[18] Hirshleifer, D. and S.H. Teoh (2005), 'Limited investor attention and stock market misreactions to accounting information', Working paper, Ohio State University.

[19] Hirshleifer, D., S.S. Lim and S.H. Teoh (2009), 'Driven to distraction: extraneous events and underreaction to earnings news', *Journal of Finance* 64, 2289-2325.

[20] Hirshleifer, D., Y. Levi, B. Lourie and S.H. Teoh (2019), 'Decision fatigue and heuristic analyst forecasts', *Journal of Financial Economics* 133(1), 83-98.

[21] International Monetary Fund (2012), 'World Economic Outlook: coping with high debt and sluggish growth', IMF Press.

[22] Kahneman, D. (1973). "Attention and Effort", Prentice-Hall, Englewood Cliffs, NJ.

[23] Kelly, B., L. Pastor and P. Veronesi (2016), 'The price of political uncertainty: theory and evidence from the option market', *Journal of Finance* 71, 2417-2480.

[24] Kothari, S.P., E. So, and R. Verdi (2016). 'Analysts' forecasts and asset pricing: A survey'. *Annual Review of Financial Economics* 8, 197-219.

[25] Malmendier, U. and D. Shanthikumar (2007), 'Are small investors naive about incentives?', *Journal of Financial Economics* 85(2), 457-489.

[26] Michaely, R., A. Rubin and A. Vedrashko (2013), 'Firm heterogeneity and investor inattention to Friday earnings announcements', Working Paper, Cornell University.

[27] Mikhail, M.B., B.R. Walther and R.H. Willis (2007), 'When Security Analysts Talk, Who Listens?', *The Accounting Review* 82(5), 1227-1253.

[28] Nagar, V., J. Schoenfeld and L. Wellman (2019), 'Economic Policy Uncertainty and Information Asymmetry', *Journal of Accounting and Economics* 67(1), 36-57.

[29] Pastor, L. and P. Veronesi (2012), 'Uncertainty about government policy and stock prices', *Journal of Finance* 72 (4), 1219-1264.

[30] Pastor, L. and P. Veronesi (2013), 'Political uncertainty and risk premia', *Journal of Financial Economics* 110, 520-545.

[31] Peng, L. and W. Xiong (2006), 'Investor attention, overconfidence and category learning', *Journal of Financial Economics*, 80, 563-602.

[32] Peng, L. (2005), 'Learning with information capacity constraints', *Journal of Financial and Quantitative Analysis* 40, 307-329.

[33] Rodrik, D. (1991), 'Policy uncertainty and private investment', *Journal of Development Economics* 36 (2), 229-242.

[34] Sheng, J. (2017), 'Macro News, Micro News, and Stock Prices', Working paper, University of California.

[35] So, E.C. (2013), 'A new approach to predicting analyst forecast errors: Do investors overweight analyst forecasts?', *Journal of Financial Economics* 108 (3), 615-640.

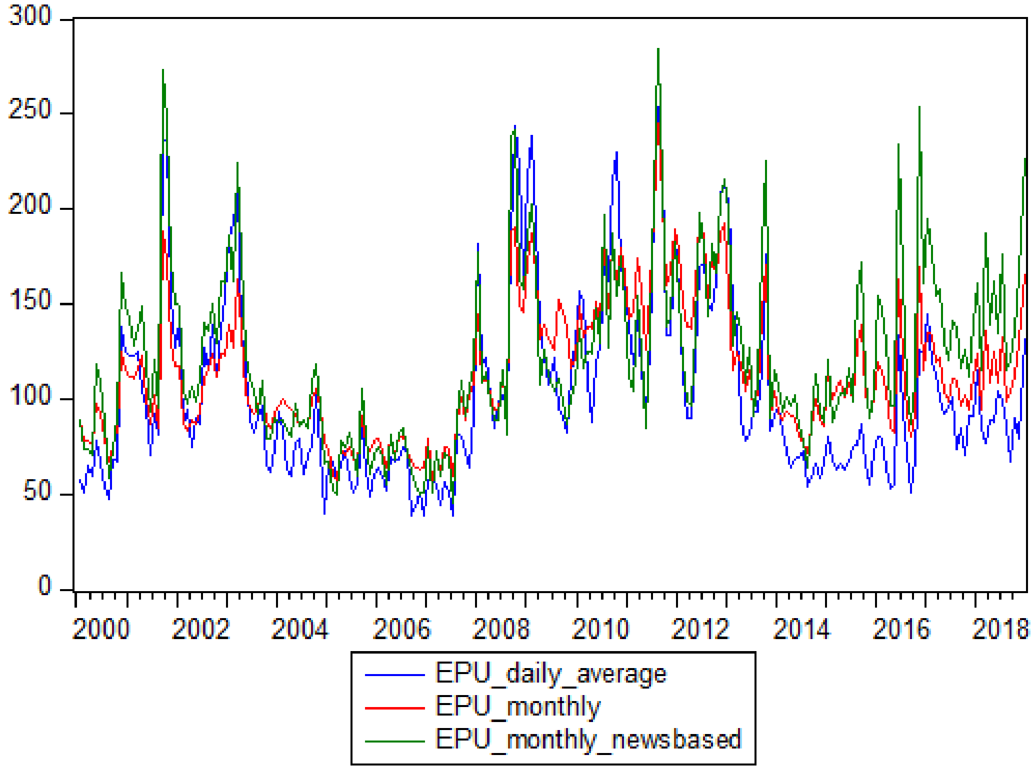
[36] Stock, J.H. and M.W. Watson (2012). Disentangling the channels of the 2007-2009 recession. *NBER Working Paper* No 18094, Harvard University, Princeton University

[37] Ter Ellen, S., W.F.C. Verschoor and R.C.J. Zwinkels (2019), 'Agreeing on Disagreement: Heterogeneity or uncertainty?', *Journal of Financial Markets* 44, 17-30.

[38] Yu, A.J. and P. Dayan, 'Uncertainty, Neuromodulation, and Attention', Neuron 46, 681-692.

Tables and Figures

Figure 1: **Economic Policy Uncertainty (EPU) over the sample period**



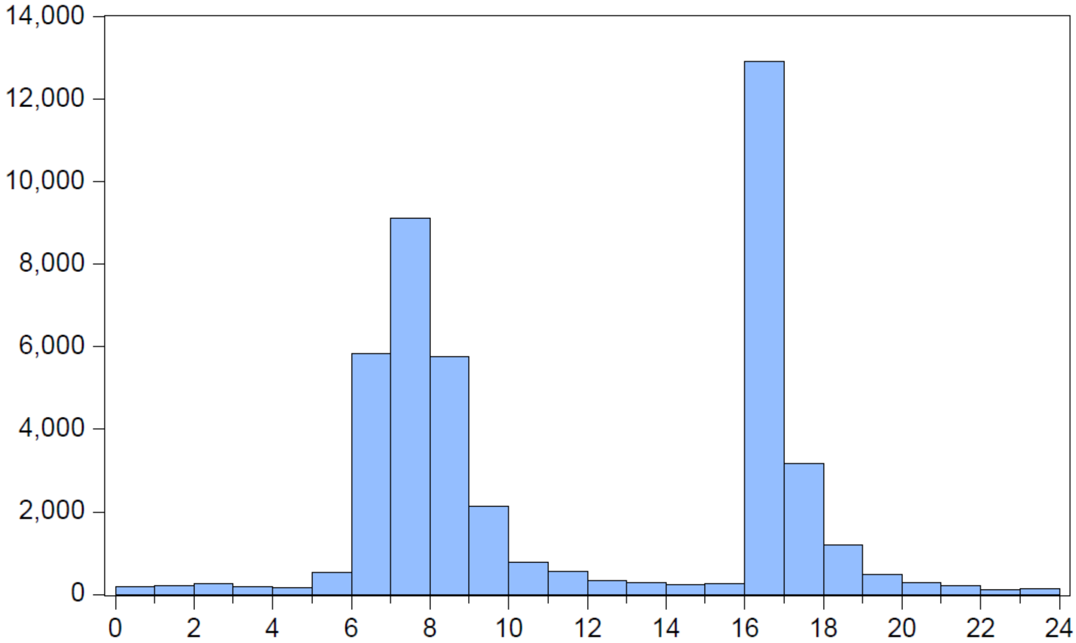
Notes: This figure shows different variants of the economic policy uncertainty (EPU) index from Baker, Bloom and Davis (2016), over the sample period. It shows the monthly index (red), the monthly index only using information from newspapers (green) and the daily index (blue), for which we computed the monthly average for each month in the sample period.

Table 1: **Earnings announcements by day of the week and month of the year**

Day of the week		Month of the year	
Monday	10.2%	January	8.4%
Tuesday	23.7%	February	11.4%
Wednesday	26.7%	March	19.4%
Thursday	32.8%	April	16.0%
Friday	6.5%	May	11.8%
		June	10.4%
		July	14.1%
		August	8.8%
		September	8.1%
		October	15.2%
		November	9.2%
		December	11.4%

Notes: This table presents the distribution of earnings announcements of the days of the week and the months of the year.

Figure 2: **Distribution of earnings announcement by hour of the day**



Notes: This figure shows the distribution of earnings announcements by the hour of the day.

Table 2: **Variable definitions for firm characteristics and announcement data**

Variable	Definition
AE	Actual earnings announced
CF	Consensus forecast or median forecast of all individual analysts
CFE	Actual earnings minus median of individual analyst forecasts (consensus forecast), normalized by the stock price at the moment of the announcement
$CFED$	Decile rank of the consensus forecast error
$ACFE$	Absolute consensus forecast error
$ACFED$	Decile rank of the absolute consensus forecast error
AFE	Average of all individual analyst's forecast errors
$AAFE$	Absolute average forecast error
$AAFED$	Decile rank of the absolute average forecast error
ATV	Abnormal trading volume over the announcement window, compared to the average trading volume over the window [t-21,t-3]
CAR[0,1]	Cumulative abnormal buy-and-hold return over the announcement window
CAR[2,a]	Cumulative abnormal buy-and-hold return over the $[2, a]$ window
$Size$	Natural logarithm of most recent balance sheet total on announcement date
$MtoB$	Price to book value
$IndustryDummies$	10 dummy variables based on the Fama-French industry classification
$Coverage$	Number of analysts that has stored an earnings forecast
$Dispersion$	Standard deviation of the analysts' earnings forecasts
$Announcements$	Number of announcements by other firms on the same day
$ReportingLag$	Number of days from the quarter-end reporting period until the actual earnings announcement
$EstLag$	Average number of days between the individual analyst forecasts and the actual earnings announcement
$EarningsVol$	Standard deviation of the actual earnings per share measured over the preceding five quarters
$StockVol$	Volatility of the stock price
$Beta$	Firm's market beta measured over the preceding 200 trading days, estimated by regression equation (4).

Notes: This table gives an overview of the variable definitions of earnings announcements and firm characteristics used in the empirical analysis.

Table 3: **Descriptive statistics**

Panel A: Earnings announcement data					
Variable	Mean	St.dev.	1st quartile	Median	3rd quartile
FE	-0.003	0.3379	-0.000	0.000	0.002
$Announcements$	185	116	88	172	279
$Coverage$	2.372	0.377	2.079	2.303	2.639
$Dispersion$	0.035	0.029	0.014	0.030	0.067
$ReportingLag$	29	10	22	28	35
Panel B: Firm characteristics					
$Size$	15.763	1.870	14.452	15.731	17.037
$MtoB$	3.620	42.068	1.370	2.130	3.550
$Beta$	1.148	0.509	0.810	1.092	1.426
$EarningsVol$	0.152	0.302	0.069	0.142	0.293
$StockVol$	20.911	710.801	1.832	3.117	5.399

Notes: This table presents the descriptive statistics for the earnings announcement data (panel A) and the firm characteristics (panel B).

Table 4: **Economic policy uncertainty and analyst disagreement**

Dependent variable: *Dispersion/CF*100*	(1)	(2)
EPU	0.061***	0.043**
	(0.020)	(0.020)
$EarningsVol/AE$		5.935***
		(0.180)
$StockVol/P$		12.119***
		(1.678)
Observations	41,319	38,901
R^2	0.0%	2.9%

Notes: This table presents the regression analysis to explain analyst disagreement by different attributes: EPU, earnings volatility, stock price volatility and analyst coverage. Standard errors are in parentheses and are adjusted for heteroskedasticity and autocorrelation. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 5: **Economic policy uncertainty and analyst forecast accuracy**

Dependent variable	$ACFED$	$AAFED$	$CFED$	$AFED$
EPU^M	0.004***	0.004***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
$EarningsVol/AE$	0.041***	0.057***	-0.020***	-0.022
	0.003	(0.003)	(0.003)	(0.003)
$StockVol/P$	1.951***	2.886***	-0.230***	-0.278***
	(0.055)	(0.063)	(0.038)	(0.038)
$Coverage$	-0.174***	1.442***	0.081***	0.625***
	(0.023)	(0.024)	(0.023)	(0.024)
$RepLag$	0.036***	0.049***	-0.002*	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)
$EstLag$	0.005***	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes
Observations	38,874	38,874	38,874	38,874
Pseudo R^2	2.3%	5.2%	0.1%	0.5%

Notes: This table presents the regression analysis to explain analyst forecast accuracy by different attributes: the (monthly) EPU index, earnings volatility, stock price volatility, analyst coverage, reporting lag and estimation lag. Controls only include day of the week and month of the year dummies. Standard errors are in parentheses and are adjusted for heteroskedasticity and autocorrelation. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 6: **Economic policy uncertainty and attention to the overall market**

Panel A: Attention proxies by EPU				
		Yearly sorting		
	$EPU1$	$EPU10$	Difference	p-value
Trading volume	2,396,666	2,660,818	1,322,616	0.000
EVT_t	-0.027	0.023	0.049	0.000
Absolute return	0.007	0.010	0.004	0.000
		No sorting		
	$EPU1$	$EPU10$	Difference	p-value
Trading volume	1,990,166	3,247,531	1,257,365	0.000
EVT_t	-0.010	0.016	0.025	0.045
Absolute return	0.006	0.013	0.007	0.000
Panel B: Regression Analysis				
Dependent variable				β^{EPU}
Trading volume				0.002
				(0.021)***
ETV_t				0.002
				(0.021)***
Absolute return				0.002
				(0.021)***

Notes: This table presents the average values of our proxies for investor attention for the overall market for the most extreme EPU deciles (Panel A). It also show the regression coefficient estimates, in which EPU is regressed on the same attention proxies, correcting for potential day-of-the-week and month-of-the-year effects (Panel B). Standard errors are in parentheses, *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 7: **Investor attention for firm news and economic policy uncertainty**

	Dependent variable: IIA			
	(1)	(2)	(3)	(4)
$EPUD$			0.002***	
			(0.001)	
EPU				-0.001
				(0.003)
d^{EA}	1.551***	1.541***	1.562***	1.539***
	(0.016)	(0.013)	(0.016)	(0.014)
$EPUD \times d^{EA}$	-0.006**		-0.008***	
	(0.003)		(0.003)	
$EPU \times d^{EA}$		-0.021*		-0.020*
		(0.000)		(0.000)
Controls	Yes	Yes	Yes	Yes
Observations	1,087,971	1,087,971	1,087,971	1,087,971
McFadden R^2	6.1%	6.1%	6.1%	6.1%

Notes: This table presents estimations of a probit regression of IIA on economic policy uncertainty (either EPU-decile or the original EPU-index/100), a dummy which is equal to 1 for earnings announcement days and the day after and the interaction between both. Controls included are $Log(size)$ and day-of-the-week dummies. Standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1%, respectively.

Table 8: **EPU and the trading volume response to earnings announcements**

Dependent variable: $ATV[0,1]$	(1)	(2)	(3)
$ACFED$	7.207***	7.380***	7.832***
	(1.320)	(1.321)	(1.336)
EPU	-0.037***	-	-
	(0.008)		
$ACFED * EPU$	-0.001	-	-
	(0.001)		
$EPUD$	-	-0.700***	-
		(0.202)	
$ACFED * EPUD$	-	-0.038	-
		(0.033)	
EPU^M	-	-	0.016
			(0.014)
$ACFED * EPU^M$	-	-	-0.006***
			(0.002)
ATV_M	56.360***	55.200***	55.135***
	(2.015)	(1.990)	(2.034)
Controls	Yes	Yes	Yes
Constant	25.112***	24.600***	19.604**
	(8.036)	(8.033)	(8.126)
Observations	36,374	36,374	36,374
R^2	10.7%	10.6%	10.4%

Notes: This table presents the results of the multivariate analysis of the effect of EPU on the trading volume response to earnings news. The dependent variable $ATV[0,1]$ is defined as in Equation (7) and expressed as percentage. $ACFED$ is the absolute earnings surprise decile, EPU is the (daily) index for economic policy uncertainty, $EPUD$ is the decile transformation, EPU^M is the monthly newsbased index, and controls include *Size*, *MtoB*, *Coverage*, *Dispersion*, *Announcements*, *ReportingLag*, *EarningsVol*, indicator variables for days of the week and Fama-French 10 industry classification. Additionally, we control for the market abnormal trading volume and interactions of the control variables with $ACFED$. Standard errors are in parentheses and are adjusted for heteroskedasticity and autocorrelation. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table 9: **EPU and price reactions to earnings announcements**

	(1) $CAR[0,1]$	(2) $CAR[0,1]$	(3) $CAR[2,10]$	(4) $CAR[2,10]$	(5) $CAR[2,60]$	(6) $CAR[2,60]$
$CFED$	0.008***	0.008***	-0.001	-0.001	-0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)
EPU	0.000	-	0.000	-	0.000***	-
	(0.000)		(0.000)		(0.000)	
$CFED$ * EPU	0.000	-	0.000	-	-0.000	-
	(0.000)		(0.000)		(0.000)	
$EPUD$	-	-0.000	-	0.001***	-	0.005***
		(0.000)		(0.000)		(0.001)
$CFED$ * $EPUD$	-	0.000	-	0.000	-	-0.000*
		(0.000)		(0.000)		(0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.041***	-0.040	0.012	0.008	0.001**	-0.005
	(0.012)	(0.012)	(0.014)	(0.014)	(0.042)	(0.034)
Observations	36,665	36,665	36,665	36,665	36,643	36,643
R^2	3.9%	3.9%	0.6%	0.7%	1.3%	1.2%

Notes: This table presents the results of the multivariate analysis of the effect of EPU on the stock price response to earnings news. The dependent variable $CAR[t,\ t{+}a]$ is defined as in Equation (3) and (4). $CFED$ is the earnings surprise decile, EPU is the (daily) index for economic policy uncertainty, $EPUD$ is the decile transformation and controls include *Size*, *MtoB*, *Coverage*, *Dispersion*, *Announcements*, *ReportingLag*, *EarningsVol*, indicator variables for days of the week and Fama-French 10 industry classification. Additionally, we control for interactions of the control variables with FED. Standard errors are in parentheses and are adjusted for heteroskedasticity and autocorrelation. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.