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Macro disagreement and analyst forecast properties

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ABSTRACT

In this study, I examine whether macro disagreement, a higher-order uncertainty, affects the accuracy and informativeness of analysts' earnings forecasts. Using macroeconomic dispersion measures from the Survey of Professional Forecasters database as a proxy for macro disagreement, I find that macro disagreement reduces forecast accuracy. I further explore this association for firms that are high in cyclicality and for analysts who enjoy more brokerage resources. The negative relationship between macro disagreement and forecast accuracy is more pronounced for firms that are high in cyclicality. I also find that brokerage resources have a moderating effect on the negative association between macro disagreement and forecast accuracy. I further find that the analyst earnings forecast is less informative to investors when macro disagreement is high.

1. Introduction

The effect of uncertainty on information flow has been scarcely studied (e.g., Bloom, 2014). This observation is also relevant to sell-side security analyst literature. Extant literature has mainly used three measures of uncertainty: (1) disagreement among financial analysts, (2) macro uncertainty (uncertainty about macro outcomes), and (3) disagreement among macro forecasters (higher-order uncertainty). All measures of uncertainty are not the same. Disagreement among financial analysts as a measure of uncertainty has been used in the literature (e.g., Diether et al., 2002; Johnson, 2004). However, Johnson (2004) argues that disagreement alone is not sufficient to warrant uncertainty. Recent studies have examined the effect of macro uncertainty – uncertainty about macro outcomes – as a proxy for uncertainty on analyst forecasts (e.g., Loh and Stulz, 2018; Amiram et al., 2018). To the best of my knowledge, no prior literature has examined the effect of higher-order uncertainty on analyst forecast. Extending this line of research, I investigate the impact of uncertainty on analyst forecast using higher-order uncertainty (disagreement among macro forecasters or macro disagreement).

In this study, I examine the effect of macro disagreement on analyst earnings forecast accuracy and informativeness. I further investigate the heterogeneous effect of the same for firms that are high in cyclicality. I use macroeconomic dispersion measures from the Survey of Professional Forecasters database as a proxy of macro disagreement. I conduct this study using a sample of U. S. analysts for the years 1999 to 2015.

Macroeconomic literature distinguishes between macro-uncertainty (uncertainty about macro-outcomes) and higher-order uncertainty (disagreement among forecasters). Although macro uncertainty and macro disagreement originate from the same source – a change in macro volatility, both are different kinds of uncertainty. Macro-uncertainty is the uncertainty created when a macroeconomic variable, such as GDP, becomes less predictable. In contrast, macro-disagreement is the higher-order uncertainty that arises when forecasters disagree. It describes the uncertainty forecasters have about the beliefs

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of other economists. Kozeniauskas et al. (2018) model macro disagreement as the conditional variance of expectation of GDP growth forecasts, which differs across forecasters. The model suggests that, besides macro uncertainty, macro-disagreement also stems from noise in the forecasters' private signals and the weight that forecasters assign to these private signals. Prior literature documents that macro disagreement stems from uncertain news, sticky information, inattentiveness, differential interpretation of public signals, and heterogeneity in the forecasters' asymmetric loss functions (e.g., Sims, 2002; Mankiw and Reis, 2002; Reis, 2006; Kandel and Pearson, 1995; Manzan, 2011; Capistran and Timmermann, 2009).

Prior literature infers that macroeconomic shocks significantly affect firm earnings (e.g., Ball and Brown, 1968). When economists' beliefs about the expected value of the macroeconomic variable are heterogeneous, their forecasts will be less precise. As analysts get less precise inputs, they need more time and effort to convert these inputs to private information. Amiram et al. (2018) find that analysts' forecasts are less timely when they face high market uncertainty, indicating that analysts require more time and effort to forecast earnings.

Less precise macroeconomic forecasts can also affect how analysts incorporate these forecasts when they forecast earnings. Zhang (2006) finds that the analyst underreacts to new information when the information is less precise. Prior literature has reported several instances of underreaction of macroeconomic news, such as that of real GDP growth and inflation, by analysts (e.g., Hugon et al., 2016; Basu et al., 2010). I expect that the underreaction of macroeconomic variables by analysts is more when these variables are less precise, leading to lower forecast accuracy.

Firm-level disagreement can be bifurcated into two components: idiosyncratic and systematic. The systematic component is a product of macro-level disagreement and the weight of the macro factors on the firm. Ceteris paribus, firms that have high absolute exposure to the macro factors will have more firm-level disagreement when macro disagreement is high. Hong and Sraer (2016) predict that high cyclical firms are more sensitive to macro disagreement. Therefore, I examine whether the negative association between analyst forecast accuracy and macro disagreement differs for firms that are high in cyclicality.

Finally, I turn to the effect of uncertainty on the informativeness of analyst forecast revision. Substantial evidence has been documented in the literature that the factors that improve earnings forecast accuracy also enhance the market reaction from investors. For instance, brokerage resources not only improve earnings forecast accuracy but also enhance the market reaction by investors (Clement, 1999; Stickel, 1995). Similarly, analyst forecasting experience improves earnings forecast accuracy as well as its informativeness to investors (Clement, 1999; Mikhail et al., 1997; De Franco et al., 2015).

On the other hand, Loh and Stulz (2018), and Amiram et al. (2018) find that even though analysts issue less accurate forecasts when the macro uncertainty is high, the forecast revision is more valuable to investors. Loh and Stulz (2018) argue that the traditional measure of forecast accuracy, i.e., forecast accuracy, scaled by the stock price, does not account for an increase in the underlying uncertainty surrounding the firm. They further argue that forecast accuracy, scaled by the stock volatility, would better account for the increased uncertainty that investors face at a time of uncertainty. They find that both forecast accuracy scaled by the stock volatility and informativeness is high during an uncertain time.

Consistent with my prediction, I find that forecast accuracy is lower when macro disagreement is high. The negative relationship between macro disagreement and forecast accuracy is more pronounced for firms that are high in cyclicality. Brokerage resources have a moderating effect on the negative association between macro disagreement and forecast accuracy. Regarding the informativeness of analyst earnings forecast, I find that the earnings forecast is less informative to investors when macro disagreement is high.

This study has several contributions to make to the existing literature. The observation made by Bloom (2014) regarding the lack of research done on the effect of uncertainty on information flow is valid, and hereby, I provide evidence of how macro disagreement affects analyst forecast accuracy and informativeness. Prior studies use lower-order uncertainty – disagreement among financial analysts, and macro uncertainty – as a measure of uncertainty (e.g., Diether et al., 2002; Johnson, 2004; Hope and Kang, 2005; Loh and Stulz, 2018; Amiram et al., 2018). I extend this in two ways: (i) I examine the effect of macro uncertainty using higher-order uncertainty (macro disagreement), and (ii) I further delve into this association for firms that are high in cyclicality and for analysts who enjoy more brokerage resources. I find that the negative relationship between macro disagreement and forecast accuracy is more pronounced for firms that are high in cyclicality. I also show that the negative association between macro disagreement and forecast accuracy will be reduced if analysts enjoy more brokerage resources.

Second, both Loh and Stulz (2018), and Amiram et al. (2018) document that analyst earnings forecast is more valuable during high market-specific uncertainty. Extending this line of research, I assess the informativeness of analyst earnings forecast when the higher-order uncertainty (macro disagreement) is high. I further study the differential effect of macro disagreement on the informativeness of analyst forecasts for firms that are high in cyclicality.

The remaining part of the paper is organized as follows. Section 2 develops the hypotheses. Section 3 describes the research design. Section 4 outlines the data sources and sample selection. Section 5 reports the empirical analysis and robustness checks. Section 6 is the conclusion.

2. Hypotheses

2.1. Macro disagreement

Before understanding the effect of macro disagreement on the analyst forecast properties, I need to establish that macroeconomic shock is relevant to firms' earnings. An extensive literature documents that macroeconomic shocks have a significant effect on firm earnings (e.g., Ball and Brown, 1968; Ball et al., 2009; Bonsall et al., 2013). Bonsall et al. (2013) show that eight macroeconomic variables explain up to 80% of the variation in earnings.[1]

When macro disagreement is high, the inputs of the economists regarding the expected values of macroeconomic variables are more varied. Amiram et al. (2018) find that analysts have greater difficulty dealing with heightened market uncertainty, as reflected by a decrease in timeliness and lower responsiveness to the news. High macro disagreement can also affect the response of an analyst to new information. In their review paper, Ramnath et al. (2008) conclude that analysts underreact to new information. Besides, analysts underreact to new information when the anticipated accuracy of the value of macroeconomic variables is less (Zhang, 2006). Also, when information is less precise, economic agents are less attentive to detail, less critical of the information available, and rely more on heuristics to make judgments.[2] Therefore, in a high macroeconomic disagreement environment, analysts are less likely to exert effort in gathering and processing public information to produce private information.

Macro disagreement is a weighted effect of individual dispersion in the forecasts of macroeconomic variables. The disagreements in these macroeconomic variables result in errors in the earnings forecast. First, I will discuss how disagreement in inflation increases errors in earnings forecasts. Disagreement in inflation causes uncertainty in the cost of production to increase, leading to volatility in firm revenues. The reasoning is as follows. Changes in expected cost pose a pricing and output dilemma for firms and leave the firms with three choices. Firms could change the output when fixed costs are expected to change. Alternately, firms could change prices without changing the output. Or the firm could not react in the face of changing costs. The action managers will take in response to expected inflation cannot be predicted, and hence, uncertainty about revenues rises, rendering difficult the task of generating revenue forecasts. Revenue and cost of production are two essential components of earnings. Uncertainty in either of them could lead to error in earnings forecast.

The next consideration is unemployment uncertainty. Workers bear huge costs[3] during unemployment; therefore, they are concerned about the risks associated with unemployment, such as the likelihood of losing the job or the firm they are employed with going bankrupt. Hence, the workers would require firms to provide a premium in wages or benefits as compensation for potential job loss (Topel, 1984); alternatively, they would prefer firms with low bankruptcy risk.

The unemployment risk of workers has a significant effect on firms. For example, firms receive less labor supply when unemployment uncertainty is high (Brown and Matsa, 2016). Therefore, firms must alter policies on layoffs and wages (Topel, 1983, 1984). Topel (1984) finds that firms provide a premium in wages or benefits as compensation for potential job loss. Jaggia and Thakor (1994) find that firms redesign job tasks that require fewer firm-specific skills or/and grant long-term wage contracts. Alternatively, when unemployment uncertainty is high, firms could reduce the risk of bankruptcy through a change in debt policy (Agrawal and Matsa, 2013) or even commission fewer risky projects (Hennessy and Whited, 2005). When unemployment uncertainty is high, firms may either offer attractive policies on layoffs and wages or offer policies that reduce their bankruptcy risk. However, it is difficult to know which line of action managers will take, thereby rendering the task of generating forecasts difficult.

Disagreement in the real GDP growth rate, which is an essential indicator of the economy, indicates uncertainty in the overall economy that may affect the firms' earnings. Also, prior literature has documented that analysts do not always fully incorporate real GDP growth, specifically the negative GDP growth, when they forecast earnings (Hugon et al., 2016). Thus, a higher uncertainty in these macroeconomic variables is likely to lead to lower forecast accuracy.

The discussion thus far leads to my first hypothesis, stated in the alternate form:

H1a: Analyst forecast accuracy decreases when macro disagreement is high

2.2. High cyclicality firms

Firm-level disagreement can be divided into two components: idiosyncratic and systematic. The systematic component is a product of macro-level disagreement and the weight of the macro factor on the firm. All other things being equal, firms that have a high exposure to the macro factor will be more sensitive to firm-level disagreement. Hong and Sraer (2016) predict that firms with high macro beta are more sensitive to macro disagreement. On the contrary, low macro beta stocks are less sensitive to macroeconomic factors; therefore, firm-level disagreement of firms that are low in cyclicality is less affected by macro disagreement. Therefore, when macroeconomic disagreement is high, firms that are high in cyclicality that are most sensitive to macro factors will be subject to additional firm-level disagreement. The discussion thus far leads to a hypothesis, stated in the alternate form:

H1b: The negative association between analyst forecast accuracy and macro disagreement is more pronounced for firms that are high in cyclicality.

[1] These eight macroeconomic variables are AAA bond yield, inflation, housing starts, industrial production, real gross domestic product, treasury bill rate, 10-year treasury bond rate, and unemployment rate.

[2] In an unreported result, I find that forecast rounding—a dummy variable that equals one if a forecast end with zero or five in the penny digit, or zero otherwise—is positive and significant when macro disagreement is high.

[3] These costs include low consumption (Gruber, 1997), limited stock market participation, high savings (Gormley et al., 2010), costly job search (Diamond, 1982), imperfect information about workers' productivity (Harris and Holmstrom, 1982), social costs (Kalil and Ziol-Guest, 2008), and wage cuts after reemployment (Farber, 2005).

2.3. Brokerage size

Analysts are not a homogeneous group; they vary in terms of several characteristics, one such being resources across brokerage firms. Analysts do not forecast earnings in isolation: they leverage in-house resources in several ways (Bradshaw, 2012). For instance, Hugon et al. (2016) find that the analysts' underreaction to negative macroeconomic news reduces in the presence of an active in-house macroeconomist.

Extant literature has used the number of analysts employed by a brokerage firm as a proxy for brokerage resources (e.g., Clement, 1999). Probably, brokerage firms with more analysts provide superior resources to the analysts. Also, the probability of hiring in-house macroeconomists is high for brokerage houses that employ a larger number of analysts. Large brokerage firms also perhaps have access to more data sets. They may even have better access to the private information of managers of the films they are following. Stickel (1995) shows that investors value the recommendations of analysts employed by large brokerage houses. The reason for this could be larger brokerage firms having advanced distribution networks, which allow them to disseminate their reports to capital market participants better. Clement (1999) finds that the brokerage resources available (employer Size) are positively associated with high earnings forecast accuracy.

Analysts employed by large brokerage firms are likely to produce accurate earnings forecasts. The discussion thus far leads to the following hypothesis stated formally as:

H1c: The negative association between high macroeconomic uncertainty and forecast accuracy will be reduced for firms followed by analysts employed by larger brokerage houses.

2.4. Market reaction to forecast revision during a high macro disagreement

There is substantial evidence that documents the fact that the factors that improve earnings forecast accuracy also enhance market reaction from investors. For instance, brokerage resources improve the accuracy of earnings forecast as analysts have access to superior resources such as data sets, and better access to the private information of managers (Clement, 1999). These earnings forecasts with higher accuracy are highly valued by investors (Stickel, 1995). Similarly, the earnings forecasts by analysts who have more experience are more accurate (Clement, 1999; Clement and Tse, 2005; Mikhail et al., 1997). The forecasts and stock recommendations issued by more experienced analysts produce stronger market reactions (De Franco et al., 2015; Mikhail et al., 1997).

On the other hand, despite low accuracy, analysts' earnings forecasts are more valuable to investors during uncertain times (e.g., Loh and Stulz, 2018; Amiram et al., 2018). Loh and Stulz (2018) argue that the traditional measure of forecast accuracy, i.e., forecast accuracy, scaled by a stock price or absolute reported earnings, does not account for an increase in uncertainty during an uncertain time. However, forecast accuracy, scaled by the stock volatility, would better account for the increased uncertainty that investors face in a time of uncertainty. They show that analysts' forecast accuracy per unit of uncertainty is higher during uncertain times; therefore, the investor should assign more value to such a forecast.

The above discussion leads to my second hypothesis, stated in the null form:

H2: Macro disagreement has no impact on the stock market reaction to analysts' forecast revision

3. Research design

I employ the following model to examine the impact of macro disagreement on the analysts' earnings forecast accuracy

$$\begin{aligned} \textit{Forecast Accuracy} = \; & \beta_0 + \beta_1 \textit{Macro Disagreement} + \beta_2 \textit{Firm} - \textit{specific Controls} \\ & + \beta_3 \textit{Analyst} - \textit{specific Controls} + \beta_4 \textit{Macroeconomic UncertaintyControls} \\ & + \textit{Firm Fixed Effects} + \textit{error} \end{aligned} \tag{1}$$

For Hypothesis 1(b), to examine the differential impact of macro disagreement on analyst forecast accuracy for firms that are high in cyclicality, I use the following modified empirical models with *High Cyclicality* and an added interaction term.

$$\begin{aligned} \textit{Forecast Accuracy} = \; & \beta_0 + \beta_1 \textit{Macro Disagreement} + \beta_2 \textit{High Cyclicality} \\ & + \beta_3 \textit{Macro Disagreement} \times \textit{High Cyclicality} + \beta_4 \textit{Firm} - \textit{specific Controls} \\ & + \beta_5 \textit{Analyst} - \textit{specific Controls} + \beta_6 \textit{Macroeconomic Uncertainty Controls} \\ & + \textit{Firm Fixed Effects} + \textit{error} \end{aligned} \tag{2}$$

For Hypothesis 1(c), to examine whether *Brokerage Size* moderates the effect of *Macro Disagreement* on the analyst forecast accuracy, I use the following modified empirical models with *Brokerage Size*, and an added interaction term.

$$\begin{aligned} \textit{Forecast Accuracy} = \; & \beta_0 + \beta_1 \textit{Macro Disagreement} + \beta_2 \textit{Brokerage Size} \\ & + \beta_3 \textit{Macro Disagreement} \times \textit{Brokerage Size} + \beta_4 \textit{Firm} - \textit{specific Controls} \\ & + \beta_5 \; \textit{Analyst} - \textit{specific Controls} + \beta_6 \textit{Macroeconomic Uncertainty Controls} \\ & + \textit{Firm Fixed Effects} + \textit{error} \end{aligned} \tag{3}$$

For Hypothesis 2, to examine the informativeness of analyst earnings forecasts when macro disagreement is high, I use the following empirical model.

$$\begin{aligned} \textit{Cumulative Abnormal Return} = \; & \beta_0 + \beta_1 \textit{Forecast Revision} + \beta_2 \textit{Macro Disagreement} \\ & + \beta_3 \textit{ Forecast Revision} \times \textit{Macro Disagreement} + \beta_4 \textit{Firm} - \textit{specific Controls} \\ & + \beta_5 \textit{Analyst} - \textit{specific Controls} + \beta_6 \textit{ Macroeconomic Uncertainty Controls} \\ & + \textit{Firm Fixed Effects} + \textit{error} \end{aligned} \tag{4}$$

3.1. Dependent variable

3.1.1. Forecast Accuracy

The dependent variable in this study is the absolute forecast accuracy of individual analysts. In line with previous research, for each analyst *j*, firm *i*, and quarter *t*, I define a forecast accuracy as the difference between reported earnings per share and analyst forecast earnings per share.[4] I then deflate the absolute value of the forecast accuracy by the stock price at the end of the month immediately preceding the month in which an analyst issued a forecast. Thus, I define forecast accuracy, scaled by stock price, for each analyst-firm-quarter tuple as:

$$\textit{ForecastAccuracy}_{jit} = (-1) \times \left(\frac{|eps_{it} - feps_{jit}|}{P_{it}} \right)$$

eps_{it} = reported earnings per share for firm i in quarter t;
$feps_{jit}$ = forecast earnings per share of analyst j for firm i in quarter t;
P_{it} = stock price at the end of the month before the analyst forecast month.

Loh and Stulz (2018) argue that the traditional measure of forecast accuracy, i.e., *Forecast Accuracy, scaled by the stock price*, does not account for an increase in the underlying uncertainty surrounding the firm at a time of uncertainty. They further argue that forecast accuracy, scaled by stock volatility, would better account for the increased uncertainty that investors face in uncertain times. As I study the impact of higher-order uncertainty on analyst forecast, I also report results where *Forecast Accuracy, scaled by the stock volatility*, is a dependent variable.

3.1.2. Cumulative Abnormal Return

I use *Cumulative Abnormal Return* as a dependent variable to examine the informativeness of analyst forecasts. I define *Cumulative Abnormal Return* as the post-2-day market-adjusted excess return from the forecast day. I use days (0, +1) for forecasts issued before the end of regular trading (4 pm), and days (+1, +2) if the forecast is issued after 4 pm. The market-adjusted return is based on the valued weighted returns.

3.2. Independent variable

3.2.1. Macro Disagreement

I use macroeconomic forecast dispersion measures of five macroeconomic variables. The five macroeconomic variables considered in this study are the real GDP growth, inflation, unemployment, industrial production, and real nonresidential private investment. The choice of variables is governed by several factors. First, those included in my analysis have a significant impact on financial markets (e.g., Chen et al., 2018). Second, Among the five macroeconomic variables, industrial production and inflation are also examined in their seminal study by Chen et al. (1986). Third, two among the five variables, real GDP growth, and inflation, are not fully incorporated by analysts when they forecast earnings (e.g., Hugon et al., 2016; Basu et al., 2010). Forth, the data for the macroeconomic variables included are available for disagreement measures.

Macro Dispersion is defined as the dispersion in one-quarter ahead forecasts of five macroeconomic variables. The dispersion measure is defined as the difference between the 75th percentile and the 25th percentile of the forecasted levels of the five variables chosen. For the inflation rate and unemployment rate, I use the levels, while quarterly growth rates are used for the real GDP, industrial production, and real nonresidential private investment. As the dispersion of these five macroeconomic variables is highly correlated, I apply the principal component analysis on them and define the first principal component as the overall indicator of macroeconomic disagreement.

I retrieve macroeconomic disagreement data are from the Survey of Professional Forecasters database of the Federal Reserve Bank of Philadelphia. This database is the continuation of the Economic Outlook Survey, conducted by the National Bureau of Economic Research, in co-operation with the American Statistical Association. The Federal Reserve Bank of Philadelphia has been conducting this survey since 1990. The database contains forecasts on both the level and the growth rate of macroeconomic variables.

[4] See, e.g., Loh and Stulz (2018), and Amiram et al. (2018) for a similar definition of forecast accuracy.

3.2.2. High and low cyclicality firms

I use the past 60 months of monthly return to estimate the macro beta for each stock in the cross-section at the beginning of each year. This is done by regressing each excess monthly return of each firm on the excess monthly return of the S&P 500 index. I require data from stock returns of a minimum of 24 months to reliably estimate a stock's macro beta. At the beginning of each year, the data of all the stocks are sorted into three terciles. *High Cyclicality* is then defined as a dummy variable that equals one if the macro beta of a firm lies in the highest tercile, and zero otherwise. I define *Low Cyclicality* as a dummy variable that equals one if the macro beta of a firm lies in the lowest tercile, and zero otherwise.

3.2.3. Forecast Revision

I use *Forecast Revision* as an independent variable to examine the informativeness of analyst forecasts. I define *Forecast Revision* as the difference between the current pre-announcement period earnings forecast and the earnings forecast issued immediately before the current forecast by the same analyst, scaled by the standard deviation of forecasts of all analysts

3.2.4. Brokerage Size

I use *Brokerage Size* as a proxy for brokerage resources. Probably the brokerage houses that hire more analysts have higher resources such as data sets, and in-house macroeconomists. I define *Brokerage Size* as the logarithm of the number of analysts employed by brokerage houses during the last quarter.

3.3. Control variables

I include the following four variables as firm-specific control variables.

1. *Size*: I include *Size* as a control for the aggregate demand for and supply of analyst services (Bhushan, 1989). I measure *Size* as the logarithm of the product of outstanding shares and the stock price at the end of the month before the analyst forecast month.
2. *Book-to-Market*: I include the *Book-to-Market* as a control for risk, growth opportunities, and information asymmetry between the firm and investors. *Book-to-Market* is defined as the ratio of the book value of the equity at the end of the last fiscal year to the market value of the equity at the month-end before the analyst forecast month.
3. *Leverage*: Following Amiram et al. (2018), I control for *Leverage*, which is defined as the ratio of total debt to total assets, both measured at the end of the most recent fiscal year before the analyst forecast month.

Loss: Following Amiram et al. (2018), I control for *Loss,* which is defined as a dummy variable that equals one when reported earnings is negative in the previous quarter and zero otherwise.

Consistent with prior research, I also include four analyst-level controls in my regressions:

1. *Forecast Horizon:* It is among the most important determinants of earnings forecast accuracy, and if analysts forecast earlier in a quarter, the error in the earnings forecast may be driven by a longer forecast horizon. *Forecast Horizon* is defined as the logarithm of the difference between the reported earnings announcement day and the analyst forecast day.
2. *Analyst Busy*: I define *Analyst Busy* as the logarithm of the number of forecasts issued by an analyst in the previous quarter. As the sample contains only the most recent analyst forecast for a firm, *Analyst Busy* also indicates the number of different firms that analysts are covering.
3. *Analyst Experience*: I define *Analyst Experience* as the logarithm of the difference in years between an analyst's first forecast as reported in the database and the current forecast.
4. *Analyst Coverage*: I define *Analyst Coverage* as the logarithm of the number of analysts that issued a forecast during the previous quarter.

Macro uncertainty (uncertainty about macro outcomes) and higher-order uncertainty (macro disagreement) originate from the same source: a change in macro volatility. However, macro uncertainty and macro disagreement are two different kinds of uncertainty. Macro uncertainty is the uncertainty shock when a macroeconomic variable, such as GDP, becomes less predictable. However, macro disagreement is the higher-order uncertainty that arises when forecasts differ. It describes the uncertainty that economists have about the beliefs of other economists. To understand the effect of macro disagreement on analyst forecast, I control for macro uncertainty. I control for four proxies of uncertainty used in recent studies (e.g., Loh and Stulz, 2018; Amiram et al., 2018).

1. *Market Uncertainty*: Following Amiram et al. (2018), I include the standard deviation of value-weighted daily market return for the past 30 days as a measure of total uncertainty.
2. *Financial Crisis*: I define a dummy variable that equals one if the forecast is issued between December 1, 2007, and June 30, 2009, and zero otherwise.
3. *NBER Recession*: Following Loh and Stulz (2018), I include *NBER Recession,* defined as a dummy variable that equals one if the forecast is issued in the month that coincides with the recession month indicated by the National Bureau of Economic Research (NBER) and zero otherwise.

4. *High Uncertainty*: Following Loh and Stulz (2018), I include *High Uncertainty*, defined as a dummy variable that equals one if the forecast is issued when the economic policy uncertainty index (Baker et al., 2016) lies in the highest tercile of the sample period of this study and zero otherwise.

4. Data sources and sample

Data used in this study are retrieved from several sources, including CRSP, Compustat, I/B/E/S, Federal Reserve Bank of Philadelphia, and FRED (Federal Reserve Bank of St. Louis). Forecasted earnings per share, reported earnings per share, and stock prices are adjusted for stock splits. I retrieve data on the dispersion of macroeconomic variables from the Survey of Professional Forecaster database from the Federal Reserve Bank of Philadelphia. Data on the economic policy uncertainty index (EPU) and recession month indicator by the National Bureau of Economic Research (NBER) are retrieved from FRED (Federal Reserve Bank of St. Louis).

The basic unit of observation is analyst-firm-quarter. The final sample consists of 656,761 analyst-firm-quarters. To arrive at this sample, I impose the following five filters. First, an observation should have non-missing values for firm code, analyst code, currency code, reported earnings, reported earnings announcement dates, and date of forecasted earnings. Following this, I retain only those observations for which values of the dependent, independent, and control variables are non-missing. This filter causes the sample to drop by 882,461 observations. Also, I exclude firms without a Fama-French 48-industry code; this causes the sample size to drop by 9417 observations. I retain only forecasts issued before the current quarter's earnings announcement date, which reduces the sample by 8478 observations. In order to remove stale forecasts from the sample, for each analyst-firm-quarter tuple, I retain only the most recent forecast before the earnings announcement date. This exclusion reduces the sample by 435,047 observations. Finally, I exclude financial firms (SIC 6000–6999) and utilities (SIC 4900–4999), which causes the sample size to drop by 385,185 observations. Panel A of Table 1 presents the sample selection procedure. In Panel B of Table 1, I report sample frequencies by the year.

5. Results

5.1. Descriptive statistics

Table 2 presents descriptive statistics for the dependent, independent, and control variables. I find that the mean *Forecast Accuracy, scaled by stock price* (multiplied by 100), is −0.325. The mean value of *Forecast Accuracy, scaled by stock volatility* (multiplied by 100), is −0.698. The mean value of *Cumulative Abnormal Return (%)* is −0.422. Turning to the independent variable, the mean value of *Macro Disagreement* is −0.043, and that of *Forecast Revision* is −0.506. The mean number of analysts employed by a brokerage firm (*Brokerage Size*) is 47.762.

For the analyst-specific control variables, the median value of the number of firms followed by an analyst in the quarter before the forecast month (*Analyst Busy*) is close to 12. The mean analyst firm-specific forecasting experience (*Analyst Experience*) is close to 9 years. The median number of analysts that issued a forecast during the last quarter (*Analyst Coverage*) is 12. I also report descriptive statistics for four measures of macroeconomic uncertainty. The mean value of the *Market Uncertainty* is 0.010. On average, 9.1% of the sample analyst forecasts were issued during a financial crisis, 11.2% were issued during *NBER Recession* months.

Turning to the firm-specific control variables, the mean value of market capitalization (*Size*) is $7.777 billion. The mean value of the book-to-market ratio (*Book-to-Market*) is 0.530, and that of the *Leverage* is 0.218. About 14.4% of the sample report a quarterly loss in the previous quarter.

Table 3 reports the Spearman correlation matrix of dependent variables, macro disagreement variables, and uncertainty variables. I find that the correlation between the *Forecast Accuracy, scaled by stock price,* and *Macro Disagreement* is −0.08 and that of *Forecast Accuracy, scaled by stock volatility,* and *Macro Disagreement* is −0.07.

5.2. Evidence on the effect of macro disagreement on analyst forecast accuracy

In this subsection, I examine the impact of macro disagreement on analyst forecast accuracy. In column (1) of Table 4, I employ the absolute *Forecast Accuracy*, *scaled by stock price*, as a dependent variable. I employ *Macro Disagreement* as a proxy for macroeconomic disagreement. I find that the coefficient of *Macro Disagreement* is significantly and negatively related to *Forecast Accuracy*, *scaled by stock price* (coefficient = −0.007, *t*-statistic = −6.82).

Loh and Stulz (2018) argue that forecast accuracy, scaled by stock price, does not account for higher uncertainty, and they suggest that *Forecast Accuracy*, *scaled by stock volatility*, would better account for the increased uncertainty that investors face at a time of uncertainty. Therefore, in column (2) of Table 4, I normalize the absolute forecast accuracy by the stock's daily return volatility (annualized) in the prior month. With this alternate definition of forecast accuracy, I find that *Forecast Accuracy*, *scaled by stock volatility*, is still negatively and significantly related to *Macro Disagreement* (coefficient = −0.039, *t*-statistic = −19.11). This result is very interesting. In contrast to Loh and Stulz's (2018) findings, I find that *Forecast Accuracy*, *scaled by stock volatility*, decreases when macro disagreement increases. Loh and Stulz (2018) use macro uncertainty as a proxy for uncertainty, whereas this study uses higher-order uncertainty (macro disagreement) as its measure. That means macro

Table 1
Sample Selection and Yearly Frequencies.

Panel A: Sample Selection Screens	
Initial Sample	2,377,349
(−) Missing firm code, analyst code, currency code, date of reported earnings, date, and time of forecasted earnings, SIC Code, dependent, independent, and control variables	882,461
(−) Missing Fama-French 48-Industry Code	9417
(−) Forecast issued after the current quarter earnings announcement date	8478
(−) Stale earnings forecasts	435,047
(−) Financial firms (SIC 6000–6999), utilities (SIC 4900–4999) firms	385,185
Final Sample	656,761

Panel B: Number of Analyst-firm-quarter Observations by Year

Year	Number of observations	%
1999	19,806	3.02
2000	18,192	2.77
2001	20,923	3.19
2002	22,378	3.41
2003	25,830	3.93
2004	31,494	4.80
2005	35,500	5.41
2006	36,713	5.59
2007	37,282	5.68
2008	37,228	5.67
2009	42,534	6.48
2010	48,089	7.32
2011	53,157	8.09
2012	55,376	8.43
2013	56,016	8.53
2014	56,150	8.55
2015	60,093	9.15
Total	656,761	100

Table 2
Descriptive Statistics This Table presents the descriptive statistics for the variables used in the study. All variables are defined in Appendix A. All continuous variables are winsorized at 1% and 99% levels.

	No. of obs.	Mean	Median	Std. Dev.	Min	Max
Measured at the firm-quarter analyst level						
Forecast Accuracy, scaled by stock price (×100)	656,761	−0.325	−0.118	0.663	−4.743	0.000
Forecast Accuracy, scaled by stock volatility (×100)	656,761	−0.698	−0.259	1.232	−7.957	0.000
Cumulative Abnormal Return (%)	190,359	−0.422	−0.113	4.884	−20.333	14.182
Macro Disagreement	656,761	−0.043	−0.238	1.018	−1.547	2.959
Forecast Revision	190,359	−0.506	−0.390	2.579	−12.827	6.928
Brokerage Size	656,761	47.762	41.000	33.263	0.000	134.000
Forecast Horizon	656,761	62.091	76.000	34.141	1.000	119.000
Analyst Busy	656,761	11.979	12.000	6.134	0.000	32.000
Analyst Experience	656,761	8.970	7.553	7.088	−0.729	27.523
Analyst Coverage	656,761	13.530	12.000	8.033	1.000	36.000
Market Uncertainty	656,761	0.010	0.009	0.006	0.004	0.045
Financial Crisis	656,761	0.091	0.000	0.287	0.000	1.000
NBER Recession	656,761	0.112	0.000	0.315	0.000	1.000
High Uncertainty	656,761	0.352	0.000	0.478	0.000	1.000
Measured at the firm-quarter level						
Size	67,600	7.777	1.587	22.161	0.111	199.936
Book-to-Market	67,600	0.530	0.408	0.464	−0.122	2.513
Leverage	67,600	0.218	0.196	0.193	0.000	0.828
Loss	67,600	0.144	0.000	0.351	0.000	1.000

uncertainty and higher-order uncertainty (macro disagreement) have the opposite impact on forecast accuracy when forecast accuracy is deflated by stock volatility.

The signs of the control variables are mostly consistent. *Size* is significantly positively correlated with *Forecast Accuracy*, suggesting that analysts produce more accurate earnings forecasts for larger firms, consistent with Lang and Lundholm's (1996) findings that large firms have a better information environment. Similarly, *Book-to-Market* and *Leverage* are negatively associated with forecast accuracy. I also find that analyst produces a less accurate forecast for the loss-making firm. Regarding analyst-specific characteristics, I further find that busy analysts produce less accurate forecasts. Consistent with

Table 3
Spearman Correlation Matrix This Table reports the Spearman correlation matrix of the dependent variable, macro disagreement variables, and uncertainty variables.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Forecast Accuracy, scaled by stock price															
2	Forecast Accuracy, scaled by stock volatility	0.77														
3	Macro Disagreement	−0.08	−0.07													
4	Brokerage Size	0.05	−0.03	−0.01												
5	Size	0.32	0.05	−0.10	0.13											
6	Book-to-Market	−0.32	−0.24	0.11	−0.03	−0.35										
7	Leverage	−0.12	−0.14	−0.01	0.10	0.06	−0.01									
8	Loss	−0.29	−0.14	0.05	−0.04	−0.29	0.09	0.05								
9	Forecast Horizon	−0.03	−0.02	−0.04	−0.02	−0.11	−0.05	−0.07	0.03							
10	Analyst Busy	−0.04	−0.04	−0.05	0.13	0.04	0.05	0.07	−0.01	0.02						
11	Analyst Experience	0.02	−0.02	−0.04	0.06	0.08	0.00	0.04	−0.05	0.02	0.33					
12	Analyst Coverage	0.15	0.04	−0.05	0.03	0.63	−0.17	−0.03	−0.12	−0.12	0.09	0.03				
13	Market Uncertainty	−0.06	−0.07	0.45	0.02	−0.08	0.09	0.01	0.04	−0.03	−0.07	−0.04	−0.08			
14	Financial Crisis	−0.09	−0.08	0.26	−0.01	−0.06	0.10	0.00	0.03	−0.04	0.00	−0.02	−0.05	0.40		
15	NBER Recession	−0.07	−0.06	0.32	0.02	−0.06	0.08	0.00	0.03	−0.05	−0.03	−0.03	−0.06	0.42	0.87	
16	High Uncertainty	−0.09	−0.07	0.46	−0.02	−0.07	0.12	−0.02	0.02	−0.02	0.01	0.01	0.00	0.35	0.21	0.24

the findings of Amiram et al. (2018), it was observed that market uncertainty significantly reduces *Forecast Accuracy*, *scaled by the stock price* (coefficient = −0.895, *t*-statistic = −5.31). Consistent with Loh and Stulz's (2018) findings, I find that *Financial Crisis* and *High Uncertainty* (when the economic policy uncertainty index (EPU) lies in the highest tercile and zero otherwise) are negatively associated with forecast accuracy.

5.3. Robustness test of evidence on the effect of macro disagreement on analyst forecast accuracy

To address endogeneity concerns, I perform a change regression analysis that examines the effect of a change in the *Macro Disagreement* on a resultant change in *Forecast Accuracy*. A change regression, unlike a level regression, is less likely to suffer from omitted variable bias because it controls for unobservable time-invariant factors that may jointly affect *Macro Disagreement* and *Forecast Accuracy.* The sample of the change regression requires two main criteria. First and foremost, observation should have two consecutive firm-quarter observations to calculate the quarter-to-quarter changes in the variables. Second, I remove the dummy variables as a change in them is not meaningful.

To address endogeneity concerns of the main results, I implement a change model that is similar to the model that is presented in Panel A of Table 4. I take the first difference of every variable from equation (1) with a one-quarter lag. Dummy variables are not included. The results are presented in Panel B of Table 4. The coefficient for change of macro disagreement (*Δ Macro Disagreement*) is significantly negative when I regress it against the change in *Forecast Accuracy*, *scaled by the stock price,* (coefficient = −0.009, *t*-statistic = −7.79) and *Forecast Accuracy*, *scaled by the stock volatility,* (coefficient = −0.025, *t*-statistic = −9.25) respectively. These results indicate that an increase in *Macro Disagreement* leads to a decrease in forecast accuracy. In addition, the signs and significance of most of the control variables in Panel B of Table 4 are similar to the results of my main analysis using Eq. (1), which is presented in Panel A of Table 4.

5.4. The differential effect of macro disagreement on forecast accuracy for firms that are high in cyclicality

In the 1(b) hypotheses, I hypothesize that the negative association between *Forecast Accuracy* and *Macro Disagreement* is more pronounced for firms that are high in cyclicality. To test this hypothesis, I employ *Forecast Accuracy*, *scaled by stock price*, as a dependent variable, and the interaction of *Macro Disagreement* and *High Cyclicality* as my main independent variable. Table (5) report the results. I find that the interaction of *High Macroeconomic Uncertainty* and *High Cyclicality is* significantly and negatively related to *Forecast Accuracy*, *scaled by the stock price,* (coefficient = −0.075, *t*-statistic = −26.16) and *Forecast Accuracy*, *scaled by the stock volatility* (coefficient = −0.071, *t*-statistic = −14.94). These results indicate that the negative association between analyst forecast accuracy and macro disagreement is more pronounced for firms that are high in cyclicality Table 5.

Table 4
The Effect of Macro Disagreement on Forecast Accuracy.

	(1) Forecast Accuracy, scaled by stock price	(2) Forecast Accuracy, scaled by stock volatility
Macro Disagreement	−0.007***	−0.039***
	(−6.82)	(−19.11)
Size	0.139***	0.180***
	(40.02)	(35.74)
Book-to-Market	−0.492***	−0.665***
	(−54.93)	(−50.09)
Leverage	−0.388***	−0.580***
	(−30.45)	(−29.64)
Loss	−0.308***	−0.384***
	(−42.64)	(−33.48)
Forecast Horizon	−0.023***	−0.049***
	(−30.43)	(−31.38)
Analyst Busy	−0.012***	−0.030***
	(−8.02)	(−10.46)
Analyst Experience	−0.001	−0.002
	(−1.30)	(−0.91)
Analyst Coverage	−0.027***	−0.090***
	(−8.24)	(−15.59)
Market Uncertainty	−0.895***	−3.729***
	(−5.31)	(−11.36)
Financial Crisis	−0.174***	−0.382***
	(−29.98)	(−35.28)
NBER Recession	0.077***	0.208***
	(18.39)	(24.32)
High Uncertainty	−0.003*	−0.021***
	(−1.86)	(−6.56)
Intercept	−2.829***	−3.650***
	(−37.78)	(−33.82)
Adjusted R^2	0.43	0.36
Observations	656,761	656,761

	(1) Δ Forecast Accuracy, scaled by stock price	(2) Δ Forecast Accuracy, scaled by stock volatility
Δ Macro Disagreement	−0.009***	−0.025***
	(−7.79)	(−9.25)
Δ Size	0.290***	0.426***
	(32.72)	(28.94)
Δ Book-to-Market	−0.355***	−0.395***
	(−20.73)	(−13.66)
Δ Leverage	−0.238***	−0.190***
	(−7.33)	(−2.87)
Δ Forecast Horizon	−0.015***	−0.038***
	(−20.31)	(−22.78)
Δ Analyst Busy	−0.005*	−0.019***
	(−1.75)	(−3.00)
Δ Analyst Experience	−0.002	−0.024
	(−0.32)	(−1.61)
Δ Analyst Coverage	−0.005*	−0.022***
	(−1.65)	(−3.30)
Δ Market Uncertainty	−1.030***	−5.598***
	(−6.52)	(−16.17)
Intercept	−0.010***	−0.014***
	(−19.04)	(−13.18)
Adjusted R^2	0.04	0.02
Observations	510,220	510,220

Panel A: Level Model In this Table, I estimate the effect of macro disagreement on the forecast accuracy. Column (1) contains the results where absolute forecast accuracy, deflated by stock price per share, is the dependent variable, and column (2) contains the results where forecast accuracy, deflated by stock volatility, is the dependent variable. Stock volatility is defined as the annualized standard deviation of the firm's daily stock return over the past 30 days. *Macro Disagreement* is the first principal component of dispersion in the consumer price index, unemployment rate, real GDP growth, industrial production growth, and real nonresidential private investment growth. I winsorize all continuous variables at 1% and 99% levels. All regressions include firm fixed effects. Standard errors are clustered by firm and analyst, and *t*-statistics are reported in parentheses. ***, **, and * correspond to 1%, 5%, and 10% significance levels, respectively. Variable definitions are contained in Appendix A.
Panel B: Change Model To address endogeneity concerns, I implement a change regression analysis. I take the first difference of every variable from Eq. (1) with a one-quarter lag. I use two filters to arrive at the final sample for a change regression. First, observation should have two consecutive firm-quarter observations to calculate the quarter-to-quarter changes in the variables. Second, I remove the dummy variables as a change in them is not meaningful. Therefore, the sample consists of 510,220 observations. All regressions include firm fixed effects. Standard errors are clustered by firm and analyst, and *t*-statistics are reported in parentheses. ***, **, and * correspond to 1%, 5%, and 10% significance levels, respectively. Variable definitions are contained in Appendix A.

5.5. Evidence on the moderating effect of brokerage resources on the relationship between Macro disagreement and the forecast accuracy

In this subsection, I examine whether brokerage resources (*Brokerage Size*) have a moderating effect on the relationship between *Macro Disagreement* and *Forecast Accuracy*. In column (1) of Table 6, I employ *Forecast Accuracy, scaled by stock price*, as a dependent variable. The main independent variable is the interaction of *Macro Disagreement* and *Brokerage Size*. I find that the interaction of *High Macroeconomic Uncertainty* and *Brokerage Size* is positively and significantly related to *Forecast Accuracy*, *scaled by the stock price,* (coefficient = 0.005, *t*-statistic = 4.99) and *Forecast Accuracy*, *scaled by the stock volatility* (coefficient = 0.004, *t*-statistic = 2.26). These findings reflect that the *Brokerage Size* has a moderating effect on the relationship between *Macro Disagreement* and *Forecast Accuracy*.

5.6. Stock market reaction to analyst forecast revisions when macro disagreement is high

Next, I test whether investors weigh *Forecast Revision* less when the *Macro Disagreement* is high. To test my prediction, I use the two-day market-adjusted return around the forecast date (*Cumulative Abnormal Return*) as the dependent variable. The interaction between *Forecast Revision* and *Macro Disagreement* is included as the main independent variable. I also include *Forecast Revision* and *Macro Disagreement* as separate independent variables. To compute *Forecast Revision,* I require a minimum of two forecasts from the same analyst for a firm-quarter. Furthermore, I require share price data to calculate *Cumulative Abnormal Return*. Thus, the sample size drops further, placing the final sample at 190,359 observations.

Column (1) of Panel A of Table 7 contains the results of the test if the market impounds information on forecast accuracy when the macro disagreement is high. I find that the coefficient on *Forecast Revision* is positive and significant (coefficient = 0. 454, *t*-statistic = 74.44); this indicates that when an analyst revises her forecast, markets react positively. Consistent with my hypothesis, I find that the coefficient of the interaction of *Forecast Revision* and *Macro Disagreement* is negative and significant (coefficient = -0.032, *t*-statistic = -5.28). This finding suggests that the stock market discounts *Forecast Revision* during high *Macro Disagreement*. However, column (1) of Panel A of Table 7 also shows that the main effect of *Macro Disagreement* is significantly positive. (coefficient = 0.090, *t*-statistic = 6.75), indicating that *Macro Disagreement*, on an average, induces a positive market reaction.

I also investigate the differential effect of the informativeness of *Forecast Revision* for firms that are low/high in cyclicality. In column (2) of Table 7, I report results for firms that are low in cyclicality. The final sample consists of 63,731 observations for such firms. I find that the coefficient of the interaction of *Forecast Revision* and *Macro Disagreement* is negative and significant (coefficient = -0.035, *t*-statistic = -3.53). This finding suggests that the stock market discounts forecast revisions during the high macro disagreement for firms that are low in cyclicality.

In column (3) of Panel A of Table 7, I report the results for firms that are high in cyclicality. The final sample contains 63,262 firm-analyst-quarter observations. I find that the coefficient of the interaction of *Forecast Revision* and *Macro Disagreement* is negative and significant (coefficient = -0.062, *t*-statistic = -5.10). This finding suggests that the stock market discounts forecast revisions during the high macro disagreement for firms that are low in cyclicality. However, the coefficient of the interaction of *Forecast Revision* and *Macro Disagreement* for firms that are high in cyclicality is 77% higher than that for firms low in cyclicality.

In contrast to Loh and Stulz's (2018) findings, I find that analyst earnings forecast is less informative to investors when the macro disagreement is high. Loh and Stulz (2018) use macro uncertainty as a proxy for uncertainty, whereas this study uses higher-order uncertainty (macro disagreement). These kinds of uncertainty are not the same. Apart from macro uncertainty, macro disagreement arises from several other factors such as private signal noise and the weight of these signals in forecasters' beliefs. It also stems from uncertain news, sticky information, inattentiveness, overconfidence, infrequent updating of information, differences in preference (i.e., risk aversion), differences in endowment, differential interpretation of public signals, and heterogeneity in the asymmetric loss function.

5.7. Robustness test of evidence on the stock market reaction to analyst forecast revisions when macro disagreement is high

To address endogeneity concerns of the findings presented in Panel A of Table 7, I perform a change regression analysis. A change regression is expected to suffer less from omitted variable bias as it controls for unobservable time-invariant factors that may jointly affect both the dependent and the independent variables. The sample of the change regression requires two main criteria. First, observation should have two consecutive firm-quarter observations to calculate the quarter-to-quarter changes in the variables. Second, I exclude the dummy variables because a change in the dummy variable is not meaningful.

The results are presented in Panel B of Table 7. I include the first difference of every variable from equation (2) with a one-quarter lag. The coefficient for change of macro disagreement (Δ *Macro Disagreement*) is significantly positive for the full sample, firms that are low in cyclicality, and firms that are high in cyclicality. In all three columns of Panel B of Table 7 indicate that either standalone effect of change of macro disagreement (Δ *Macro Disagreement*) or the interaction of change of macro disagreement (Δ *Macro Disagreement*) and change in forecast revision (Δ *Forecast Revision)* are negative.

Table 5
The Differential Effect of The Effect of Macro Disagreement on Forecast Accuracy for High Cyclicality Firms.

	(1) Forecast Accuracy, scaled by stock price	(2) Forecast Accuracy, scaled by stock volatility
Macro Disagreement	0.014***	−0.018***
	(14.82)	(−8.50)
High Cyclicality	−0.038***	−0.042***
	(−14.04)	(−9.03)
Macro Disagreement × High Cyclicality	−0.075***	−0.071***
	(−26.16)	(−14.94)
Size	0.138***	0.179***
	(40.18)	(35.66)
Book-to-Market	−0.488***	−0.661***
	(−55.02)	(−50.04)
Leverage	−0.377***	−0.570***
	(−30.19)	(−29.24)
Loss	−0.299***	−0.376***
	(−42.15)	(−33.01)
Forecast Horizon	−0.023***	−0.048***
	(−30.45)	(−31.37)
Analyst Busy	−0.012***	−0.029***
	(−7.76)	(−10.32)
Analyst Experience	−0.001	−0.002
	(−1.45)	(−1.00)
Analyst Coverage	−0.031***	−0.093***
	(−9.40)	(−16.21)
Market Uncertainty	−0.849***	−3.685***
	(−5.03)	(−11.21)
Financial Crisis	−0.169***	−0.377***
	(−29.71)	(−35.20)
NBER Recession	0.075***	0.205***
	(17.86)	(24.07)
High Uncertainty	−0.004**	−0.022***
	(−2.29)	(−6.78)
Intercept	−2.802***	−3.617***
	(−37.76)	(−33.58)
Adjusted R^2	0.43	0.37
Observations	656,761	656,761

In this Table, I estimate the differential effect of macro disagreement on forecast accuracy for firms that are high in cyclicality. Column (1) and (3) contains the results where absolute forecast accuracy, deflated by stock price per share, is the dependent variable, and column (2) and (4) contains the results where forecast accuracy, deflated by stock volatility, is the dependent variable. Stock volatility is defined as the annualized standard deviation of the firm's daily stock return over the past 30 days. *Macro Disagreement* is the first principal component of dispersion in the consumer price index, unemployment rate, real GDP growth, industrial production growth, and real nonresidential private investment growth. I define *High Cyclicality* as a dummy variable that equals one if the macro beta of the firm lies in the highest tercile, and zero otherwise. I winsorize all continuous variables at 1% and 99% levels. All regressions include firm fixed effects. Standard errors are clustered by firm and analyst, and t−statistics are reported in parentheses. ***, **, and * correspond to 1%, 5%, and 10% significance levels, respectively. Variable definitions are contained in Appendix A.

6. Conclusion

Economics and finance literature have used mainly three measures of uncertainty: (1) disagreement among financial analysts, (2) macro uncertainty (uncertainty about macro outcomes), and (3) disagreement among macro forecasters (higher-order uncertainty). All measures of uncertainty are not the same. Disagreement among financial analysts, and macro uncertainty have been used in previous literature as a measure of uncertainty (e.g., Diether et al., 2002; Loh and Stulz, 2018). Extending this line of research, I investigate the impact of uncertainty on analyst forecasts using macro disagreement, a higher-order uncertainty.

Using macroeconomic dispersion measures from the Survey of Professional Forecasters database as a proxy for macro disagreement, I find that macro disagreement reduces forecast accuracy. The negative relationship between macro disagreement and forecast accuracy is more pronounced for firms that are high in cyclicality. Brokerage resources have a moderating effect on the negative association between macro disagreement and forecast accuracy. Regarding the informativeness of analyst earnings forecast, I find that the earnings forecast is less informative to investors when macro disagreement is high.

This study makes significant contributions to the literature. First, Prior studies use lower-order uncertainty – disagreement among financial analysts, and macro uncertainty—as a measure of uncertainty (e.g., Diether et al., 2002; Loh and Stulz, 2018). I extend the prior studies by examining the effect of macro uncertainty using higher-order uncertainty. I further explore this association for firms that are high in cyclicality and for analysts who enjoy more brokerage resources. Second, both Loh and Stulz (2018), and Amiram et al. (2018) document that analyst earnings forecast is more valuable during high

Table 6
Evidence on the Moderating Effect of Brokerage Resources on the Relationship.

	(1) Forecast Accuracy, scaled by stock price	(2) Forecast Accuracy, scaled by stock volatility
Macro Disagreement	−0.026***	−0.054***
	(−6.58)	(−7.63)
Brokerage Size	0.006***	0.014***
	(6.43)	(8.12)
Macro Disagreement × Brokerage Size	0.005***	0.004**
	(4.99)	(2.26)
Size	0.139***	0.180***
	(40.13)	(35.84)
Book-to-Market	−0.492***	−0.664***
	(−54.92)	(−50.07)
Leverage	−0.388***	−0.580***
	(−30.48)	(−29.66)
Loss	−0.308***	−0.384***
	(−42.68)	(−33.51)
Forecast Horizon	−0.023***	−0.048***
	(−30.30)	(−31.25)
Analyst Busy	−0.013***	−0.033***
	(−8.95)	(−11.55)
Analyst Experience	−0.001	−0.002
	(−1.25)	(−0.88)
Analyst Coverage	−0.027***	−0.088***
	(−8.09)	(−15.40)
Market Uncertainty	−0.914***	−3.765***
	(−5.43)	(−11.48)
Financial Crisis	−0.171***	−0.377***
	(−29.57)	(−34.93)
NBER Recession	0.075***	0.203***
	(17.79)	(23.78)
High Uncertainty	−0.003*	−0.021***
	(−1.90)	(−6.55)
Intercept	−2.853***	−3.704***
	(−38.08)	(−34.27)
Adjusted R^2	0.43	0.36
Observations	656,761	656,761

Between Macro disagreement and the Forecast Accuracy: In this Table, I estimate the moderating effect of brokerage resources on the relationship between macro disagreement and the forecast accuracy. Column (1) contains the results where absolute forecast accuracy, deflated by stock price per share, is the dependent variable, and column (2) contains the results where forecast accuracy, deflated by stock volatility, is the dependent variable. Stock volatility is defined as the annualized standard deviation of the firm's daily stock return over the past 30 days. *Macro Disagreement* is the first principal component of dispersion in the consumer price index, unemployment rate, real GDP growth, industrial production growth, and real nonresidential private investment growth. I winsorize all continuous variables at 1% and 99% levels. All regressions include firm fixed effects. Standard errors are clustered by firm and analyst, and *t*-statistics are reported in parentheses. ***, **, and * correspond to 1%, 5%, and 10% significance levels, respectively. Variable definitions are contained in Appendix A.

market-specific uncertainty. Extending this line of research, I examine the informativeness of analyst earnings forecast when higher-order uncertainty (macro disagreement) is high.

My study is subject to certain limitations. First, I examine the effect of macro disagreement on analyst forecasts using a sample of U. S. analysts. Therefore, I might not be able to generalize my results to other non-U. S. countries with legislative, regulatory, and cultural institutions that are different from those in the U. S. Second, an omitted variable might drive common variation in macro disagreement and analyst forecasts. While I attempt to address this issue with a change regression analysis, future research might uncover omitted variables. Third, there may be alternative explanations for the association between analyst forecast and macro disagreement. For example, behavioral biases, such as limited attention, might explain analysts' sub-optimal forecasts when macro disagreement is high. Notwithstanding these limitations, this study represents an essential step toward understanding whether analysts issue sub-optimal forecasts when macro disagreement is high.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Table 7
The Differential Effect of Stock Market Reaction to Analyst Forecast Revisions and Macro Disagreement for High Cyclicality and Low Cyclicality Firms Panel A: Level Model

	(1)	(2)	(3)
	Dependent Variable: *Cumulative Abnormal Return (%)*		
	Full Sample	Low Cyclicality	High Cyclicality
Forecast Revision	0.454***	0.395***	0.504***
	(74.44)	(39.22)	(42.32)
Macro Disagreement	0.090***	−0.099***	0.283***
	(6.75)	(−4.74)	(9.44)
Forecast Revision × Macro Disagreement	−0.032***	−0.035***	−0.062***
	(−5.28)	(−3.53)	(−5.10)
Size	−0.357***	−0.292***	−0.658***
	(−10.72)	(−5.59)	(−8.42)
Book-to-Market	−0.070	0.412***	−0.400***
	(−1.06)	(3.02)	(−3.32)
Leverage	−0.352**	−0.612**	−0.447
	(−2.19)	(−2.11)	(−1.35)
Loss	0.067	0.165	0.068
	(1.14)	(1.38)	(0.74)
Forecast Horizon	−0.038***	−0.062***	−0.022
	(−3.30)	(−3.56)	(−0.90)
Analyst Busy	0.005	−0.011	0.019
	(0.25)	(−0.34)	(0.44)
Analyst Experience	−0.026**	−0.018	−0.043*
	(−2.18)	(−1.01)	(−1.77)
Analyst Coverage	−0.111**	−0.035	−0.240**
	(−2.27)	(−0.45)	(−2.32)
Market Uncertainty	−32.764***	−12.090***	−40.464***
	(−11.79)	(−2.59)	(−7.46)
Financial Crisis	−0.368***	−0.299**	−1.203***
	(−4.05)	(−2.19)	(−5.73)
NBER Recession	0.295***	0.137	0.969***
	(3.45)	(1.13)	(4.90)
High Uncertainty	0.045*	−0.078*	0.174***
	(1.81)	(−1.95)	(3.16)
Intercept	8.698***	6.888***	15.567***
	(11.93)	(5.90)	(9.09)
Adjusted R^2	0.13	0.17	0.15
Observations	190,359	63,731	63,262

	(1)	(2)	(3)
	Dependent Variable: *Δ Cumulative Abnormal Return (%)*		
	Full Sample	Low Cyclicality	High Cyclicality
Δ Forecast Revision	0.453***	0.408***	0.518***
	(56.18)	(32.29)	(33.81)
Δ Macro Disagreement	−0.093***	−0.177***	0.020
	(−4.03)	(−4.88)	(0.42)
Δ Forecast Revision * Δ Macro Disagreement	−0.024***	−0.018	−0.044***
	(−3.09)	(−1.42)	(−2.84)
Δ Size	−2.782***	−2.536***	−3.072***
	(−23.13)	(−12.64)	(−15.03)
Δ Book-to-Market	−0.289	0.994***	−0.525*
	(−1.45)	(2.60)	(−1.70)
Δ Leverage	−0.454	−0.842	0.643
	(−1.00)	(−1.14)	(0.74)
Δ Forecast Horizon	−0.016	−0.036	0.004
	(−0.96)	(−1.47)	(0.11)
Δ Analyst Busy	0.070	0.104	0.071
	(0.97)	(0.94)	(0.49)
Δ Analyst Experience	0.403***	0.229	0.374*
	(3.60)	(1.27)	(1.71)
Δ Analyst Coverage	0.056	0.082	0.031
	(0.59)	(0.56)	(0.16)
Δ Market Uncertainty	−42.342***	−19.527***	−61.795***
	(−13.08)	(−3.98)	(−9.88)
Intercept	−0.022	−0.054**	−0.034
	(−1.61)	(−2.40)	(−1.15)
Adjusted R^2	0.07	0.08	0.07
Observations	135,298	45,292	44,917

Panel A: Level Model
In this Table, I estimate the stock market reaction to analyst *Forecast Revision* when the *Macro Disagreement* is high. Column (1) contains the results where the post-2-day market-adjusted excess return from the forecast day (*Cumulative Abnormal Return*) is a dependent variable. The main independent variable is the interaction of *Forecast Revision* and *Macro Disagreement*. *Forecast Revision* is the difference between the current pre-announcement period earnings forecast and the earnings forecast issued immediately before the current forecast by the same analyst, scaled by the standard deviation of forecasts of all analysts (*Forecast Revision*). *Cumulative Abnormal Return* is the post-2-day market-adjusted excess return from the forecast day. I use days (0, +1) for forecasts issued before the ending of regular trading (4 pm), and days (+1, +2) if the forecast is issued after 4 pm. The market-adjusted return is based on the valued weighted returns. To compute *Forecast Revision,* I require a minimum of two forecasts from the same analyst for a firm-quarter. Furthermore, I require share price data to calculate *Cumulative Abnormal Return*. Thus, the sample size drops further, placing the final sample at 190,359 observations. *Macro Disagreement* is the first principal component of dispersion in the consumer price index, unemployment rate, real GDP growth, industrial production growth, and real nonresidential private investment growth. I define *High Cyclicality* as a dummy variable that equals one if the macro beta of a firm lies in the highest tercile, and zero otherwise. I define *Low Cyclicality* as a dummy variable that equals one if the macro beta of a firm lies in the lowest tercile, and zero otherwise. I winsorize all continuous variables at 1% and 99% levels. All regressions include firm fixed effects. Standard errors are clustered by firm and analyst, and *t*-statistics are reported in parentheses. ***, **, and * correspond to 1%, 5%, and 10% significance levels, respectively. Variable definitions are contained in Appendix A.
Panel B: Change Model
To address endogeneity concerns of the findings reported in Panel A of Table 7, I implement a change model that is similar to a model that is presented in Panel A of Table 7. I take the first difference of every variable from equation (2) with a one-quarter lag. I use two filters to arrive at the final sample for a change regression. First, observation should have two consecutive firm-quarter observations to calculate the quarter-to-quarter changes in the variables. Second, I remove the dummy variables as a change in them is not meaningful. Therefore, the sample consists of 135,298 observations. All regressions include firm fixed effects. Standard errors are clustered by firm and analyst, and *t*-statistics are reported in parentheses. ***, **, and * correspond to 1%, 5%, and 10% significance levels, respectively. Variable definitions are contained in Appendix A.

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Appendix A

Variable	Definition
Dependent variable	
Forecast Accuracy	The absolute difference between reported earnings per share and the pre-announcement period forecast earnings per share, deflated by the stock price at the end of the month that is one month before the analyst forecast month
Cumulative Abnormal Return	The post 2-day market-adjusted excess return from the forecast day. I use days (0, +1) for forecasts issued before the ending of regular trading (4 pm), and days (+1, +2) if the forecast is issued after 4 pm. The market-adjusted return is based on the valued-weighted returns
Independent Variable: Macro Disagreement	
Macro Disagreement	The first principal component of dispersion in the consumer price index, unemployment rate, real GDP growth, industrial production growth, and real nonresidential private investment growth.
Forecast Revision	The difference between the current pre-announcement period earnings forecast and the earnings forecast issued immediately before the current forecast by the same analyst, scaled by the standard deviation of forecasts of all analysts
Low Cyclicality	A dummy variable that equals one if the macro beta of a firm lies in the lowest tercile, and zero otherwise. I use the past 60 months of monthly return to estimate the macro beta for each stock in the cross-section at the beginning of every year. This is done by regressing excess monthly return of each firm on the excess monthly return of the S&P 500 index.
High Cyclicality	A dummy variable that equals one if the macro beta of a firm lies in the highest tercile, and zero otherwise.
Brokerage Size	The logarithm of the number of analysts employed by the brokerage house during the last quarter
Control Variable	
Size	The logarithm of the product of shares outstanding and the stock price at the end of one month before the analyst forecast month
Book-to-Market	The ratio of the book value of equity at the end of the last fiscal year to the market value of

(*continued on next page*)

Appendix 1 (*continued*)

Variable	Definition
	equity at the end of one month before the analyst forecast month
Leverage	The ratio of total debt to total assets, both measured at the end of the most recent fiscal year before the analyst forecast month
Loss	A dummy variable that equals one if reported earnings is negative in the previous quarter and zero otherwise
Forecast Horizon	The logarithm of the difference between reported earnings announcement day and analyst' forecast day.
Analyst Busy	The number of forecasts issued by analysts in the previous quarter
Analyst Experience	The logarithm of the number of years since the analyst started issuing forecasts
Analyst Coverage	The logarithm of the number of analysts that issued a forecast during the last quarter
Market Uncertainty	The standard deviation of value-weighted daily market return over the past 30 days
Financial Crisis	A dummy variable that equals one if the forecast is issued between December 1, 2007 and June 30, 2009 and zero otherwise
NBER Recession	A dummy variable that equals one if the forecast is issued in the month that coincides with the recession month indicated by the National Bureau of Economic Research (NBER), and zero otherwise
High Uncertainty	A dummy variable that equals one if the forecast is issued when the economic policy uncertainty index (EPU) lies in the highest tercile and zero otherwise of available values (1999 to 2015)

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