Concurrent Earnings Announcements and the (Rational) Allocation of Investor Attention

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Abstract

We investigate rational inattention as an explanation for the documented reduction in the processing of firm-specific information by investors on busy earnings announcement (EA) days. We show that on days with many contemporaneous EAs, firm-specific uncertainty increases while aggregate uncertainty declines. We interpret these results as consistent with investors' attention being drawn away from idiosyncratic toward aggregate information during these days. We also show a significant increase in the trading of securities with higher exposure to aggregate risk, as well as an increase in Google searches of macroeconomic terms on busy EA days. Jointly, these results suggest that investors take actions that are consistent with a shift in attention from idiosyncratic to aggregate information on busy EA days. Lastly, we show that macroeconomic forecasters are more likely to update their forecasts and that forecast dispersion declines on busy EA weeks, which supports our assumption that busy EA days provide information about the economy at large. Overall, our results support rational inattention as an explanation for the lower transmission of firm-specific information on busy earnings announcement days documented in the literature.

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Keywords: Attention Allocation; Earnings Announcements; Uncertainty.

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1 Introduction

Previous research has shown that investors process firm-specific information in earnings announcements less thoroughly during busy earnings announcement (EA) days relative to non-busy EA days.[1] This empirical regularity has generally been interpreted as evidence of investor irrationality due to behavioral biases such as distraction or information overload (Hirshleifer, Hou, and Teoh 2009). However, the underlying mechanism driving these results remains unclear, and models that incorporate constrained investor rationality have been proposed as more likely explanations (Blankespoor, DeHaan, and Marinovic 2020). Nevertheless, evidence that clearly distinguishes between these competing explanations remains scant.

In this paper, we propose and provide evidence in favor of a new explanation for the effect of busy EA days on investors' processing of firm-specific information that preserves investor rationality but acknowledges that agents have attention/information processing constraints. Our explanation is founded on rational inattention theory which maintains that agents rationally allocate their limited attention or resources to processing information with the highest expected marginal benefit (Sims 2003). We therefore preserve the typical assumption from the behavioral literature that agents are constrained in terms of their attention and information processing capacity (Hirshleifer, Hou, and Teoh 2009; DeHaan, Shevlin, and Thornock 2015), but depart from these papers by also assuming investor rationality within these constraints.

We build our theoretical arguments from the framework proposed in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016), who model mutual fund managers' attention allocation between firm-specific and aggregate information. Kacperczyk, Van Nieuwerburgh, and Veldkamp show

1. "Busy earnings announcement days," "busy earnings days," or simply "busy EA days" are terms used in the literature to refer to days in which multiple firms announce earnings contemporaneously.

that because macroeconomic fluctuations have a greater impact on portfolio values than idiosyncratic fluctuations, mutual funds managers reallocate their attention from idiosyncratic to aggregate information when the net benefit of resolving aggregate uncertainty increases. We combine this intuition with a burgeoning literature showing that aggregated accounting disclosures have macroeconomic content (Nallareddy and Ogneva 2017; Shivakumar and Urcan 2017; Konchitchki and Patatoukas 2014; Lind 2020) to hypothesize that as the number of firms announcing earnings on a given day increases, so too does the macroeconomic content of their aggregated disclosures, which induces rational investors to reallocate their attention from firm- to macro-level information.

We test this hypothesis using two approaches. First, we use panel regressions of changes in the idiosyncratic uncertainty of announcing firms around their EAs on the number of concurrent EAs. We find that as the number of EAs on a given day increases, so does announcing firms' firm-specific uncertainty, consistent with existing evidence documenting a decrease in investor processing of firm-specific information on these days. Second, we use daily time-series regressions of aggregate uncertainty on the number of concurrent EAs and observe that aggregate uncertainty declines as the number of concurrent EAs increases. Taken together, these results are consistent with investors reallocating their attention from processing idiosyncratic to processing aggregate information in EAs when more firms announce earnings on a given day.

Our "attention reallocation" interpretation of the results rests upon our assumption that opposite directions in the resolution of idiosyncratic and aggregate uncertainty reflect a substitution in investors' information processing activities. While this assumption is consistent with the predictions of information theory (e.g., Shannon 1948), we attempt to substantiate it by studying whether investors' *actions* reveal the processing of aggregate information on busy EA days. We predict that if investors process additional information about the macroeconomy on busy EA days, their trading activity during these days should be concentrated on securities that allow them to adjust the exposure of their portfolio to aggregate uncertainty. We show that the trading volume of firms with more exposure to aggregate uncertainty (i.e., high beta and bellwether firms) increases in the number of concurrent EAs. We also show that the trading volume of VIX-based options increases in the number of contemporaneous EAs. We interpret these results as consistent with investors processing aggregate information on busy earnings announcement days and trading accordingly to adjust their exposure to aggregate uncertainty.

We also predict that if investors process information about the macroeconomy on busy EA days, they are more likely to acquire contextual macroeconomic information from sources that go beyond EAs. We use counts of Google searches for macroeconomic information as a proxy for investors' macroeconomic information acquisition and find that the number of searches increases significantly with the number of concurrent EAs, while the same does not apply to non-macro search terms. Paired with the evidence in Drake, Roulstone, and Thornock (2012) that Google searches for announcing firms' tickers decline on busy EA days, these results suggest that investors reallocate their information acquisition efforts from idiosyncratic to macro information on busy EA days. Further, the results run counter to the interpretation that busy EA days overwhelm investors with information; rather, they suggest that agents rationally allocate their information-processing resources to the most economically salient information.

Our interpretation of the results also assumes that as the number of concurrent EAs increases, so too does the macroeconomic salience of their aggregate disclosures. We assess whether busier EA days provide investors with more macroeconomic information by studying how the forecasting behavior of macroeconomic analysts changes as a function of the number of concurrent EAs. We intuit that increased macroeconomic information should be reflected in the decision to issue or revise a GDP forecast, in the magnitude of the GDP forecast revision, and in the dispersion in GDP forecasts issued by different macroeconomic analysts. Using GDP forecasts from Bloomberg, we find that as the number of EAs in a week increases, the probability of changes in the GDP forecast consensus increases, the size of forecast revisions increases, and that forecast dispersion declines. These results are consistent with the notion that days in which more firms announce earnings provide investors with more salient macroeconomic information.

Lastly, we exploit the cross-sectional prediction in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) that the strength of the incentive to reallocate attention from firm-specific to aggregate information depends on the relative marginal utility of processing each signal, to predict that investor attention allocation on busy EAs behaves accordingly. That is, we predict that investors allocate more attention to processing aggregate information when the marginal utility of doing so increases relative to processing idiosyncratic information. We proxy for the marginal utility of processing aggregate information using two aspects of the macroeconomic salience of the EAs: the percentage of daily EAs from firms designated as "bellwethers"—firms whose performance provides a leading indicator of macroeconomic performance—and the staleness of the most recent macroeconomic information available to investors. We predict that these variables increase investors' incentive to reallocate their attention to aggregate uncertainty because the earnings of bellwethers likely contain more macro-relevant information and because stale macroeconomic information makes new information more salient. Consistent with our predictions, we find that the ratio of bellwether to announcing firms and stale macro information magnify the association between the number of concurrent EAs and both flavors of uncertainty in the predicted directions.

Finally, we assess the robustness of our findings by performing several permutations of our empirical models. Our inferences remain unchanged when using alternative proxies for aggregate uncertainty and for the number of EAs per day. Further, our idiosyncratic uncertainty results are robust to different fixed effect strategies, while our aggregate uncertainty results are robust to different autocorrelation structures, moving averages, ARCH terms, and estimation techniques. We also perform a placebo analysis by randomly reshuffling the number of EAs per day over the sample period and repeating our main regressions. We observe that neither idiosyncratic nor aggregate uncertainty move as a a function of these "placebo" EA dates, which provides some assurance against a spurious relation between the number of EAs and uncertainty driving our results.

We view our paper as contributing to the literature in four ways. First, we shed additional light and understanding on investors' behavior during busy EA days. Our results suggest that investors are rational in their allocation of attention to firm and aggregate information in the presence of multiple EAs. While it is likely that, to some degree, behavioral biases contribute to the reduced information processing shown in the literature, our evidence suggests that the role of investor rationality is, at a minimum, greater than previously thought. Furthermore, by focusing on uncertainty resolution, we complement the previous literature that has examined patterns in stock prices around EAs. We believe that our approach is consistent with previous research and helps complete the picture of information flows surrounding EAs.

Second, our paper provides a likely explanation for the conflicting evidence that, while the trading volume of announcing firms declines during busy EA days, aggregate trading volume increases. We show that the increase in aggregate volume is driven by investors trading to adjust their exposure to aggregate uncertainty, consistent with a reallocation of attention away from processing idiosyncratic toward processing aggregate information.

Third, our findings that aggregated accounting disclosures have an impact on macroeconomic uncertainty are, to our knowledge, a novel contribution to the literature. While it has long been recognized that accounting reports are informative at the firm level, researchers are still working toward a better understanding of how firm-specific disclosures aggregate to affect the macroeconomy. We view our paper as an additional step toward that understanding.

Lastly, our paper is, to the best of our knowledge, among the first attempts to identify a suitable setting to empirically test the implications of rational inattention theory, therefore contributing to the emerging literature in accounting that studies how and why investors allocate constrained resources (Koester, Lundholm, and Soliman 2016; Hirshleifer and Sheng 2019; Drake et al. 2017).

2 Theoretical Framework

2.1 Prior Literature

There is considerable evidence that investors process earnings announcements less thoroughly when many firms announce earnings on the same day (see Blankespoor, DeHaan, and Marinovic 2020 for a review of the literature). For example, Hirshleifer, Lim, and Teoh (2009) find that the immediate price and volume response to earnings surprises weakens, while the post-earnings announcement drift strengthens, in the number of concurrent EAs. Similarly, DeHaan, Shevlin, and Thornock (2015) show that investors reduce their firm-specific information acquisition activities, measured with EDGAR 8-K downloads and abnormal Google ticker search volume, when more firms announce earnings on the same day. Much of the extant literature interprets these results as evidence of investors' behavioral biases, since the findings are at odds with the prediction from fully-rational investor models that investors should quickly incorporate all publicly available information into their expectations. From the behavioral perspective, agents' biases (e.g., cognitive limitations, distractibility, etc.) cause them to irrationally process and use less information in their trades, which then manifests in decreased price response, decreased volume, and longer post-earnings-announcement drift (Hirshleifer and Teoh 2003; DellaVigna and Pollet 2009).

While the above results are pervasive, the mechanism driving them remains open to multiple interpretations. Furthermore, behavioral explanations like investor distraction imply increased disagreement in beliefs between distracted and informed investors, and therefore higher trading volume and liquidity, contrary to what we observe in the data (Blankespoor, DeHaan, and Marinovic 2020). Rational inattention models, on the other hand, provide non-behavioral explanations for investors' partial use of information, and help bridge the gap between fully rational and behavioral models. For these reasons, we propose rational inattention as an alternative plausible mechanism driving the documented association between market outcomes and concurrent EAs, and devise tests to differentiate between behavioral and rational inattention models as explanations of this important empirical regularity.

2.2 Rational Inattention and Contemporaneous EAs

2.2.1 The Theory of Rational Inattention

Rational inattention models combine the classical assumption of investor rationality with the notion that investors have limited information-processing ability, as commonly assumed in behavioral models. Limited processing capacity means that investors cannot process all the information available to them (Hirshleifer and Teoh 2003), while rationality implies that investors allocate their limited processing capacity across different pieces of information in a way that maximizes their utility (Veldkamp 2011). Following the seminal work of Sims (2003), applications of the theory of rational inattention have shown that various agents disregard information in a way that is consistent with a cost-benefit analysis, not irrationality (see for example Driskill, Kirk, and Tucker 2020 for financial analysts, Corwin and Coughenour 2008 for market specialists, and Blankespoor, DeHaan, and Zhu 2018 for information intermediaries). In the context of busy EA days, Blankespoor, DeHaan, and Marinovic (2020) have suggested rational inattention models as a more plausible explanation for the decrease in firm-specific information transmission around EAs because, unlike behavioral explanations, these models predict reduced volume and liquidity on busy EA days, as observed in the data. However, little work has been done to empirically distinguish between the predictions of these two classes of models. We attempt to offer such evidence in this paper.

We build directly on Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016), who develop a rational inattention model that studies investors' attention allocation decisions under three key assumptions: First, investors are rational but subject to an information capacity constraint that limits the amount of information they can process; Second, investors are exposed to aggregate uncertainty, which reflects the risk of the economy at large and therefore affects the future cash flows of all firms in their portfolio, and idiosyncratic uncertainty, which reflects the risk of the future cash flows of each individual firm in their portfolio; And third, processing information about sources of aggregate uncertainty resolves more portfolio uncertainty than processing information about sources of idiosyncratic uncertainty because aggregate uncertainty has a larger impact on portfolio value. Under these assumptions, information acquisition shows strategic substitutability, meaning that if one source of information has a higher marginal utility for signal precision, investors will focus on it, causing its marginal utility to fall until it equals the next most valuable source of information (Grossman and Stiglitz 1980). The model leads to the prediction, supported in the data, that investors reallocate their attention away from idiosyncratic and toward aggregate information during economic downturns, when holding risk is more costly and the marginal benefit of resolving aggregate uncertainty is greater.

We propose that a similar dynamic applies to earnings announcements. We argue that EAs contain both idiosyncratic and aggregate information, that investors' ability and net benefit of using EAs to resolve idiosyncratic and aggregate uncertainty change as a function of the number of concurrent EAs, and that therefore investors allocate their attention between processing aggregate versus idiosyncratic information as a function of the number of concurrent EAs.

2.2.2 The Theory of Rational Inattention and Contemporaneous EAs

Earnings announcements convey information not only about expected future cash flows, but also about the uncertainty surrounding these cash flows. For example, Patell and Wolfson (1979, 1981) show that a firm's implied volatility declines sharply following an EA, consistent with earnings information facilitating the resolution of uncertainty about the future performance of the firm. Truong, Corrado, and Chen (2012) and Neururer, Papadakis, and Riedl (2016) confirm this finding using more recent sample periods, and show that the direction and magnitude of the earnings news also play a role in the resolution of idiosyncratic uncertainty induced by EAs.

Research has also shown that EAs convey information that goes beyond the announcing firm. A burgeoning literature shows a connection between aggregated accounting information and macroeconomic phenomena (Konchitchki and Patatoukas 2014; Shivakumar and Urcan 2017; Nallareddy and Ogneva 2017), indicating that EAs may be useful in gauging the state of the economy. Relatedly, researchers have shown that a firm's earnings can help investors form expectations about market discount rates (Cready and Gurun 2010; Gallo, Hann, and Li 2016) and mitigate uncertainty about the economy at large (Kim et al. 2020; Lind 2020).

Overall, the literature suggests that EAs help investors resolve both idiosyncratic and aggregate uncertainty. We maintain that the benefits and costs of using EAs to resolve the two types of uncertainty change as a function of the number of concurrent EAs. As the number of concurrent EAs increases, investors receive a clearer signal about the macroeconomic outlook because announced earnings represent a larger proportion of the economy, and because industrial and geographic diversification allow investors to better isolate aggregate from idiosyncratic information in earnings. Furthermore, as the number of concurrent EAs increases, processing one firm's EA forces investors to forgo the benefit of processing others, which increases the opportunity cost of resolving idiosyncratic uncertainty. This discussion suggests that both the marginal benefit of processing aggregate information and the marginal cost of processing idiosyncratic information increase in the number of concurrent EAs. We therefore predict that as the number of contemporaneous earnings announcement increases, rationally inattentive investors reallocate their attention from processing EAs for idiosyncratic information to processing them for aggregate information. This leads to the main hypothesis of our paper:

Hypothesis 1: *Investors reallocate their attention from idiosyncratic to aggregate information as the number of concurrent earnings announcements increases.*

Our hypothesis implies the following relations between firm and aggregate uncertainty, which reflects investors' information processing activity, and the number of concurrent EAs:

Hypothesis 1a: *Ceteris paribus, the number of concurrent earnings announcements is associated with higher idiosyncratic uncertainty.*

Hypothesis 1b: *Ceteris paribus, the number of concurrent earnings announcements is associated with lower aggregate uncertainty.*

Our first hypothesis studies patterns of uncertainty resolution around EAs under the assumption that fluctuations in uncertainty provide a meaningful measure of investors' information processing activity. If our predictions in our first hypothesis were correct, we would expect agents' actions to reflect their information choices. This leads to our second hypothesis:

Hypothesis 2: *Investors' reallocation of attention from idiosyncratic to aggregate information in response to the number of concurrent earnings announcements leads to changes in their behavior.*

We expect that as investors process EAs for aggregate information during busy EA days, their priors about aggregate risk change, which should affect their portfolio choices. Therefore, we should observe an increase in the trading of securities that allow investors to adjust their exposure to aggregate uncertainty.

Hypothesis 2a: *Ceteris paribus, the number of concurrent EAs is positively associated with the trading volume of securities more exposed to aggregate uncertainty.*

We further expect that the increase in aggregate information in EAs on busy days should prompt investors to gather contextual macroeconomic information from other sources.

Hypothesis 2b: *Ceteris paribus, the number of concurrent EAs is positively associated with investors' macroeconomic information acquisition.*

The above predictions are in contrast to the implications of the "investor distraction" hypothesis put forth in the extant literature, which explains lower price reactions on busy EA days as the result of information overload and poor information processing performance (Hirshleifer, Lim, and Teoh 2009). If this were the case, we would not expect to see investors processing yet *more* information at the aggregate level on top of firm-specific disclosures, nor would we expect investors to acquire additional information. Rather, we would expect an increase in firm uncertainty, and either a decrease or no change in aggregate uncertainty, and no increase in other forms of information acquisition, such as Google searches. Further, our hypotheses regarding the increase in trading volume for non-announcing firms is in contrast with those of the investor distraction hypothesis, which predicts reduced overall volume on busy EA days. Extant evidence contradicts this prediction (Blankespoor, DeHaan, and Marinovic 2020), however, and the increase in overall volume is consistent with predictions such as ours. Thus, the above hypotheses allows us to empirically distinguish between the predictions of these competing models.

3 Data and Sample Formation

In this section we outline the measurement of our key constructs (Section 3.1) and our sample construction methodology (Section 3.2).

3.1 Measurement of Key Variables

3.1.1 Proxies for Uncertainty

While there are a number of proxies for uncertainty in the literature, we focus our efforts on measures that possess three characteristics: an ability to reflect forward-looking uncertainty in equity markets at the aggregate and firm levels, respectively; comparability in the way the two constructs are measured; and availability at high frequencies. We focus on equity-based proxies for uncertainty because we are interested in investors' effort to resolve uncertainty around EAs. We focus on comparable proxies to allow for meaningful comparisons between aggregate and idiosyncratic uncertainty. Finally, we require high-frequency measures of the evolution of uncertainty over time to tease out the effects of daily EAs. These conditions lead us to rely on the following proxies.

We measure idiosyncratic uncertainty using the implied volatility derived from options prices, a measure that has been used extensively in the literature on firm-specific uncertainty because of its forward-looking nature and its daily frequency (Patell and Wolfson 1979, 1981; Billings, Jennings, and Lev 2015; Hann, Kim, and Zheng 2019). We measure the change in idiosyncratic uncertainty induced by an EA as the difference in average implied volatility across the three days after and the three days before the EA. This six-day window centered on the EA attempts to capture the effects of information leakage leading up to the EA and is consistent with similar studies of uncertainty around EAs (Neururer, Papadakis, and Riedl 2016; Gallo 2017). We obtain implied volatilities from Options Metrics Standardized Options database. The database provides implied volatilities calculated using at-the-money options with different duration, which overcomes the problem induced by mechanical changes in implied volatility that occur as options draw closer to expiration. We focus on the sub-set of options with a 30-day duration to match the duration of our proxy for aggregate uncertainty.

We measure aggregate uncertainty using the Chicago Board Options Exchange volatility index (VIX), a commonly used proxy for macroeconomic uncertainty (Bloom 2014; Alfaro, Bloom, and Lin 2018). Similar to implied volatility derived from option markets at firm level, this proxy has the benefit of being derived from forward-looking equity options, more specifically from S&P 500 index options with a 30-day duration, and of being available at daily frequencies. Because the majority of EAs occur outside of trading hours (Lyle, Stephan, and Yohn 2020), we use the opening value of VIX in $t+1$ to capture the level of VIX corresponding to EAs on day t, and calculate the change in VIX as the difference between the opening value of VIX from day $t+1$ and the closing value of VIX from day $t-1$. We use a shorter, one-day window for our aggregate tests to better isolate the information coming from EAs at the aggregate level and to reduce measurement error in our time series.

3.1.2 Concurrent EAs

We count the number of EAs during a day using EA dates from the intersection of Compustat and I/B/E/S, keeping only the dates that agree between the two databases (Blankespoor, DeHaan, and Marinovic 2020). Using these dates, we sum the number of firms announcing earnings on a given day to obtain our count of EAs. This procedure ensures a proxy for which announcement dates are precisely measured, but causes the loss of EAs for which the two databases disagree. Since EAs that are dropped as a byproduct of this procedure may be relevant in inducing a reallocation of investor attention, in our robustness tests we trade off the precision of our measure for its relevance by using two alternative approaches, calculating the number of daily EAs using either the unrestricted Compustat sample or taking a firm's EA date as the earlier of Compustat or I/B/E/S as in Hirshleifer, Lim, and Teoh (2009) and DellaVigna and Pollet (2009).

3.2 Sample Formation and Descriptive Statistics

Testing our hypotheses requires two different samples. The first sample, which we use to study idiosyncratic uncertainty, is a panel dataset constructed at the firm-quarter level. We eliminate firms lacking necessary data, as well as those having less than one million dollars of assets, or stock prices of less than one dollar. We also exclude firms with a lag between consecutive EAs larger than ninety days. We further winsorize all continuous independent variables at the 1st and 99th percentiles to reduce the influence of outliers. This selection procedure results in a sample that includes 199,550 observations, representing 7,273 firms over the period 1995, the first year for which data on implied volatilities is available, to 2019. Table 1, Panel A reports descriptive statistics for this sample. The distribution of our variables is consistent with related studies (Neururer, Papadakis, and Riedl 2016).

The second sample, which we use to study aggregate uncertainty, is a time-series dataset constructed at the daily level. This sample includes 5,627 observations, distributed over the period 1995 to 2019 to match the time frame of our firm-level analysis. Table 1, Panel A reports summary statistics for this sample. The distribution of our variables is consistent with related studies (Baker et al. 2019).

Table 1 Panel B reports correlations among variables in each sample. We note that the univariate correlation between firm-specific uncertainty (*IVol*) and the number of daily EAs (EAs) is positive, while the opposite is true for the correlation between aggregate uncertainty (ΔVIX) and (*EAs*), consistent with our hypotheses. Other correlations also follow economic intuition.

4 Research Design and Empirical Results

In this section we outline our research design and describe our findings.

4.1 Uncertainty Resolution and Concurrent Earnings Announcements

We test our first hypothesis in two stages. First, we use panel regressions of changes in the idiosyncratic uncertainty of announcing firms around their EAs on the number of concurrent EAs, as described in Section 4.1.1. Second, we use time-series regressions of aggregate uncertainty on the number of concurrent EAs, as described in Section 4.1.2.

4.1.1 Idiosyncratic Uncertainty

Our first hypothesis predicts that investors reallocate their attention from processing idiosyncratic to processing aggregate information in response to more concurrent EAs. If this is the case, we expect idiosyncratic uncertainty to increase in the number of concurrent EAs. We test this prediction using the following panel regression:

$$\Delta\, IVol_{i;t-3,t+3} = \alpha + \beta EAs_t + \sum \gamma_j Controls_{j,i,t} + \nu_i + \eta_h + \varepsilon_{i,t} \tag{1}$$

The dependent variable is the change in idiosyncratic uncertainty induced by an EA, as defined in Section 3.1.1, and our variable of interest is the number of concurrent EAs *(EAs)*, as defined in Section 3.1.2. *Controls* is a vector of determinants of a firm's implied volatility around EAs: unexpected earnings *(UE)* to control for the direction of the news in the firm's EA; the firm's buy-and-hold return from $t-3$ to $t+3$ *(Ret)* to control for the leverage effect between price and volatility (Christie 1982; Schonberger, Subramanyam, and Wells 2014); the book to market ratio *(B-to-M)* to control for the different risks of value versus glamour stocks/firms; financial leverage *(Leverage)* to control for the effect of leverage on uncertainty; firm size *(Size)* to control for differences in uncertainty over the future performance of small and large firms; analyst following *(# Analysts)* to control for differences in the information environment; analyst forecast dispersion *(Disp)* to control for the level of disagreement among market participants; and the VIX index *(VIX)* to proxy for overall changes in market uncertainty around the EA. We standardize all continuous variables to ease interpretation of coefficients. Variable definitions are reported in Appendix A. Finally, we use different fixed effect structures (ν_i for firm fixed effects, η_h for time fixed effects) and cluster standard errors at firm level to address correlations across observations due to the inclusion of multiple observations per firm.

Table 2, Panel A presents parameter estimates from Equation (1). We observe that the coefficient for *EAs* is positive and statistically different from zero at the one percent level with either no fixed effects (Column 1), firm-fixed effects (Column 2), or firm, year, and month fixed effects (Column 3). These results suggests that, on average, firm-specific uncertainty increases as the number of concurrent EAs increases, consistent with previous findings that firm-specific information processing declines on busy EA days. Coefficients on the control variables are consistent with economic intuition and with previous literature (Neururer, Papadakis, and Riedl 2016).

We also consider an alternative definition of concurrent EAs that incorporates the aggregate size of announcing firms relative to the total size of firms announcing earnings in the last quarter (*Size EAs*), which may serve as a more direct proxy of the macroeconomic information supplied to investors by EAs. Table 2, Panel B presents parameter estimates from Equation (1), in which *Size EAs* replaces *EAs* as the variable of interest. The table shows that the coefficient on *Size EAs* is positive and statistically different from zero at the one percent level with no fixed effect (Column 1) or firm, year, and month fixed effects (Column 3). The coefficient, however, is not statistically different from zero when including only firm-fixed effects (Column 2).

Overall, we interpret the results in this section as consistent with our conjecture that investors allocate their attention away from idiosyncratic information when more firms announce earnings on the same day.

4.1.2 Aggregate Uncertainty

Approaching our first hypothesis from the aggregate perspective, if investors reallocate their attention from processing idiosyncratic to processing aggregate information, we expect aggregate uncertainty to decline as the number of concurrent EAs increases. We test this prediction using the following time-series regression:

$$VIX_t = \alpha + \beta EAs_t + \sum \gamma_j Controls_{j,t} + \sum \theta_k VIX_{t-k} + \varepsilon_t \tag{2}$$

The dependent variable is the VIX index, as defined in Section 3.1.1. Our variable of interest is the number of concurrent EAs *(EAs)*, defined in Section 3.1.2. We control for the effect that the direction of earnings news has on aggregate uncertainty, we include aggregate ROA of announcing firms (*Agg ROA*). We also control for days on which important macroeconomic announcements are made, namely monetary policy (*Monetary Release*), unemployment and jobs updates (*Labor Release*), release of estimates for inflation (*Inflation Release*),[2] and announcements of initial GDP estimates (*GDP Release*). We identify monetary policy announcements using Fed-issued press releases after each FOMC meeting; unemployment and jobs report dates as occurring on the first Friday of every quarter, as in the Bureau of Labor Statistics (BLS) calendar of release dates; inflation releases as listed on the BLS calendar; and initial GDP announcements (i.e. the announcements of the "advance" estimates) using the Bureau of Economic Analysis' (BEA) history of announcements. Finally, we include market returns on the day of the announcement as a control for potential leverage effects at the aggregate level (Christie 1982). The autocorrelation structure we use to estimate Equation (2) is determined by the Akaike information criteria, which indicates that two lags are appropriate for both our dependent variables, though results are robust to permutations of this choice. Finally, we employ ARMAX estimation to correct parameter estimates and standard errors for autocorrelation and heteroscedasticity. We note that, given the inclusion of AR terms, the

2. Consistent with Savor and Wilson (2013), we use the PPI rather than the CPI, since the former is released one to two days before the latter, and therefore CPI contains less new information.

regression using the level of VIX is a more general model that allows the coefficient on the lagged value of VIX to vary, rather than restricting it to one, as in the use of changes in VIX. Nevertheless, we estimate Equation 4.2.1 using both levels and changes of VIX as the dependent variable.

Table 3 Panel A presents parameter estimates of Equation (2). The coefficient on *EAs* is, as expected, negative and statistically different from zero at conventional significance levels for the both the level and the change in VIX, with and without controlling for other factors. Coefficients on the control variables are also consistent with economic intuition. For example, more positive news and monetary releases are both associated with the resolution of aggregate uncertainty (Savor and Wilson 2013). We check for stationarity of all time-series variables using the Dickey-Fuller and Phillips-Perron unit root tests before estimation, and find that these tests strongly reject the null hypothesis of the presence of a unit root for all variables. This reduces concerns about spurious correlation driving our results.

We consider an alternative definition of concurrent EAs that incorporates the aggregate size of announcing firms relative to the total size of all firms (*Size EAs*). Table 3, Panel B presents parameter estimates of Equation (2) with *Size EAs* in place of *EAs*, and shows that the coefficient of interest is always negative and statistically different from zero at conventional significance levels.

Overall, the evidence in Tables 2 and 3 is consistent with our hypothesis: the resolution of idiosyncratic uncertainty worsens in the number of concurrent EAs, consistent with investors allocating attention away from firm-specific information, while the resolution of aggregate uncertainty improves in the number of concurrent EAs, consistent with investors allocating attention toward aggregate information.

4.2 Investors' Actions and Concurrent Earnings Announcements

In our second hypothesis we study whether investors' actions are consistent with their processing aggregate information to a larger extent during busy EA days. We do so by looking at two actions: the trading of securities and information acquisition.

4.2.1 Investors' Trading Activity

We expect that if investors allocate their limited attention to aggregate information during busy EA days, then they should also trade securities that allow them to adjust the exposure of their portfolio to aggregate uncertainty. We test this hypothesis by focusing on the trading volume of instruments that allow investors to adjust the exposure of their portfolio to aggregate uncertainty: the shares of firms with high exposure to aggregate uncertainty and VIX-based options. We focus on volume rather than returns because we expect volume to increase regardless of the direction of uncertainty-resolving news, while returns require a directional prediction, which neither the theory nor our hypotheses provide.

Using a panel data structure at the daily level, we model a firm's daily trading volume as a function of daily EAs and test whether investors trade the shares of firms with high exposure to aggregate uncertainty to a larger extent during busy EA days as follows:

$$Trad\ Volume_{i,t} = \alpha + \beta_1 EAs_t \times \mathrm{Z}_{i,t} + \beta_2 EAs_{i,t} + \beta_3 Z_{i,t} + \sum \gamma_j Controls_{i,t} + \varepsilon_t \tag{3}$$

where *Trad Volume* measures either the level or the percentage change in firm *i*'s daily trading volume, defined as the ratio of the number of firm *i*'s shares traded each day to the number of its shares outstanding at the end of each day; *EAs* is defined as before; while *Z* identifies firms with high exposure to aggregate uncertainty, defined either as $High\ Beta_{i,t}$, an indicator variable set to one if the firm's 90-day stock beta is above the sample median, and zero otherwise; or $Bellwether_{i,t}$, an indicator variable set to one if the correlation between firm *i*'s sales and detrended GDP is above the sample median, and zero otherwise.

Table 4 lends support to our conjecture: we observe that β_1 is always positive and statistically different from zero at the one percent level, which suggests that the trading volume of firms with high exposure to aggregate uncertainty increases in the number of earnings announced during a day. The coefficients on *Own EA* and *EAs*×*Own EAs* indicate that announcing firms' volume is significantly lower than non-announcing firms, consistent with results in the literature (Hirshleifer, Lim, and Teoh 2009; Blankespoor, DeHaan, and Marinovic 2020). In this context, our findings of increased volume indicate that the increases in total volume on high-EA days shown in Blankespoor, DeHaan, and Marinovic (2020) are driven by non-announcing firms' volume, and most particularly, increases in beta and bellwether firms' trading volume, consistent with investors adjusting their portfolios' exposure to aggregate risk.

We next test whether investors trade VIX-based options to a larger extent during busy EA days using the following time-series regression:

$$VIX\ Trad\ Volume_t = \alpha + \beta EAs_t + \sum \gamma_j Controls_{j,t} + \sum \theta_k VIX\ Trad\ Volume_{t-k} + \varepsilon_t \qquad (4)$$

where *VIX Trad Volume* measures either the level or the percentage change in the amount of VIX call or put options traded during a day, while *EAs* is defined as before. We also include the lagged level of VIX in *Controls* to control for the effect of prevailing uncertainty on VIX trading volume.

Table 5 provides evidence consistent with our conjecture: we observe that β is positive and statistically different from zero at conventional significance levels in three out of four specifications, which suggests that the trading volume of VIX-based options increases in the number of earnings announced during a day.

Overall, the evidence in this section is consistent with the notion that as the number of concurrent EAs increases, investors shift their attention to processing aggregate information and thereby trade to adjust the exposure of their portfolio to aggregate risk.

4.2.2 Investors' Information Acquisition

The next action we explore is investors' information acquisition on busy EA days. We expect that if investors allocate their limited attention to aggregate information during busy EA days, then they should also acquire contextual macroeconomic information from sources other than EAs.

We test this prediction applying the intuition from Drake, Roulstone, and Thornock (2012) that investors acquire information through Internet searches. Accordingly, we estimate a modified version of Equation 4 in which we replace *VIX Trad Volume* with *Macro Search* as the dependent variable, where *Macro Search* is the aggregate Google search volume index for a variety of macroeconomic search terms (e.g., "gross domestic product," "gdp," "exchange rate," "manufacturing activity," "monetary policy," "unemployment rate," "industrial production," "inflation," etc.). These data are available starting in 2004. Details on the full dictionary of search terms used in these regressions is included in Appendix B.

Table 6 consistently documents a significantly positive association between the number of EAs per day and the amount of macro search, irrespective of whether we use an index of macro search terms, as shown in Panel A, categories of macro search terms (Panel B), or individual search terms (untabulated) as the dependent variable. The table also shows that the search of non-macro terms decreases on days when more EAs occur, which suggests that we are not simply capturing days in which Internet searches are more voluminous. We interpret these results as consistent with the notion that as the number of concurrent EAs increases, investors reallocate their attention toward gathering and processing aggregate information, consistent with our hypothesis, and inconsistent with investors being overwhelmed by information, as predicted by the investor distraction hypothesis in Hirshleifer, Lim, and Teoh (2009).

5 Additional Analyses

5.1 GDP Forecasts and Concurrent EAs

A fundamental assertion underlying our prediction for the relationship between investor attention and multiple concurrent EAs is that the greater the number of firms announcing earnings on a given day, the greater the macroeconomic information content that arises when aggregating these reports. To test this assertion, we employ Bloomberg on data on forecasts for future GDP growth, conjecturing that increased information content in aggregate EAs should prompt to changes in GDP forecasts. We use Bloomberg macro forecasts because, unlike other macroeconomic forecasters such as those contributing to the Survey of Professional Forecasters (SPF), which publishes macro forecasts once a quarter on a fixed schedule,[3] Bloomberg forecasters contribute and revise their forecasts at their own discretion. Practically speaking, this results in time-series variation in the number of GDP forecasts made or revised at the weekly level. This variation in the number of forecasts and revisions, in the consensus forecast, and in forecast dispersion allows us to test for a

3. For details on the SPF forecasts, see the Philadelphia Fed's Website, https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/

relationship between these variables and the number of weekly EAs, a test that would not be well identified at the quarterly level.

If the macroeconomic signal in aggregated EAs grows with the number of concurrent EAs, we would expect the number of changes in the GDP forecast consensus per week to increase as forecasters respond to the infusion of macroeconomic information. Further, we predict that the greater macroeconomic information content in multiple EAs results in a greater absolute change in the consensus forecast, and a reduction in forecasters' uncertainty. To test these assertions, we regress three different dependent variables on the number of weekly EAs and on controls for other macroeconomic announcements. These dependent variables are *New Forecast*, an indicator variable equal to one if the consensus GDP forecast changes during the week; $|\Delta \mathit{Forecast}|$, the absolute change in the consensus forecast; and *Forecast Disp*, the forecast dispersion, all measured on a weekly basis.

Results from these regressions are reported in Table 7. In Panel A, using contemporaneous forecast updates, we find a positive and significant association between the number of EAs and the probability that the consensus GDP forecast changes. The coefficient on the number of EAs when using the absolute value of forecast revisions is also positive, but not statistically different from zero. These results are consistent with forecasters updating their forecasts when more macroeconomic information becomes available through EAs, and with those EAs containing information that changes the consensus. Further we find a negative and significant association between forecast dispersion and the number of concurrent EAs, consistent with the macro information content in the EAs reducing forecasters' uncertainty. Panel B presents similar regression using the leading week's forecast updates, to account for any delay in forecaster's updating. Results are of the same tenor, though marginally more or less significant as those in Panel A. Together, they are consistent with our assumption that the aggregate information content in concurrent EAs increases in the number of EAs.

5.2 Uncertainty, Concurrent EAs, and Incentives to Reallocate Attention

In this section, we leverage the insight in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) that the strength of the incentive to reallocate attention between aggregate and idiosyncratic information depends on the relative marginal utility for signal precision to conjecture that the relation between the allocation of attention and the number of concurrent EAs strengthens as the marginal utility of processing aggregate information increases.

We identify two sources of variation in the marginal utility of processing aggregate information. First, we maintain that EAs contain more aggregate information when the announcing firms are bellwethers because their economic performance is highly correlated with the economic performance of the economy (e.g., Bonsall, Bozanic, and Fischer 2013). Given that rational investors put more weight on more precise signals, we expect that the marginal utility of processing aggregate information increases with the proportion of announcing firms that are bellwethers.

Second, we argue that investors experience increasing uncertainty about the economic outlook as the time elapsed since the latest macroeconomic announcement increases. Hence, we expect that the marginal utility of processing aggregate information increases in the staleness of the macroeconomic information available to investors.

If these conjectures are true, we should observe that idiosyncratic uncertainty increases even more in the number of concurrent EAs when the proportion of announcing firms that are bellwethers and the time elapsed since the latest macroeconomic announcement increase. We test this prediction using the following panel regressions:

$$\Delta\, IVol_{i;t-3,t+3} = \alpha + \beta_1 Z \times EAs_t + \beta_2 Z + \beta_3 EAs_t + \sum \gamma_j Controls_{j,i,t} + \varepsilon_{i,t} \tag{5}$$

where Z represents either *Bell Ratio*, the proportion of announcing firms that are bellwethers, or *Stale Macro Info*, an indicator variable set to one if the time between day t and the most recent macro announcement is above the sample median, zero otherwise, based on the announcement dates for *Monetary Release*, *Labor Release*, *GDP Release*, or *Inflation Release*.

Table 8 columns (1) and (2), which present parameter estimates of Equation (5), support our conjecture: the coefficient of interest (β_1) is positive and statistically significant at the one percent level irrespective of how we measure investors' incentives to reallocate attention away from idiosyncratic information.

Conversely, from the perspective of aggregate uncertainty, if our conjectures are true we should observe that aggregate uncertainty decreases even more in the number of concurrent EAs when the proportion of announcing firms that are bellwethers and the time elapsed since the latest macroeconomic announcement increase. We test this prediction with the following time-series regression:

$$\Delta VIX_t = \alpha + \beta_1 Z \times EAs_t + \beta_2 Z + \beta_3 EAs_t + \sum \gamma_j Controls_{j,t} + \sum \theta_k VIX_{t-k} + \varepsilon_t \tag{6}$$

where variables are as previously defined.

Table 8 columns (3) and (4), which present parameter estimates of Equation (6), provide further support our conjecture: the coefficient of interest (β_1) is negative in both cases, although statistically different from zero (at the one percent level) only when we measure investors' incentive to reallocate attention toward aggregate information with *Stale Macro Info*.

Jointly, the results in this section are consistent with a strengthening of the relation between the two flavors of uncertainty and the number of concurrent EAs when the marginal utility of processing aggregate information increase.

5.3 Identification - Placebo Analysis

In our firm level tests, we rely on an event-study framework to identify the effects of the number of EAs on changes in firm-specific uncertainty. Our event windows are selected in order to capture the information effects of EAs while minimizing the contamination of other sources of information. At the aggregate level, we rely on time-series variation alone to identify the effects of the number of EAs on aggregate uncertainty. While we do our best to control for other sources of macroeconomic news, it is an impossible task to include every possible piece of macro-relevant information. However, given the length of our time series, unless there were some systematic relation between the number of EAs and some non-accounting source of aggregate information, we believe time-series variation in the relation between aggregate uncertainty and the number of EAs is sufficient.

A potential criticism of our tests is that firms may choose to announce bad news on busy EA days in order to avoid scrutiny, thus introducing a systematic relation between increased firm-specific uncertainty and the number of EAs. While it is true that firms have discretion over the precise timing of their EAs, we do not see this as a challenge to our identification strategy for several reasons. First, if firm's bad news were to drive an increase in uncertainty at the firm level, we would also expect the resultant bad news in aggregate EAs to cause *aggregate* uncertainty to increase, which is the reverse of what we find. Second, in order for bad EA news to have an effect on firm-specific uncertainty, it needs to be processed by the market, which contradicts the assumption that firms schedule their EAs to *avoid* such processing. Finally, the most common reasons for changing the timing of EAs are likely benign (DeHaan, Shevlin, and Thornock 2015, p. 39). While we cannot completely eliminate the possibility that such factors influence our results, we don't see them as a grave threat to our identification.

To provide assurance against concerns of spurious correlation, we run our main regressions at both the firm and aggregate level using "placebo" EAs. That is, we take the actual distribution of EAs over our sample period and randomly scramble them over days in the sample, being careful to preserve the correct data structure (i.e., at the firm level, all firms announcing earnings on the same day are assigned the same placebo EAs). Results, presented in Table 9, show that the placebo EAs have no significant association with firm- or aggregate-level uncertainty, indicating that our main results are not likely to be driven by chance or a spurious relationship between EAs and uncertainty. We also repeat these regressions 1,000 times, randomly reshuffling the number of reports announced each day, and collecting the coefficient and standard error on placebo reports in each iteration. Results show that 77.70 percent of estimated coefficients are statistically insignificant at the firm level, and 99.20 percent are insignificant at the macro level. These results provide assurance that our results are not due to chance.

5.4 Robustness Tests

We assess the robustness of our results to different measurement and empirical choices. We test whether our results are driven by the choice to keep only the sub-sample of EAs for which the dates provided by Compustat and I/B/E/S agree. We repeat our analyses calculating the number of daily EAs using either the unrestricted Compustat sample or taking a firm's EA date as the earlier of Compustat or I/B/E/S, as in Hirshleifer, Lim, and Teoh (2009) and DellaVigna and Pollet (2009), and find that our results are either unchanged or stronger. Our aggregate uncertainty results are robust to different autocorrelation structures, moving averages, ARCH terms, and estimation techniques.

6 Conclusion

In this paper, we propose and provide evidence in support of a new interpretation of the "busy EA" evidence in the literature. We argue that as the number of concurrent EAs increases, so too does the macroeconomic salience of their aggregate disclosures, which diverts the attention of rational agents from the resolution of firm/idiosyncratic uncertainty to the resolution of aggregate/macroeconomic uncertainty, as predicted by the theory of rational inattention in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016).

Our empirical analysis supports this prediction. We show that as the number of concurrent EAs increases: idiosyncratic uncertainty significantly increases, aggregate uncertainty significantly declines, and trading behavior increases for assets with exposure to aggregate risk. Furthermore, we also find that investors acquire more contextual macroeconomic information through Google searches during busy EA days, which, combined with previous evidence that announcing firms'

Google ticker searches decline on these days, provides further support to our hypotheses. Additionally, as the number of concurrent EAs increase, macroeconomic forecasters issue more forecast and revisions, change the consensus forecast by a greater amount, and reduce their forecast dispersion. Lastly, we show that these effects vary with the strength of investors' incentives to reallocate their attention toward aggregate uncertainty.

The paper contributes to two streams of literature. First, we shed light on the underlying mechanism driving decreased firm information transfer on busy EA days. While this result has been interpreted so far as evidence of investors' behavioral biases, our evidence suggest that the rational allocation of investors' limited attention is also at play. We also resolve the paradoxical finding in the literature that, on busy EA days, announcing firm's trading volume declines, while aggregate trading volume increases. Our explanation and evidence show that these are symptoms of investors' reallocation of attention from firm- to aggregate-level information in EAs.

Second, we also contribute to the aggregate earnings literature by showing that aggregated accounting disclosures have an impact on macroeconomic uncertainty; to our knowledge, a novel finding. It has long been recognized that accounting reports are informative at the firm level, but only recently have aggregate effects come to researchers' attention. We view our results as a step toward understanding accounting's potential contribution to the macroeconomic information environment.

Lastly, we view our paper as among the first attempts to empirically test the implications of rational inattention theory. Our findings contribute to an emerging literature in accounting that studies how and why investors allocate constrained information processing resources (e.g., Koester, Lundholm, and Soliman 2016; and Drake et al. 2017).

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Tables

Table 1: **Summary Statistics**

Panel A: Summary Statistics						
	N	Mean	SD	25%	50%	75%
Firm-Level Data (194,309 Firm-Quarters)						
ΔIVol	194,309	−0.09	0.16	−0.17	−0.07	0.00
EAs	194,309	181.00	114.42	84.00	162.00	273.00
Size EAs	194,309	0.04	0.03	0.02	0.04	0.06
UE	194,309	0.00	0.01	−0.00	0.00	0.00
Ret	194,309	0.00	0.10	−0.04	0.00	0.05
B/M	194,309	0.48	0.38	0.23	0.41	0.65
Leverage	194,309	0.21	0.20	0.02	0.17	0.33
Size	194,309	7.48	1.82	6.14	7.41	8.71
# Analysts	194,309	9.99	7.13	5.00	8.00	14.00
Dispersion	194,309	0.02	0.04	0.00	0.01	0.02
VIX	194,309	19.56	8.33	13.75	17.68	22.92
Bell Ratio	194,309	0.06	0.05	0.02	0.04	0.08
Stale Macro Info	194,309	0.60	0.49	0.00	1.00	1.00
Macro-Level Data (5,626 Days)						
VIX	5,627	20.17	8.25	14.20	18.59	23.68
EAs	5,627	63.87	82.82	10.00	27.00	86.00
Agg ROA	5,627	0.01	0.02	0.00	0.01	0.01
Mon Rel	5,627	0.03	0.17	0.00	0.00	0.00
Lab Rel	5,627	0.05	0.21	0.00	0.00	0.00
GDP Rel	5,627	0.02	0.13	0.00	0.00	0.00
Bell Ratio	5,627	0.13	0.17	0.03	0.09	0.17
Stale Macro Info	5,627	0.58	0.49	0.00	1.00	1.00
Market Ret	5,627	0.00	0.01	−0.00	0.00	0.01
VIX Volume	3,188	409,625.23	358,278.32	141,073.00	346,523.00	567,484.50
Macro Search	3,704	41.92	10.53	34.52	42.36	49.59
Non-Macro Search	3,704	13.45	6.62	8.09	11.90	17.61

Panel B: Correlations

Firm-Level Data

	ΔIVol	*EAs*	*Size EAs*	*UE*	*Ret*	*B/M*	*Leverage*	*Size*	*# Analysts*	*Dispersion*	*VIX*	*Bell Ratio*	*Stale Macro Info*
ΔIVol	1.000												
EAs	0.010	1.000											
Size EAs	-0.008	0.568	1.000										
UE	-0.070	0.023	0.027	1.000									
Ret	-0.171	-0.018	0.002	0.128	1.000								
B/M	0.088	-0.003	-0.018	-0.061	0.012	1.000							
Leverage	0.011	0.067	0.003	-0.034	0.001	-0.062	1.000						
Size	-0.077	-0.022	0.106	0.008	0.012	0.202	0.231	1.000					
# Analysts	-0.133	-0.054	0.067	0.045	0.015	-0.162	-0.021	0.497	1.000				
Dispersion	0.082	0.012	-0.065	-0.172	0.006	0.245	0.130	-0.089	-0.186	1.000			
VIX	0.171	-0.048	-0.026	-0.029	-0.006	0.046	-0.032	-0.037	-0.011	0.042	1.000		
Bell Ratio	-0.035	0.076	0.059	-0.004	-0.016	-0.019	-0.037	0.072	0.006	-0.014	0.176	1.000	
Stale Macro Info	0.025	0.044	0.009	0.008	0.001	-0.010	-0.033	-0.003	0.032	-0.037	0.072	0.043	1.000

Macro-Level Data

	VIX	*EAs*	*Agg ROA*	*Mon Rel*	*Lab Rel*	*GDP Rel*	*Bell Ratio*	*Stale Macro Info*	*Market Ret*	*VIX Volume*	*Macro Search*	*Non-Macro Search*
VIX	1.000											
EAs	-0.016	1.000										
Agg ROA	-0.057	-0.056	1.000									
Mon Rel	-0.005	0.121	0.024	1.000								
Lab Rel	-0.001	0.020	0.004	-0.006	1.000							
GDP Rel	-0.008	0.147	-0.004	0.093	-0.029	1.000						
Bell Ratio	0.197	-0.006	0.031	-0.002	-0.020	-0.002	1.000					
Stale Macro Info	-0.006	-0.064	-0.003	-0.207	-0.260	-0.148	-0.002	1.000				
Market Ret	-0.026	-0.009	-0.000	0.054	-0.008	0.008	-0.031	0.003	1.000			
VIX Volume	-0.224	-0.030	0.006	0.013	0.023	-0.025	-0.269	-0.086	-0.039	1.000		
Macro Search	-0.161	0.163	0.031	0.120	0.046	0.026	-0.255	-0.064	-0.011	0.429	1.000	
Non-Macro Search	-0.358	-0.042	-0.004	-0.004	-0.020	0.017	-0.326	0.024	0.014	0.468	0.423	1.000

Table 2: **Idiosyncratic Uncertainty and Concurrent EAs**

Panel A: Idiosyncratic Uncertainty and Number of EAs

$$\Delta\, IVol_{i;t-3,t+3} = \alpha + \beta EAs_t + \sum \gamma_j Controls_{j,i,t} + \nu_i + \eta_h + \varepsilon_{i,t}$$

	(1)	(2)	(3)
EAs_t	0.009^{**}	0.013^{***}	0.013^{***}
	(2.09)	(4.11)	(3.77)
$UE_{i,t}$	-0.030^{***}	-0.025^{***}	-0.020^{***}
	(-11.96)	(-10.22)	(-8.40)
$Ret_{i,t}$	-0.164^{***}	-0.162^{***}	-0.159^{***}
	(-60.53)	(-61.49)	(-61.16)
$B/M_{i,t}$	0.068^{***}	0.063^{***}	0.039^{***}
	(14.38)	(12.52)	(8.84)
$Leverage_{i,t}$	0.023^{***}	-0.013^{*}	0.005
	(4.33)	(-1.87)	(0.90)
$Size_{i,t}$	-0.041^{***}	-0.609^{***}	-0.159^{***}
	(-6.51)	(-42.25)	(-10.34)
$\#\, Analysts_{i,t}$	-0.089^{***}	-0.001	-0.048^{***}
	(-11.78)	(-0.13)	(-7.75)
$Disp_{i,t}$	0.030^{***}	0.004	0.021^{***}
	(8.95)	(1.10)	(6.66)
VIX_t	0.165^{***}	0.122^{***}	0.104^{***}
	(56.98)	(45.89)	(35.94)
Firm FEs	No	Yes	Yes
Year and Month FEs	No	No	Yes
SE Clustering	Firm	Firm	Firm
Adj. R^2	0.08	0.24	0.28
N Firm-Quarters	194,309	194,309	194,309

Panel B: Idiosyncratic Uncertainty and Size-Weighted EAs			
$\Delta\, IVol_{i;t-3,t+3} = \alpha + \beta Size\ EAs_t + \sum \gamma_j Controls_{j,i,t} + \nu_i + \eta_h + \varepsilon_{i,t}$			
	(1)	(2)	(3)
$Size\ EAs_t$	0.012^{***}	-0.003	0.012^{***}
	(2.95)	(-1.06)	(4.19)
$UE_{i,t}$	-0.030^{***}	-0.025^{***}	-0.020^{***}
	(-11.94)	(-10.12)	(-8.38)
$Ret_{i,t}$	-0.165^{***}	-0.163^{***}	-0.159^{***}
	(-60.71)	(-61.57)	(-61.26)
$B/M_{i,t}$	0.069^{***}	0.062^{***}	0.039^{***}
	(14.48)	(12.46)	(8.90)
$Leverage_{i,t}$	0.024^{***}	-0.013^{*}	0.006
	(4.48)	(-1.81)	(0.96)
$Size_{i,t}$	-0.043^{***}	-0.607^{***}	-0.159^{***}
	(-6.77)	(-42.16)	(-10.36)
$\#\ Analysts_{i,t}$	-0.090^{***}	-0.001	-0.048^{***}
	(-11.84)	(-0.16)	(-7.75)
$Disp_{i,t}$	0.031^{***}	0.003	0.021^{***}
	(9.08)	(1.04)	(6.68)
VIX_t	0.164^{***}	0.122^{***}	0.105^{***}
	(57.01)	(45.75)	(35.95)
Firm FEs	No	Yes	Yes
Year and Month FEs	No	No	Yes
SE Clustering	Firm	Firm	Firm
Adj. R^2	0.08	0.24	0.28
N Firm-Quarters	194,309	194,309	194,309

Estimation: Ordinary least square regressions with the absorption of firm, year, and month fixed effects. Standard errors are adjusted for clustering at the firm level. Statistical significance is denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$, t statistics are in parentheses. All continuous variables are standardized. Intercept suppressed. **Dependent Variable:** $\Delta IVol_{i,t-3,t+3}$, the difference between the post- and pre-EA three-day average implied volatility for firm i, or $\Delta IVol_{i,t-3,t+3}$, the difference between the post- and pre-EA three-day average implied volatility for firm i. **Variable of Interest:** *EAs*, the number of firms announcing earnings on day t (Panel A), or $Size\ EAs_t$, the size-weighted number of firms announcing earnings on day t, calculated as the sum of the assets of announcing firms over the size of all announcing firms from the previous quarter **Control Variables:** $UE_{i,t}$, a proxy for firm i's earnings surprise; $B\text{-}to\text{-}M_{i,t}$ is the book to market ratio; $Leverage_{i,t}$ is firm i's leverage ratio; $Size_{i,t}$ is firm i's total assets at the beginning of the quarter; $\#\ Analysts_{i,t}$ is the number of analysts following firm i; $Disp_{i,t}$ is analyst dispersion, and VIX_t is the level of VIX. Detailed variable definitions and data sources are provided in Appendix A.

Table 3: **Aggregate Uncertainty and Concurrent EAs**

Panel A: Aggregate Uncertainty and Number of EAs				
$VIX_t = \alpha + \beta EAs_t + \sum \gamma_j Controls_{j,t} + \sum \theta_k VIX_{t-k} + \varepsilon_t$				
Dependent Variable:	VIX_t		ΔVIX_t	
	(1)	(2)	(3)	(4)
EAs_t	-0.021^{***}	-0.020^{***}	-0.041^{***}	-0.037^{***}
	(-6.30)	(-6.37)	(-3.06)	(-3.75)
$Agg\ ROA_t$		-0.005^{***}		-0.029^{***}
		(-3.01)		(-2.68)
$Monetary\ Release_t$		-0.015		-0.263^{***}
		(-1.49)		(-4.61)
$Labor\ Release_t$		0.023^{***}		0.028
		(2.92)		(0.62)
$GDP\ Release_t$		-0.007		0.113
		(-0.46)		(1.54)
$Inflation\ Release_t$		0.023^{***}		-0.008
		(2.68)		(-0.17)
$Market\ Ret_t$		-0.052^{***}		-0.586^{***}
		(-20.38)		(-35.25)
AR Terms Included:	3	3	4	4
Prob $> \chi^2$	0.00	0.00	0.00	0.00
N Days	5,627	5,627	5,627	5,627

Panel B: Aggregate Uncertainty and Size-Weighted EAs				
$VIX_t = \alpha + \beta Size\ EAs_t + \sum \gamma_j Controls_{j,t} + \sum \theta_k VIX_{t-k} + \varepsilon_t$				
Dependent Variable:	VIX_t		ΔVIX_t	
	(1)	(2)	(3)	(4)
Size EAs$_t$	-0.003^{***}	-0.003^{***}	-0.002^{*}	-0.002^{**}
	(-3.14)	(-3.38)	(-1.71)	(-2.05)
Agg ROA$_t$		-0.002^{***}		-0.002^{***}
		(-3.29)		(-2.71)
Monetary Release$_t$		-0.006		-0.020^{***}
		(-1.55)		(-4.74)
Labor Release$_t$		0.009^{***}		0.002
		(3.25)		(0.67)
GDP Release$_t$		0.002		0.008
		(0.43)		(1.47)
Inflation Release$_t$		0.009^{***}		0.000
		(2.93)		(0.05)
Market Ret$_t$		-0.019^{***}		-0.044^{***}
		(-20.42)		(-35.30)
AR Terms Included:	3	3	4	4
Prob $> \chi^2$	0.00	0.00	0.09	0.00
N Days	5,627	5,627	5,627	5,627

Estimation: ARMAX estimation with lags of the dependent variable selected using the Akaike Information Criteria, with standard errors adjusted for heteroscedasticity and autocorrelation. All continuous variables are standardized. Statistical significance is denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$, t statistics are in parentheses. Intercept suppressed. **Dependent Variable:** VIX_t, the level of VIX measured as the opening value the morning after day t (columns 1 and 2); or ΔVIX_t, the difference between the opening value of VIX on $t+1$ and the closing VIX value on $t-1$ (columns 3 and 4). **Variable of Interest:** *EAs*, the number of firms announcing earnings on day t (Panel A), or *Size EAs$_t$*, the size-weighted number of firms announcing earnings on day t, calculated as the sum of the assets of announcing firms over the size of all announcing firms from the previous quarter **Control Variables:** *Agg ROA$_t$*, the aggregate ROA of announcing firms; and *Monetary Release$_t$*, *Labor Release$_t$*, *GDP Release$_t$*, and *Inflation Release$_t$*, indicators for macroeconomic announcements of the type indicated occurring on day t. Detailed variable definitions and data sources are provided in Appendix A.

Table 4: **Trading Volume and Concurrent EAs**

$$Trad\ Volume_{i,t} = \alpha + \beta_1 EAs_t \times Z_{i,t} + \beta_2 EAs_{i,t} + \beta_3 Z_{i,t} + \sum \gamma_j Controls_{i,t} + \varepsilon_t$$

Dependent Variable:	*Trad Volume$_{i,t}$*		Δ*Trad Volume$_{i,t}$*	
	(1)	(2)	(3)	(4)
$EAs_{i,t} \times High\ Beta_{i,t}$	0.009***		0.002***	
	(11.58)		(8.95)	
$EAs_{i,t} \times Bellwether_{i,t}$		0.004***		0.001***
		(4.58)		(4.49)
$EAs_{i,t}$	0.004***	0.008***	0.001***	0.002***
	(7.28)	(15.20)	(4.51)	(8.59)
$High\ Beta_{i,t}$	0.074***		0.000*	
	(23.71)		(1.93)	
$Bellwether_{i,t}$		0.006*		−0.000
		(1.67)		(−0.22)
$EAs_{i,t} \times Own\ EA_{i,t}$	−0.054***	−0.053***	−0.029***	−0.029***
	(−16.35)	(−16.18)	(−10.21)	(−10.19)
$Own\ EA_{i,t}$	0.314***	0.314***	0.271***	0.271***
	(36.57)	(36.55)	(35.46)	(35.46)
Controls:	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Year and Month FEs	Yes	Yes	Yes	Yes
SE Clustering	Firm	Firm	Firm	Firm
Adj. R^2	0.08	0.08	0.00	0.00
N Firm-Days	19,215,777	19,215,777	19,211,398	19,211,398

Estimation: Ordinary least square regressions with the absorption of firm, year, and month fixed effects. Standard errors are adjusted for clustering at the firm level. All continuous variables are standardized. Statistical significance is denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$, t statistics are in parentheses. Intercept suppressed. **Dependent Variable:** $Trad.Volume_{i,t}$, the number of firm i shares traded on day t (columns 1 and 2); or $\Delta Trad.Volume_{i,t}$, the percentage change in the number of firm i shares traded between day t and day $t-1$ (columns 1 and 2). **Variable of Interest:** EAs_t, the number of firms announcing earnings on day t; $Z_{i,t}$ is $High\ Beta_{i,t}$, an indicator variable set to 1 if the firm's stock beta is above the sample median, 0 otherwise (columns 1 and 3); or $Bellwether_{i,t}$, an indicator variable set to 1 if the correlation between the firm's sales and GDP is above the sample median, 0 otherwise (columns 2 and 4). **Control Variables:** $UE_{i,t}$, a proxy for firm i's earnings surprise; $B\text{-}to\text{-}M_{i,t}$ is the book to market ratio; $Leverage_{i,t}$ is firm i's leverage ratio; $Size_{i,t}$ is firm i's total assets at the beginning of the quarter; $\#\ Analysts_{i,t}$ is the number of analysts following firm i; $Disp_{i,t}$ is analyst dispersion, and VIX_t is the level of VIX. Detailed variable definitions and data sources are provided in Appendix A.

Table 5: **VIX Trading Volume and Concurrent EAs**

$$VIX\ Trad\ Volume_t = \alpha + \beta EAs_t + \sum \gamma_j Controls_{j,t} + \sum \theta_k VIX\ Trad\ Volume_{t-k} + \varepsilon_t$$

Dependent Variable:	*VIX Trad Volume$_t$*		*ΔVIX Trad Volume$_t$*	
	(1)	(2)	(3)	(4)
EAs_t	−0.001		0.020***	
	(−0.08)		(3.09)	
Size EAs_t		0.030**		0.018**
		(2.35)		(2.06)
Agg ROA_t	0.017*	0.019*	0.001	0.000
	(1.67)	(1.87)	(0.06)	(0.00)
Monetary $Release_t$	0.133**	0.124**	0.105*	0.116**
	(2.44)	(2.29)	(1.85)	(2.05)
GDP $Release_t$	−0.069	−0.079	−0.007	−0.011
	(−0.99)	(−1.15)	(−0.08)	(−0.11)
Inflation $Release_t$	0.105***	0.101***	−0.067*	−0.082**
	(2.77)	(2.73)	(−1.67)	(−2.08)
Market Ret_t	−0.006	−0.005	−0.018*	−0.019**
	(−0.69)	(−0.64)	(−1.90)	(−1.96)
VIX_{t-1}	0.173***	0.171***	0.002	0.002
	(4.20)	(4.17)	(0.27)	(0.23)
AR Terms Included:	4	4	3	3
Prob $> \chi^2$	0.00	0.00	0.00	0.01
N Days	2,377	2,377	2,376	2,376

Estimation: ARMAX estimation with lags of the dependent variable selected using the Akaike Information Criteria, with standard errors adjusted for heteroscedasticity and autocorrelation. All continuous variables are standardized. Statistical significance is denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$, t statistics are in parentheses. Intercept suppressed. **Dependent Variable:** *VIX Trad.Volume$_t$*, the natural logarithm of 1 + the number of call/put options on VIX traded during day t (columns 1 and 2); or *ΔVIX Trad.Volume$_t$*, the percentage change in the number of call/put options on VIX traded during day t (columns 3 and 4). **Variable of Interest:** *EAs_t*, the number of firms announcing earnings on day t (columns 1 and 3); *Size EAs_t*, he size-weighted number of firms announcing earnings on day t, calculated as the sum of the assets of announcing firms over the size of all announcing firms from the previous quarter (columns 2 and 4). **Control Variables:** *Agg ROA_t*, the aggregate ROA of announcing firms; and *Monetary $Release_t$*, *Labor $Release_t$*, *GDP $Release_t$*, and *Inflation $Release_t$* indicators for macroeconomic announcements of the type indicated occurring on day t; and *VIX_{t-1}*, the lagged level of the VIX index. Detailed variable definitions and data sources are provided in Appendix A.

Table 6: **Macro Information Acquisition and Concurrent EAs**

Panel A: Google Searches for Macro vs Non-Macro Terms and Number of EAs				
$Search\ Var_t = \alpha + \beta EAs_t + \sum \gamma_j Controls_{j,t} + \varepsilon_t$				
Dependent Variable:	*All Macro Search$_t$*		*Non-Macro Search$_t$*	
	(1)	(2)	(3)	(4)
EAs$_t$	0.103***		−0.018***	
	(10.25)		(−4.05)	
Size EAs$_t$		0.038***		0.000
		(3.68)		(0.10)
Agg ROA$_t$	0.013*	0.015**	−0.002	−0.001
	(1.93)	(2.20)	(−0.37)	(−0.32)
Monetary Release$_t$	0.376***	0.377***	−0.006	−0.007
	(10.78)	(10.74)	(−0.33)	(−0.40)
Labor Release$_t$	0.042	0.035	−0.042***	−0.040***
	(1.33)	(1.07)	(−3.24)	(−3.10)
GDP Release$_t$	0.013	−0.067	0.037	0.050**
	(0.25)	(−1.16)	(1.44)	(1.97)
Inflation Release$_t$	−0.072**	−0.083**	−0.035**	−0.034**
	(−2.08)	(−2.37)	(−2.52)	(−2.42)
Market Ret$_t$	−0.005	−0.006	0.001	0.001
	(−0.77)	(−0.86)	(0.29)	(0.36)
AR(1)	0.823***	0.821***	0.965***	0.965***
	(98.33)	(96.89)	(181.06)	(181.04)
Prob $> \chi^2$	0.00	0.00	0.00	0.00
N Days	3,704	3,704	3,704	3,704

Panel B: Google Searches - Macro Search Categories and Number of EAs					
	$Search\ Var_t = \alpha + \beta EAs_t + \sum \gamma_j Controls_{j,t} + \varepsilon_t$				
Dependent Variable:	*Demand Search$_t$*	*Supply Search$_t$*	*Outcome Search$_t$*	*Policy Search$_t$*	*Stock Search$_t$*
EAs_t	0.047***	0.047***	0.078***	0.147***	0.027
	(3.12)	(3.00)	(6.20)	(10.35)	(1.61)
Agg ROA_t	0.004	−0.016	−0.001	0.026***	0.009
	(0.54)	(−1.58)	(−0.13)	(3.32)	(0.66)
Monetary $Release_t$	−0.047	−0.028	0.004	1.334***	0.134*
	(−0.99)	(−0.50)	(0.10)	(17.33)	(1.76)
Labor $Release_t$	−0.003	0.050	−0.009	−0.000	0.027
	(−0.06)	(0.94)	(−0.24)	(−0.01)	(0.41)
GDP $Release_t$	0.040	0.104	0.231***	−0.037	−0.090
	(0.45)	(1.06)	(3.28)	(−0.48)	(−0.95)
Inflation $Release_t$	−0.025	−0.003	−0.018	−0.006	0.042
	(−0.53)	(−0.07)	(−0.49)	(−0.13)	(0.65)
Market Ret_t	0.018**	−0.004	−0.010	−0.016*	−0.007
	(2.17)	(−0.43)	(−1.08)	(−1.68)	(−0.45)
AR(1)	0.742***	0.661***	0.797***	0.674***	0.500***
	(48.58)	(36.66)	(87.89)	(41.32)	(27.18)
Prob > χ^2	0.02	0.06	0.00	0.00	0.35
N Days	3,704	3,704	3,704	3,704	3,704

Estimation: ARMAX estimation with lags of the dependent variable selected using the Akaike Information Criteria. Standard errors are adjusted for heteroscedasticity and autocorrelation. All continuous variables are standardized. Statistical significance is denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$, t statistics are in parentheses. Intercept suppressed. **Dependent Variable:** *All Macro Search$_t$*, the daily average of Google searches for all macro terms we selected (see Appendix B for details on our term selection) (Panel A, Columns 1 and 2); or *Non-Macro Search$_t$*, the daily average of our non-macro control terms (Panel A Columns 3 and 4); or *Demand Search$_t$*, *Supply Search$_t$*, *Outcome Search$_t$*, *Policy Search$_t$*, or *Stock Search$_t$* (Panel B), categories of macro search terms (see Appendix B for details on our term selection). **Variable of Interest:** *EAs_t*, the number of firms announcing earnings on day t. **Control Variables:** *Agg ROA_t*, the aggregate ROA of announcing firms; and *Monetary $Release_t$*, *Labor $Release_t$*, *GDP $Release_t$*, and *Inflation $Release_t$*, indicators for macroeconomic announcements of the type indicated occurring on day t. Detailed variable definitions and data sources are provided in Appendix A, and details on Google search extraction are provided in Appendix B.

Table 7: **GDP Forecasts and Concurrent EAs**

Panel A: GDP Forecasting Behavior (Concurrent)			
$Y_t = \alpha + \beta EAs_t + \sum \gamma_j Controls_{j,t} + \sum \theta_k Dep\ Var_{t-k} + \varepsilon_t$			
Dependent Variable:	$New\ Forecast_t$	$\lvert \Delta Forecast \rvert_t$	$Forecast\ Disp_t$
	(1)	(2)	(3)
EAs_t	0.033*	0.004	−0.013**
	(1.65)	(1.15)	(−2.20)
$Agg\ ROA_t$	0.009	0.000	0.005**
	(0.53)	(0.02)	(2.11)
$Monetary\ Release_t$	0.072	0.006	0.013
	(1.51)	(0.95)	(1.64)
$Labor\ Release_t$	0.099**	0.009*	0.004
	(2.22)	(1.75)	(0.79)
$GDP\ Release_t$	0.072	0.017	−0.012
	(0.91)	(1.08)	(−0.72)
$Inflation\ Release_t$	0.087*	−0.005	−0.006**
	(1.82)	(−1.37)	(−2.41)
$Market\ Ret_t$	−0.011	−0.002	0.000
	(−0.66)	(−0.61)	(0.00)
$Days\ to\ End\ of\ Quarter_t$	0.001**	0.000***	−0.000
	(1.98)	(3.42)	(−1.63)
AR Terms Included:	4	1	1
Prob > χ^2	0.00	0.00	0.01
N Weeks	840	840	840

Panel B: GDP Forecasting Behavior (Leading)

$$Y_{t+1} = \alpha + \beta EAs_t + \sum \gamma_j Controls_{j,t} + \sum \theta_k Dep\ Var_{t-k} + \varepsilon_t$$

Dependent Variable:	$New\ Forecast_{t+1}$	$\lvert\Delta Forecast\rvert_{t+1}$	$Forecast\ Disp_{t+1}$
	(1)	(2)	(3)
EAs_t	0.073***	0.011***	−0.006
	(3.82)	(3.28)	(−1.06)
$Agg\ ROA_t$	0.003	−0.002	−0.002
	(0.17)	(−0.82)	(−0.88)
$Monetary\ Release_t$	0.002	0.002	−0.009*
	(0.04)	(0.31)	(−1.70)
$Labor\ Release_t$	0.082	0.000	−0.000
	(1.57)	(0.05)	(−0.06)
$GDP\ Release_t$	−0.023	0.017	−0.005
	(−0.31)	(1.20)	(−0.32)
$Inflation\ Release_t$	−0.110***	−0.023***	0.006*
	(−2.64)	(−6.07)	(1.69)
$Market\ Ret_t$	0.024	0.000	−0.006
	(1.38)	(0.14)	(−1.39)
$Days\ to\ End\ of\ Quarter_t$	−0.003***	−0.001***	0.000
	(−5.11)	(−5.44)	(0.91)
AR Terms Included:	4	1	1
Prob > χ^2	0.00	0.00	0.61
N Weeks	839	839	839

Estimation: ARMAX estimation with lags of the dependent variable selected using the Akaike Information Criteria. Standard errors are adjusted for heteroscedasticity and autocorrelation. All continuous variables are standardized. Statistical significance is denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$, t statistics are in parentheses. Intercept suppressed. **Dependent Variable:** Y_t is either $New\ Forecast_t$, an indicator variable equal to one if the consensus GDP forecast changes during week t; or $\lvert\Delta Forecast\rvert_t$, the absolute value of the change in the change in the Bloomberg consensus forecast between week $t-1$ and week t.; or $Forecast\ Disp_t$, The dispersion of GDP forecasts issued up to week t. **Variable of Interest:** EAs_t, the number of firms announcing earnings on day t. **Control Variables:** $Agg\ ROA_t$, the aggregate ROA of announcing firms; and $Monetary\ Release_t$, $Labor\ Release_t$, $GDP\ Release_t$, and $Inflation\ Release_t$, indicators for macroeconomic announcements of the type indicated occurring on day t. Detailed variable definitions and data sources are provided in Appendix A.

Table 8: **Uncertainty, Concurrent EAs, and Incentives to Reallocate Attention**

$Y_t = \alpha + \beta_1 Z \times EAs_t + \beta_2 Z + \beta_3 EAs_t + \sum \gamma_j Controls_j + \varepsilon_t$				
Dependent Variable	$\Delta IVol_{i;t-3,t+3}$		ΔVIX_t	
	(1)	(2)	(1)	(2)
$EAs_t \times Bell\ Ratio_t$	0.013^{***}		0.001	
	(5.514)		(0.336)	
$Bell\ Ratio_t$	-0.021^{***}		0.001	
	(-7.722)		(0.724)	
$EAs_t \times Stale\ Macro\ Info_t$		0.077^{***}		-0.002
		(16.352)		(-0.974)
$Stale\ Macro\ Info_t$		0.005		-0.002
		(1.002)		(-1.143)
EAs_t	0.015^{***}	-0.034^{***}	-0.003^{***}	-0.002
	(4.746)	(-7.789)	(-3.692)	(-1.425)
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	No	No
SE Clustering	Firm	Firm	No	No
Adj. R^2	0.24	0.24		
Prob $> \chi^2$	0.00	0.00	0.00	0.00
N Firm-Quarters (Quarters)	194,309	194,309	5,627	5,627

Estimation: Ordinary least square regressions with the absorption of firm, year, and month fixed effects and standard errors adjusted for clustering at the firm level (columns 1 and 2); ARMAX estimation with lags of the dependent variable selected using the Akaike Information Criteria, and standard errors adjusted for heteroscedasticity and autocorrelation (columns 3 and 4). All continuous variables are standardized. Statistical significance is denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$, t statistics are in parentheses. Intercepts suppressed in both models. **Dependent Variable:** $\Delta IVol_{i,t-3,t+3}$, the difference between the post- and pre-EA three-day average implied volatility for firm i (columns 1 and 2); ΔVIX_t, the difference between the opening value of VIX on $t+1$ and the closing VIX value on $t-1$ (columns 3 and 4). **Variable of Interest:** EAs_t, the number of firms announcing earnings on day t. $Z_{i,t}$ is $Bell\ Ratio_t$, the percentage of firms announcing on day t designated as bellwethers (columns 1 and 3); or $Stale\ Macro\ Info_t$, an indicator variable set to 1 if the time since the last macro announcement is above the median time, 0 otherwise (columns 2 and 4). **Control Variables:** defined as in previous relevant models. Detailed variable definitions and data sources are provided in Appendix A.

Table 9: **Uncertainty Resolution with Placebo EAs**

Panel A: Placebo EAs Regression Analysis - Firm Level			
$\Delta\ IVol_{i;t-3,t+3} = \alpha + \beta Placebo\ EAs_t + \sum \gamma_j Controls_{j,i,t} + \nu_i + \eta_h + \varepsilon_{i,t}$			
	(1)	(2)	(3)
Placebo EAs$_t$	-0.003	-0.004^{**}	-0.007^{***}
	(-1.23)	(-2.20)	(-3.54)
$UE_{i,t}$	-0.030^{***}	-0.025^{***}	-0.020^{***}
	(-11.87)	(-10.13)	(-8.35)
Firm Controls:	Yes	Yes	Yes
Firm FEs	No	Yes	Yes
Year and Month FEs	No	No	Yes
SE Clustering	Firm	Firm	Firm
Adj. R^2	0.08	0.24	0.28
N Firm-Quarters	194,309	194,309	194,309

Estimation: Ordinary least square regressions with the absorption of firm, year, and month fixed effects, and standard errors adjusted for clustering at the firm level. All continuous variables are standardized. Statistical significance is denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$, t statistics are in parentheses. Intercept suppressed. **Dependent Variable:** $\Delta IVol_{i,t-3,t+3}$, the difference between the post- and pre-EA three-day average implied volatility for firm i. **Variable of Interest:** *Placebo EAs$_t$*, the number of firms announcing earnings on day t, randomized over days in the sample. **Control Variables:** $UE_{i,t}$, a proxy for firm i's earnings surprise; *B-to-M$_{i,t}$* is the book to market ratio; *Leverage$_{i,t}$* is firm i's leverage ratio; *Size$_{i,t}$* is firm i's total assets at the beginning of the quarter; *# Analysts$_{i,t}$* is the number of analysts following firm i; *Disp$_{i,t}$* is analyst dispersion, and *VIX$_t$* is the level of VIX. Detailed variable definitions and data sources are provided in Appendix A.

Panel B: Placebo EAs Regression Analysis - Aggregate Level				
$VIX_t = \alpha + \beta Placebo\ EAs_t + \sum \gamma_j Controls_{j,t} + \sum \theta_k VIX_{t-k} + \varepsilon_t$				
Dependent Variable:	VIX_t		ΔVIX_t	
	(1)	(2)	(3)	(4)
Placebo EAs$_t$	−0.001	−0.000	−0.000	0.000
	(−1.08)	(−0.38)	(−0.18)	(0.63)
Inflation Release$_t$		0.009***		0.000
		(2.98)		(0.13)
Market Ret$_t$		−0.019***		−0.044***
		(−20.56)		(−35.26)
AR(1)	0.801***	0.789***	0.133***	0.106***
	(35.00)	(34.46)	(5.26)	(4.16)
AR(2)	0.186***	0.200***	−0.039**	−0.020
	(8.22)	(8.76)	(−2.03)	(−1.05)
Controls:	Yes	Yes	Yes	Yes
Prob $> \chi^2$	0.28	0.00	0.85	0.00
N Days	5,627	5,627	5,627	5,627

Estimation: ARMAX estimation with lags of the dependent variable selected using the Akaike Information Criteria, with standard errors adjusted for heteroscedasticity and autocorrelation. All continuous variables are standardized. Statistical significance is denoted as follows: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$, t statistics are in parentheses. Intercept suppressed. **Dependent Variable:** *VIX$_t$*, the level of VIX measured as the opening value the morning after day t (columns 1 and 2); or ΔVIX_t, the difference between the opening value of VIX on $t+1$ and the closing VIX value on $t-1$ (columns 3 and 4). **Variable of Interest:** *Placebo EAs$_t$*, the number of firms announcing earnings on day t, randomized over the sample. **Control Variables:** *Agg ROA$_t$*, the aggregate ROA of announcing firms; and *Monetary Release$_t$*, *Labor Release$_t$*, *GDP Release$_t$*, and *Inflation Release$_t$*, indicators for macroeconomic announcements of the type indicated occurring on day t. Detailed variable definitions and data sources are provided in Appendix A.

Appendices

A Variable Definitions and Sources

1.1 Firm-Level Uncertainty Sample

- $\Delta IVol_{i;t-3,t+3}$ - The change in firm-specific uncertainty around firm i's day t's earnings announcement.

  This variable is the natural logarithm of the ratio of the three day averages after and before the earnings announcement, i.e., $\log(IVol_{i,t+3}/IVol_{i,t-3})$.

  (Source: Options Metrics Standardized Options database via WRDS)

- EAs_t - The number of firms announcing earnings on day t.

  This variable is measured as the number of firms whose announcement date as found in the Compustat Quarterly database agrees with the date from I/B/E/S on day t.

  (Source: Compustat and I/B/E/S via WRDS)

- *Size* EAs_t - The size-weighted number of firms announcing earnings on day t.

  Defined as the sum of total assets (Compustat variable *atq*) for all firms that announce earnings during time t, divided by the sum of total assets for all firms in the sample during the previous quarter.

  (Source: Compustat via WRDS)

- $UE_{i,t}$ - Firm i's unexpected earnings announced on day t.

  Calculated as firm i's actual EPS minus its mean consensus EPS forecast prior to the earnings announcement date, scaled by its stock price at the end of the quarter.

  (Source: I/B/E/S via WRDS)

- $Ret_{i,t}$ - Firm i's buy-and-hold return around day t.

  Calculated as the cumulated return over the window -3,3 centered on the EA date, t.

  (Source: CRSP)

- $B/M_{i,t}$ - The book-to-market ratio for firm i in the quarter for which earnings are reported on day t.

  This variable is the Book value of common equity (Compustat variable *ceq*) scaled by the market value of common equity (Compustat variables *prccq*$\times$*cshoq*), at the beginning of quarter t.

  (Source: Compustat via WRDS)

- *Leverage*$_{i,t}$ - Firm i's leverage for the quarter for which earnings are announced on day t.

  Calculated as the ratio of long-term debt to total assets (Compustat variables *dlttq* / *atq*), prior to forecast issuance. (Source: Compustat via WRDS)

- *Size*$_{i,t}$ - Firm i's size at the beginning of the quarter for which earnings are announced on day t.

  Calculated as the natural logarithm of firm i's assets at the beginning of the quarter (Compustat variable *atq*).

  (Source: Compustat via WRDS)

- *# Analysts*$_{i,t}$ - The number of analysts following firm i in the quarter for which earnings are announced on day t.

  The sum of analyst forecasts for firm i in quarter for which earnings are reported on day t.

  (Source: I/B/E/S via WRDS)

- *Disp*$_{i,t}$ - The dispersion in analysts forecasts for firm i's earnings announced on day t.

  Calculated as the standard deviation in analysts forecasts before the earnings announcement, divided by stock price.

  (Source: I/B/E/S via WRDS)

- *VIX*$_t$ - The level of the VIX volatility index on day t.

  The opening value of the VIX index on day $t+1$.

  (Source: The Chicago Board Options Exchange)

- *Bellwether*$_{i,t}$ - An indicator for firm i being a bellwether in quarter t.

  Bellwethers firms are determined by being above the sample median of the absolute correlation of firm i's previous five quarters' earnings stream with GDP detrended using the Baxter and King (1999) bandpass filter.

  (Source: Compustat via WRDS for accounting data and the St. Louis Federal Reserve for GDP data)

- *Bell Ratio*$_t$ - The ratio of bellwether to total announcing firms on day t.

  Calculated as the number of firms designated as bellwethers divided by the total number of firms announcing earnings on day t.

  (Source: Compustat via WRDS for accounting data and the St. Louis Federal Reserve for GDP data)

- *Stale Macro Info*$_t$ - An indicator for stale macro data.

  An indicator for the difference between day t and the most recent macro announcement (see *Monetary Release*, *Labor Release*, and *GDP Release* below for definitions) being above the sample median.

(Source: See below for data sources)

- *High Beta*$_{i,t}$ - An indicator for firm i having an above-median beta time t.

  Beta is estimated using the CAPM with daily returns over the 90 trading days preceding the earnings announcement.

  (Source: CRSP for daily security data; Compustat and IBES for quarterly earnings announcement dates)

- *Own EA*$_{i,t}$ - An indicator for firm i's earnings announcement taking place on date t.

  Earnings announcement dates are taken as the agreement between Compustat and IBES.

  (Source: Compustat and IBES for earnings announcement dates)

1.2 Aggregate Uncertainty Sample

- *VIX*$_t$ - The level of the VIX volatility index on day t.

  The opening value of the VIX index on day $t+1$.

  (Source: The Chicago Board Options Exchange)

- ΔVIX_t - The change in VIX around day t.

  Calculated as the opening value of VIX on day $t+1$ less the closing value of VIX on day $t-1$.

  (Source: The Chicago Board Options Exchange)

- *EAs*$_t$ - The number of firms announcing earnings on day t.

  This variable is measured as the number of firms whose announcement date as found in the Compustat Quarterly database agrees with the date from I/B/E/S.

- *Size EAs*$_t$ - The size-weighted number of firms announcing earnings on day t.

  Defined as the sum of total assets (Compustat variable *atq*) for all firms that announce earnings during time t, divided by the sum of total assets for all firms in the sample during the previous quarter.

  (Source: Compustat via WRDS)

- *Agg ROA*$_t$ - Aggregate ROA for all firms announcing earnings in time t.

  Defined as the sum of earnings before extraordinary items (*ibq*) over the sum of lagged total assets (*atq*) for firms that announce earnings during time t.

  (Source: Compustat via WRDS)

- *Monetary Release$_t$* - Indicator for a monetary policy announcement made during time t.

  An indicator for period t having a monetary announcement, taken from the Federal Reserve's calendar.

  (Source: Board of Governors of the Federal Reserve System website)

- *Labor Release$_t$* - Indicator for a labor announcement made during time t.

  An indicator for period t having a BLS labor announcement, taken from the BLS release calendar. The BLS makes "Employment Situation" announcements on the first Friday of every month.

  (Source: Bureau of Labor Statistics labor release schedule from the BLS website, filtered for "employment situation")

- *GDP Release$_t$* - Indicator for a GDP announcement made during time t.

  An indicator for period t having a BEA GDP announcement. We use the announcement of the "advance" estimate, which is the first official estimate of GDP made by the BEA. Dates are taken from the BEA's release calendar.

  (Source: Bureau of Economic Analysis news schedule from the BEA website, filtered for GDP)

- *Inflation Release$_t$* - Indicator for an inflation announcement made during time t.

  An indicator for period t having a BLS inflation announcement, taken from the BLS release calendar. The BLS makes "Producer Price Index" announcements near the middle of each month.

  (Source: Bureau of Labor Statistics labor release schedule from the BLS website, filtered for "Producer Price Index")

- *All Macro Search$_t$* - Total Google searches for macro terms on day t.

  Calculated as the sum of searches for all macro search terms (see Appendix B for details on macro search terms) on day t.

  (Source: Google Trends https://trends.google.com/trends/?geo=US)

- *VIX Trad Volume$_t$* - Total volume of VIX call and put options traded on day t.

  (Source: Options Metrics vis WRDS)

- *New Forecast$_t$* - An indicator for a change in the Bloomberg consensus forecast during week t.

  Set to equal one if the Bloomberg consensus forecast changes during week t.

  (Source: Bloomberg ECFT)

- $|\Delta Forecast|_t$ - The absolute value of the change in the Bloomberg consensus forecast.

  Calculated as the absolute value of the change in the Bloomberg consensus forecast between $t-1$ and time t. Bloomberg calculates the forecast consensus as the median of contributing forecasts.

  (Source: Bloomberg ECFT)

- $Forecast\ Dispersion_t$ - The dispersion of GDP forecasts issued up to time t.

  Calculated as the standard deviation of extant forecasts from all Bloomberg forecast participants.

  (Source: Bloomberg ECFT)

- $Days\ to\ End\ of\ Quarter_t$ - The number of days until the end of the quarter from time t.

  Calculated as the difference between the end of the calendar quarter and the day ending time t.

  (Source: Bloomberg ECFT)

- $Market\ Ret_t$ - The market return for day t.

  Calculated including dividends.

  (Source: CRSP)

B Google Search Term Extraction

Using *gtrends* in R, we programatically extract Google SVI indices for each of the following search terms for the available time series length (2004 to 2019). Because Google deflates search volume by the maximum search in a given search time frame, and because Google does not provide daily time series longer than 9 months at a time, we extract the daily data for each search term in one-month increments, then deflate each daily series by its monthly SVI value, yielding time series that are comparable from start to finish.

2.1 Google Search Terms

We collect daily SVI series for the following dictionary.[4]

- aggregate consumption
- aggregate demand
- aggregate investment
- aggregate production
- economic activity
- economic forecast
- economic outlook
- gross domestic product
- gdp
- exchange rate
- deficit
- interest rate
- manufacturing activity
- monetary policy
- unemployment rate
- industrial production
- inflation
- production capacity
- unemployment
- jobs numbers
- recession
- bear market
- stock crash
- financial crisis
- yield curve
- inverted yield
- consumer spending
- fed announcement
- fomc
- macroeconomy
- factors of production
- bull market
- pet food
- oil change
- nfl
- nba
- mlb

4. Note: Google search terms are *not* case sensitive. See https://support.google.com/websearch/answer/134479?hl=en&rd=1.

We then form category indices of search by taking averages of the SVIs for each variable in the category, as follows:

- ***Demand Search***
  - aggregate consumption
  - aggregate demand
  - consumer spending
- ***Supply Search***
  - aggregate investment
  - aggregate production
  - manufacturing activity
  - industrial production
  - production capacity
- ***Outcome Search***
  - economic activity
  - economic forecast
  - economic outlook
  - gdp
  - gross domestic product
  - jobs numbers
  - recession
  - unemployment rate
- ***Policy Search***
  - interest rate
  - monetary policy
  - yield curve
  - inverted yield
  - fed announcement
  - fomc
- ***Equity Search***
  - bear market
  - bull market
  - stock crash
  - financial crisis
- ***Non-Macro Search***
  - pet food
  - oil change
  - nfl
  - nba
  - mlb