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Uncertainty and Sectoral Shifts: The Interaction Between Firm-Level and Aggregate-Level Shocks, and Macroeconomic Activity

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This study predicts and finds that the interaction of firm-level and aggregate-level shocks explains a significant portion of shocks to macroeconomic activity. Specifically, we hypothesize that the relation between uncertainty and economic growth is most pronounced when both firm-level and aggregate-level uncertainty are high simultaneously. Similarly, we hypothesize that aggregate performance affects unemployment most when both firm-level dispersion is high and aggregate performance is low, based on the sectoral shift theory. Our hypotheses and empirical results show that the interactive effect of firm-level and aggregate-level shocks are larger than the sum of the individual effects.

Keywords: earnings dispersion; aggregate earnings; uncertainty; sectoral shifts; macroeconomic activity
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1. Introduction

This paper examines the interaction between firm-level and aggregate-level shocks and how it relates to overall macroeconomic activity. Specifically, we examine this interaction for two types of shocks: uncertainty shocks and performance shocks.[1] Two central theories in economics predict an interaction for these types of shocks. First, a recent stream of literature suggests that uncertainty is an important driver of economic activity (e.g., Bloom 2009, Bloom et al. 2012, Baker and Bloom 2013).[2] Analytical and empirical results suggest that uncertainty about both aggregate growth and/or firm-level growth lowers investment and impedes the reallocation of labor and capital. Consequently, higher uncertainty dampens economic activity. Second, the sectoral-shift theory predicts that unemployment increases with cross-sectional dispersion in firm-level performance, in addition to aggregate-level performance (e.g., Lucas and Prescott 1974, Lilien 1982).

We hypothesize and show empirically that the two theories imply an interaction between firm-level and aggregate-level shocks, and that this interaction is an important driver of aggregate economic activity. In the case of uncertainty, we argue that the effect of uncertainty on macroeconomic activity is most pronounced when both aggregate-level and firm-level uncertainties are high simultaneously because of the interaction effect. Similarly, we argue that the implications of the sectoral shift hypothesis on unemployment are most pronounced when aggregate performance is poor and when the cross-sectional dispersion of firm-level performances is high. In sum, our study suggests that macroeconomic shocks are best understood when examining aggregate-level and firm-level shocks simultaneously.

Consider the relation between uncertainty and economic growth. Portfolio theory suggests that aggregate

[1] We employ residuals from AR(2) models for all the variables employed in the analysis. Therefore, the aggregate-level and firm-level uncertainty and performance measures we use capture time-series shocks, which help explain time-series shocks to macroeconomic activity.

[2] In a recent review, Bloom (2014) describes the varieties of uncertainty that investors and firms face. One form is aggregate uncertainty, regarding macroeconomic conditions. A second is firm-level uncertainty, that is, uncertainty about which firm, industry, or sector is more likely to grow. Our analysis shows that the correlations between cross-sectional dispersion and policy uncertainty—common measures of firm-level and macrolevel uncertainty, respectively—are approximately 20%. This suggests that these two types of uncertainty differ and that there are multiple periods when only one type of uncertainty is high.

uncertainty limits investors' ability to mitigate the effects of firm-level uncertainty, and vice versa. When firms and investors face only one type of uncertainty, diversification and resource reallocation allow them to mitigate the effects of a specific form of uncertainty. For example, if firms/investors are uncertain about which sector of the economy will grow faster but have more clarity regarding overall growth, they can invest in a large portfolio of projects/firms to mitigate the effect of firm-level uncertainty. By investing in this way, they gain the average growth of the economy. However, if firms/investors are also uncertain about the aggregate growth in the economy, diversification simply substitutes firm-level uncertainty with aggregate-level uncertainty. A related argument, based on resource reallocation, can be made during periods with minimal firm-level uncertainty and significant aggregate uncertainty (see Section 2). Therefore, while uncertainty hurts investment, as shown by Bloom et al. (2012), the effect of firm-level uncertainty is exacerbated when economic agents also face aggregate uncertainty, and vice versa.

A similar argument can be made with respect to the sectoral shift hypothesis (Lucas and Prescott 1974, Lilien 1982, Abraham and Katz 1986, Hosios 1994, Lazear and Spletzer 2012). The sectoral shift theory suggests that cross-sectional dispersion in firm-level performance increases unemployment. This occurs because employees migrate from poorly performing firms or sectors to better performing ones, and this migration takes time because of frictions in the labor market (such as search costs). Thus, unemployment increases with layoffs, even when the hiring rate remains constant. All else equal, higher dispersion implies a greater proportion of poorly performing firms, which inevitably lay off employees. Consequently, unemployment increases during periods of high firm-level dispersion in performance. We extend this logic and argue that the relation between unemployment and sectoral shifts also depends on the overall state of the economy. Specifically, periods when both dispersion is high and macroeconomic conditions are poor, are the periods with the highest proportion of poorly performing firms. In other words, the proportion of firms that need to layoff employees results from the simultaneous effect of the mean and the standard deviation (dispersion). Thus, according to the sectoral shift theory, the interaction between firm-level and aggregate-level performance affects unemployment.

The empirical tests of these theories to date, employ similar measures, but assign different interpretations to these measures. Specifically, cross-sectional dispersion in firm-level performance has been used as both a measure of firm-level uncertainty (Bloom 2009) and as a measure of cross-sectional variation in performance (e.g., Loungani et al. 1990). Similarly, Bloom et al. (2012) suggest that aggregate uncertainty is higher during periods of poor aggregate profitability. Our analysis confirms that these measures proxy for both performance and uncertainty. In addition to the similarity in the empirical measures employed, the theories are likely related. The sectoral shift theory assumes a constant hiring rate. However, it is possible or even likely that uncertainty slows the migration process because it lowers hiring rates, which exacerbates the frictions described in the sectoral shift theory and results in even greater unemployment. Thus, we are unable to distinguish between these theories and do not attempt to do so in this paper. Instead, we rely on both theories to motivate our hypothesis and empirical tests related to the role of the interaction between firm-level and aggregate-level shocks in understanding macroeconomic activity.

Our empirical analysis focuses on the interaction of aggregate shocks and firm-level shocks. For aggregate-level shocks, we employ aggregate profitability, economic policy uncertainty, and the Chicago Board Options Exchange (CBOE) Volatility Index (VIX). For firm-level shocks, we employ cross-sectional earnings dispersion and idiosyncratic return volatility. Consistent with prior studies, we find that our measures of aggregate shocks and firm-level shocks are associated with lower levels of investment and industrial production and higher levels of unemployment. To test the existence of an interactive relation between firm-level and aggregate-level shocks, we add interaction terms for our aggregate- and firm-level shocks. Consistent with our predictions, we find that the effects of dispersion are exacerbated in periods of low aggregate growth and/or high aggregate uncertainty, and that the combined effects of firm-level and aggregate-level shocks are larger than the sum of the individual effects. The explanatory power of the model increases significantly when we add the interaction term. We find similar results when we interact the VIX and idiosyncratic volatility measures.

While aggregate-level profitability and dispersion in firm-level performances are not obvious measures of aggregate and firm-level uncertainty, they are likely related, as suggested by prior studies (e.g., Bloom 2009, Bloom et al. 2012, Baker and Bloom 2013). For example, uncertainty is more likely to be high during recessions. To validate the relation between our performance measures (aggregate profitability and dispersion) and uncertainty, we examine the relation between these measures and macroeconomists forecasting errors. If the measures are related to uncertainty, we expect the absolute forecast error to rise in periods of poor profitability and high dispersion, because forecasting is more difficult during periods of increased uncertainty. Our empirical analysis is consistent with this conjecture.[3]

The rest of the paper is organized as follows. Section 2 describes our hypotheses in more detail. Section 3 discusses our research design and variable measurement. Section 4 presents our main empirical results. Section 5 presents our additional analysis related to macroeconomists' absolute forecast errors. Section 6 concludes.

2. The Interaction Between Firm-Level and Aggregate-Level Economic Shocks

In this section, we build on prior theories that relate uncertainty and sectoral shifts to aggregate economic activity. We develop our predictions and explain why aggregate and firm-level shocks likely interact according to these theories, and how this interaction affects macroeconomic activity.

2.1. Uncertainty and Macroeconomic Activity

Recent analytical and empirical analyses suggest uncertainty is a significant determinant of macroeconomic activity (e.g., Bloom 2009, Bloom et al. 2012, Baker and Bloom 2013). These studies show that macroeconomic activity slows during periods of high uncertainty, because investors and firms are more uncertain about the prospects of their investments, which increases the option value of postponing investments. These postponements lead to significant shortfalls in hiring, investment, and output. Consequently, the reallocation of capital and labor is then hindered, resulting in lower growth in investments, production, and employment. Consistent with this theory, empirical analysis shows that shocks to uncertainty result in lower growth and may even cause recessions.

In a recent review of this literature, Bloom (2014) highlights that uncertainty may take different forms. Agents in the economy can be uncertain about overall macroeconomic conditions and future growth, the prospects of different individual firms, or both. Consistently, prior studies employ both aggregate uncertainty measures, such as VIX and policy uncertainty, and firm-level measures of uncertainty, such as the cross-sectional dispersion in earnings and stock returns, when examining the effect of uncertainty on macroeconomic activity. Prior evidence suggests that both types of uncertainty, while different, can lower economic growth because they hinder investments and limit the reallocation of resources (from poorly performing to better performing firms). The two types of uncertainty not only differ but may also occur independently, as shown in Table 2 (see Section 3.5). Economic agents can face uncertainty about economic policy and overall growth, while having a clearer understanding of which sector/industry/firm in the economy is more likely to succeed and capture a larger portion of overall growth. In contrast, investors can be confident about the overall state of the economy but uncertain about which sectors/industries/firms are more likely to succeed. Take, for example, the development of the high-definition video market. Several companies and technologies competed for the same market, with only one potential winner. While there was relative certainty regarding the demand for the product and the overall growth in the market, it was not clear which firm and technology would win.

Prior studies explore both types of uncertainty but fail to consider how they overlap and interact. Bloom et al. (2012) show that both microeconomic and macroeconomic uncertainty ebb and flow through the business cycle, by examining uncertainty at the plant, firm, and industry level (see also Kozeniauskas et al. 2014). They build a dynamic stochastic general equilibrium (DSGE) model to study how the economy reacts to uncertainty shocks. In their model, a single process determines the economy's uncertainty regime, leading to two possible scenarios. Specifically, both microeconomic and macroeconomic uncertainty can be either high or low. In this study, we extend their analysis and empirically examine the effects of high macroeconomic and microeconomic uncertainty relative to scenarios where only one type of uncertainty is high, in addition to scenarios where both types of uncertainty are low (four possible cases). We argue that the effects of uncertainty are most pronounced when economic agents are uncertain about both macroeconomic growth and firm-level prospects because the combined/interactive effects are larger than the sum of the individual affects. We aim to show that the effects of uncertainty are not driven solely by high levels of uncertainty but also by the interaction of firm-level and macroeconomic uncertainty.

Our hypothesis is based on how investors and firms react to different types of uncertainty. Consider an economy with two firms, A and B. In the first scenario, investors have some certainty about overall economic growth but are uncertain about which firm

[3] Our paper also extends the literature that shows accounting information is useful for understanding and predicting macroeconomic activity. Much of the prior evidence suggests that aggregate earnings contain macroeconomic information (e.g., Anilowski et al. 2007, Shivakumar 2007, Hann et al. 2012, Bonsall et al. 2013, Ogneva 2013, Shivakumar and Urcan 2014) and that aggregate earnings predict the U.S. Federal Reserve's monetary policy (Gallo et al. 2016). While prior literature uses aggregate earnings to understand and predict macroeconomic indicators, we employ dispersion in earnings and conditional dispersion to further highlight the usefulness of accounting information in understanding macroeconomic activity. In a contemporaneous paper, Nallareddy and Ogneva (2016) find that earnings dispersion predicts errors in initial macroeconomic estimates released by government statistical agencies.

will succeed. Investors will find it difficult to reallocate resources between the firms, as they cannot identify where capital and labor will be most productive.[4] However, because investors know that the overall economy—that is, firms A and B together—will grow, they can invest in both firms. On average, their investment will succeed as long as the economy grows. While productivity and growth will suffer from overinvestment (underinvestment) in the less (more) productive firm, investment will still occur as long as investors can diversify and invest in both firms. In sum, as long as the overall economy grows, investment will occur, though at a somewhat slower pace than when there is no firm-level uncertainty.

Alternatively, consider a second scenario where investors know that firm A will be more productive than firm B but are uncertain about the growth of the economy. In this scenario, investors do not know how much to invest overall, because of the difficulty forecasting growth. However, they do know that, all else equal, diverting labor and capital from firm B to firm A will increase efficiency and thus productivity and growth. Thus, overall aggregate investment will be lower because of aggregate uncertainty, but some reallocation of resources and investment will still occur, increasing productivity and growth. Similar to the first scenario, diversification and resource allocation allow investors and firms to react to, and mitigate, the effects of a single and specific form of uncertainty.

Finally, consider the scenario where investors are uncertain about both overall economic growth as well as which firm in the economy will be more productive and profitable. In this scenario, not only will overall investment decline because of uncertainty about aggregate performance, but investment will also be affected by the difficultly of reallocating resources. In such a scenario, diversification helps mitigate the effects of firm-level uncertainty but does not mitigate the effects of aggregate-level uncertainty. Hence it simply replaces one form of uncertainty with another and does not help investors/firms protect themselves against the effects of uncertainty. Thus, aggregate uncertainty exacerbates the effects of firm-level uncertainty. Also, cross-sectional resource allocation, which helps mitigate the effects of aggregate uncertainty on investments, is difficult in this scenario because it is not clear which firm, if any, will better employ the resources. Thus, firms and investors have less ability to react to, and mitigate, the effects of aggregate uncertainty during such periods. Thus, firm-level uncertainty exacerbates the effects of aggregate-level uncertainty. Therefore, we predict that the negative effects of uncertainty on macroeconomic activity to be most pronounced during periods when aggregate as well as firm-level uncertainty are high, due to their interactive effect.

[4] Temporary resource misallocation can also be an outcome of ambiguity aversion (Caskey 2009).

2.2. Sectoral Shifts and Unemployment

In addition to business cycles, economists have long recognized that sectoral shifts are one of the main drivers of unemployment. The underlying causes for unemployment under this theory are frictions in the labor market and layoffs.[5] Lucas and Prescott (1974) and Lilien (1982) develop and empirically test the sectoral shift theory.[6] They argue that unemployment depends not only on the state of the economy and the overall hiring rate but also on the amount of layoffs. Since it takes time for employees to find new jobs, layoffs increase unemployment, irrespective of the overall hiring rate. Consider, for example, an economy that is growing at 2%, where all firms have a growth rate of 2%. In such an economy, layoffs are minimal because all firms are using employees efficiently, and no gains are achieved by reallocating employees across firms. In contrast, consider a different economy that is also growing at 2%. However, in this economy, firms grow at different rates. Some firms grow at rates significantly above 2%, while others have negative growth rates. In such an economy, the poor performers lay off employees. Since these employees need time to move to the more productive firms, unemployment rises. Thus, while both economies grow at the same rate, dispersion in performance is associated with higher levels of unemployment.

According to the sectoral shift hypothesis, macroeconomic conditions as well as dispersion affect unemployment through layoffs. We extend the sectoral shift hypothesis and argue that, since layoffs occur when firm performance is low, overall layoffs are highest during periods of low aggregate growth and high dispersion. In other words, there is an interactive effect. This is because the proportion of firms performing poorly, which are likely to layoff employees, is highest when the economy is performing poorly and cross-sectional dispersion is high. Consider, for example, two economies with a 2% dispersion, one has an average growth of 20% and the other 1%. The economy with 20% average growth will have minimal layoffs and little unemployment, while the economy growing at 1% will incur layoffs and unemployment. Thus, Lilien's

[5] These frictions include job training, education, geographical distance, and search costs, among others. They are the main reason why economists consider a 4%–6% unemployment rate as full employment as opposed to a zero unemployment rate.

[6] Since the work of Lilien (1982), the economics literature has debated whether sectoral shifts or business cycles are the main driver of unemployment (e.g., Abraham and Katz 1986, Hosios 1994, Lazear and Spletzer 2012). This literature does not examine how these two effects interact.

(1982) model suggests that unemployment is jointly determined by aggregate economic growth and dispersion. In other words, the effects of dispersion are conditional on the aggregate state of the economy. Prior studies include aggregate economic growth and dispersion independently. However, the correct specification with which to examine Lilien's (1982) model is to employ an interaction term. The use of an interaction term captures the idea that aggregate performance and dispersion jointly determine layoffs and unemployment.

The sectoral shift hypothesis is based on variations in performance, not uncertainty. However, it is likely that uncertainty affects sectoral shifts as well. Lilien's (1982) model assumes a constant hiring rate, which implies that the reallocation of employees is time invariant (an assumption questioned by Lilien as well). In other words, in the sectoral shift model, dispersion affects unemployment only because it increases layoffs. We extend Lilien's (1982) model to include the uncertainty framework introduced by Bloom (2009). As discussed above, empirical and analytical studies on uncertainty suggest that employers are generally more reluctant to hire during periods when uncertainty is high. Therefore, according to these studies, hiring rates are not constant. Hence employee migration during periods of poor economic growth and high dispersion will take longer, because of increased uncertainty, and lengthier migration results in greater unemployment. In other words, when the uncertainty framework introduced by Bloom (2009) is superimposed onto Lilien's (1982) sectoral shift model, the hiring rate becomes a decreasing function of uncertainty. Since we hypothesize that the implications of uncertainty are most pronounced during periods of both high aggregate and firm-level uncertainty, we expect unemployment to increase more significantly during periods when both macroeconomic and microeconomic uncertainty are high. In sum, one reason why the impact of uncertainty is most pronounced when both firm-level and aggregate-level uncertainty interact, is because unemployment increases more significantly because of their interactive effect.

3. Variable Measurement and Research Design

This section describes the measures employed in the paper and our research design.

3.1. Measuring Firm-Level and Aggregate-Level Economic Shocks

Our empirical analysis focuses on the relation between the interaction of aggregate and firm-level shocks, and macroeconomic activity. A large literature in economics and finance suggests that persistent variables can provide misleading predictive evidence (e.g., Yule 1926, Granger and Newbold 1974, Ferson et al. 2003). Specifically, if two variables are highly persistent over time, a regression including one as a dependent variable and one as an independent variable is likely to find evidence of predictability, even if the two variables are unrelated. Persistent variables are ones that have large autocorrelations. Macroeconomic variables are highly persistent, as are our aggregate and dispersion based measures.

To overcome the spurious regression bias, Campbell (1991) and Ferson et al. (2003) suggest stochastic detrending of persistent variables. That is, removing the persistent component in both the independent and dependent variables. In our analysis, we use an AR(2) model to isolate the persistent component of all the key variables. We then employ the residuals from the AR(2) models in our analysis. We refer to the residuals as shocks. This should alleviate concerns related to the spurious regression bias. In addition, since our variables have no serial correlation, there is no serial correlation in the error term. Therefore, we do not need to correct for any time-series autocorrelation in the residuals when employing the shocks in our regression analysis. In untabulated robustness tests we reestimate our main regression models using Newey West adjusted standard errors and find identical results.

To measure aggregate-level shocks, we utilize (1) a performance-based measure, (2) the economic policy uncertainty index employed in Baker et al. (2015), and (3) an implied volatility measure (described below). As we note above, since aggregate uncertainty is highly related to aggregate performance, we do not link each measure to a distinct theory. Rather, we view all three measures as potential measures of aggregate uncertainty and/or performance. We view periods of low aggregate performance, periods of high policy uncertainty, and periods with high implied volatility as periods with poor aggregate performance and/or high aggregate uncertainty (e.g., Barry and Brown 1985, Bloom et al. 2012).

Our performance-based measure is an aggregate earnings measure, computed using forward-looking analyst forecasts. We estimate aggregate earnings shocks in three steps. First, we measure the revision in earnings expectations for firm i during quarter t for the next fiscal year (one-year-ahead):

$$rev^t_{i,s+1} = \left(\frac{E_t(earn_{i,s+1}) - E_{t-1}(earn_{i,s+1})}{P_{i,t-1}}\right), \qquad (1)$$

where $rev^t_{i,s+1}$ is the revision in quarter t; s represents the current year, whereas $s+1$ represents the next full year; $E_t(earn_{i,s+1})$ is the median analyst earnings forecast at the end of quarter t for firm i, for the year $s+1$; and $P_{i,t-1}$ is the price per share for firm i at the end of quarter $t-1$.

Second, we estimate aggregate revisions for each quarter as the equally weighted average of all firm-level revisions:

$$AggREV_t = \frac{1}{N}\sum_{i=1}^{N_t} rev_i^t, \tag{2}$$

where $AggREV_t$ equals the aggregate revision for quarter t, and N is the number of eligible firms (common stocks) during that quarter.

Third, because aggregate revisions in earnings are more persistent than at the firm level, we use the following AR(2) model to estimate the aggregate earnings shock:

$$AggREV_t = \rho_0 + \rho_1 \cdot AggREV_{t-1} + \rho_2 \cdot AggREV_{t-2} + e_t, \tag{3}$$

where e_t is the aggregate earnings shock for quarter t. Finally, we convert aggregate earnings shocks into a binary variable (REV_t). Specifically, aggregate earnings (revisions) shocks in the lowest quartile are assigned a value of one, and the rest of the observations are assigned a value of zero. (We explain the rationale for converting aggregate earnings shocks into a binary variable below.) Put differently, the most negative quartile of aggregate earnings shock quarters is assigned a value of one, and the remaining quarters receive a value of zero.[7] We use the variable REV_t in our analysis (see model (5a)).

As an alternative measure of aggregate shocks, we employ the economic policy uncertainty index (Baker et al. 2015). We follow similar steps to the ones used when computing REV. First, we use an AR(2) model similar to Equation (3) to compute the aggregate policy uncertainty shock.[8] Next, we define the variable *Unc*, which is an indicator variable equal to one for the highest quartile of political uncertainty shocks. In other words, the variable *Unc* receives the value of one for the most positive quartile of political uncertainty shock quarters and zero otherwise. We view periods of low performance and high policy uncertainty as periods with high aggregate-level shocks. Therefore, we employ the variable *Unc* in our alternative specification (see model (5b)).

As our third measure, we employ a stock price-based measure that is commonly used in the finance literature. Specifically, we employ the CBOE market VIX. First, we compute the residuals from an AR(2) model of the VIX index.[9] Next, similarly to *REV* and *Unc*, we employ an indicator variable equal to one for the highest quartile of VIX shocks as our measure of aggregate-level shocks (*VIX*). In other words, the variable *VIX* receives the value of one for the most positive quartile of implied volatility shock quarters and zero otherwise (see model (5c)).

Firm-level earnings dispersion is the first firm-level shock we employ. Cross-sectional dispersion in firm-level performance has been used as both a measure of firm-level uncertainty (e.g., Bloom 2009, Bloom et al. 2012) and as a measure of cross-sectional variation in performance (e.g., Loungani et al. 1990). First, we estimate earnings revisions as described in step 1. Next, we estimate earnings dispersion as the standard deviation of revisions in a quarter as follows:

$$Dis_t = \sqrt{\frac{1}{N}\sum_{i=1}^{N_t}(rev_i^t - AggRev_t)^2}, \tag{4}$$

where variable Dis_t is the dispersion for quarter t, $AggRev_t$ is the aggregate earnings revision for quarter t, and n is the number of firms (eligible common stocks) during that quarter. Finally, to isolate the nonpersistent component in earnings dispersion, we employ an AR(2) model, similar to Equation (3). The AR(2) residual is the proxy we use to measure earning dispersion shocks (*Rev_Disp*).[10] *Rev_Disp* is the variable we employ in our analysis (see models (5a) and (5b)).

As an alternative measure of firm-level shocks, we employ the average idiosyncratic-return volatility. We estimate the idiosyncratic volatility measure using the following steps. First, for each firm and quarter we estimate the daily idiosyncratic returns as the residuals from the regression of daily stock returns on daily market, size, book-to-market, and momentum factors (Fama and French 1993, Carhart 1997). Second, for each firm-quarter, we compute the standard deviations of daily idiosyncratic returns (from step 1) and define them as firm-level idiosyncratic volatility. Third, using all firms in a quarter, we compute the average firm-level idiosyncratic volatility (from step 2) and define it as aggregate idiosyncratic volatility. Finally, shocks to aggregate idiosyncratic volatility, *Idio_vol*, are defined as the residuals from an AR(2) model of aggregate idiosyncratic volatility (from step 3).[11]

[7] The AR(1) coefficient of aggregate revision shocks is 0.02 and is statistically insignificant (t-value 0.21), suggesting that the AR(2) process does a good job of isolating aggregate revision shocks.

[8] The AR(1) coefficient of aggregate uncertainty shocks is −0.03 and is statistically insignificant (t-value −0.28), suggesting that the AR(2) process does a good job of isolating aggregate uncertainty shocks.

[9] The AR(1) coefficient of the VIX shocks is 0.01 and is statistically insignificant (t-value 0.08), suggesting that the AR(2) process does a good job of isolating aggregate VIX shocks.

[10] The AR(1) coefficient for earnings dispersion shocks is −0.02 and statistically insignificant (t-value −0.23), suggesting that the AR(2) process does a good job of isolating earnings dispersion shocks.

[11] The AR(1) coefficient for the idiosyncratic volatility shocks is 0.10 and statistically insignificant (t-value 0.93), suggesting that the AR(2) process does a good job of isolating idiosyncratic volatility shocks.

Finally, we create an interaction term between aggregate-level shocks and firm-level shocks. Specifically, we convert the aggregate variables into binary variables (as described above). We do this because both firm-level shocks and aggregate-level shocks can obtain positive and negative values, which in turn affects the sign of the interaction term. For example, consider a positive shock to both aggregate performance and earnings dispersion, and consider a negative shock to both aggregate performance and earnings dispersion, both cases result in a positive sign for the interaction term. However, the two scenarios are economically different. To address this issue, we convert the aggregate variables into binary variables. Thus, our aggregate measures are always nonnegative, and the interaction term will not have the same sign in the two scenarios described above. In our empirical models, we include aggregate gross domestic product (GDP) as an additional continuous control variable. This variable is added to ensure that our results are not driven by the use of a binary variable to measure aggregate uncertainty.

3.2. Research Design

We test whether the interaction of aggregate and firm-level shocks is associated with investment, unemployment, and industrial production. To test our hypothesis, we estimate the following time-series regression model for each of our macroeconomic indicators:

$$\begin{aligned} Macro\_ind_t = {} & \beta_0 + \beta_1 \cdot Rev_t + \beta_2 \cdot Rev\_Disp_t \\ & + \beta_3 \cdot [Rev_t \cdot Rev\_Disp_t] + \beta_4 \cdot [D\_GDP_t] \\ & + \beta_5 \cdot [D\_Cons_t] + \beta_6 \cdot [D\_Term_t] \\ & + \beta_7 \cdot [D\_Yield_t] + \beta_8 \cdot [D\_Inf_t] \\ & + \beta_9 \cdot [D\_Def_t] + \varepsilon_t, \end{aligned} \tag{5a}$$

where $Macro\_ind_t$ is one of the three macroeconomic indicators examined, D_Inv_t, D_Unemp_t, and D_Ind_t, which equal the residuals from an AR(2) model of quarterly investment, unemployment rates, and industrial production growth, respectively; *Rev* is an aggregate earnings dummy equal to one for the lowest quartile of aggregate earnings shocks; and *Rev_Disp* measures earnings dispersion shocks using the residuals from an AR(2) model of earnings dispersion. As we note above, since the variables employed in the regression are residuals from AR(2) models, they are not serially correlated. Therefore, we do not need to correct for any time-series correlation in the error terms.

Our predictions for investment and industrial production are as follows. First, based on prior literature, we expect a negative coefficient on aggregate earnings shocks, $\beta_1 < 0$. A negative coefficient implies that investment and industrial production are lower when aggregate profitability is lower. In other words, investment and production are lower during contractions. Second, also based on prior literature, if higher levels of firm-level dispersion in earnings impede investment, we expect the coefficient for earnings dispersion to be negative, that is, $\beta_2 < 0$. Third, as discussed in Section 2, we hypothesize that the effects of dispersion are conditional on aggregate conditions in the economy. Specifically, we expect the impact of dispersion on investment and industrial production to increase (become more negative) when aggregate profitability is lower. Therefore, we expect the coefficient on the interaction term to be negative, that is, $\beta_3 < 0$. In other words, the adverse effects of firm-level shocks on investment and production are exacerbated during periods of low or negative economic growth, when aggregate uncertainty is high.

Our predictions for unemployment have the opposite sign. First, we expect a positive coefficient on aggregate earnings shocks, $\beta_1 > 0$. A positive coefficient implies that unemployment is higher when aggregate profitability is lower. In other words, unemployment is higher during contractions. Second, if higher levels of dispersion in earnings increase unemployment, we expect the coefficients on the dispersion measures to be positive, that is, $\beta_2 > 0$. Finally, as discussed in Section 2, we hypothesize that the effects of dispersion are conditional on the state of the economy. Specifically, we expect the impact of dispersion on unemployment to increase (become more positive) when aggregate profitability is lower. Therefore, we expect the coefficient on the interaction term to be positive, that is, $\beta_3 > 0$. In other words, the adverse effects of dispersion on employment are exacerbated during periods of low or negative economic growth, when aggregate uncertainty is high.

In our second specification, we replace our performance-based measure with the policy uncertainty index, and estimate the following model:

$$\begin{aligned} Macro\_ind_t = {} & \gamma_0 + \gamma_1 \cdot Unc_t + \gamma_2 \cdot Rev\_Disp_t \\ & + \gamma_3 \cdot [Unc_t \cdot Rev\_Disp_t] + \gamma_4 \cdot [D\_GDP_t] \\ & + \gamma_5 \cdot [D\_Cons_t] + \gamma_6 \cdot [D\_Term_t] \\ & + \gamma_7 \cdot [D\_Yield_t] + \gamma_8 \cdot [D\_Inf_t] \\ & + \gamma_9 \cdot [D\_Def_t] + \varepsilon_t, \end{aligned} \tag{5b}$$

where Unc_t is an indicator variable equal to one for the highest quartile of policy uncertainty shocks. Our predictions for $\gamma_1, \gamma_2, \gamma_3$ are the same as our predictions for $\beta_1, \beta_2, \beta_3$, respectively, because we expect aggregate uncertainty to be higher during periods of low performance and high policy uncertainty.

In our final specification, we employ VIX and idiosyncratic volatility, and estimate the following model:

$$\begin{aligned} Macro\_ind_t = {} & \delta_0 + \delta_1 \cdot VIX_t + \delta_2 \cdot Idio\_vol_t \\ & + \delta_3 \cdot [VIX_t \cdot Idio\_vol_t] + \delta_4 \cdot [D\_GDP_t] \\ & + \delta_5 \cdot [D\_Cons_t] + \delta_6 \cdot [D\_Term_t] \\ & + \delta_7 \cdot [D\_Yield_t] + \delta_8 \cdot [D\_Inf_t] \\ & + \delta_9 \cdot [D\_Def_t] + \varepsilon_t, \end{aligned} \tag{5c}$$

where VIX_t is an indicator variable equal to one for the highest quartile of implied volatility shocks, and *Idio_vol* measures idiosyncratic volatility shocks. Our predictions for $\delta_1, \delta_2, \delta_3$ are the same as our predictions for $\gamma_1, \gamma_2, \gamma_3$, respectively, because we expect aggregate implied volatility to be higher during periods of low performance and high policy uncertainty.

3.3. Unemployment and Industrial Production Forecast Error Data

Unemployment and industrial production forecast error data are obtained from the Survey of Professional Forecasters (SPF). We are interested in measuring the precision of the predictions. Therefore, we employ absolute forecast errors (Baghestani 2009). The absolute forecast error is estimated as follows:

$$AFE = |Actual_{q+1} - Forecast_q^{q+1}|, \tag{6}$$

where *AFE* equals the absolute forecast error, $Actual_{q+1}$ is the realized macroeconomic value released in quarter $t+1$, and $Forecast_q^{q+1}$ is the consensus SPF forecast of the macroeconomic variable, based on the median forecast for quarter $t+1$, as of quarter t.

3.4. Sample

Our sample is constructed from the intersection of I/B/E/S, CRSP, and Compustat during 1985 to 2011. We restrict the sample to ordinary common shares (share codes 10, 11) that are traded on the NYSE, AMEX, or NASDAQ exchanges. Further, to align data across firms, we include only firms with fiscal year-ends in March, June, September, or December. Finally, every quarter, we winsorize the extreme 2% of observations when calculating the aggregate earnings revision measures.[12]

Macroeconomic data are collected from FRED, the Federal Reserve Bank of St. Louis. Investment equals the quarter-over-quarter growth in seasonally adjusted U.S. aggregate gross private domestic investment (measured and reported by the U.S. Department of Commerce's Bureau of Economic Analysis). The quarterly average unemployment data (averaged over three months) is the seasonally adjusted civilian unemployment rate, which is defined as the number of unemployed people as a percent of the labor force (measured and reported by the U.S. Department of Labor's Bureau of Labor Statistics). The quarterly average industrial production data (averaged over three months) is the seasonally adjusted real output in production, expressed as a percentage growth term (measured and reported by Board of Governors of the Federal Reserve System). Economic policy uncertainty is the average quarterly (three-month average) economic policy uncertainty index from Baker et al. (2015). The index is constructed from three components: (1) newspaper coverage of policy-related economic uncertainty, (2) the number of federal tax code provisions set to expire in future years, and (3) disagreement among economic forecasters.[13] Unemployment and industrial production forecast error data are obtained from the Survey of Professional Forecasters (SPF).[14]

3.5. Descriptive Statistics

Table 1 presents descriptive statistics for our variables. Our sample includes 105 quarters from the fourth quarter of 1985 up to and including the fourth quarter of 2011.[15] The mean values of the macro, idiosyncratic volatility, and dispersion variables are zero by construction, as these estimates are residuals from various AR(2) specifications. More specifically, the mean values of investment shocks (D_Inv_t), unemployment shocks (D_Unemp_t), industrial production shocks (D_Iprod_t), earnings dispersion shocks (Rev_Disp_t), hereafter earnings dispersion, and idiosyncratic volatility shocks ($Idio\_Vol_t$) are zero. The variables Rev_Disp_t and $Idio\_Vol_t$ have a negative median value, while the median unemployment and industrial production shocks have a value of zero. The median investment shock is slightly positive.

The univariate results are presented in Table 2. Consistent with our expectations, aggregate earnings shocks are negatively related to investment and industrial production shocks and positively related to unemployment shocks. For example, aggregate earnings shocks have a Pearson (Spearman) correlation of −0.36 (−0.31) with investment shocks. That is, investment shocks are lower during periods of lower aggregate

[12] Our results are robust to winsorizing the extreme 1% of observations.

[13] The economic policy uncertainty data are taken from the webpage http://www.policyuncertainty.com/us_monthly.html (accessed August 2014).

[14] http://www.phil.frb.org/research-and-data/real-time-center/survey-of-professional-forecasters/ (accessed August 2014).

[15] The sample when employing VIX is restricted to 86 quarters from Q3:1990 to Q4:2011, because the VIX data are unavailable prior to 1990.

Table 1 Descriptive Statistics

	Mean	Std. dev.	5th percentile	Median	95th percentile
D_Inv_t	0.00	3.01	−5.11	0.02	4.69
D_Unemp_t	0.00	0.20	−0.27	0.00	0.32
D_Iprod_t	0.00	0.85	−1.39	0.00	1.18
$Unemp\_AFE_{t+1}$	0.11	0.08	0.00	0.09	0.27
$Iprod\_AFE_{t+1}$	2.02	1.65	0.16	1.56	5.27
Rev_t	0.25	0.43	0.00	0.00	1.00
$Rev\_Disp_t (\times 100)$	0.00	0.65	−0.65	−0.08	0.88
$Rev_t \times Rev\_Disp_t (\times 100)$	0.14	0.38	0.00	0.00	0.76
UNC_t	0.26	0.44	0.00	0.00	1.00
$UNC_t \times Rev\_Disp_t (\times 100)$	0.06	0.38	−0.25	0.00	0.56
VIX_t	0.26	0.44	0.00	0.00	1.00
$Idio\_Vol_t (\times 100)$	0.00	0.45	−0.57	−0.04	0.84
$VIX_t \times Idio\_Vol_t (\times 100)$	0.03	0.31	−0.31	0.00	0.14
D_GDP_t	0.00	0.54	−0.86	0.01	0.80
D_Cons_t	0.00	0.49	−0.80	−0.05	0.89
D_Term_t	0.00	0.42	−0.68	−0.05	0.76
D_Yield_t	0.00	0.17	−0.26	0.01	0.32
D_CPI_t	0.00	0.49	−0.61	0.02	0.68
D_Def_t	0.00	0.21	−0.21	−0.01	0.25

Notes. This table presents descriptive statistics for the macroeconomic variables, firm-level shocks, and aggregate-level shocks. The sample includes 105 quarters from Q4:1985 to Q4:2011. The variable D_Inv_t is the residual from an AR(2) model of quarterly private domestic investments, in quarter t; D_Unemp_t is the residual from an AR(2) model of quarterly unemployment rates, in quarter t; D_Iprod_t is the residual from an AR(2) model of quarterly industrial production growth measures in percentages; and *AFE* is the absolute forecast error related to the macroeconomic indicator forecasted. All forecast error data are obtained from the Survey of Professional Forecasters. The variable *Rev* is an indicator variable equal to one for the lowest quartile of aggregate earnings shocks. Aggregate earnings shocks equal the residual from an AR(2) model of aggregate earnings revisions. Aggregate earnings revisions are defined as the equally weighted average of firm-level earnings forecast revisions, for one-year-ahead earnings, that occur during the current quarter, deflated by the beginning of the quarter stock price:

$$rev^t_{i,s+1} = \left(\frac{E_t(earn_{i,s+1}) - E_{t-1}(earn_{i,s+1})}{P_{i,t-1}} \right), \quad AggRev_t = \frac{1}{N_t} \sum_{i=1}^{N_t} (rev^t_{i,s+1}).$$

Earnings dispersion (*Rev_Disp*) is the residual from an AR(2) model of aggregate earnings dispersion (*AggDis*); and *AggDis* is the standard deviation of firm-level earnings forecast revisions, deflated by beginning of the quarter stock price:

$$AggDis_t = \sqrt{\frac{1}{N_t} \sum_{i=1}^{N_t} (rev_{i,t} - AggRev_t)^2}.$$

UNC is an indicator variable equal to one for the highest quartile of economic policy uncertainty shocks. Economic policy uncertainty shocks equal the residuals from an AR(2) model of the economic policy uncertainty index. *VIX* is an indicator variable equal to one for the highest quartile of VIX shocks. VIX shocks equal the residuals from an AR(2) model of the VIX index, which is the CBOE market volatility index. The sample for the VIX data is restricted to 86 quarters from the Q3:1990–Q4:2011 period because of data unavailability prior to 1990. The variable *Idio_Vol* is defined as the shocks to aggregate idiosyncratic volatility. *Idio_Vol* is estimated as follows: First, for each firm and quarter daily idiosyncratic returns are estimated as the residuals from the regression of daily stock returns on daily market, size, book-to-market, and momentum factors (Fama and French 1993, Carhart 1997). Second, for each firm-quarter the standard deviations of daily idiosyncratic returns (from step 1) are computed and defined as firm-level idiosyncratic volatility. Third, using all firms in a quarter, the average firm-level idiosyncratic volatility (from step 2) is computed and defined as aggregate idiosyncratic volatility. Finally, shocks to aggregate idiosyncratic volatility are defined as the residuals from an AR(2) model of aggregate idiosyncratic volatility (from step 3). For the calculation of aggregate earnings revisions and dispersion, to align data across firms in a quarter, we only include firms with fiscal year-ends in March, June, September, and December. Further, every quarter, we winsorize the top and bottom 2% of observations when calculating aggregate earnings and revision measures. The variable *D_GDP* is the AR(2) residual of seasonally adjusted quarterly real gross domestic product; *D_CON* is the AR(2) residual of seasonally adjusted quarterly real personal consumption expenditures; *D_Term* is the AR(2) residual of change in term spread (10-Year Treasury constant maturity rate *minus* three-month Treasury bill secondary market rate); *D_Yield* is the AR(2) residual of change in yield spread (effective Federal Funds Rate minus three-month Treasury bill secondary market rate); *D_Def* is the AR(2) residual of change in default spread (Moody's seasoned Baa corporate bond yield *minus* Moody's seasoned Aaa corporate bond yield); and *D_CPI* is the AR(2) residual of seasonally adjusted quarterly consumer price index.

profitability. The correlations between political uncertainty shocks, VIX, and aggregate revisions, supports the notion that uncertainty is high during periods of poor performance. Additionally, investment and industrial production shocks are negatively correlated with earnings dispersion and idiosyncratic volatility, while unemployment shocks are positively related to both measures. Finally, investment and industrial production shocks are negatively correlated with the interaction terms, and unemployment shocks are positively related to the interaction terms. For example, the Pearson correlation between investment shocks and the interaction terms ranges from −0.45 to −0.50, depending on the measures employed.

Table 2 Correlation Matrix

	Inv_Res_t	$Unemp\_Res_t$	$Iprod\_Res_t$	$Unemp\_AFE_{t+1}$	$Iprod\_AFE_{t+1}$	Rev_t	Rev_Disp_t	$Rev_t \times Rev\_Disp_t$	Unc_t	$Unc_t \times Rev\_Disp_t$	VIX_t	$Idio\_Vol_t$	$VIX_t \times Idio\_Vol_t$
Inv_Res_t	1	**−0.39**	**0.51**	−0.08	0.06	**−0.36**	**−0.43**	**−0.50**	**−0.26**	**−0.45**	**−0.34**	**−0.35**	**−0.45**
$Unemp\_Res_t$	**−0.35**	1	**−0.55**	**0.23**	0.06	**0.16**	**0.41**	**0.46**	**0.34**	**0.46**	**0.36**	**0.27**	**0.40**
$Iprod\_Res_t$	**0.47**	**−0.50**	1	0.06	**0.18**	**−0.25**	**−0.38**	**−0.44**	**−0.28**	**−0.46**	**−0.25**	**−0.31**	**−0.38**
$Unemp\_AFE_{t+1}$	−0.08	**0.22**	0.14	1	**0.21**	0.01	0.12	−0.05	0.01	−0.02	0.01	−0.13	−0.07
$Iprod\_AFE_{t+1}$	**0.18**	0.01	**0.20**	0.13	1	−0.05	0.16	−0.08	−0.06	−0.08	−0.01	−0.13	−0.06
Rev_t	**−0.31**	0.12	**−0.22**	0.00	−0.09	1	**0.49**	**0.63**	**0.22**	**0.39**	**0.29**	**0.40**	**0.44**
Rev_Disp_t	**−0.30**	**0.25**	**−0.25**	0.08	−0.07	**0.65**	1	**0.66**	**0.20**	**0.59**	0.12	**0.35**	**0.56**
$Rev_t \times Rev\_Disp_t$	**−0.34**	**0.18**	**−0.25**	0.00	−0.10	**0.99**	**0.68**	1	**0.25**	**0.81**	**0.33**	**0.65**	**0.85**
Unc_t	**−0.23**	**0.33**	**−0.25**	0.00	−0.07	**0.22**	**0.21**	**0.23**	1	**0.25**	**0.39**	**0.30**	**0.28**
$Unc_t \times Rev\_Disp_t$	**−0.25**	**0.18**	**−0.34**	−0.01	**−0.16**	**0.44**	**0.49**	**0.45**	**0.18**	1	**0.29**	**0.62**	**0.88**
VIX_t	**−0.28**	**0.32**	**−0.18**	0.05	−0.04	**0.29**	0.00	**0.31**	**0.39**	**0.18**	1	0.15	0.17
$Idio\_Vol_t$	−0.11	0.06	**−0.19**	−0.09	−0.10	**0.38**	**0.23**	**0.40**	**0.24**	**0.25**	0.08	1	**0.69**
$VIX_t \times Idio\_Vol_t$	−0.14	0.05	**−0.21**	−0.01	**−0.19**	**0.40**	**0.33**	**0.41**	**0.18**	**0.35**	−0.09	**0.45**	1

Notes. This table presents Pearson (above diagonal) and Spearman (below diagonal) correlations among the key variables of interest. The sample and variable definitions are described in Table 1. Correlations significant at the 10% level or better are in bold.

4. Empirical Analysis

4.1. The Interaction of Firm-Level and Aggregate-Level Shocks, and Macroeconomic Activity

The multivariate results are presented in Tables 3, 4, and 5. The results for models (5a), (5b), and (5c) are presented in columns (1)–(3), (4)–(6), and (7)–(9), respectively. The investment-related results are presented in Table 3. When both the aggregate and firm-level shocks are included simultaneously in the regression model (columns (1), (4), and (7)), the coefficients are negative and significant, consistent with our predictions. The R-squared for these models varies from 19% to 20%. When we interact the firm- and aggregate-level shocks, the interaction term is significantly negative, and the R-squared increases to 24% and 25% across the specifications. Furthermore, the joint effect of the firm- and aggregate-level shocks on investment is statistically significant (F-values ranging from 16.64 to 22.17). Interestingly, some of the main effects are no longer statistically significant when the interaction term is included.

These results highlight that the combined effect of aggregate and firm-level shocks are larger than the sum of the individual effects. Moreover, the results are consistent with our predictions related to both economic theories. First, uncertainty impedes investment most when investors and firms are uncertain about the overall growth in the economy, and also about which firms/industries/sectors are likely to succeed. Second the effect of dispersion on economic activity is most pronounced when aggregate performance is low and aggregate uncertainty is high.

The unemployment-related results are presented in Table 4. The result in specifications (1), (4), and (7) highlight that both firm-level and aggregate-level shocks explain unemployment (e.g., Abraham and Katz 1986, Lilien 1982). On their own, the firm- and aggregate-level shocks explain 16%–22% of the shocks to unemployment. The results in columns (2) and (5) are consistent with our hypothesis that the effects of dispersion on unemployment are conditional on the state of the economy. The coefficient for the interaction term is positive and statistically significant across the specifications, and the joint effect of the interaction terms on unemployment is also statistically significant (F-values of 20.81 and 29.53) Moreover, the R-squared in columns (2) and (5) increases by between 23% and 56%, when we include the interaction term. These results support our hypothesis that the correct specification with which to test the Lilien (1982) model is with an interaction term. We find similar results when we employ idiosyncratic volatility and VIX. While both measures explain unemployment on their own (column (7)), the R-squared increases by approximately 47% when the interaction term is included in the model (column (8)). The coefficient for the interaction term is also positive and statistically significant, as is the joint effect of the interaction terms on unemployment (F-value of 13.42). Taken together, this evidence highlights the importance of the relation between firm-level and aggregate-level shocks when explaining unemployment shocks.

The multivariate regression results related to industrial production are presented in Table 5. The results in Table 5 are also consistent with our hypothesis that the effects of firm-level shocks on industrial production are conditional on the state of the economy. The coefficients on the interaction terms in columns (2), (5), and (8) are negative and statistically significant. Furthermore, the interaction term explains an additional 3%–5% of the variation in industrial production shocks. Moreover, the joint effect of the firm- and aggregate-level shocks on industrial production is

Table 3 Firm-Level and Aggregate-Level Shocks, and Contemporaneous Investment Shocks

	Dependent variable: D_INV_t								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Intercept$	0.34 (1.07)	0.47 (1.53)	0.45 (1.47)	0.32 (1.05)	0.38 (1.26)	0.36 (1.22)	0.52 (1.52)	0.58* (1.78)	0.60* (1.78)
Rev_t	−1.36 (−1.95)*	−0.41 (−0.54)	0.15 (0.19)						
Unc_t				−1.25 (−2.05)**	−0.98 (−1.62)	−0.86 (−1.37)			
VIX_t							−2.05*** (−3.01)	−1.89*** (−2.89)	−1.89*** (−2.73)
Rev_Disp_t	−154.81 (−3.34)***	−80.76 (−1.53)	−72.02 (−1.36)	−182.55 (−4.44)***	−111.09 (−2.28)**	−108.99 (−2.24)**			
$Idio\_Vol_t$							−202.49*** (−3.06)	−33.53 (−0.39)	−15.36 (−0.16)
$Rev_t \times Rev\_Disp_t$		**−269.70** (**−2.67**)***	**−355.08** (**−3.35**)***						
$Unc_t \times Rev\_Disp_t$					**−219.96** (**−2.57**)**	**−256.03** (**−2.93**)***			
$VIX_t \times Idio\_Vol_t$								**−361.96***** (**−2.84**)	**−400.29***** (**−2.81**)
D_Cons_t			−1.62 (−2.78)***			−1.53 (−2.68)***			−0.71 (−1.00)
D_Term_t			−0.05 (−0.08)			0.10 (0.17)			−0.61 (−0.84)
D_Yield_t			−1.56 (−1.00)			0.01 (0.01)			−0.63 (−0.32)
D_CPI_t			−0.06 (−0.10)			−0.26 (−0.43)			−0.18 (−0.25)
D_Def_t			−2.26 (−1.51)			−1.71 (−1.13)			−1.24 (−0.72)
Adj. R^2	0.20	0.25	0.27	0.20	0.24	0.26	0.19	0.25	0.22
F-test		16.64***	22.42***		22.17***	25.27***		18.05***	17.29***
No. of obs.	105	105	105	105	105	105	86	86	86

Notes. This table reports the contemporaneous relation between investment shocks and measures of firm-level and aggregate-level shocks. F-test measures the joint effect of firm-level and aggregate-level shocks on investment shocks. Bold numbers represent our key results. All the variables are defined in Table 1.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

statistically significant (F-values ranging from 11.91 to 21.71). The evidence in these analyses suggests that aggregate- and firm-level shocks jointly explain industrial production shocks better than each measure individually.

Additionally, in Tables 3–5, the specifications in columns (3), (6), and (9) include the various macroeconomic control variables. Including these control variables adds to the explanatory power of the model. For example, in Table 3 the adjusted R-squared increases by 2% when we include the control variables.[16] While the control variables enhance the explanatory power of the model, they do not significantly alter the relation between the interaction term and the macroeconomy. These findings suggest that the observed relation between the interaction term and the macroeconomy is not attributable to prior known factors.

In sum, both aggregate- and firm-level shocks are associated with lower levels of macroeconomic activity (investment, unemployment, and industrial production shocks). Moreover, consistent with our predictions in Section 2, we find that the effects of the firm-level shocks are exacerbated during periods of high aggregate shocks. Therefore, the addition of an interaction term substantially improves our understanding of how uncertainty and aggregate performance relates to the macroeconomy.

[16] The exception is the model that employs *VIX* and *Idio_Vol*, where the addition of the control variables lowers the adjusted R^2. The control variables also have little impact on the adjusted R^2 when *VIX* and *Idio_Vol* are employed in Table 4.

Table 4 Firm-Level and Aggregate-Level Shocks, and Contemporaneous Unemployment Shocks

	Dependent variable: D_UNEMP_t								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.01	−0.01	0.00	−0.03	−0.04	−0.03	−0.04	−0.04*	−0.03
	(0.25)	(−0.37)	(−0.16)	(−1.61)	(−1.83)*	(−1.66)*	(−1.48)	(−1.76)	(−1.30)
Rev_t	−0.02	−0.11	−0.10						
	(−0.48)	(−2.14)**	(−1.99)**						
Unc_t				0.12	0.10	0.10			
				(3.02)***	(2.60)**	(2.41)**			
VIX_t							0.16***	0.15***	0.11**
							(3.20)	(3.09)	(2.22)
Rev_Disp_t	13.44	6.72	7.00	11.07	6.24	7.02			
	(4.22)***	(1.90)*	(2.00)**	(4.08)***	(1.94)*	(2.23)**			
$Idio\_Vol_t$							10.28**	−2.33	−4.69
							(2.14)	(−0.37)	(−0.69)
$Rev_t \times Rev\_Disp_t$		**24.46**	**20.32**						
		(**3.63**)***	(**2.83**)***						
$Unc_t \times Rev\_Disp_t$					**14.88**	**10.44**			
					(**2.64**)***	(**1.78**)*			
$VIX_t \times Idio\_Vol_t$								**27.00*****	**27.76*****
								(**2.93**)	(**2.73**)
D_GDP_t			−0.10			−0.08			−0.06
			(−2.57)**			(−2.27)**			(−1.40)
D_Cons_t			−0.01			−0.04			−0.02
			(−0.32)			(−0.99)			(−0.43)
D_Term_t			−0.03			−0.05			−0.03
			(−0.80)			(−1.19)			(−0.64)
D_Yield_t			0.10			0.02			−0.06
			(0.94)			(0.17)			(−0.42)
D_CPI_t			0.02			0.02			0.06
			(0.47)			(0.47)			(1.20)
D_Def_t			0.03			−0.07			0.06
			(0.31)			(−0.67)			(0.49)
Adj. R^2	0.16	0.25	0.30	0.22	0.27	0.31	0.15	0.22	0.22
F-test		29.536***	20.12***		20.81***	12.69***		13.42***	9.91***
No. of obs.	105	105	105	105	105	105	86	86	86

Notes. This table reports the contemporaneous relation between unemployment shocks and measures of firm-level and aggregate-level shocks. F-test measures the joint effect of firm-level and aggregate-level shocks on unemployment shocks. Bold numbers represent our key results. All the variables are defined in Table 1.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

4.2. Alternative Cutoffs

As we explain in Section 3, the measures of aggregate shocks employed in our analyses are indicator variables that measure aggregate earnings shocks in the lowest quartile (*Rev*), and the most positive quartile of political uncertainty shock quarters (*Unc*) and implied volatility shock quarters (*VIX*). We further explain the requirement to use indicator variables in Section 3.1. To ensure that our results are not sensitive to the cutoff used to define the indicator variables, we reestimate the models presented in Tables 3–5, columns (3), (6), and (9), using alternative cutoffs to define the indicator variables. More specifically, we redefine *Rev* to equal 1 for observations in the lowest quintile, tercile, median, and for all negative shocks. Similarly, we redefine *Unc* to equal 1 for observations in the highest quintile, tercile, median, and for all positive shocks. For brevity, we do not tabulate the results using *VIX* as they are similar. The results from this analysis are presented in Table 6. The results for investment, unemployment, and industrial production shocks are presented in panels A–C, respectively. Our main results are robust to the alternative cutoffs. We continue to find a robust relation between our interaction terms and macroeconomic indicators. The main difference relative to Tables 3–5 is that the relation between industrial production and the interaction term using the policy uncertainty index (panel C) is more sensitive to alternative cutoffs. However, the coefficient remains negative in all the specifications, with t-statistics ranging form −1.49 to −2.77. Furthermore, the R-squared values presented across the panels are similar in magnitude to those presented in Tables 3–5.

In untabulated analysis, we also examine how the relation between the interaction between firm-level and aggregate-level shocks and macroeconomic indicators differs across groups of high and low aggregate

Table 5 Firm-Level and Aggregate-Level Shocks, and Industrial Production Shocks

	Dependent variable: D_IPROD_t								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.05	0.09	0.05	0.11	0.13	0.07	0.10	0.11	0.02
	(0.49)	(0.95)	(0.57)	(1.25)	(1.50)	(0.94)	(0.91)	(1.08)	(0.26)
Rev_t	−0.16	0.13	0.15						
	(−0.77)	(0.57)	(0.71)						
Unc_t				−0.40	−0.31	−0.15			
				(−2.29)**	(−1.82)*	(−0.95)			
VIX_t							−0.42**	−0.38*	−0.03
							(−2.00)	(−1.85)	(−0.16)
Rev_Disp_t	−44.79	−22.41	−23.44	−44.61	−21.22	−23.14			
	(−3.29)***	(−1.45)	(−1.67)*	(−3.77)***	(−1.53)	(−1.83)*			
$Idio\_Vol_t$							−55.37***	−15.49	−3.51
							(−2.71)	(−0.57)	(−0.13)
$Rev_t \times Rev\_Disp_t$		**−81.52**	**−56.67**						
		(**−2.76**)***	(**−1.97**)*						
$Unc_t \times Rev\_Disp_t$					**−71.99**	**−48.11**			
					(**−2.96**)***	(**−2.04**)**			
$VIX_t \times Idio\_Vol_t$								**−85.43****	**−75.87***
								(**−2.13**)	(**−1.91**)
D_GDP_t			0.57			0.54			0.49***
			(3.83)***			(3.66)***			(2.73)
D_Cons_t			0.05			0.08			0.28
			(0.28)			(0.50)			(1.28)
D_Term_t			0.24			0.28			0.21
			(1.48)			(1.72)*			(1.05)
D_Yield_t			−0.34			−0.12			−0.22
			(−0.82)			(−0.31)			(−0.41)
D_CPI_t			0.02			−0.01			−0.04
			(0.11)			(−0.09)			(−0.21)
D_Def_t			−0.58			−0.47			−0.65
			(−1.44)			(−1.18)			(−1.36)
Adj. R^2	0.14	0.19	0.36	0.17	0.23	0.38	0.12	0.15	0.32
F-test		17.09***	10.73***		21.71***	13.10***		11.91***	7.75***
No. of obs.	105	105	105	105	105	105	86	86	86

Notes. This table reports the contemporaneous relation between industrial production shocks and measures of firm-level and aggregate-level shocks. F-test measures the joint effect of firm-level and aggregate-level shocks on industrial production shocks. Bold numbers represent our key results. All the variables are defined in Table 1.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

shocks. We find that the relation between the interaction term and the macroeconomic shocks is significantly stronger for the high group (quarters with the highest quartile or tercile of aggregate shocks) compared to that of the low group.

4.3. Uncertainty Shocks and the Macroeconomy

One caveat of our empirical analysis so far is that the results only report associations and do not imply a causal link. Bloom (2014) discusses the difficulty in determining causality in this literature, as uncertainty and dispersion can arise endogenously during recessions. Thus, to identify causality, empirical studies must identify exogenous shocks or instrumental variables to identify the causal link.

Dealing with causality is particularly challenging in our study because we focus on an interaction term. This makes identifying exogenous variation difficult, as we need exogenous variation that is related to our interaction term but not to the individual components. In other words, we would require a shock to the interaction term that does not impact the firm-level and aggregate-level shocks. Since such exogenous variation does not exist, determining causality in our study is difficult.

Nevertheless, we employ several exogenous shocks employed in Bloom et al. (2012) to highlight the importance of the interaction between firm-level and aggregate-level shocks. We attempt to identify shocks that likely affect aggregate uncertainty as well as firm-level uncertainty and compare them to shocks that affect only one type of uncertainty. In particular, we focus on three shocks. First, we focus on Bill Clinton's presidential election in 1992, which represents the first democratic president after 12 consecutive years of republican presidents. We expect such a shock to

Table 6 Firm-Level and Aggregate-Level Shocks, and Contemporaneous Macro Shocks: Alternative Cut-Offs

	Quintile		Tercile		Median		Negative/Positive	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Contemporaneous investment shocks				
Intercept	0.34	0.38	0.31	0.42	0.43	0.46	0.38	0.34
	(1.14)	(1.35)	(0.92)	(1.30)	(1.12)	(1.30)	(1.04)	(1.00)
Rev_t	0.45		0.63		0.02		0.16	
	(0.50)		(0.91)		(0.03)		(0.26)	
Unc_t		−1.11		−0.64		−0.69		−0.43
		(−1.67)*		(−1.13)		(−1.34)		(−0.83)
Rev_Disp_t	−91.32	−104.00	−88.63	−92.97	−70.04	−74.15	−84.75	−74.50
	(−1.75)*	(−2.20)**	(−1.59)	(−1.83)*	(−1.23)	(−1.41)	(−1.49)	(−1.42)
$Rev_t \times Rev\_Disp_t$	**−346.11**		**−339.03**		**−321.55**		**−304.65**	
	(**−3.10**)***		(**−3.29**)***		(**−3.43**)***		(**−3.14**)***	
$Unc_t \times Rev\_Disp_t$		**−275.46**		**−269.62**		**−281.87**		**−291.10**
		(**−3.15**)***		(**−3.11**)***		(**−3.50**)***		(**−3.58**)***
D_Cons_t	−1.80	−1.63	−1.66	−1.45	−1.59	−1.36	−1.57	−1.38
	(−3.05)***	(−2.89)***	(−2.85)***	(−2.54)**	(−2.72)***	(−2.42)**	(−2.69)***	(−2.45)**
D_Term_t	−0.01	0.16	−0.09	−0.11	−0.14	−0.02	−0.09	0.02
	(−0.02)	(0.27)	(−0.14)	(−0.18)	(−0.23)	(−0.04)	(−0.14)	(0.03)
D_Yield_t	−1.49	−0.16	−1.38	−0.27	−1.49	0.09	−1.26	0.03
	(−0.93)	(−0.10)	(−0.87)	(−0.18)	(−0.94)	(0.06)	(−0.80)	(0.02)
D_CPI_t	−0.13	−0.17	−0.09	−0.37	−0.15	−0.36	−0.15	−0.38
	(−0.22)	(−0.28)	(−0.15)	(−0.60)	(−0.25)	(−0.60)	(−0.24)	(−0.62)
D_Def_t	−2.50	−1.63	−2.44	−2.16	−2.35	−2.15	−2.33	−2.28
	(−1.63)	(−1.10)	(−1.64)	(−1.44)	(−1.57)	(−1.47)	(−1.55)	(−1.55)
Adj. R^2	0.26	0.29	0.25	0.26	0.26	0.27	0.25	0.27
F-test: $Rev\_Disp_t + Interaction = 0$								
	20.76***	26.72***	25.65***	27.08***	29.19***	34.46***	25.60***	35.04***
				Panel B: Contemporaneous unemployment shocks				
Intercept	−0.01	−0.02	−0.02	−0.04	−0.02	−0.04	−0.01	−0.04
	(−0.44)	(−1.27)	(−0.75)	(−1.91)*	(−0.82)	(−1.81)*	(−0.39)	(−1.93)*
Rev_t	−0.10		−0.05		0.00		−0.04	
	(−1.73)*		(−1.15)		(0.04)		(−1.14)	
Unc_t		0.09		0.08		0.08		0.08
		(1.99)**		(2.29)**		(2.30)**		(2.43)**
$Rev\_ Disp_t$	6.25	8.02	4.89	5.38	5.28	6.28	5.53	6.01
	(1.84)*	(2.53)**	(1.35)	(1.64)	(1.40)	(1.79)*	(1.50)	(1.74)*
$Rev_t \times Rev\_Disp_t$	**22.26**		**20.98**		**15.14**		**18.42**	
	(**3.02**)***		(**3.06**)***		(**2.34**)**		(**2.86**)***	
$Unc_t \times Rev\_Disp_t$		**8.11**		**13.25**		**10.73**		**11.18**
		(**1.33**)		(**2.28**)**		(**1.90**)*		(**1.98**)**
D_GDP_t	−0.09	−0.09	−0.09	−0.07	−0.09	−0.08	−0.09	−0.08
	(−2.58)**	(−2.26)**	(−2.43)**	(−2.03)**	(−2.37)**	(−1.96)*	(−2.57)**	(−2.02)**
D_Cons_t	−0.01	−0.04	−0.02	−0.05	−0.03	−0.05	−0.02	−0.05
	(−0.25)	(−0.87)	(−0.51)	(−1.18)	(−0.74)	(−1.23)	(−0.54)	(−1.17)
D_Term_t	−0.03	−0.05	−0.04	−0.03	−0.04	−0.04	−0.03	−0.05
	(−0.84)	(−1.28)	(−0.90)	(−0.80)	(−0.88)	(−1.09)	(−0.86)	(−1.15)
D_Yield_t	0.10	0.03	0.12	0.03	0.11	0.01	0.11	0.03
	(0.96)	(0.27)	(1.18)	(0.35)	(1.01)	(0.13)	(1.07)	(0.32)
D_CPI_t	0.02	0.01	0.01	0.03	0.01	0.02	0.02	0.02
	(0.51)	(0.24)	(0.36)	(0.75)	(0.36)	(0.55)	(0.47)	(0.60)
$D\_ Def_t$	0.04	−0.06	0.02	−0.02	0.00	−0.03	0.01	−0.02
	(0.38)	(−0.64)	(0.17)	(−0.24)	(0.03)	(−0.27)	(0.13)	(−0.24)
Adj. R^2	0.30	0.28	0.30	0.32	0.27	0.30	0.30	0.30
F-test: $Rev\_Disp_t + Interaction = 0$								
	20.10***	9.77***	21.08***	15.82***	16.65***	15.96***	22.02***	16.04***

Table 6 (Continued)

	Quintile		Tercile		Median		Negative/Positive	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel C: Contemporaneous industrial production shocks				
Intercept	0.03	0.04	0.08	0.11	0.11	0.15	0.11	0.13
	(0.36)	(0.48)	(0.97)	(1.34)	(1.13)	(1.62)	(1.13)	(1.49)
Rev_t	0.25		0.09		−0.06		−0.02	
	(1.09)		(0.53)		(−0.37)		(−0.15)	
Unc_t		−0.05		−0.17		−0.27		−0.25
		(−0.27)		(−1.15)		(−1.98)*		(−1.80)*
Rev_Disp_t	−25.96	−28.22	−15.27	−14.98	−14.50	−23.88	−14.53	−22.50
	(−1.90)*	(−2.22)**	(−1.06)	(−1.15)	(−0.98)	(−1.71)*	(−1.00)	(−1.63)
$Rev_t \times Rev\_Disp_t$	**−59.10**		**−71.12**		**−58.69**		**−62.27**	
	(**−1.99**)**		(**−2.62**)**		(**−2.32**)**		(**−2.44**)**	
$Unc_t \times Rev\_Disp_t$		**−37.00**		**−63.73**		**−33.44**		**−36.92**
		(**−1.51**)		(**−2.77**)***		(**−1.49**)		(**−1.64**)*
D_GDP_t	0.59	0.56	0.55	0.49	0.54	0.52	0.55	0.52
	(4.02)***	(3.73)***	(3.82)***	(3.39)***	(3.68)***	(3.40)***	(3.81)***	(3.47)***
D_Cons_t	0.02	0.07	0.05	0.11	0.08	0.13	0.07	0.12
	(0.10)	(0.44)	(0.28)	(0.68)	(0.50)	(0.82)	(0.42)	(0.75)
D_Term_t	0.24	0.27	0.24	0.23	0.23	0.26	0.24	0.27
	(1.44)	(1.68)*	(1.48)	(1.46)	(1.44)	(1.64)	(1.49)	(1.67)*
D_Yield_t	−0.30	−0.17	−0.41	−0.17	−0.39	−0.05	−0.39	−0.11
	(−0.73)	(−0.41)	(−1.02)	(−0.45)	(−0.96)	(−0.13)	(−0.96)	(−0.29)
D_CPI_t	0.00	0.02	0.01	−0.06	0.01	−0.01	0.00	−0.02
	(0.03)	(0.11)	(0.05)	(−0.37)	(0.06)	(−0.06)	(0.01)	(−0.11)
D_Def_t	−0.63	−0.48	−0.61	−0.59	−0.56	−0.46	−0.58	−0.49
	(−1.55)	(−1.19)	(−1.57)	(−1.53)	(−1.41)	(−1.19)	(−1.48)	(−1.25)
Adj. R^2	0.36	0.36	0.38	0.40	0.38	0.38	0.38	0.38
F-test: $Rev\_Disp_t + Interaction = 0$								
	11.05***	9.93***	14.94***	18.01***	13.93***	11.48***	14.40***	12.00***

Notes. This table reports the contemporaneous relation between macroeconomic shocks and measures of firm-level and aggregate-level shocks using alternative cutoffs to measure aggregate uncertainty. The variable *Rev* is an indicator variable equal to one for the lowest quintile of aggregate earnings shocks for the "Quintile" partition, the lowest tercile for the "Tercile" partition, below the median for the "Median" partition, and below zero for the "Negative/Positive" partition. The variable *UNC* is an indicator variable equal to one for the highest quintile of economic policy uncertainty shocks for the "Quintile" partition, the highest tercile for the "Tercile" partition, above the median for the "Median" partition, and above zero for the "Negative/Positive" partition. All the remaining variables are defined in Table 1. Panel A reports the contemporaneous relation between investment shocks and firm-level and aggregate-level shocks. Panel B presents the contemporaneous relation between unemployment rate shocks and firm-level and aggregate-level shocks. Panel C presents the contemporaneous relation between industrial production shocks and firm-level and aggregate-level shocks. Bold numbers represent our key results.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

affect policy uncertainty but not firm-level uncertainty (or dispersion). Second, we examine the Sept. 11, 2001, terrorist attacks. We expect the attacks to affect policy and aggregate uncertainty, as the United States was considering how to deal with the implications of the event and future threats. In addition, since the attacks affected some industries more than others (e.g., airline and transportation), we expect dispersion and firm-level uncertainty to rise as well. Finally, we focus on the collapse of Lehman Brothers in 2008. We expect both aggregate uncertainty as well as firm-level uncertainty to rise following this event. The prospects of new financial regulations following the collapse increased policy uncertainty in 2008. Also, since firms vary in their sensitivity to shocks in the financial industry (e.g., real estate and housing, banks), we expect dispersion to rise following this event as well.

Consistent with our expectations, in untabulated results we find that only aggregate uncertainty rises following the Clinton election in 1992, while both aggregate uncertainty and firm-level uncertainty rise following the other two other shocks. In other words, Sept. 11 and the collapse of Lehman Brothers resulted in higher firm-level and aggregate-level uncertainty. By comparing the macroeconomic implications of these different shocks, we can examine how higher levels of both firm-level and aggregate-level uncertainty affect the economy, compared to how aggregate uncertainty alone affects macroeconomic activity. Our findings are consistent with our expectations where economic activity slows down more following shocks that increase both firm-level and aggregate-level uncertainty.

In addition to these shocks, in unreported results, we also examine China's accession to the World Trade Organization (WTO) in 2005. Consistent with Bloom et al. (2012), we find that dispersion increased following this event.[17] However, while dispersion increased following the event, aggregate uncertainty did not. Consistent with our hypothesis, China's accession to the WTO did not have significant adverse effects for U.S. macroeconomic activity. These findings, which are similar to those presented in Bloom et al. (2012), further show that the effects of uncertainty on macroeconomic activity are most pronounced when both firm-level and aggregate-level uncertainty are high simultaneously, because of their interactive effect.

4.4. Employing Normalized Variables

In our primary analysis, we use an indicator variable to measure aggregate uncertainty. As an alternative approach, we normalize the earnings dispersion, idiosyncratic volatility, and aggregate-level shocks, and then add a constant to ensure that both the firm-level and aggregate-level variables are positive. Thus, each variable as well as the interaction term is always positive. We then use the normalized variables when estimating models (5a), (5b), and (5c), capturing the full variation in each variable. Our findings using this approach are largely consistent with our primary results using the indicator variable. However, the standardized model is not intuitive to interpret. For brevity, we do not report these results.

5. Additional Analysis

5.1. The Interaction of Firm-Level and Aggregate-Level Shocks and Market Returns

Jorgensen et al. (2012) show that earnings dispersion has a strong association with aggregate stock returns. Specifically, they find a negative association between aggregate stock returns and the cross-sectional standard deviation of earnings changes. The negative association between aggregate stock returns and earnings dispersion is most pronounced between aggregate stock returns and future earnings dispersion. Their findings are consistent with the vast amount of firm-level evidence showing that information in prices leads earnings (e.g., Collins et al. 1987, Collins and Kothari 1989). Our findings in Tables 3–5 suggest that the relation between earnings dispersion and the macroeconomy is conditional on the state of the economy. Therefore, we extend the analysis in Jorgensen et al. (2012) to examine whether the relation between aggregate stock returns and future earnings dispersion is also conditional on the state of the economy. Since the relation between earnings dispersion and the macroeconomy is conditional on the state of the economy, we expect the relation between aggregate stock returns and earnings dispersion to depend on the state of the economy.

In untabulated analyses, we find that lower aggregate stock returns are associated with higher future dispersion in earnings, and that the relation between aggregate stock returns and future dispersion dominates the relation between aggregate stock returns and aggregate earnings growth. More importantly, the results from this analysis are consistent with the conclusions drawn from Tables 3–5. The relation between aggregate stock returns and future earnings dispersion is conditional on the state of the economy. The coefficient on the interaction term is negative and statistically significant. In addition, the explanatory power of the model increases when the interaction term is included. Taken together, these findings suggest that the surprising relation between aggregate stock returns and earnings dispersion is driven (at least in part) by the relation between earnings dispersion, the interaction of earnings dispersion and aggregate performance, and the macroeconomy.

5.2. Uncertainty and Macroeconomic Forecast Errors

In this section, we examine whether unemployment and industrial production absolute forecast errors are predicted by the interaction of firm-level and aggregate-level shocks.[18] Unemployment and industrial production forecast error data are obtained from the SPF.[19]

We hypothesize that our performance-based interaction terms also capture uncertainty. Therefore, we expect the absolute forecast errors to be positively associated with the interaction term, because forecasting is more difficult during periods of increased uncertainty. This test helps us validate that our interaction term is indeed a measure of uncertainty. Table 7 presents the relation between unemployment forecast errors and the interaction term. The results in the first two columns show that the interaction of firm-level dispersion and aggregate-level performance predicts macroeconomists' absolute forecast errors. The results in the third and fourth columns test whether our interaction term predicts absolute forecast errors related to

[17] We find that the increase in dispersion occurred largely in the third quarter of 2006.

[18] In a similar vein, Konchitchki and Patatoukas (2014a, b) show that aggregate earnings predict GDP forecast errors.

[19] The SPF does not forecast investment. Hence we restrict this analysis to unemployment and industrial production.

Table 7 Firm-Level and Aggregate-Level Shocks, and One-Quarter-Ahead Macroeconomist Absolute Forecast Errors

	$UNEMP\_AFE_{t+1}$		$IPROD\_AFE_{t+1}$	
Intercept	0.09	0.10	1.73	1.82
	(9.59)***	(9.51)***	(9.60)***	(0.52)
Rev_t	0.01	0.01	0.23	0.12
	(0.60)	(0.32)	(0.51)	(0.27)
Rev_Disp_t	−2.93	−3.17	2.76	−5.07
	(−1.75)*	(−1.83)*	(0.09)	(−0.17)
$Rev_t \times Rev\_Disp_t$	**6.41**	**6.09**	**154.02**	**126.32**
	(**2.01**)**	(**1.72**)*	(**2.61**)**	(**2.09**)**
D_GDP_t		−0.01		−0.61
		(−0.29)		(−1.93)*
D_Cons_t		−0.01		−0.52
		(−0.62)		(−1.51)
D_Term_t		0.02		0.32
		(1.23)		(0.94)
D_Yield_t		−0.03		−0.06
		(−0.63)		(−0.07)
D_CPI_t		0.00		−0.15
		(0.20)		(−0.44)
D_Def_t		0.03		1.34
		(0.65)		(1.57)
Adj. R^2	0.04	0.02	0.14	0.26
F-test: $Rev\_Disp_t + Rev_t \times Rev\_Disp_t = 0$				
	1.64	0.94	9.70***	5.58**

Notes. This table reports the relation between one-quarter-ahead macroeconomist absolute forecast errors and firm-level and aggregate-level shocks for 104 quarters from Q4:1985 to Q3:2011. *UNEMP_AFE* (*IPROD_AFE*) is the unemployment (industrial production) absolute forecast error. All forecast error data are obtained from the *Survey of Professional Forecasters*. Bold numbers represent our key results. All the variables are defined in Table 1.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

industrial production. We find that it predicts macroeconomists' absolute forecast errors. The positive relation between the interaction terms and the absolute forecast errors supports our conjecture that the performance based interaction term is also related to uncertainty about macroeconomic growth.

6. Conclusion

We examine the interaction between firm-level and aggregate-level shocks, and how it relates to overall macroeconomic activity. We examine two types of aggregate- and firm-level shocks—uncertainty shocks and performance shocks. We hypothesize and find that the interaction of firm-level and aggregate-level shocks explains a significant portion of the time-series variation in macroeconomic activity. Empirically, we document that the interaction of cross-sectional dispersion in earnings (dispersion) and aggregate earnings, the interaction of dispersion and the policy uncertainty index, and the interaction of idiosyncratic volatility and VIX, all explain a significant portion of the variation in aggregate investments, unemployment, and industrial production. Our study highlights the importance of examining aggregate shocks and firm-level shocks simultaneously when analyzing their relation with macroeconomic activity.

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References

Abraham KG, Katz LF (1986) Cyclical unemployment: Sectoral shifts or aggregate disturbances? *J. Political Econom.* 94(3): 507–522.

Anilowski C, Feng M, Skinner DJ (2007) Does earnings guidance affect market returns? The nature and information content of aggregate earnings guidance. *J. Accounting Econom.* 44(1–2): 36–63.

Baghestani H (2009) Survey evidence on forecast accuracy of U.S. term spreads. *Rev. Financial Econom.* 18(3):156–162.

Baker SR, Bloom N (2013) Does uncertainty reduce growth? Using disasters as natural experiments, NBER Working Paper 19475, National Bureau of Economic Research, Cambridge, MA.

Baker SR, Bloom N, Davis SJ (2015) Measuring economic policy uncertainty. NBER Working Paper 21633, National Bureau of Economic Research, Cambridge, MA.

Barry CB, Brown SJ (1985) Differential information and security market equilibrium. *J. Financial Quant. Anal.* 20(4):407–422.

Bloom N (2009) The impact of uncertainty shocks. *Econometrica* 77(3):623–685.

Bloom N (2014) Fluctuations in uncertainty. *J. Econom. Perspect.* 28(2):153–176.

Bloom N, Floetto M, Jaimovich N, Saporta-Eksten I, Terry SJ (2012) Really uncertain business cycles. NBER Working Paper 18245, National Bureau of Economic Research, Cambridge, MA.

Bonsall S, Bozanic Z, Fischer P (2013) What do management earnings forecasts convey about the macroeconomy? *J Accounting Res.* 51(2):225–266.

Campbell JY (1991) A variance decomposition for stock returns. *Econom. J.* 101(405):157–179.

Carhart M (1997) On persistence in mutual fund performance. *J. Finance* 52(1):57–82.

Caskey JA (2009) Information in equity markets with ambiguity-averse investors. *Rev. Financial Stud.* 22(9):3595–3627.

Collins DW, Kothari SP (1989) An analysis of intertemporal and cross-sectional determinants of earnings response coefficients. *J. Accounting Econom.* 11(2–3):143–181.

Collins DW, Kothari SP, Rayburn JD (1987) Firm size and the information content of prices with respect to earnings. *J. Accounting Econom.* 9(2):111–138.

Fama E, French K (1993) Common risk factors in the returns on stocks and bonds. *J. Financial Econom.* 33(1):3–56.

Ferson WE, Sarkissian S, Simin TT (2003) Spurious regressions in financial economics? *J. Finance* 58(4):1393–1414.

Gallo L, Hann R, Li C (2016) Aggregate earnings surprises, monetary policy, and stock returns. *J. Accounting Econom.* 62(1): 103–120.

Granger CWJ, Newbold P (1974) Experiencing with forecasting univariate time series and the combination of forecasts. *J. Royal Statist. Soc.* 137(2):131–165.

Hann RN, Ogneva M, Horacio S (2012) Forecasting the macroeconomy: Analysts versus economists. Working paper, University of Maryland, College Park.

Hosios AJ (1994) Unemployment and vacancies with sectoral shifts. *Amer. Econom. Rev.* 84(1):124–144.

Jorgensen B, Li J, Sadka G (2012) Earnings dispersion and aggregate stock returns. *J. Accounting Econom.* 53(1–2):1–20.

Konchitchki Y, Patatoukos PN (2014a) Accounting earnings and gross domestic product. *J. Accounting Econom.* 57(1):76–88.

Konchitchki Y, and Patatoukos PN (2014b) Taking the pulse of the real economy using financial statement analysis: Implications for macro forecasting and stock valuation. *Accounting Rev.* 89(2):669–694.

Kozeniauskas N, Orlik A, Veldkamp L (2014) Black swans and the many shades of uncertainty. Working paper, New York University, New York.

Lazear E, Spletzer J (2012) The U.S. labor market: Status quo or a new normal. NBER Working Paper 18386, National Bureau of Economic Research, Cambridge, MA.

Lilien DM (1982) Sectoral shifts and cyclical unemployment. *J. Political Econom.* 90(4):777–793.

Loungani P, Rush M, Tave W (1990) Stock market dispersion and unemployment. *J. Monetary Econom.* 25(3): 367–388.

Lucas RE, Prescott EC (1974) Equilibrium search and unemployment. *J. Econom. Theory* 7(2):188–209.

Nallareddy S, Ogneva M (2016) Predicting restatements in macroeconomic indicators using accounting information. *Accounting Rev.* Forthcoming.

Ogneva M (2013) Discussion of what do management earnings forecasts convey about the macroeconomy? *J. Accounting Res.* 51(2):267–279.

Shivakumar L (2007) Aggregate earnings, stock market returns and macroeconomic activity: A discussion of does earnings guidance affect market returns? The nature and information content of aggregate earnings guidance. *J. Accounting Econom.* 44(1–2): 64–73.

Shivakumar L, Urcan O (2014) Why do aggregate earnings shocks predict future inflation shocks? Working paper, London Business School, London.

Yule GU (1926) Why do we sometimes get nonsense—Correlations between time-series?—A study in sampling and the nature of time-series. *J. Royal Statist. Soc.* 89(1):1–63.