Conditional Earnings Dispersion, the Macroeconomy and Aggregate Stock Returns*

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Abstract

Prior studies document a robust relation between the equity premium and cross-sectional dispersion in firm-level earnings changes (earnings dispersion). We hypothesize that this relation is driven by an underlying relation between earnings dispersion and the macroeconomy (in particular, unemployment and industrial production). We further hypothesize that the relation between earnings dispersion and the macroeconomy is conditional on the state of the economy. Specifically, the adverse effects of earnings dispersion on the macroeconomy are exacerbated during periods of low aggregate earnings growth. Our results show that earnings dispersion and conditional dispersion relate to unemployment and industrial production as well as aggregate stock returns. Furthermore, we show that conditional dispersion predicts the forecast errors of economists who forecast unemployment and industrial production. Our results highlight that dispersion and conditional dispersion have separate, additive, relations with the macroeconomy.

JEL classification: E32, G12, G14, M41

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1 Introduction

Excluding frictions, cross-sectional dispersion in earnings should not affect aggregate stock prices because dispersion per-se does not affect aggregate earnings. Yet, several recent studies document that cross-sectional earnings dispersion (in both earnings changes and forecasted earnings) is significantly associated with aggregate stock returns (e.g., Ma (2011), Jorgensen, Li and Sadka (2012), Maio (2013) and Johnson and Lee (2014)).[1] This paper examines the relation between earnings dispersion and the macroeconomy to explain this phenomenon. First, we examine whether earnings dispersion is associated with macroeconomic conditions. Second, we test whether the relation between earnings dispersion and the macroeconomy is conditional on aggregate earnings. Finally, we test and find that the relation between aggregate stock returns and earnings dispersion is conditional on aggregate earnings.

While dispersion per-se should not be priced, prior studies suggest dispersion in performance has aggregate (undiversifiable) effects. Lucas and Prescott (1974) and Lilien (1982) develop the Sectoral Shift Theory, which suggests dispersion in performance results in increased unemployment. This occurs because employees need to migrate from poorly performing firms/sectors to better performing ones. Furthermore, labor market frictions delay employee migration across firms (and sectors), and increase unemployment levels in the interim.[2] Since employee migration increases with performance dispersions, dispersion results in increased unemployment. Earnings dispersion captures dispersion in performance. Therefore, the sectoral shift hypothesis suggests earnings dispersion is related to macroeconomic activity and thus should be priced.

The economics literature further tries to determine whether the main driver of unem-

[1] Maio examines dispersion in returns.

[2] The macroeconomics literature generally assumes unemployment is cyclical. That is, variation in employment is driven by aggregate shocks. In addition, a broad literature in economics develops the hypothesis that cross-sectional dispersion in sectors' demand for employees can generate aggregate unemployment. The sectoral-shifts hypothesis, developed by Lucas and Prescott (1974) and Lilien (1982), uses labor market frictions to develop the economic prediction that unemployment rises with dispersion in performance, as employees migrate from poor performing firms (sectors) to more productive firms (sectors). In other words, unemployment increases due to the time required for employees to retrain and/or find alternative employment. Several studies find evidence consistent with this prediction. For example, Lilien (1982) shows that dispersion in employment demands across sectors explains a large portion of unemployment shocks in the U.S. economy.

ployment is aggregate performance or dispersion in performance. However, this literature stream fails to study how these effects interact (Lilien (1982), Abraham and Katz (1986), and Hosios (1994), Lazear and Spletzer (2012)).[3] In other words, does aggregate performance and dispersion matter jointly, and does dispersion matter more during periods of poor performance? In this paper, we hypothesize that the relation between earnings dispersion and unemployment is conditional on aggregate profitability.

Intuitively, the effects of dispersion should depend on aggregate profitability. Earnings dispersion can generate unemployment as employees migrate from less successful to more successful firms. We further hypothesize that potential employees likely experience a more difficult migration process when the economy is contracting. This is because employers, including the more successful ones, are less profitable and are more cautious about hiring new employees during a contraction. In contrast, the migration of employees should be smoother and more rapid during growth periods, when employers are more likely to grow their workforce.

For example, consider a growing economy where all firms are growing and unemployment is consequently declining. Dispersion would cause some sectoral shifts, but the shifts could happen more gradually with fewer frictions. Since firms are less likely to reduce their labor force during such periods, individual employees (currently employed) will "shift" only when the frictions in the labor market are relatively small, thus not increasing unemployment. Also, new employees entering the market will find it easier to gain employment, due to the increased amount of growing firms. In contrast, during a contraction, firms reduce their labor force and force employees to shift across employers in periods where frictions in the labor market are high. Thus, these shifts will exacerbate the level of unemployment. Therefore, we predict that the effects of dispersion in earnings (performance) on unemployment depend on aggregate profitability.

The theory relating dispersion and industrial production is similar in essence to the sectoral shift hypothesis. More specifically, resources are reallocated from firms with lower

[3] Loungani, Rush and Tave (1990) find that dispersion in stock prices is associated with higher unemployment.

productivity to firms with higher productivity, and the potential for reallocation is greater during periods with higher dispersion in productivity. However, frictions slow down this process which leads to temporary resource misallocation and lower output levels.[4] The loss in aggregate output due to such misallocation can be economically significant (Hsieh and Klenow 2009). Further, Bloom et al. (2012) argue that dispersion in productivity impedes economic activity specifically during periods of increased performance uncertainty. Uncertainty impedes investments in, and the reallocation of resources to, more productive sectors/firms. Since capital is not reallocated efficiently as a result, capital is applied less efficiently which results in slower growth or a decline in industrial production. Following this logic, we hypothesize that the effects of dispersion on industrial production increase during periods of poor performance when performance uncertainty tends to increase (e.g., Barry and Brown (1985)). In sum, we predict both earnings dispersion, and conditional dispersion to be negatively related to industrial production.

This paper employs two different measures of aggregate profitability and cross-sectional earnings dispersion. First, we employ aggregate earnings changes and cross-sectional dispersion in earnings changes, scaled by beginning of period stock prices. Second, we employ analyst forecasts to generate measures of aggregate forecast revisions and cross-sectional dispersion in firm-level forecast revisions. We employ both measures to ensure that we have both contemporaneous and forward looking profitability measures. Our prior is that since analyst forecasts are forward looking we expect analyst forecast dispersion to predict variations in macroeconomic activity whereas earnings dispersion may not.

We begin our empirical analysis by examining the contemporaneous relation between our macroeconomic indicators, our two measures of aggregate profitability, and cross-sectional dispersion in performance. Consistent with economic theory, we find that our measures of cross-sectional dispersion in firm-level performance are associated with higher levels of unemployment and lower industrial production. To test the conditional relation between dispersion and the macroeconomy, we add an interaction term related to aggregate profitability and earnings dispersion. Consistent with our predictions, we find that the effects of

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

dispersion are more pronounced in periods with low aggregate profitability. Moreover, the explanatory power of the model increases significantly when we add the interaction term. To strengthen our main findings, we identify a setting where the migration of employees and capital is more difficult, and test whether the effects of dispersion and conditional dispersion are stronger in this setting. More specifically, employees are likely to find it more difficult to migrate across industries, than to migrate across similar firms in the same industry. Consistently, we find that the marginal effect of industry-level dispersion and conditional dispersion on unemployment is approximately twice as large as the effect of firm-level dispersion. We find similar results with respect to the marginal effect of industry-level dispersion and conditional dispersion on industrial production. Our results also hold after controlling for measures of aggregate uncertainty, including VIX and the economic policy uncertainty index (Baker et. al 2014). These results suggest that the effects of earnings dispersion and conditional dispersion are incremental to market and economic policy uncertainty.

In addition to the contemporaneous association, we also examine the relation between future macroeconomic indicators, cross-sectional dispersion, and conditional dispersion. The relation between future macroeconomic indicators and conditional dispersion is only present when we employ analyst forecast revisions to estimate aggregate profitability and dispersion but not when seasonally adjusted earnings are employed. These findings are consistent with the notion that analyst based measures are more forward looking, while accounting income is an important statistic related to the state of the economy, but not a timely one.

We build on the above findings to shed light on the relation between cross-sectional earnings dispersion and aggregate stock returns. We examine whether the relation between earnings dispersion, conditional dispersion, and the macroeconomy help explain the robust relation between earnings dispersion and stock returns. We show that lower aggregate stock returns are associated with higher future dispersion in earnings, and forecasts of earnings. We further document that the relation between aggregate stock returns and future dispersion dominates the relation between aggregate stock returns and aggregate earnings growth. More importantly, we find that the relation between aggregate stock returns and future earnings dispersion is conditional on the state of the economy. Since earnings dispersion is associated with higher unemployment and lower industrial production during periods of low aggregate earnings, we find that investors react more negatively to expected earnings dispersion when they expect lower aggregate earnings in the economy. Thus, our findings suggest that economic theories such as the sectoral shift theory help explain, at least in part, the somewhat surprising relation between earnings dispersion and aggregate stock returns.

Our findings have a somewhat surprising implication for the relation between dispersion and macroeconomic indicators (unemployment and industrial production in particular). Prior studies such as Lilien (1982) and Jorgensen, Li and Sadka (2012) focus on dispersion and find that performance dispersion is related to the macroeconomy and aggregate stock returns. Our findings imply that the relation between dispersion and the macroeconomy is driven largely by periods of lower aggregate productivity. Once conditional dispersion is included in the model, the relation between dispersion and both unemployment and industrial production becomes largely insignificant. Thus, our findings imply that the effects of dispersion are not just exacerbated during recessions, but rather the effects of dispersion occur predominantly during periods of low economic growth. Absent poor economic growth, dispersion has little effect on the unemployment rate and industrial production. The results in this paper highlight the importance of conditional dispersion rather than dispersion per se as it relates to unemployment and industrial production.

Finally, we examine whether macro economists incorporate the predictive relation between conditional dispersion and macroeconomic activity into their forecasts. We find that conditional dispersion predicts macroeconomists' forecast errors. Further, adding conditional dispersion to the predictive model increases the predictive ability of the specification substantially.

Our paper also extends the literature showing that accounting information is useful to understand and predict macroeconomic indicators. Much of the existing evidence suggests that aggregate earnings contain macroeconomic information (e.g., Anilowski et al. 2007; Shivakumar, 2007; Kothari et al. 2013; Hann et al. 2012; Bonsall et al. 2013; Ogneva, 2013) and that aggregate earnings predict the Fed's future monetary policy (Gallo et al. 2013). 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. Furthermore, economic theory suggests the mechanisms through which earnings dispersion and conditional dispersion relate to the macroeconomy are distinct from the mechanisms that link aggregate earnings to macroeconomic activity. Our results support this notion and show that dispersion and conditional dispersion have separate, additive, relations with the macroeconomy.

One caveat of our study is the disconnect between the causal inference the theories imply and the associative nature of our empirical analysis. Specifically, the theories imply that dispersion is causally associated with unemployment and industrial production. For example, higher dispersion causes short-run unemployment. However, our empirical analyses cannot determine causality. We are only able to demonstrate an association between dispersion, conditional dispersion and unemployment. As we lack an instrumental variable to empirically document causality, we leave this important extension to future research.

The rest of the paper is organized as follows. Section 2 describes our hypotheses. Section 3 discusses our sample selection procedures and variable measurement. Section 4 presents our main empirical results. Section 5 concludes.

2 Hypotheses

While there are many macroeconomic indicators that may be related to dispersion and conditional dispersion, we limit our analysis to unemployment and industrial production. We do so because there are well developed theories in economics that suggest causal links between dispersion and both unemployment and industrial production. In what follows we outline these theories and our hypotheses.

2.1 Sectoral Shifts and Unemployment

It is well documented and known that employment varies with the business cycles. Specifically, unemployment rises in recession and declines in growth periods. Since recession are periods with lower sales and profits, firms reduce their workforce to cut costs as they require less employees to generate sales. In contrast, during growth periods both profits and sales grow and firms increase their workforce in order to meet higher demand. As noted, this relation between unemployment and the business cycle is largely accepted and well known.

In addition to business cycles, economist have long recognized that sectoral shifts are one of the main drivers of unemployment. The underlying cause for unemployment under this theory is frictions in the labor market. These frictions include job training, education, geographical distance and search costs among others. These frictions are the main reason why economists consider a four to six percent unemployment rate as full employment as opposed to a zero unemployment rate. Since employees take time to migrate across employers, sectors and geographical locations, unemployment will always occur even in periods where there is sufficient demand for employees.

Lucas and Prescott (1974) and Lilien (1982) develop and empirically test the Sectoral Shift Theory. The theory stipulates that migration will increase and become more costly when employees need to migrate across sectors. Specifically, consider an economy with two sectors. One sector is growing and the other contracting. Thus, employees will have to migrate from the poor performing sector (as it requires less employees over time) to the growing (more productive) sector. Because frictions in the labor market exist, this migration will take time resulting in unemployment (at least in the short-run). Moreover, when employees need to migrate across sectors, frictions in the labor market are exacerbated. For example, it takes longer to locate and train employees when they move across sectors compared to migration within an industry/sector. Thus, dispersion in the performances of sectors will result in unemployment as employees migrate from poor performing to better performing sectors. Lilien (1982) provides evidence which suggests that sectoral shifts rather then business cycles are the primary drivers of unemployment.

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), and Hosios (1994), Lazear and Spletzer (2012)). However, this literature fail to examine how these two effects interact. In this paper, we argue and present supporting evidence for the idea that the effects of dispersion increase during periods of poor economic growth. This is because employers are generally more reluctant to hire during such periods. Hence, employee migration during periods of poor economic growth will take longer, and such lengthy migration results in higher levels of unemployment. In addition, during recessions, poor performing employers are more likely to lay off employees due to low and perhaps negative profits resulting in more employees searching for employment in other firms/sectors. In contrast, in growth periods, even the declining sectors could be performing adequately and the growth sectors will be recruiting aggressively. Thus, it is not clear that sectoral shifts and employee migration will result in high unemployment during growth periods. In sum, we expect the implications of dispersion to be exacerbated during periods of poor economic growth.

2.2 Dispersion and Industrial Production

The theory relating dispersion and industrial production is similar to the sectoral shift hypothesis. Specifically, resources are reallocated from low productivity firms to high productivity firms, and the potential for reallocation increases when dispersion in productivity is higher. However, frictions slow down this process which leads to a temporary misallocation of resources and lower output levels. The loss in aggregate output due to the misallocation of resources can be economically significant (Hsieh and Klenow 2009). Bloom et al. (2012) argue that dispersion in productivity impedes economic activity during periods of increased performance uncertainty. Since some firms/sectors are performing better than others, capital (including physical capital) needs to migrate to more productive firms/sectors. However, dispersion in performance adds uncertainty to the process and slows the migration process. Since migration is slowed, the productivity of the physical capital declines, resulting in lower industrial production. Also, retooling equipment and transferring it to a different firm/sector is a lengthy process, which may result in idle equipment in the short-run. Thus, dispersion in performance and productivity can results in lower levels of industrial production.

As with the case of unemployment, we expect the implications for dispersion on industrial production to be more pronounced in periods of slow economic growth. This is because uncertainty about productivity increases during periods of poor economic growth. This increased uncertainty results in a slower migration of capital and equipment across firms and sectors resulting in lower industrial production. As we note below, our findings indeed demonstrate that the effects of dispersion on industrial production are more pronounced during periods of poor economic growth.

3 Sample Selection and Variable Measurement

3.1 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 percent of observations when calculating aggregate earnings and revision measures.

Macroeconomic data are collected from the Federal Reserve Bank of St. Louis. The quarterly average unemployment data (averaged over 3 months) is based on 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: Bureau of Labor Statistics). The quarterly average industrial production data (averaged over 3 months) is based on 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). Unemployment and industrial production forecast error data is obtained from the Survey of Professional Forecasters (SPF).[5]

3.2 Estimating Aggregate Earnings Shocks, Earnings Dispersion Shocks, and Conditional Earnings Dispersion Shocks

We employ both a seasonal random walk model and analyst forecasts to measure earnings shocks. Each of these approaches has advantages and limitations. The seasonal random walk model can be estimated for a larger cross-section of firms, but earnings expectations and shocks are estimated using historical information and are not timely. In contrast, analyst forecasts are forward looking and timely, but may not depict investors' expectations of future earnings accurately and are subject to analyst forecasting biases.

When utilizing actual earnings, we estimate aggregate earnings shocks in three steps. First, we estimate the seasonal random walk model for each firm, at the end of each quarter, as follows:

$$UE_{i,t} = \frac{(X_{i,t} - X_{i,t-4})}{P_{i,t-1}} \tag{1}$$

where X_{it} is realized earnings for firm i in quarter t, X_{it-4} is realized earnings for firm i in quarter $t-4$, and P_{it-1} is the price per share for firm i at the end of quarter $t-1$. Second, we estimate aggregate earnings changes for each quarter as the equally weighted average of firm-level earnings changes:

$$AggEar_t = \frac{1}{N}\sum_{i=1}^{N_t}(UE_{i,t}) \tag{2}$$

where $AggEar_t$ is the aggregate earnings change for quarter t, and is the number of eligible firms (common stocks) during that quarter. Third, because aggregate changes in earnings are more persistent than at the firm level, we use the following AR (2) model to

[5] http://www.phil.frb.org/research-and-data/real-time-center/survey-of-professional-forecasters/

estimate the aggregate earnings shock:

$$AggEar_t = \rho_0 + \rho_1 \cdot AggEar_{t-1} + \rho_2 \cdot AggEar_{t-2} + e_t \tag{3}$$

e_t is the aggregate earnings shock for quarter t.[6] Finally, we convert aggregate earnings shocks into a binary variable (Ear_t). Specifically, aggregate earnings 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]

To estimate aggregate earnings dispersion, we estimate the seasonal random walk model as described in step 1 above. Next, we estimate earnings dispersion as the standard deviation of earnings in a quarter as follows:

$$AggDis_t = \sqrt{\frac{1}{N} \sum_{i=1}^{N_t} \left(UE_{i,t} - AggEar_t\right)^2} \tag{4}$$

where $AggDis_t$ is the aggregate dispersion for quarter t, $AggEar_t$ is the aggregate earnings for quarter t, and is the number of firms (eligible common stocks) during that quarter. Finally, to isolate the non-persistent component in aggregate dispersion, we employ an AR (2) model, similar to equation (3) above. The AR (2) residual is the proxy we use to measure aggregate earnings dispersion shocks ($Earn\_Disp$).[8]

Conditional earnings dispersion equals the interaction between aggregate earnings shocks and aggregate earnings dispersion shocks. We convert the aggregate earnings shock variable into a binary variable (as described above). We do this because both dispersion shocks and aggregate earnings shocks can obtain positive and negative values, which in turn

[6] The AR (1) coefficient of the aggregate earning shock (e_t) is -0.02, and statistically insignificant (t-value -0.20), suggesting that the AR(2) process does a good job of isolating e aggregate earnings shocks.

[7] The main results are robust to alternative classifications of aggregate earnings shocks. Specifically, results are robust to tercile, quintile, and decile cut-offs.

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

affect the sign of the interaction term.

		Sign of Earnings Dispersion Shock	
		+	-
Sign of Aggregate Earnings Shocks	+	+	-
	-	-	+

The table above illustrates how the sign of both aggregate earnings shocks, and aggregate dispersion shocks, affect the sign of the interaction term (the four lower right hand cells). This relation creates a problem when trying to employ a simple interaction term. A positive shock to both aggregate earnings and earnings dispersion, and a negative shock to both aggregate earnings and earnings dispersion, both result in positive sign for the interaction term. However, the two scenarios are economically different. To address this issue, we convert the aggregate earnings shock variable into a binary variable. Thus, the aggregate earnings measure is always non-negative, and the interaction term will not have the same sign in the two scenarios described above. In our empirical models, we include aggregate GDP as an additional continuous control variable for the aggregate state of the economy. This variable is added to ensure that our results are not driven by the use of a binary variable to measure aggregate earnings.

3.3 Estimating Aggregate Revisions, Revision Dispersion, and Conditional Revision Dispersion Shocks

When utilizing analyst forecasts to measure earnings shocks and dispersion shocks, we repeat the process described above with one exception. In place of $UE_{i,t}$ (constructed using the seasonal random walk model), we use revisions to the one-year-ahead earnings expectations, deflated by beginning of the quarter price, that occur during the current quarter:

$$rev^{t}_{i,s+1} = \left(\frac{E_t\left(earn_{i,s+1}\right) - E_{t-1}\left(earn_{i,s+1}\right)}{P_{i,t-1}} \right) \tag{5}$$

$rev^{t}_{i,t+1}$ is the revision during quarter t to the year $s+1$ (one-year-ahead) median analyst forecast for firm i. s is the current year, 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 $t-1$. We then estimate $AggREV_t$, e_t, Rev_t, $AggDis_t$ (based on revisions), and dispersion shocks based on revisions (Rev_Disp) as described above, utilizing $rev^{t}_{i,s+1}$ in place of $UE_{i,t}$.[9]

3.4 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 the precision of the predictions as well as the forecast errors. Therefore, in addition to the signed forecast errors, we examine absolute forecast errors. The forecast error is estimated as follows:

$$FE = Actual_{q+1} - Forecast^{q+1}_{q} \tag{6}$$

where FE equals the forecast error, $Actual_{q+1}$ is the realized macroeconomic value released in quarter $t+1$, and $Forecast^{q+1}_{q}$ is the consensus SPF forecast of the macroeconomic variable, based on the median forecast for quarter $t+1$, as of quarter t. The absolute forecast errors are defined as follows:

$$AFE = \left| Actual_{q+1} - Forecast^{q+1}_{q} \right|$$

Where AFE equals the absolute forecast error (Baghestani, 2009).

[9] 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.

3.5 De-trending of Key Variables

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 auto correlations. Macroeconomic variables are highly persistent, as are aggregate earnings and dispersion measures.

To overcome the spurious regression bias, Campbell (1991) and Ferson et al. (2003) suggest stochastic de-trending 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 the variables: unemployment, industrial production, aggregate earnings, earnings dispersion, aggregate revision, and revision dispersion. We then employ the residuals from the AR(2) models in our analysis. This should alleviate concerns related to the spurious regression bias.

3.6 Descriptive Statistics

Table 1 presents descriptive statistics for the macro and aggregate earnings variables. Our sample includes 105 quarters from the 4^{th} quarter of 1985 up to and including the 4th quarter of 2011. The mean values of the macro and earnings based variables are zero by construction, as these estimates are residuals from various AR (2) specifications. More specifically, the mean values of unemployment shocks (D_Unemp_t), industrial production shocks (D_Iprod_t), earnings dispersion shocks (Ear_Disp_t), hereafter earnings dispersion, and revision dispersion shocks (Rev_Disp_t), hereafter revision dispersion, are zero. The median dispersion measures have negative values, while the median unemployment and industrial production shocks are zero. One-quarter-ahead mean and median unemployment forecast errors are negative. That is, unemployment forecasts are higher than their realizations. This evidence suggests that unemployment forecasts are optimistic. Industrial production forecast errors are on average negative but the median forecast error is positive. Therefore, unlike unemployment forecasts, we do not observe any optimism in industrial production forecasts. This evidence is consistent with findings in prior literature that show macro forecasts are not systematically optimistic (Hann et al. 2012).

4 Empirical Results

4.1 Conditional Dispersion and Contemporaneous Macroeconomic Shocks

We begin our empirical analysis by examining the relation between dispersion, conditional dispersion and macroeconomic conditions. Specifically, we test whether dispersion and conditional dispersion is associated with unemployment shocks. We estimate the following time-series regression model for each of our macroeconomic indicators.

$$\begin{aligned} D\_Unemp_t \quad = \quad & \beta_0 + \beta_1 \cdot Ear_t + \beta_2 \cdot Ear\_Disp_t + \beta_3 \cdot [Ear_t \cdot Ear\_Disp_t] \\ & + \beta_4 \cdot [D\_GDP_t] + \beta_5 \cdot [D\_Cons_t] + \beta_6 \cdot [D\_Term_t] \\ & + \beta_7 \cdot [D\_Yield_t] + \beta_8 \cdot [D\_Inf_t] + \beta_9 \cdot [D\_Def_t] + \varepsilon_t \end{aligned} \tag{8a}$$

where D_Unemp_t equals the residuals from an AR (2) model of quarterly unemployment rates in percentages. Ear_t is an aggregate earnings dummy equal to one for the lowest quartile of aggregate earnings shocks, and Ear_Disp_t measures earnings dispersion using the residuals from an AR(2) model of aggregate dispersion, as defined in Section 2. To control for the contemporaneous macroeconomic information, we add the following macroeconomic variables to the specification: D_GDP is the AR (2) residual of seasonally adjusted quarterly real gross domestic product; D_Cons 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 3-Month treasury bill secondary market rate); D_Yield is the AR(2) residual of change in yield spread (Effective Federal Funds Rate minus 3-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_Inf is the AR (2) residual of seasonally adjusted quarterly consumer price index.

In an alternative specification, we replace the earnings based measures with the forecasts revision based measures described in Section 2, and estimate the following model:

$$\begin{aligned} D\_Unemp_t &= \beta_0 + \beta_1 \cdot \mathrm{Re}\, v_t + \beta_2 \cdot \mathrm{Re}\, v\_Disp_t + \beta_3 \cdot [\mathrm{Re}\, v_t \cdot Ear\_Disp_t] \\ &\quad + \beta_4 \cdot [D\_GDP_t] + \beta_5 \cdot [D\_Cons_t] + \beta_6 \cdot [D\_Term_t] \\ &\quad + \beta_7 \cdot [D\_Yield_t] + \beta_8 \cdot [D\_Inf_t] + \beta_9 \cdot [D\_Def_t] + \varepsilon_t \end{aligned} \tag{8b}$$

Where Rev is an aggregate earnings dummy equal to one for the lowest quartile of aggregate forecast revisions shocks, and Rev_Disp measures revision dispersion shocks using the residuals from an AR(2) model of aggregate revision dispersion.

Our predictions are as follows. 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, i.e., $\beta_2 > 0$. Finally, 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, i.e., $\beta_3 > 0$. In other words, the adverse effects of dispersion on employment are exacerbated during periods of low or negative economic growth.

The univariate results presented in Table 2 are consistent with our expectations. First, unemployment shocks and aggregate profitability (indicator variable) are positively associated with a Pearson (Spearman) correlation of 0.32 (0.31). That is, unemployment shocks are higher during periods of lower aggregate profitability. Second, unemployment shocks are also positively correlated with earnings dispersion, consistent with our predictions. Finally, unemployment shocks are positively correlated with conditional earnings dispersion. Specifically, the Pearson correlation between unemployment shocks and conditional earnings dispersion is 0.43. Table 2 also provides univariate evidence using analyst forecast revisions to measure earnings shocks. Similar inferences are drawn using the analyst forecast based measures.

The multivariate results are presented in Table 3. Panel A presents the results using the earnings based measures, while Panel B presents the results using the revision based measures. Consistent with our predictions, the coefficient on aggregate earnings is positive. The relation is robust to our alternative earnings shocks measures. Specifically, the coefficient estimates for the aggregate earnings dummy ranges from 0.08 to 0.15 across the Panels. This result suggests that periods with negative aggregate earnings shocks (in the bottom quartile) have higher unemployment shocks. These results are statistically significant at conventional levels. These findings are consistent with the considerable amount of prior evidence which demonstrates that unemployment rises during periods of low economic growth (e.g., Abraham and Katz (1986)). Aggregate earning shocks explain 2-10 percent of the variation in unemployment shocks.

The results in column (2) also are consistent with the arguments presented in Lilien (1982). On its own, dispersion explains approximately 5-16 percent of the shocks to unemployment. Including aggregate earnings or revisions and dispersion together increases the explanatory power of the model. Specifically, the R-squared in column (3) increases weakly to 12-16 percent depending on the measure of earnings shocks employed. This evidence suggests that aggregate earnings and earnings dispersion together do a better job of explaining unemployment shocks, relative to each measure independently.

Finally, the results in column (4) 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 in both models. More importantly, conditional dispersion explains an additional 9-13 percent of the variation in unemployment, increasing the R-squared to 25% in both panels. This evidence highlights the importance of the relation between dispersion and aggregate performance when explaining unemployment shocks.

The increase in R-squared is the key takeaway from Table 3. However, one puzzling result is the change in sign for the coefficients related to Ear_Disp and Rev, once conditional dispersion is introduced into the regression. While we do not have an explanation for this result, we note that it only occurs in Table 3. The signs of the coefficients do not change at statistically significant levels when examining industrial production or industry level dispersion (discussed below). Thus, we do not believe this is a robust result.

To examine the relation between cross-sectional dispersion, conditional dispersion and industrial production, we employ the following specifications:

$$\begin{aligned} D\_Iprod_t &= \gamma_0 + \gamma_1 \cdot Ear_t + \gamma_2 \cdot Ear\_Disp_t + \gamma_3 \cdot [Ear_t \cdot Ear\_Disp_t] \\ &\quad + \gamma_4 \cdot [D\_GDP_t] + \gamma_5 \cdot [D\_Cons_t] + \gamma_6 \cdot [D\_Term_t] \\ &\quad + \gamma_7 \cdot [D\_Yield_t] + \gamma_8 \cdot [D\_Inf_t] + \gamma_9 \cdot [D\_Def_t] + \varepsilon_t \end{aligned} \tag{9a}$$

$$\begin{aligned} D\_Iprod_t &= \gamma_0 + \gamma_1 \cdot \mathrm{Re}\, v_t + \gamma_2 \cdot \mathrm{Re}\, v\_Disp_t + \gamma_3 \cdot [\mathrm{Re}\, v_t \cdot Ear\_Disp_t] \\ &\quad + \gamma_4 \cdot [D\_GDP_t] + \gamma_5 \cdot [D\_Cons_t] + \gamma_6 \cdot [D\_Term_t] \\ &\quad + \gamma_7 \cdot [D\_Yield_t] + \gamma_8 \cdot [D\_Inf_t] + \gamma_9 \cdot [D\_Def_t] + \varepsilon_t \end{aligned} \tag{9b}$$

where we replace D_Unemp_t with D_Iprod_t, in equation (8)(a) / (8)(b) respectively. D_Iprod_t equals the residual from an AR (2) model of quarterly industrial production growth, expressed in percentages (also defined in Section 2).

We expect to find a negative coefficient on aggregate earnings shocks, $\gamma_1 < 0$. A negative coefficient implies that industrial production is lower when aggregate profitability is lower. We also expect high levels of dispersion to decrease industrial production, such that $\gamma_2 < 0$. Finally, we hypothesize the effects of dispersion are conditional on the state of the economy, and that the impact of dispersion on industrial production decreases when aggregate profitability is lower. Therefore, we expect the coefficient on the interaction term to be negative, i.e., $\gamma_3 < 0$. In other words, the adverse effects of dispersion on industrial production are exacerbated during periods of low expected economic growth.

Table 2 presents univariate correlations between industrial production, aggregate earnings, and the dispersion measures. These correlation coefficients are consistent with our expectations. Industrial production shocks and aggregate profitability (indicator variables) is negatively associated. The correlation coefficient ranges from -0.17 to -0.26 depending on the type of the correlation and earnings shock measure employed. Industrial production shocks are also negatively correlated with earnings dispersion. Finally, industrial production shocks are negatively correlated with conditional earnings dispersion. These results are robust to the use of our alternative earnings measures.

The multivariate regression results presented in Table 4 provide further evidence consistent with our predictions. The coefficient on aggregate earnings shocks in column (1) is negative across both panels. Aggregate earnings explain 4-5 percent of the variation in industrial production shocks. Next, we examine the relation between dispersion and industrial production. In column (2) we show that dispersion explains approximately 7-14 percent of the shocks to industrial production. Furthermore, including aggregate earnings or forecasts revisions and dispersion together (column (3)) increases the explanatory power of the model. Specifically, the R-squared increases weakly to between 9-14 percent depending on the measure of earnings shocks used. This evidence suggests that aggregate earnings shocks and dispersion jointly explain industrial production shocks better than each measure individually.

The results in Table 4 are also consistent with our hypothesis that the effects of dispersion on industrial production are conditional on the state of the economy. The coefficient on the interaction term in column (4) is negative and statistically significant in both models.

Furthermore, conditional dispersion explains an additional 5-6 percent of the variation in industrial production shocks. This evidence also highlights the importance of the relation between aggregate earnings shocks and dispersion in understanding industrial production shocks.

Finally, in Tables 3 and 4, the specification in column (5) includes the various macroeconomic control variables. Including these control variables adds to the explanatory power of the model. For example, in Table 3 Panel A, the adjusted R^2 increases by 4% when we include the control variables. Not surprisingly, real GDP growth has a significant association with unemployment and industrial production. While the control variables add to the explanatory power of the model, they do not significantly alter the relation between conditional dispersion and the macroeconomy. These findings suggest that the observed relation between conditional dispersion and the macroeconomy is not attributable to prior known factors.

In sum, our measures of cross-sectional dispersion in firm-level performance are associated with lower levels of macroeconomic activity (unemployment and industrial production shocks). Furthermore, we find that the effects of dispersion are more pronounced in periods with low aggregate profitability. Therefore, the addition of an interaction between aggregate earnings shocks and earnings dispersion substantially improves our understanding of how earnings dispersion relates to the macroeconomy.

4.2 Industry-Level Analysis

Our hypotheses suggest that the effects of dispersion and conditional dispersion are heightened when the migration of employees and capital is more difficult. More specifically, employees are likely to find it more difficult to migrate across industries than to migrate across similar firms in the same industry. Thus, we expect the marginal effect of industry-level dispersion and conditional dispersion to be larger than that of firm-level dispersion.

To test our prediction, we construct industry-level measures of dispersion and conditional dispersion. Industry-level dispersion is estimated as follows: (1) Every quarter, firms are assigned to one of 38 industries according to the classification in Professor Kenneth French's website; (2) Each quarter, industry-level analyst based earnings revisions are computed, defined as the equally-weighted average of all firm-level analyst based earnings revisions in an industry; (3), The standard deviation of the industry-level revisions (from step 2) is estimated, and defined as industry-level revision dispersion; (4) Our final measure of industry dispersion is estimated as the residual from an AR (2) model of the industry-level revision dispersion from step (3).

The results for the industry based analysis are reported in Table 5. The results in Table 5 are consistent with our hypotheses. Specifically, the marginal effect of dispersion at the industry level is significantly larger than the marginal effect of dispersion at the firm level. In Table 5, Panel A (column (3)), the coefficient for dispersion is 33.25. This is compared to a coefficient of 13.44 in Table 3, Panel B (column (3)). In Table 5, Panel A (column (4)), the coefficient for conditional dispersion is 55.05. This is compared to a coefficient of 24.46 in Table 3, Panel B (column (4)). Thus, the marginal effect of industry-level dispersion on unemployment is approximately twice as large as the effect of firm-level dispersion. We find similar results with respect to industrial production. The marginal effect of industry-level dispersion on industrial production is approximately twice as large as the effect of firm-level dispersion. In untabulated analyses, we find similar results using earnings changes instead of analyst revisions to calculate dispersion, and draw the same inferences.

4.3 Conditional Dispersion and Market Returns

As we note above, Jorgensen, Li and Sadka (2012) show that earnings dispersion has a strong association with aggregate stock returns. 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, Kothari and Rayburn (1987), Collins and Kothari (1989)). Our findings in Tables 2-4 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, Li and Sadka (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 as well.

The results in Table 6 are consistent with those reported in Jorgensen, Li and Sadka (2012). The negative coefficient on EAR_{t+1} implies that higher contemporaneous stock returns are associated with higher future earnings. We also find that stock returns predict future forecast revisions. As for dispersion, our findings are also consistent with Jorgensen, Li and Sadka (2012). We show that lower aggregate stock returns are associated with higher future dispersion in earnings, and forecasts of earnings (column (2)), and that the relation between aggregate stock returns and future dispersion dominates the relation between aggregate stock returns and aggregate earnings growth (column (3)).

More importantly, the results in Table 6 are consistent with the conclusions drawn from Tables 2-4. 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 conditional dispersion is included. For example, in Panel A when using earnings rather than forecasts, the explanatory power increases from 12% to 16%. 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 and the macroeconomy.

4.4 Conditional Dispersion and Future Macro Shocks

In this section, we examine the predictive relation between future (one quarter ahead) macroeconomic shocks and current aggregate profitability and dispersion measures. It is important to note that since all of the variables employed in the regression are residuals form various AR (2) models (see Section 2), this analysis is not likely to be affected by the spurious regression bias identified in the economics and finance literature (e.g., Yule (1926); Granger and Newbold (1974); Ferson et. al (2003)). Furthermore, we focus on the revision based variables in this analysis because they are forward looking in nature, and are more likely to predict future macroeconomic activity.

Table 7 reports results for the predictive regression models of future macroeconomic shocks on current profitability and revision dispersion. Panel A (B) reports results for the predictive regression of one-quarter-ahead unemployment shocks (industrial production shocks). Conditional dispersion predicts both unemployment and industrial production shocks. In untabulated analysis, we do not find any predictive evidence using the seasonal random walk model to measure earnings shocks. These findings are consistent with analyst-based measures being more forward looking.

In column (5), we include the additional macroeconomic control variables. These variables add significant predictive ability to the model. The explanatory power of the model increases significantly for both industrial production and unemployment. However, the predictive power of conditional dispersion with respect to industrial production remains largely unchanged. In contrast, the predictive power with respect to unemployment becomes weaker when these variables are included.

Overall, we document that macroeconomic shocks are somewhat predictable using conditional dispersion measured using analyst forecasts. In the next section, we explore whether macroeconomists take into account this predictive relation when forecasting unemployment and industrial production.

4.5 Conditional Dispersion and Macroeconomic Forecast Errors

In this section we examine whether macroeconomists incorporate the predictive relation between conditional dispersion and future macroeconomic conditions in their forecasts.[10] Specifically, we examine whether unemployment and industrial production forecast errors

[10] In a similar vein, Konchitchki and Patatoukas (2013a) and Konchitchki and Patatoukas (2013b) show that aggregate earnings predict GDP forecast errors.

are predicted by conditional dispersion. Unemployment and industrial production forecast error data are obtained from the Survey of Professional Forecasters (SPF). We are interested in the precision of the predictions as well as the level of errors. Therefore, we examine both absolute forecast errors and signed forecast errors.

Table 8, Panel A, presents the relation between absolute unemployment forecast errors and conditional dispersion. Aggregate revisions are able to predict unemployment absolute forecast errors (column (3)). However, the predictive relation between aggregate revisions and absolute unemployment forecast errors disappears after accounting for conditional dispersion (columns (4) and (5)). The results in columns (4) and (5) also show that dispersion and conditional dispersion both predict macroeconomists' forecast errors. Furthermore, the explanatory power of the predictive model increases substantially when conditional dispersion is included in the regression. This evidence implies that macroeconomic forecasters do not incorporate the predictive relation between conditional dispersion and unemployment in their forecasts.

In Panel B, we test whether conditional dispersion predicts absolute forecast errors related to industrial production. Both aggregate revisions and revision dispersion predict industrial production (absolute) forecast errors. However, conditional dispersion subsumes the predictive power of aggregate revisions and dispersion. Once again, the explanatory power of the predictive model increases substantially when conditional dispersion is included in the regression.

Table 9, Panel A, reports the relation between one quarter-ahead unemployment forecast errors and dispersion. The evidence suggests that dispersion and conditional dispersion predict unemployment forecast errors. Quarters with higher forecast revision dispersion have subsequent higher unemployment rates, and macro analysts do not seem to incorporate this predictive relation in their forecasts. Strikingly, after adding conditional dispersion to the specification, the marginal effect of revision dispersion is substantially attenuated (column (4)). Furthermore, adding conditional dispersion to the specification increases the R-squared from 2 to 5 percent. Therefore, conditional dispersion improves the ability to predict unemployment forecast errors. This result suggests forecast error predictability arises from conditional dispersion. In other words, quarters with higher dispersion have higher subsequent unemployment rates relatively more when the economy is performing poorly. It is in these instances, that macroeconomic forecasters underestimate the effect of dispersion on the economy, leading to predictable forecast errors.

The specification in column (5) includes the additional macroeconomic control variables. While the coefficient for conditional dispersion in column (5) is no longer significant, it remains positive and has a similar economic magnitude to the coefficient in column (4). Furthermore, the reduction in significance likely arises from the number of variables include in the regression, none of which have significance levels higher than that of conditional dispersion.

Table 9, Panel B, reports the relation between one quarter-ahead industrial production forecast errors and dispersion. Our findings are similar to those reported in Panel A with respect to unemployment. Once again, conditional dispersion is the main predictor of forecast errors. In sum, conditional dispersion predicts one quarter ahead unemployment and industrial production shocks, and macro-economists do not take this predictive relation into account when forecasting these macro variables. This results in predictable forecast errors. Furthermore, adding conditional dispersion to the various predictive models increases the overall predictive ability, and subsumes the predictive ability of aggregate revisions and dispersion. This evidence highlights the importance of conditional dispersion in understanding and predicting macroeconomic activity.

4.6 Robustness Tests

4.6.1 The Recent Financial Crisis

One potential concern is that our sample period includes the most recent financial crisis, which is abnormally severe. To test whether our findings are driven solely by the recent crisis, we include a dummy variable which receives the value of one for the crisis period (Q4:2007–Q2:2009) and zero otherwise. The dummy variable is included separately in the regression, and is also interacted with all the other primary variables in the model (revisions, dispersion, and conditional dispersion). In untabulated results, we find that our results are not driven solely by the crisis period. While dispersion and conditional dispersion have incremental effects during the recent crisis, we find similar results for the non-crisis periods, when the dummy variable and the related interactions are included in the regression.

4.6.2 Return Dispersion

Our hypotheses relate to dispersion in performance and are not specific to earnings. However, we believe earnings are the most appropriate measure of performance in our context, because they represent a sufficient statistic for the current period dispersion in performance. To test this idea, we conduct the same analyses presented in Tables 3 and 4, using stock returns instead of earnings to measure performance. Consistent with our results in Tables 3 and 4, Conditional dispersion measured using returns does have some contemporaneous relation with macroeconomic shocks. However, the results are significantly weaker than our tabulated results using earnings and forecast revisions. Thus, our findings are consistent with the usefulness of earnings as a performance measure. For brevity, these findings are untabulated.

4.6.3 Controlling for alternative uncertainty measures

Earnings dispersion may also be correlated with overall market uncertainty or economic policy uncertainty, which, in turn, is related to macroeconomic activity. Therefore, we investigate whether the role of earnings dispersion is incremental to market and economic policy uncertainty. To measure market uncertainty, we employ implied market volatility (VIX). VIX captures the implied volatility of S&P 500 index options and is collected from the Chicago Board Options Exchange (CBOE). VIX data is available from 1990 onwards, and hence we restrict our sample to post 1990 for this analysis (86 quarterly observations). We use the economic policy uncertainty index to measure economic policy uncertainty (Baker et al. 2014). This index is widely used in the economics literature to capture economic policy uncertainty. More specifically, 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.[11]

To examine whether the role of earnings dispersion and conditional earnings dispersion is incremental to market and economic uncertainty, we re-estimate specifications (8) and (9) after adding VIX and the economic policy uncertainty index as additional control variables.[12] In untabulated results we find that earnings dispersion is significantly related to both unemployment and industrial production after we include these measures as controls. Moreover, the earnings dispersion coefficient estimates are marginally higher in these specifications. Overall, our results suggest that earnings dispersion significantly explains unemployment and industrial production shocks incremental to market and economic policy uncertainty.

5 Conclusion

This paper examines how cross-sectional earnings dispersion impacts macroeconomic activity. Economic theory suggests that dispersion in performance can result in higher unemployment and lower levels of industrial production. Consistent with economic theory, our empirical tests show that earnings dispersion is related to macroeconomic activity. Specifically, earnings dispersion is positively related to unemployment and negatively related to industrial production.

We further hypothesize and show that the relation between earnings dispersion and the macroeconomy is conditional on the state of the economy. We find that the adverse effects of dispersion on the macroeconomy are exacerbated during periods of low earnings growth. Adding an interaction term which takes conditional dispersion into account doubles the explanatory power of our model, suggesting that conditional earnings dispersion (conditional on the state of the economy) is an important determinant of both unemployment and industrial production. Finally, we find that macroeconomic forecasters fail to incorporate the implications of conditional dispersion in their forecasts, leading to predictable forecast errors.

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[11] Economic policy uncertainty data is from the webpage:http://www.policyuncertainty.com/us_monthly.html.

[12] Similar to our primary analysis, to purge out the persistent components in these measures we use AR (2) time series model residuals.

Our findings help explain why recent research has uncovered a robust relation between earnings dispersion and the equity premium.

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Table 1: Descriptive statistics

	Mean	Std Dev	5 Perc	Median	95 perc
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
Mktret$_{t-1}$ (%)	1.18	9.17	-17.08	2.66	14.47
Unemp_FE$_{t+1}$	-0.03	0.13	-0.23	-0.05	0.22
Unemp_AFE$_{t+1}$	0.11	0.08	0.00	0.09	0.27
Iprod_FE$_{t+1}$	-0.22	2.61	-4.58	0.06	3.27
Iprod_AFE$_{t+1}$	2.02	1.65	0.16	1.56	5.27
Ear$_t$	0.25	0.43	0.00	0.00	1.00
Ear_Disp$_t$ (*100)	0.00	2.08	-1.96	-0.36	2.57
Ear_Cond_Disp$_t$ (*100)	0.16	1.52	-0.57	0.00	1.14
Rev$_t$	0.25	0.43	0.00	0.00	1.00
Rev_Disp$_t$ (*100)	0.00	0.65	-0.65	-0.08	0.88
Rev_Cond_Disp$_t$ (*100)	0.14	0.38	0.00	0.00	0.76
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

This table presents descriptive statistics for the macro and aggregate earnings variables. The sample includes 105 quarters from Q4:1985–Q4:2011. *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. *Mktret* is the quarterly value-weighted market return. *FE (AFE*) is the forecast error (absolute forecast error) related to the macroeconomic indicator forecasted. All forecast error data is obtained from the *Survey of Professional Forecasters*.

Ear (Rev) is an indicator variable equal to one for the lowest quartile of aggregate earnings (aggregate revision) shocks. Aggregate earnings (revisions) shocks equal the residual from an AR (2) model of aggregate earnings (revisions).

Aggregate earnings are defined as the equally weighted average of firm-level earnings shocks estimated via a seasonal random walk model, scaled by the price at the beginning of the quarter.

$$UE_{i,t} = \frac{(X_{it} - X_{it-4})}{P_{it-1}}, \quad AggEar_t = \frac{1}{N_t}\sum_{i=1}^{N_t}(UE_{i,t})$$

Aggregate revisions are defined as the equally weighted average of firm-level forecast revisions, for one-year-ahead earnings, that occur during the current quarter, deflated the by beginning of the quarter price.

$$rev_{i,s+1}^{t} = \left(\frac{E_t(earn_{i,s+1}) - E_{t-1}(earn_{i,s+1})}{P_{i,t-1}}\right), Agg\,\mathrm{Re}v_t = \frac{1}{N_t}\sum_{i=1}^{N_t}(rev_{i,s+1}^{t})$$

Earnings dispersion (*Ear_Disp*) is the residual from an AR (2) model of *AggDis*. *AggDis* is the standard deviation of earnings shocks estimated using a seasonal random walk model, deflated by beginning of the quarter stock price.

$$AggDis_t = \sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}(UE_{i,t} - AggEar_t)^2}$$

Revision dispersion *(Rev_Disp)* is measured the same way as *(Ear_Disp)* except that we replace *UE* and *AggEar* with *rev* and *AggRev* respectively in the calculations.

Conditional earnings dispersion (*Ear_Cond_Disp*) is the interaction between the aggregate earnings shock indicator variable (*Ear*) and aggregate earnings dispersion (*Ear_Disp*). Conditional revision dispersion (*Rev_Cond_Disp*) is the interaction between the aggregate earnings shock indicator variable (*Rev*) and aggregate revision dispersion (*Rev_Disp*).

For the calculation of aggregate earnings and dispersion, to align data across firms in a quarter, we only include firms with fiscal year end in March, June, September and December. Further, every quarter, we winsorize the top and bottom two percent of observations when calculating aggregate earnings and revision measures.

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* 3-Month treasury bill secondary market rate), *D_Yield* is the AR(2) residual of change in yield spread (Effective Federal Funds Rate minus 3-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.

Table 2: Correlation matrix

	D_ $Unemp_t$	D_ $Iprod_t$	Mkt Ret_{t-1}	Unemp FE_{t+1}	Unemp AFE_{t+1}	Iprod FE_{t+1}	Iprod AFE_{t+1}	Ear_t	Ear $Disp_t$	Ear_Cond $Disp_t$	Rev_t	Rev $Disp_t$	Rev_Cond $Disp_t$
D_Unemp_t	1	**-0.55**	**-0.24**	-0.04	**0.23**	-0.07	0.06	**0.32**	**0.24**	**0.43**	**0.16**	**0.41**	**0.46**
D_Iprod_t	**-0.50**	1	**0.41**	-0.02	0.06	-0.01	**0.18**	**-0.23**	**-0.27**	**-0.38**	**-0.26**	**-0.38**	**-0.44**
$Mktret_{t-1}$	-0.10	**0.27**	1	-0.10	0.03	0.08	0.07	**-0.16**	**-0.35**	**-0.41**	**-0.33**	**-0.56**	**-0.48**
$Unemp\_FE_{t+1}$	-0.09	-0.03	-0.11	1	**-0.16**	**-0.55**	**0.47**	0.12	-0.02	0.10	**0.22**	0.12	**0.16**
$Unemp\_AFE_{t+1}$	**0.22**	0.14	0.02	**-0.28**	1	-0.12	**0.21**	0.09	0.02	-0.12	-0.01	0.12	-0.05
$Iprod\_FE_{t+1}$	-0.01	-0.01	0.04	**-0.48**	0.00	1	**-0.41**	-0.04	-0.07	-0.06	-0.15	**-0.25**	-0.16
$Iprod\_AFE_{t+1}$	0.01	**0.20**	0.15	**0.36**	0.13	-0.10	1	-0.02	-0.07	-0.05	-0.08	0.16	-0.08
Ear_t	**0.31**	**-0.17**	-0.15	0.12	0.13	-0.05	-0.03	1	**0.18**	**0.19**	**0.44**	**0.27**	**0.42**
Ear_Disp_t	0.06	**-0.19**	**-0.19**	0.11	-0.13	-0.10	0.00	**0.19**	1	**0.74**	**0.18**	**0.36**	**0.56**
$Ear\_Cond\_Disp_t$	0.12	**-0.25**	**-0.27**	0.16	-0.06	-0.08	0.07	0.00	**0.46**	1	**0.20**	**0.42**	**0.73**
Rev_t	0.12	**-0.24**	**-0.24**	**0.23**	-0.04	**-0.19**	-0.13	**0.44**	**0.17**	0.05	1	**0.49**	**0.63**
Rev_Disp_t	**0.25**	**-0.25**	**-0.42**	0.08	0.08	-0.11	-0.07	**0.33**	0.06	-0.05	**0.66**	1	**0.66**
$Rev\_Cond\_Disp_t$	**0.17**	**-0.26**	**-0.26**	**0.23**	-0.03	**-0.21**	-0.13	**0.48**	**0.20**	0.09	**0.99**	**0.68**	1

This table presents Pearson (above diagonal) and Spearman (below diagonal) correlations among the key variables of interest for 105 quarters from Q4:1985–Q4:2011. The sample and variable definitions are described in Table 1. Correlations significant at the 10% level or better are highlighted in bold.

Table 3: Conditional dispersion and contemporaneous unemployment shocks

Panel A: Conditional earnings dispersion and contemporaneous unemployment shocks

	Dependent Variable : D_UNEMP_t				
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.04 (-1.78)*	0.00 (0.06)	-0.03 (-1.62)	-0.04 (-2.14)**	-0.03 (-1.79)*
Ear_t	0.15 (3.47)***		0.13 (3.11)***	0.12 (3.01)***	0.09 (2.30)**
Ear_Disp_t		2.28 (2.47)**	1.78 (1.97)*	-2.01 (-1.64)	-2.36 (-1.89)*
$Ear\_Cond\_Disp_t$				7.10 (4.24)***	6.64 (4.03)***
D_GDP_t					-0.10 (-2.66)***
D_Cons_t					-0.02 (-0.46)
D_Term_t					-0.01 (-0.35)
D_Yield_t					0.07 (0.73)
D_CPI_t					0.00 (0.09)
D_Def_t					-0.01 (-0.11)
Adj. R^2	0.10	0.05	0.12	0.25	0.29

Table 3: Continued

Panel B: Conditional revision dispersion and contemporaneous unemployment shocks

	Dependent Variable : D_UNEMP_t				
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.02 (-0.87)	0.00 (0.06)	0.01 (0.25)	-0.01 (-0.37)	0.00 (-0.16)
Rev_t	0.08 (1.69)*		-0.02 (-0.48)	-0.11 (-2.14)**	-0.10 (-1.99)**
Rev_Disp_t		12.70 (4.59)***	13.44 (4.22)***	6.72 (1.90)*	7.00 (2.00)**
$Rev\_Cond\_Disp_t$				24.46 (3.63)***	20.32 (2.83)***
D_GDP_t					-0.10 (-2.57)**
D_Cons_t					-0.01 (-0.32)
D_Term_t					-0.03 (-0.80)
D_Yield_t					0.10 (0.94)
D_CPI_t					0.02 (0.47)
D_Def_t					0.03 (0.31)
Adj. R^2	0.02	0.16	0.16	0.25	0.30

This table reports the contemporaneous relation between unemployment shocks and earnings dispersion (reversion dispersion) for 105 quarters from Q4:1985−Q4:2011. All the variables are defined in Table 1. Panel A reports the contemporaneous relation between unemployment shocks and earnings dispersion. Panel B presents the contemporaneous relation between unemployment shocks and revision dispersion.

Table 4: Conditional dispersion and contemporaneous industrial production shocks

Panel A: Conditional earnings dispersion and contemporaneous industrial production shocks

	Dependent Variable : D_IPROD_t				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.12 (1.24)	0.01 (0.08)	0.09 (1.04)	0.12 (1.33)	0.06 (0.73)
Ear_t	-0.44 (-2.36)**		-0.36 (-1.93)*	-0.32 (-1.76)*	-0.09 (-0.53)
Ear_Disp_t		-11.13 (-2.88)***	-9.78 (-2.52)**	1.40 (0.25)	2.70 (0.53)
$Ear\_Cond\_Disp_t$				-20.99 (-2.78)***	-18.99 (-2.82)***
D_GDP_t					0.59 (3.88)***
D_Cons_t					0.03 (0.21)
D_Term_t					0.18 (-1.07)
D_Yield_t					-0.29 (-0.69)
D_CPI_t					0.04 (0.26)
D_Def_t					-0.69 (-1.64)
Adj. R^2	0.04	0.07	0.09	0.15	0.33

Table 4: Continued

Panel B: Conditional revision dispersion and contemporaneous industrial production shocks

	Dependent Variable : D_IPROD_t				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.13 (1.37)	0.01 (0.08)	0.05 (0.49)	0.09 (0.95)	0.05 (0.57)
Rev_t	-0.49 (-2.61)**		-0.16 (-0.77)	0.13 (0.57)	0.15 (0.71)
Rev_Disp_t		-49.92 (-4.22)***	-44.79 (-3.29)***	-22.41 (-1.45)	-23.44 (-1.67)*
$Rev\_Cond\_Disp_t$				-81.52 (-2.76)***	-56.67 (-1.97)*
D_GDP_t					0.57 (3.83)***
D_Cons_t					0.05 (0.28)
D_Term_t					0.24 (1.48)
D_Yield_t					-0.34 (-0.82)
D_CPI_t					0.02 (0.11)
D_Def_t					-0.58 (-1.44)
Adj. R^2	0.05	0.14	0.14	0.19	0.36

This table reports the contemporaneous relation between industrial production shocks and earnings dispersion (reversion dispersion) for 105 quarters from Q4:1985–Q4:2011. All the variables are defined in Table 1. Panel A reports the contemporaneous relation between unemployment shocks and earnings dispersion. Panel B presents the contemporaneous relation between industrial production shocks and revision dispersion.

Table 5: Industry dispersion and contemporaneous macroeconomic shocks

Panel A: Conditional industry-level dispersion and contemporaneous unemployment shocks

	Dependent Variable : D_UNEMP_t				
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.02 (-0.69)	0.00 (0.06)	0.00 (0.21)	-0.01 (-0.37)	0.00 (0.22)
Rev_t	0.06 (1.29)		-0.02 (-0.49)	-0.07 (-1.62)	-0.07 (-1.37)
Ind_Disp_t		31.65 (4.43)***	33.25 (4.21)***	13.24 (1.41)	13.15 (1.33)
$Ind\_Cond\_Disp_t$				55.05 (3.54)***	43.19 (2.50)**
D_GDP_t					-0.09 (-2.25)**
D_Cons_t					-0.02 (-0.49)
D_Term_t					-0.03 (-0.80)
D_Yield_t					0.04 (0.39)
D_CPI_t					0.01 (0.33)
D_Def_t					0.01 (0.11)
Adj. R^2	0.01	0.15	0.15	0.23	0.26

Table 5: Continued

Panel B: Conditional industry-level dispersion and contemporaneous industrial production shocks

	Dependent Variable : D_IPROD_t				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.12 (1.44)	0.01 (0.08)	0.04 (0.50)	0.08 (0.94)	0.06 (0.69)
Rev_t	-0.46 (-2.45)**		-0.16 (-0.80)	0.01 (0.07)	0.01 (0.06)
Ind_Disp_t		-135.08 (-4.48)***	-123.97 (-3.73)***	-59.05 (-1.46)	-49.60 (-1.27)
$Ind\_Cond\_Disp_t$				-178.59 (-2.66)***	-117.84 (-1.72)*
D_GDP_t					0.53 (3.51)***
D_Cons_t					0.08 (0.48)
D_Term_t					0.25 (1.52)
D_Yield_t					-0.16 (-0.37)
D_CPI_t					0.03 (0.17)
D_Def_t					-0.51 (-1.23)
Adj. R^2	0.06	0.16	0.15	0.20	0.35

This table reports the contemporaneous relation between macroeconomic shocks and industry dispersion for 105 quarters from Q4:1985−Q4:2011. Industry level dispersion is estimated as follows: (1) Every quarter, firms are assigned to one of 38 industries according to the classification in Professor Kenneth French's website; (2) Then, industry-level analyst based earnings revisions are computed, defined as the equally-weighted average of all firm-level analyst based earnings revisions, in an industry; (3), The standard deviation of the industry-level revisions (from step 2) is estimated, and defined as industry-level revision dispersion;

(4) Finally, Industry Dispersion (Ind_Disp) equals the residual from an AR (2) model of the industry-level revision dispersion form step (3). All the remaining variables are defined as in Table 1. Panel A reports the relation between unemployment shocks and industry dispersion. Panel B presents the relation between industrial production shocks and industry dispersion.

Table 6: Conditional dispersion and market returns

Panel A: Conditional earnings dispersion and market returns

	Dependent Variable : Market Ret_t				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.02 (1.98)*	0.01 (1.39)	0.02 (1.76)*	0.02 (2.03)**	0.02 (1.71)*
Ear_{t+1}	-0.04 (-1.69)*		-0.02 (-1.11)	-0.02 (-0.94)	0.00 (0.23)
Ear_Disp_{t+1}		-1.54 (-3.78)***	-1.46 (-3.52)***	-0.40 (-0.67)	-0.68 (-1.13)
$Ear\_Cond\_Disp_{t+1}$				-1.99 (-2.46)**	-2.04 (-2.57)**
D_GDP_{t+1}					0.00 (0.28)
D_Cons_{t+1}					0.01 (0.46)
D_Term_{t+1}					0.02 (0.94)
D_Yield_{t+1}					0.01 (0.18)
D_CPI_{t+1}					-0.01 (-0.62)
D_Def_{t+1}					-0.15 (-2.94)***
Adj. R^2	0.02	0.11	0.12	0.16	0.21

Table 6: Continued

Panel B: Conditional revision dispersion and market returns

	Dependent Variable : Market Ret_t				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.03 (2.80)***	0.01 (1.47)	0.01 (1.55)	0.02 (1.84)*	0.02 (1.79)*
Rev_{t+1}	-0.07 (-3.33)***		-0.01 (-0.56)	0.01 (0.32)	0.01 (0.37)
Rev_Disp_{t+1}		-7.98 (-6.90)***	-7.61 (-5.76)***	-6.16 (-4.02)***	-6.10 (-3.97)***
$Rev\_Cond\_Disp_{t+1}$				-5.27 (-1.80)*	-5.44 (-1.73)*
D_GDP_{t+1}					0.00 (0.18)
D_Cons_{t+1}					0.02 (0.88)
D_Term_{t+1}					0.03 (1.68)*
D_Yield_{t+1}					0.02 (0.44)
D_CPI_{t+1}					-0.01 (-0.61)
D_Def_{t+1}					-0.10 (-2.18)**
Adj. R^2	0.10	0.31	0.31	0.32	0.35

This table reports the relation between market returns and conditional earnings dispersion (revision dispersion) for 105 quarters from Q4:1985−Q4:2011. All the variables are defined in Table 1. Panel A reports the relation between market returns and earnings dispersion. Panel B presents the relation between market returns and revision dispersion.

Table 7: Conditional dispersion and future macroeconomic shocks

Panel A: Conditional revision dispersion and future unemployment shocks

	Dependent Variable : D_UNEMP_{t+1}				
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.01 (-0.44)	0.00 (0.03)	-0.02 (-0.64)	-0.02 (-0.95)	-0.01 (-0.65)
Rev_t	0.04 (0.84)		0.06 (1.12)	0.01 (0.15)	0.01 (0.13)
Rev_Disp_t		-0.89 (-0.29)	-2.80 (-0.80)	-6.76 (-1.67)*	-7.11 (-1.85)*
$Rev\_Cond\_Disp_t$				14.40 (1.86)*	8.88 (1.13)
D_GDP_t					-0.04 (-1.07)
D_Cons_t					-0.11 (-2.36)**
D_Term_t					0.00 (0.02)
D_Yield_t					-0.15 (-1.35)
D_CPI_t					-0.03 (-0.72)
D_Def_t					0.16 (1.46)
Adj. R^2	0.00	0.00	0.00	0.02	0.16

Table 7: Continued

Panel B: Conditional revision dispersion and future industrial production shocks

	Dependent Variable : D_IPROD_{t+1}				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.05 (0.56)	0.00 (0.00)	0.12 (1.28)	0.14 (1.64)	0.15 (1.74)*
Rev_t	-0.22 (-1.12)		-0.50 (-2.31)**	-0.26 (-1.09)	-0.23 (-1.04)
Rev_Disp_t		21.83 (1.72)*	37.90 (2.66)***	56.38 (3.43)***	61.85 (4.08)***
$Rev\_Cond\_Disp_t$				-67.21 (-2.15)**	-69.89 (-2.25)**
D_GDP_t					0.03 (0.20)
D_Cons_t					0.48 (2.72)***
D_Term_t					0.04 (0.22)
D_Yield_t					-0.08 (-0.17)
D_CPI_t					-0.26 (-1.54)
D_Def_t					-1.24 (-2.83)***
Adj. R^2	0.00	0.02	0.05	0.08	0.27

This table reports the relation between future macroeconomic shocks and revision dispersion for 104 quarters from Q4:1985−Q3:2011. Panel A reports the relation between one quarter ahead unemployment shocks and revision dispersion. Panel B presents the relation between one quarter ahead industrial production shocks and revision dispersion.

Table 8: Conditional dispersion and one-quarter-ahead macroeconomist absolute forecast errors

Panel A: Conditional revision dispersion and unemployment absolute forecast errors

	Dependent Variable : $UNEMP\_AFE_{t+1}$				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.10 (10.54)***	0.11 (12.89)***	0.10 (9.91)***	0.09 (9.59)***	0.10 (9.51)***
Rev_t	0.03 (1.49)		0.04 (1.69)*	0.01 (0.60)	0.01 (0.32)
Rev_Disp_t		0.04 (0.03)	-1.17 (-0.81)	-2.93 (-1.75)*	-3.17 (-1.83)*
$Rev\_Cond\_Disp_t$				6.41 (2.01)**	6.09 (1.72)*
D_GDP_t					-0.01 (-0.29)
D_Cons_t					-0.01 (-0.62)
D_Term_t					0.02 (1.23)
D_Yield_t					-0.03 (-0.63)
D_CPI_t					0.00 (0.20)
D_Def_t					0.03 (0.65)
Adj. R^2	0.01	0.00	0.01	0.04	0.02

Table 8: Continued

Panel B: Conditional revision dispersion and industrial production absolute forecast errors

	Dependent Variable : $IPROD\_AFE_{t+1}$				
	(1)	(2)	(3)	(4)	(5)
Intercept	1.75 (9.72)***	2.02 (12.95)***	1.83 (9.89)***	1.73 (9.60)***	1.82 (0.52)
Rev_t	1.10 (3.06)***		0.77 (1.87)*	0.23 (0.51)	0.12 (0.27)
Rev_Disp_t		70.08 (2.93)***	45.16 (1.66)*	2.76 (0.09)	-5.07 (-0.17)
$Rev\_Cond\_Disp_t$				154.02 (2.61)**	126.32 (2.09)**
D_GDP_t					-0.61 (-1.93)*
D_Cons_t					-0.52 (-1.51)
D_Term_t					0.32 (0.94)
D_Yield_t					-0.06 (-0.07)
D_CPI_t					-0.15 (-0.44)
D_Def_t					1.34 (1.57)
Adj. R^2	0.07	0.07	0.09	0.14	0.26

This table reports the relation between one-quarter-ahead macroeconomist absolute forecast errors and revision dispersion for 104 quarters from Q4:1985–Q3:2011. All the variables are defined in Table 1. Panel A reports the relation between one quarter ahead unemployment absolute forecast errors and revision dispersion. Panel B presents the relation between one-quarter-ahead industrial production absolute forecast errors and revision dispersion.

Table 9: Conditional dispersion and one-quarter-ahead macroeconomist mean forecast errors

Panel A: Conditional revision dispersion and unemployment mean forecast errors

	Dependent Variable : $UNEMP\_FE_{t+1}$				
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.04 (-2.92)***	-0.03 (-2.60)	-0.04 (-2.41)**	-0.04 (-2.74)***	-0.04 (-2.46)**
Rev_t	0.04 (1.37)		0.02 (0.46)	-0.02 (-0.50)	-0.02 (-0.60)
Rev_Disp_t		3.93 (2.01)**	3.69 (1.63)	0.72 (0.28)	0.79 (0.30)
$Rev\_Cond\_Disp_t$				9.82 (1.97)*	7.29 (1.36)
D_GDP_t					-0.04 (-1.29)
D_Cons_t					-0.04 (-1.35)
D_Term_t					0.00 (0.01)
D_Yield_t					-0.07 (-0.87)
D_CPI_t					0.02 (0.79)
D_Def_t					0.10 (1.31)
Adj. R^2	0.00	0.03	0.02	0.05	0.10

Table 9: Continued

Panel B: Conditional revision dispersion and industrial production mean forecast errors

	Dependent Variable : $IPROD\_FE_{t+1}$				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.09 (0.32)	-0.22 (-0.88)	0.05 (0.16)	0.18 (0.60)	0.08 (0.33)
Rev_t	-1.27 (-2.18)**		-1.08 (-1.62)	-0.19 -(0.26)	-0.15 (-0.23)
Rev_Disp_t		-60.22 (-1.55)	-25.06 (-0.57)	44.89 (0.89)	55.57 (1.28)
$Rev\_Cond\_Disp_t$				-254.37 (-2.64)***	-194.54 (-2.19)**
D_GDP_t					1.15 (2.48)**
D_Cons_t					1.44 (2.83)***
D_Term_t					0.17 (0.34)
D_Yield_t					-0.12 (-0.10)
D_CPI_t					-0.31 (-0.63)
D_Def_t					-3.21 (-2.56)**
Adj. R^2	0.04	0.01	0.03	0.08	0.36

This table reports the relation between one-quarter-ahead macroeconomist mean forecast errors and revision dispersion, for 104 quarters from Q4:1985–Q3:2011. All the variables are defined in Table 1. Panel A reports the relation between one quarter ahead unemployment mean forecast errors and revision dispersion. Panel B presents the relation between one-quarter-ahead industrial production mean forecast errors and revision dispersion.