Price Informativeness in the Time Series and the Cross Section*

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This Draft: June 2018

Preliminary and Incomplete
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* We benefited from conversations with Gavin Cassar and Peter Easton. We thank Shuping Chen, Bin Miao and Terry Shevlin for sharing their disclosure-quality proxy with us.

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Abstract

We propose a new measure of price informativeness. Our measure reflects the accuracy of the levels of the expectations embedded in observed equity prices. Hence, it is intuitive yet rigorous. Moreover, it can be used at both the firm- and economy-level and to separately evaluate forecast bias, forecast precision and their combined effect on price informativeness. Our empirical results show that economy-level price informativeness is high when: (1) there is moderate investor sentiment (either positive or negative); (2) limits to arbitrage are low; (3) uncertainty is low; (4) unemployment is low; and, (5) the aggregate earnings-to-price ratio is high. Our firm-level tests show that firms have more informative prices when: (1) they provide more transparency in terms of more-*dis*aggregated accounting data and/or longer 10-Ks or (2) they have good information environments in terms of analyst following and the intensify of that following.

Keywords: Price efficiency and price informativeness

JEL classification codes: D84, G10, G14 and M40

1. Introduction

Equity markets play a central role in the economy. They facilitate risk sharing and intergenerational consumption smoothing. They provide a mechanism for entrepreneurs to obtain funding; and, they generate price signals that economic agents can use when making real decisions or determining contractual performance.

The extent to which equity markets fulfill their role depends on price informativeness, which we define as the degree of accuracy of the expectations of future earnings embedded in a firm's current equity market value. When price informativeness is high, investors pay a fair price for risk sharing and consumption smoothing, entrepreneurs receive funding that is commensurate with their value-creation potential and prices are informative about economic fundamentals.

With the above motivation in mind, we do two things. First, we propose a new measure of price informativeness. Second, we provide initial evidence about the determinants of the: (1) temporal variation in our economy-level measures of price informativeness and (2) cross-sectional variation in our firm-level measures of price informativeness.

To measure price informativeness, we use the fact that a firm's equity market value can be written as a function of its capitalized *expected* future aggregate earnings (e.g., Easton, Harris and Ohlson [1992]). Hence, we evaluate the variable $ERR_{i,t}^{T}$, which equals the difference between firm $i's$ equity market value at the end of quarter t and its capitalized *realized* aggregate earnings for the subsequent T quarters. (We deflate $ERR_{i,t}^{T}$ by firm $i's$ equity market value at the end of quarter t and we set $T = 20$ quarters.)[1] The intuition for $ERR_{i,t}^{T}$ is straightforward: When its magnitude is

[1] We evaluate the sensitivity of our results to the value of T. In particular, we repeat all of our tests using a value of $T = 28$, which is equivalent to seven years. The results of these robustness tests, which are not tabulated, are similar to the results shown in the paper.

small (large) the earnings expectations embedded in equity market value are more (less) accurate, and thus price informativeness is relatively high (low).

In addition to being rigorous and intuitive, our measure of price informativeness has two crucial advantages vis-à-vis alternative extant measures. First, $ERR_{i,t}^{T}$ is a price-based measure not a returns-based measure.[2] This implies that it is a function of the level of equity market value, and thus it reflects the difference between the *level* of expected future earnings and the *level* of *ex post* realized earnings. This is important because it is the accuracy of the levels of expectations that matters. Hence, price-informativeness measures that are based on realized stock returns are incomplete and possibly misleading. The reason for this is that *realized* stock returns primarily reflect *changes* in expectations; and, even if these changes reflect rational updating on the part of investors, the underlying level of the expectation may be biased or imprecise. For example, large positive stock returns may be the result of rational informed traders impounding their positive private information into price. However, if private and public information are substitutes, or the amount of unresolved uncertainty remains high, or there are constraints on trading that lead to asymmetric pricing of good and bad news (e.g., short-selling constraints), etc., the expectations embedded in price may still be inaccurate.

Second, our price-based measure is determined at the firm-level, Hence, it is more general than the price-based measure recently developed by Bai, Phillipon and Savov [2016] (BPS hereafter), which can only be used to infer the average economy-level covariance between current prices and realized future earnings. $ERR_{i,t}^{T}$, on the other hand, can be used to evaluate cross-sectional relations between firm-level characteristics (e.g., disclosure choices) and firm-level price

[2] Examples of returns-based price-informativeness measures include synchronicity, which reflects the unexplained variation in realized stock returns (e.g., Morck, Yeung and Yu [2000], Durnev, Morck, Yeung and Zarowin [2003] and Piotroski and Roulstone [2004]) and future earnings response coefficients, which reflect the relation between current realized stock returns and future earnings (e.g., Gelb and Zarowin [2002] and Lundholm and Myers [2002]).

informativeness. Moreover, we can use temporal variation in the cross-sectional average and standard deviation of $ERR_{i,t}^{T}$ to evaluate how economy-level forecast bias and forecast precision: (1) vary across time and (2) covary with other economy-level phenomena such as investor sentiment, uncertainty, etc.

We begin our empirical analyses by evaluating temporal variation in economy-wide measures of price informativeness. For each quarter in our sample, we calculate the cross-sectional average and standard deviation of $ERR_{i,t}^{T}$, which we refer to as $BIAS_t^T$ and STD_t^T. These variables reflect the degree of optimism and precision in investors' forecasts, respectively. (Larger values of STD_t^T imply *lower* forecast precision.) We also calculate the absolute value of $BIAS_t^T$, which we refer to as $ABS\_BIAS_t^T$. $ABS\_BIAS_t^T$ reflects the degree of bias (either positive or negative) in investors forecasts. Finally, we calculate the variable $RMSE_t^T = \sqrt{(BIAS_t^T)^2 + (STD_t^T)^2}$—i.e., root mean squared $ERR_{i,t}^{T}$. $RMSE_t^T$ reflects the combined effects of bias and precision, and thus it is a measure of overall price informativeness.

After calculating the statistics described above we evaluate their temporal associations with a number of economy-level variables. We begin with the measure of investor sentiment developed by Baker and Wurgler [2007]. We show that when sentiment is positive: (1) investors' forecasts are more optimistic, biased and precise and (2) overall price informativeness is high. However, when we consider the absolute value of sentiment, we find the exact opposite results. Hence, it is extreme sentiment, and especially extreme negative sentiment, that is associated with less informative prices.

Next, we consider the effects of limits to arbitrage and uncertainty. To measure limits to arbitrage we use the noise measure developed by Hu, Pan and Wang [2013]. We find that when this measure indicates that there are high limits to arbitrage, investors' forecasts are more optimistic, biased and imprecise. Consequently, and not surprisingly, when there are high limits to arbitrage, overall price informativeness is low. A similar result holds when there is high uncertainty as measured by the historical volatility of returns on the S&P 500 index.

We then evaluate the relations between price informativeness and several variables that reflect the state of the economy: industrial production, unemployment and growth in GDP. We find weak evidence that price informativeness is pro-cyclical. Specifically, investors' forecasts tend to be more optimistic, biased and precise during periods of low unemployment. And, the precision effect dominates the bias effect causing $RMSE_t^T$ to be low when unemployment is low.

Finally, we evaluate how informativeness varies with the economy-level book-to-market and earnings-to-price ratios. We find that, perhaps not surprisingly, when values are high relative to accounting fundamentals, investors' forecasts are more optimistic and biased. Moreover, high price-to-earnings ratios coincide with high $RMSE_t^T$, which is consistent with the argument that divergence between prices and accounting fundamentals is a sign of low price informativeness.

In our second (and final) set of analyses, we evaluate cross-sectional variation in firm-level price informativeness. To do this we estimate panel regressions of either $ERR_{i,t}^T$ or its absolute value, $ABS\_ERR_{i,t}^T$, on various firm-level characteristics that relate to firms' disclosure choices and information environments. By analyzing $ERR_{i,t}^T$ we learn about variation in forecast bias whereas our analyses of $ABS\_ERR_{i,t}^T$ provide evidence about variation in forecast precision.

We show that forecast bias is lower for firms that provide more-disaggregated accounting data and forecast precision is higher for firms that provide more financial information in terms of longer 10-Ks. We also find that analyst following and the the intensity of that following are each negatively associated with forecast bias and positively associated with forecast precision. Taken together, these results are consistent with the common-sense argument that price informativeness is higher for firms that make high-quality disclosures or that have "good" information environments.

We make two contributions. First, we develop an intuitive yet rigorous measure of price informativeness that reflects the accuracy of the expectations embedded in observed equity prices. Our measure is flexible and comprehensive in the sense that it can be used to evaluate forecast bias and forecast precision at both the economy- and firm-level. Second, we provide initial evidence about the factors that determine temporal variation in economy-level price informativeness and cross-sectional variation in firm-level price informativeness.

2. Motivation and Contribution

We define price informativeness as the degree of accuracy of the expectations of future earnings embedded in a firm's current equity market value; and, higher (lower) accuracy implies higher (lower) price informativeness. Accuracy is a function of bias and precision. Although biased forecasts are, *ceteris paribus*, inaccurate, unbiased forecasts are also inaccurate to the extent that they are imprecise—i.e., the forecast errors exhibit high dispersion.

Our definition of price informativeness is similar to the definition of *fundamental valuation efficiency* described in Tobin [1984] and the definition of *forecast price efficiency* described in Bond, Edmans and Goldstein [2012] (BEG, hereafter). As discussed in BEG, price informativeness overlaps with but is not equal to *revelatory price efficiency*, which they define as "the extent to which prices reveal the information necessary for real efficiency."

Broadly speaking, price informativeness is important for two reasons. First, investors can use equity securities to smooth their consumption across states and dates (e.g., Arrow [1964]). Hence, equity prices play a role in determining the amount that investors pay for risk sharing and consumption smoothing. To the extent the expectations embedded in equity prices accurately reflect future payoffs, investors pay a "fair" price, and thus are more likely to achieve optimal risk sharing and the optimal intergenerational consumption allocation.

Second, price informativeness can have real effects. In the primary market (i.e., the market for initial public offerings, IPOs), the offer prices determine the amount of funding that entrepreneurs receive. Hence, when price informativeness is high (low) resource allocations are efficient (inefficient) in the sense that more funding is given *ex ante* to entrepreneurs who will generate larger average payoffs *ex post*. As discussed in BEG, price informativeness in the secondary market can also have real effects. If equity prices are informative then, as described in Hayek [1945], economic agents (e.g., the firm's managers, its competitors, suppliers, customers, employees, etc.) can learn from them, and then adjust their real decisions accordingly. Price informativeness also affects the likelihood that contractual outcomes and regulatory decisions will be contingent on equity prices (e.g., executive compensation contracts, monitoring the solvency of financial institutions, etc.). And, to the extent equity prices are used in contracts and by regulators, price informativeness affects the behavior of contracting parties, regulators and the managers of the companies being regulated.

Given the important potential consequences of price informativeness, understanding temporal variation in economy-level price informativeness and cross-sectional variation in firm-level price informativeness is important. However, obtaining this understanding requires an empirical approach for measuring price informativeness and, at present, there is no consensus regarding the best approach. With this in mind, our objective is to add to the extant literature in two ways. First, we propose a new empirical approach for measuring price informativeness. Second, we provide initial empirical evidence about the determinants of: (1) temporal variation in our economy-level measures of price informativeness and (2) cross-sectional variation in our firm-level measures of price informativeness.

In the remainder of this section we elaborate on our second contribution—i.e., providing initial evidence about the determinants of temporal and cross-sectional variation in price informativeness. We discuss our approach to measuring price informativeness in Section 3.

Determinants of Price Informativeness

There are many factors that determine price informativeness; and, developing an exhaustive list and evaluating each item on that list is outside the scope of our study. Rather, we identify four general determinants. The first is uncertainty, which is the root cause of price *un*informativeness. Specifically, if there is no uncertainty, investors will make perfect forecasts and prices will be fully revealing. However, when there is uncertainty, investors forecasts will be imprecise and possibly, but not necessarily, biased.

The second general determinant relates to firms' information production decisions. *Ceteris paribus*, firms that produce more information will have higher price informativeness. The third general determinant relates to investors' information-acquisition decisions and the manner in which they process the information that they acquire. *Ceteris paribus*, when investors conduct more private information acquisition, their forecasts are more precise and price informativeness is higher. Moreover, to the extent that investors process the information they acquire in a rational manner, their forecasts are unbiased and more precise, and prices are more informative.

The final general determinant of price informativeness that we discuss is trading constraints. The quintessential example of a trading constraint is a prohibition on short selling. As discussed in Miller [1977], short selling is a way for investors to profit from negative private information—i.e., private information that implies that the current price is too high. Consequently, a prohibition on short selling will cause the expectations embedded in price to be biased upwards. Trading constraints can also arise endogenously. For example, high uncertainty and information asymmetry can lead to illiquidity that acts as a *de facto* constraint on trade. Regardless of their origin, trading constraints typically imply lower price informativeness.

With the above discussion in mind, we make three observations. First, the determinants of price informativeness are related and interdependent. For example, as discussed in Beber and Pagano [2013], high uncertainty, concerns about firms' information production decisions and biased information processing motivated numerous regulators to impose short-selling constraints during the 2007-2009 global financial crisis. Second, it is likely that there is endogeneity between price informativeness and the different determinants that we identify. For example, managers who perceive their firm's shares to be mis-valued may react by disclosing more information, which, in turn, affects the accuracy of the forecasts embedded into price. Finally, we do not argue that our discussion of the determinants of price informativeness is exhaustive. Rather, we simply seek to fix ideas and motivate our empirical tests in which we explore the relation between our measures of price informativeness and various phenomena.

3. Measuring Price Informativeness

Our measures of price informativeness are motivated by the following expression for firm i's equity market value at the end of quarter t, $V_{i,t}$:

$$V_{i,t} = \frac{\mathbb{E}_t\left[\sum_{\tau=1}^{T}\left\{EARN_{i,t+\tau}+\left(R_{f,t}^{T-\tau}-1\right)\times DIV_{i,t+\tau}\right\}+\left\{\left(V_{i,t+T}-V_{i,t}\right)-\left(B_{i,t+T}-B_{i,t}\right)\right\}|I_t\right]}{R_{i,t}^{T}-1}$$

$$= \frac{\mathbb{E}_t\left[ACE_{i,t}^{T}+\Delta PREM_{i,t}^{T}|I_t\right]}{R_{i,t}^{T}-1} \qquad (1)$$

In equation (1), $\mathbb{E}_t[\cdot\,|I_t]$ is the expectation at the end of quarter t conditional on the information available at that time, which we denote as I_t. $EARN_{i,t+\tau}$ is firm $i's$ earnings for quarter $t\ +\tau$ and $DIV_{i,t+\tau}$ is the dividend paid by firm i at the end of quarter $t\ +\tau$. $B_{i,t}$ is firm $i's$ equity book value at the end of quarter t. $R_{f,t}=\left(1+r_{f,t}\right)$ and $R_{i,t}=\left(1+r_{i,t}\right)$; and, $r_{f,t}$ and $r_{i,t}$ are the quarterly risk-free rate and the expected quarterly rate of return on firm $i's$ equity capital, respectively. Finally, $ACE_{i,t}^{T}=\sum_{\tau=1}^{T}\left\{EARN_{i,t+\tau}+\left(R_{f,t}^{T-\tau}-1\right)\times DIV_{i,t+\tau}\right\}$ is firm $i's$ aggregate cum-dividend earnings for the time period spanning quarter $t+1$ through $t+T$ and $\Delta PREM_{i,t}^{T}=\left(V_{i,t+T}-V_{i,t}\right)-\left(B_{i,t+T}-B_{i,t}\right)=\left(V_{i,t+T}-B_{i,t+T}\right)-\left(V_{i,t}-B_{i,t}\right)$ is the change in the premium of equity market value over equity book value.

Equation (1) is not new to the literature. Rather, as shown in Easton et al. [1992], if we assume that dividends are paid out of excess cash that the firm would have invested in risk-free bonds and $R_{i,t}$ is non-stochastic, $\mathbb{E}_t\left[R_{i,t}^{T}-1\right]=R_{i,t}^{T}-1$ is equal to the following:[3]

$$R_{i,t}^{T}-1=\frac{\mathbb{E}_t\left[V_{i,t+T}+\sum_{\tau=1}^{T}R_{f,t}^{T-\tau}\times DIV_{i,t+\tau}-V_{i,t}|I_t\right]}{V_{i,t}} \tag{2}$$

Finally, if we also assume clean-surplus accounting in expectation, which implies that $\mathbb{E}_t\left[\left(B_{i,t+T}-B_{i,t}\right)|I_t\right]=\mathbb{E}_t\left[\sum_{\tau=1}^{T}\left(EARN_{i,t+\tau}-DIV_{i,t+\tau}\right)|I_t\right]$, equation (1) follows directly from equation (2) and *vice versa*.[4]

[3] The term $\sum_{\tau=1}^{T}R_{f,t}^{T-\tau}\times DIV_{i,t+\tau}$ in equation (2) is necessary to preserve dividend-policy irrelevance per Miller and Modigliani [1961]. That is, holding the firm's investment opportunities constant, the expected change in value is the same regardless of whether the firm pays a dividend or withholds the funds and invests them in risk-free bonds.

[4] In particular, $R_{i,t}^{T}-1=\frac{\mathbb{E}_t\left[V_{i,t+T}+\sum_{\tau=1}^{T}R_{f,t}^{T-\tau}\times DIV_{i,t+\tau}-V_{i,t}|I_t\right]}{V_{i,t}}$

$\Rightarrow V_{i,t}=\frac{\mathbb{E}_t\left[V_{i,t+T}+\sum_{\tau=1}^{T}R_{f,t}^{T-\tau}\times DIV_{i,t+\tau}-V_{i,t}+\left(B_{i,t+T}-B_{i,t}\right)-\left(B_{i,t+T}-B_{i,t}\right)|I_t\right]}{R_{i,t}^{T}-1}$

$=\frac{\mathbb{E}_t\left[\left(B_{i,t+T}-B_{i,t}\right)+\sum_{\tau=1}^{T}R_{f,t}^{T-\tau}\times DIV_{i,t+\tau}+\left(V_{i,t+T}-V_{i,t}\right)-\left(B_{i,t+T}-B_{i,t}\right)|I_t\right]}{R_{i,t}^{T}-1}$

$=\frac{\mathbb{E}_t\left[\sum_{\tau=1}^{T}\left\{EARN_{i,t+\tau}+\left(R_{f,t}^{T-\tau}-1\right)\times DIV_{i,t+\tau}\right\}+\left\{\left(V_{i,t+T}-V_{i,t}\right)-\left(B_{i,t+T}-B_{i,t}\right)\right\}|I_t\right]}{R_{i,t}^{T}-1}$

In addition to being consistent with first principles, equation (1) motivates an intuitively appealing approach for measuring price informativeness: Compare *ex ante* equity market value to the capitalized *ex post realized* value of $ACE_{i,t}^{T}$. In particular, we calculate the following variable, which we refer to as $ERR_{i,t}^{T}$:

$$ERR_{i,t}^{T} = \frac{V_{i,t} - \left(\frac{ACE_{i,t}^{T}}{R_{i,t}^{T} - 1}\right)}{V_{i,t}} \quad (3)$$

There are two key issues with using $ERR_{i,t}^{T}$ as a measure of price informativeness. Below we describe each issue and how our empirical design addresses it.

Ignoring $\Delta PREM_{i,t}^{T}$

$ERR_{i,t}^{T}$ is only a function of $V_{i,t}$ and $ACE_{i,t}^{T}$—i.e., we ignore $\Delta PREM_{i,t}^{T}$. The advantage of ignoring $\Delta PREM_{i,t}^{T}$ is that it is a function of the *realized* value of $\left(V_{i,t+T} - V_{i,t}\right)$, which equals the revision in investors' expectations during the time period spanning quarters t through $t + T$. However, if investors are rational, revisions in their expectations are, by definition, unpredictable. Hence, ignoring $\Delta PREM_{i,t}^{T}$ allows us to ignore the effect of unpredictable "noise" on our inferences about price informativeness at quarter t.

There are two disadvantages to ignoring $\Delta PREM_{i,t}^{T}$. First, if investors are not fully rational, revisions in their expectations reflect both unpredictable noise and price *un*informativeness. Consequently, a disadvantage of ignoring $\Delta PREM_{i,t}^{T}$ is that we ignore *some* of the variation in price informativeness attributable to irrational information processing at time t. That said, to the extent that irrational information processing leads to biased or imprecise forecasts of $ACE_{i,t}^{T}$, not all of its effect on price informativeness is lost.

The second disadvantage of ignoring $\Delta PREM_{i,t}^{T}$ is truncation bias. That is, ignoring $\Delta PREM_{i,t}^{T}$ can cause us to infer that price informativeness is low when it is not. The reason for this is that $ACE_{i,t}^{T}$ only reflects the portion of value created (or destroyed) after quarter t that is captured by the accounting system during the time period spanning quarters t through $t+T$. Hence, if at time t investors accurately predict future events that create (or destroy) value but these events do not affect $ACE_{i,t}^{T}$, $ERR_{i,t}^{T}$ will be confounded. Moreover, because accounting earnings tend to recognize good news with a lag (e.g., Basu [1997]) and are understated for firms that experience growth in expenditures that are accounted for conservatively (e.g., Zhang [2000]), even events that occur before quarter $t+T$ may not be fully captured by $ACE_{i,t}^{T}$.

Dealing with truncation bias involves making a tradeoff. On the one hand, larger values of of T are better in the sense that there will be less truncation bias. However, because $ACE_{i,t}^{T}$ is a function of *ex post* realizations, increases in T lead to decreases in the sample size. With this tradeoff in mind, we choose to set $T=20$ quarters (i.e., five years). We do this for two reasons. First, as discussed in Koeva [2000], investment plans tend to take roughly two years to implement. Hence, a five-year period will capture the effects of investment plans initiated in year t as well as a portion of the effects of plans initiated between year t and year $t+3$.

Second, to calculate $ACE_{i,t}^{T}$ we obtain *ex post* realizations of earnings and dividends from Compustat; and, the Compustat files that we use only have data for fiscal quarters ending on or before December 2016. Hence, by choosing $T=20$, we can observe price informativeness for quarters up to December 2011. Consequently, we can evaluate the behavior of price informativeness during the period around the global financial crisis of 2007 through 2009.

Bias versus Precision

Low price informativeness does not necessarily imply that the sign of $ERR_{i,t}^{T}$ will be either positive or negative. The reason for this is that, if investors are rational, their conditional expectations are unbiased even when they have low-quality information. Consequently, there is no clear relation between the sign of $ERR_{i,t}^{T}$ and degree of price informativeness. Moreover, the time-series and cross-sectional averages of $ERR_{i,t}^{T}$ can be close to zero despite the fact that prices are based on imprecise forecasts. We address these issues in two ways. First, when the unit of observation is measured at the firm-quarter level, we evaluate both $ERR_{i,t}^{T}$ and its absolute value—i.e., $\left|ERR_{i,t}^{T}\right|$, which we refer to as $ABS\_ERR_{i,t}^{T}$. We evaluate $ERR_{i,t}^{T}$ because it is informative about the degree of bias embedded in investors' forecasts. $ABS\_ERR_{i,t}^{T}$, on the other hand, is informative about the precision of those forecasts. In particular, higher values of $ABS\_ERR_{i,t}^{T}$ imply lower precision.

Second, when the unit of observation is measured at the economy level, we evaluate the temporal behavior of the cross-sectional average and standard deviation of $ERR_{i,t}^{T}$, which we refer to as $BIAS_{t}^{T}$ and STD_{t}^{T}, respectively. We evaluate $BIAS_{t}^{T}$ because price informativess is a function of both the quality of the information available to investors and how they process that information. For example, investors may exhibit excess optimism in some time periods and excess pessimism in others. This, in turn, implies that the cross-sectional average of $BIAS_{t}^{T}$ will vary over time. We evaluate STD_{t}^{T} because it is informative about the precision of investors' forecasts. In particular, higher values of STD_{t}^{T} imply less precise forecasts and lower price informativeness, *ceteris paribus*. Finally, we also evaluate temporal variation in root mean squared $ERR_{i,t}^{T}$, which we refer to as $RMSE_{t}^{T}$. This is a comprehensive measure that reflects the combined effects of bias and precision. Specifically, $RMSE_t^T = \sqrt{(BIAS_t^T)^2 + (STD_t^T)^2}$. Hence, higher values of $RMSE_t^T$ imply lower overall price informativeness.

Comparison to Extant Approaches

Ignoring our approach, there are three commonly-used extant approaches for measuring price informativeness. The first is often referred to as synchronicity and it is motivated by empirical results shown in Roll [1988]. He estimates regressions of realized firm-level stock returns on contemporaneous "authenticated" information (e.g., the realized return on the market portfolio, the realized return on a size- and industry-matched portfolio, etc.) and he finds that the average of the r-squareds from these regressions is roughly 35 percent for monthly data and 20 percent for daily data.

An interpretation of Roll's results is that high unexplained stock return volatility is attributable to rational, informed traders impounding their unobservable, private information into price. Hence, as discussed in Morck et al. [2000], Durnev et al. [2003] and Piotroski and Roulstone [2004], *low* synchronicity between a firm's stock returns and contemporaneous returns on various portfolios (e.g., the market portfolio and/or an industry-matched portfolio, etc.) can be interpreted as an indicator of *high* price informativeness.

Using synchronicity to measuring price informativeness has two limitations. First, as discussed in Roll [1988] and West [1988], an alternative interpretation of low synchronicity is that it reflects excess volatility attributable to either "frenzies" or uninformed noise trading. Second, even if low synchronicity is the result of informed traders impounding their private information into price, it is not necessarily synonymous with high price informativeness – at least, not as we define it. High informed trade could be accompanied by high uncertainty, private information and public information might be substitutes, etc. Consequently, low synchronicity could reflect rational updating of expectations that are, nonetheless, relatively imprecise and biased.

The second commonly-used approach for measuring price informativeness is to evaluate future earnings response coefficients, FERCs (e.g., Gelb and Zarowin [2002] and Lundholm and Myers [2002]). A FERC is the slope coefficient on "future" earnings obtained from a cross-sectional regression of annual realized stock returns for year t on earnings reported in years subsequent to year t. The argument is that higher FERCs imply greater price informativeness. However, this interpretation is not obvious. As shown in Vuolteenaho [2002], realized stock returns reflect *changes* in expectations about future earnings. However, price informativeness relates to the properties of the *levels* of the expectations; and, a high correlation between changes in expectations and realized future earnings does not necessarily imply that the levels of those expectations are unbiased and precise.

The final alternative price-informativeness measure that we discuss is the one described in BPS. They measure price informativeness as the slope coefficient from a cross-sectional regression of annual realized earnings for year $t + h$ on equity market value at the end of year t.[5] They consider horizons (i.e., values of h) between one and five years and interpret higher slope coefficients as an indication of higher price informativeness. This approach overlaps with ours in the sense that BPS evaluate prices, which reflect levels of expectations, and not returns, which reflect revisions in expectations. Nonetheless, it has two limitations. First, BPS' measure can only be used to evaluate temporal variation in economy-level price informativeness. Our approach, on the other hand, generates measures of both economy- and firm-level price informativeness. Hence,

[5] BPS deflate both variables by total assets at the end of year t.

we can evaluate how price informativeness varies with firms' disclosure choices, investors' information acquisition decisions, etc.

Second, the approach developed by BPS relates a firm's price at the end of year t to a *single* earnings realization for a *particular* subsequent year $t + h$. Hence, in order to evaluate multiple horizons, a separate regression must be estimated for each horizon, and then the coefficients from the separate regressions must be combined. However, there is no obvious way to do this. We circumvent this issue in the natural way: We use the fact that earnings aggregate over time. In particular, we use $ACE_{i,t}^{T}$, which equals a firm's aggregate cum-dividend earnings for the entire time period of interest, as our earnings measure. Using $ACE_{i,t}^{T}$ also reduces the influence of any specific year. For example, suppose a firm manipulates its reported accruals in quarter $t + i$. Under accrual accounting, this manipulation will eventually reverse and, if that reversal occurs in quarter $t + j \leq t + T$, there is no effect on either $ACE_{i,t}^{T}$ or our inferences about price informativeness.[6]

Summary

Our approach to measuring price informativeness is intuitive yet rigorous. It provides evidence about the bias and precision of the *levels* of the expectations embedded in observed equity market values. The measures derived from it are comprehensive in the sense that they reflect the combined effects of uncertainty, firms' information production decisions, investors' information-acquisition decisions and information-processing, and trading constraints. Moreover, they can be used to evaluate variation in both economy-level and firm-level price informativeness.

[6] A third advantage of using $ACE_{i,t}^{T}$ is that it is a cum-dividend measure; hence, it preserves dividend policy irrelevance.

4. Data, Sample and Descriptive Statistics

Data and Sample

We obtain our data from several sources. We collect our fundamental accounting data from Compustat. To construct our initial sample, we consider the time period between 1975 and 2016 inclusive; and, we include all firm-quarter observations in the database that are US-incorporated and not ADRs. We exclude firms that do not have a calendar quarter fiscal year-end and firms that only have semi-annual reporting frequency. Our full sample does *not* exclude financial services or utility firms. We trim this initial sample using the following rules. First, we remove firm quarters with $SALES_{i,t}$, $TA_{i,t}$ (total assets) or $TL_{i,t}$ (total liabilities) that are either missing or not greater than zero. We also remove firm quarters that have a stock price that is less than or equal to one dollar. Next, we adopt a set of additional trimming rules related to fundamental accounting variables (see Appendix A for all variable definitions). We require return on equity, $ROE_{i,t}$, and, return on assets, $ROA_{i,t}$, to each be between four and negative four; profit margin, $MARGIN_{i,t}$, to be below one; and, $LEVERAGE_{i,t}$ to be between one and 20. In Appendix B, we describe how we calculate $ERR_{i,t}^{T}$, our key price informativeness measure. We remove observations with extreme values of $ERR_{i,t}^{T}$. In particular, for each quarterly cross-section we delete observations for which $ERR_{i,t}^{T}$ is either below the first percentile or above the 99th percentile of the cross-sectional distribution of $ERR_{i,t}^{T}$. Our exclusion and trimming procedures result in the elimination of 444,058 firm-quarters (331,318 because of missing values and 112,740 attributable to our filters) leading to a main dataset of 473,569 firm-quarter observations, covering 148 quarters.

We use this main dataset as the data source for two sets of tests. First, we perform time-series analyses of economy-level measures of price informativeness. For each quarterly cross-section, we create economy-level measures of price informativeness by aggregating the firm-level price informativeness measures for that quarter. This leads to a sample of 148 quarterly observations. Next, we perform firm-level cross-sectional analysis by using the firm-year sample that is a subset of the main dataset. In particular, we extract all quarters from the main dataset that relate to the fourth fiscal quarter, and then we obtain annual data for the corresponding fiscal year. We then match these observations with firm-level informativeness measures estimated two quarters ahead, i.e., $ERR_{i,t+2q}^{T}$ and $ABS\_ERR_{i,t+2q}^{T}$. This ensures that our price informativeness measures reflect the annual accounting information from the most-recent fiscal year. This procedure leads to an initial sample of 125,471 firm-year observations. We trim this sample at the top and bottom one percentile based on the value of $ERR_{i,t+2q}^{T}$, removing 9,818 observations. Finally, we require availability of all control variables in the firm-level regressions, leading to a final firm-year sample with 79,382 observations.[7]

5. Time-series Analyses

In our first set of analyses we study the temporal variation in price informativeness at the economy-level over our sample period. In these analyses, we consider the three price informativeness measures mentioned in Section 3: $BIAS_t^T$, STD_t^T and $RMSE_t^T$. We also compute an additional variable, $ABS\_BIAS_t^T$, which equals the absolute value of $BIAS_t^T$. Vis-à-vis $BIAS_t^T$, $ABS\_BIAS_t^T$ is a better indicator of the implications of biased forecasts for price informativeness. The reason for this is that, holding the magnitude of $BIAS_t^T$ constant, its sign is irrelevant in the sense that positive $BIAS_t^T$ implies the same level of uninformativeness as negative $BIAS_t^T$. Nonetheless, we also evaluate $BIAS_t^T$ because it sheds light on the extent to which investors'

[7] Note that availability of some of the disclosure variables of interest will further constrain the sample. See Section 6 below.

forecasts are either optimistic or pessimistic. In Appendix A we present the detailed definitions of the variables and in Appendix C we describe how we aggregate firm-level measures to calculate the quarterly measures that we use in our time-series analyses.

To study the temporal variation in the price informativeness variables, we explore their association with several economy-level variables. We start by including the sentiment index from Baker and Wurgler [2007]. Baker and Wurgler [2007] describe how investor sentiment in markets can affect the extent to which prices reflect fundamentals of stocks, in particular for so-called harder-to-arbitrage stocks. They develop a sentiment index and find empirical evidence that this index not only relates to current stock returns, but also helps predict returns across different categories of stocks. We include the sentiment index from Baker and Wurgler [2007] in two ways: $SENT_t$ measures the signed index as defined by Baker and Wurgler [2007]; and, $ABSSENT_t$ is the absolute value of $SENT_t$. We distinguish between $SENT_t$ and $ABSSENT_t$ because they potentially influence price informativeness differently: Although $SENT_t$is directional, $ABSSENT_t$ reflects the extent of sentiment in the market, regardless of its direction. In other words, larger values of $ABSSENT_t$ capture whether investors are more exuberant or gloomy relative to being more "neutral."

Next, we include the noise index, $NOISE_t$, developed by Hu et al. [2013] to capture a broad measure of market-wide liquidity. As discussed by Hu et al. [2013], this broad measure of noise connects with the amount of arbitrage capital available in the market and, as the name of the index suggests, this amount will affect the extent to which information enters into market prices through trading (see also BPS). We further include an additional metric of market uncertainty in our design, namely $SPVOL_t$, which is the standard deviation of the daily returns on the S&P 500 measured during the last month of the quarter. We opt for this metric as opposed to the more traditional metric of the VIX index because observations for the VIX, as it is currently measured, only go back to 2003. In untabulated analysis, we observe a strong correlation between our metric $SPVOL_t$ and the VIX index (the Pearson correlation is 0.87).

Next, we focus on three metrics of "real" economic activity: industrial production, $INDPROD_t$, the level of unemployment, $UNEMP_t$, and realized GDP growth $GDPGROWTH_t$. We include these variables for two reasons. First, Chen, Roll and Ross [1986] examine the influence of economic "state" variables on asset prices and stock market returns. They find that innovations in a number of these state variables are priced in the market and reflected in stock returns. By considering the relation between the levels of these economic variables and our measures, we aim to understand whether the time-series variation of our metrics at the aggregate level is a function of the business cycle. Second, we introduce these variables as complements to the sentiment index proxy. As Baker and Wurgler [2007] discuss, their sentiment index components have been orthogonalized relative to a set of macro-economic indicators. Finally, we focus on the aggregate book-to-market, BM_t, and earnings-to-price, EP_t, ratios. We include both variables so that we can evaluate whether the time-series variation in our informativeness measures is associated with changes in valuation multiples that reflect the premium of current price vis-à-vis current accounting fundamentals.

We report the results of the time-series analyses in Tables 1 through 4. Table 1 reports descriptive statistics on both the main price informativeness variables and the macro variables. Panel A shows that $BIAS_t^T$ is positive during our sample period (the average is 0.69 and the median 0.78). Further, there is considerable variation in $BIAS_t^T$, $ABS\_BIAS_t^T$, STD_t^T and $RMSE_t^T$. Importantly, since we observe a time-trend in our main variables of interest, we detrend them when we study their association with the macro variables.[8] (We also detrend the macro variables.) Panel B shows descriptive statistics on the detrended variables. As shown in Panel B, $BIAS_t^T$ exhibits more *positive* deviations from the sample time-trend, whereas a majority of the detrended $ABS\_BIAS_t^T$ observations are negative. STD_t^T and $RMSE_t^T$ also show significant variation across the sample period. Panels C and D show both the raw values and the detrended values for all the macro variables. We observe in Panel C that over the sample period $SENT_t$ is on average positive, while $ABSSENT_t$ shows significant variation, suggesting that over the period investor sentiment exhibited wild swings. Similarly, both panels show that the other macro variables also exhibit strong variation across the sample quarters.

In Table 2 we present univariate correlations between the price informativeness variables across the sample quarters. The table shows a strong correlation between $BIAS_t^T$ and $ABS\_BIAS_t^T$. This strong correlation relates to the fact that, per Panel A of Table 1, $BIAS_t^T$ tends to be positive, and thus there is a lot of overlap between it and $ABS\_BIAS_t^T$. The fact that $BIAS_t^T$ is typically positive is likely a manifestation of truncation bias. Importantly, the Pearson correlations in Table 2 show that both $BIAS_t^T$ and $ABS\_BIAS_t^T$ are negatively correlated with STD_t^T and $RMSE_t^T$. The latter two metrics therefore appear to capture different phenomena from the bias metrics. Further, there is high positive correlation between STD_t^T and $RMSE_t^T$, which implies that, vis-à-vis bias, precision is the dominant determinant of overall price informativeness as measured by $RMSE_t^T$. Table 3 presents the univariate correlations between the macro variables in our design. Not surprisingly, we observe that a number of these variables are correlated over time.

[8] To verify the presence of a time trend we construct the variable $TIME\_TREND_t$, which equals one in the first quarter of our dataset, and then it increases by increments of one until it reaches its maximum value of 148. We observe that that correlation between each of the price informativeness measures and $TIME\_TREND_t$ is roughly 0.70. Similarly, five out of the nine macro variables exhibit correlations with $TIME\_TREND_t$ above 0.70. Consequently, we detrend each variable by separately regressing it on $TIME\_TREND_t$, and then using the residuals from the regression as our detrended variables of interest.

We present our main time-series results on Table 4. These are univariate correlations between the price informativeness variables and the individual macro variables. The table presents both Pearson and Spearman correlations, which are similar. Hence, we focus our discussion mainly on the Pearson correlations in Panel A. To start, $SENT_t$ is positively correlated with $BIAS_t^T$ and $ABS\_BIAS_t^T$ but negatively correlated with STD_t^T and $RMSE_t^T$. This implies that investor sentiment is positively associated with the level of optimism, degree of bias and the level of precision. Moreover, per the negative correlation between $SENT_t$ and $RMSE_t^T$, the precision effect dominates the bias effect so that overall price informativeness is increasing in the level of investor sentiment.

On the other hand, $ABSSENT_t$ is negatively correlated with $BIAS_t^T$ and $ABS\_BIAS_t^T$ but positively correlated with STD_t^T and $RMSE_t^T$. Hence, extreme (positive or negative) investor sentiment is associated with less optimistic forecasts that are less biased but also less precise. And, the precision effect dominates so that overall price informativeness is lower when sentiment is extreme. Taken together, the results for $SENT_t$ and $ABSENT_t$ suggest that positive sentiment and extreme sentiment are different phenomena. In particular, it is extreme sentiment, and especially extreme negative sentiment, that is associated with less informative prices.

$NOISE_t$ exhibits a positive correlation with both bias variables (Spearman only), STD_t^T and $RMSE_t^T$. This suggests that limits to arbitrage are associated with relatively optimistic forecasts, that are more biased and less precise, and thus lower price informativeness. $SPVOL_t$ is uncorrelated with the bias variables but exhibits a positive correlation with STD_t^T and $RMSE_t^T$. Hence, when economy-level uncertainty is high (low), investors make less (more) precise forecasts and price informativeness is lower (higher).

The correlations between the state variables—i.e., $INDPROD_t$, $UNEMP_t$ and $GDPGROWTH_t$—and the informativeness measures are mixed. The bias variables are negatively correlated with $UNEMP_t$, which in turn, is positively correlated with STD_t^T and $RMSE_t^T$. Hence, when the economy is good in the sense that unemployment is low, investors tend to make forecasts that are more optimistic, more biased and more precise; and, the precision effect dominates the bias effect so that price informativeness is high. This last result is reinforced by the fact that $INDPROD_t$ exhibits negative (but weakly significant) Pearson correlations with STD_t^T and $RMSE_t^T$. However, $GDPGROWTH_t$ is not associated with either STD_t^T or $RMSE_t^T$ and it exhibits a somewhat counter-intuitive negative association with both $BIAS_t^T$ and $ABS\_BIAS_t^T$. Taken together, these results weakly suggest that price informativeness is pro-cyclical.

Both the book-to-market and earnings-to-price ratio are negatively correlated with each of the bias measures. This is consistent with the notion that high aggregate price multiples are observed in time periods when investors are biased and relatively optimistic. However, the two ratios exhibit different relations with precision. BM_t is positively correlated with STD_t^T. This implies that investors make more precise forecasts when market prices are high relative to the accounting fundamentals. Moreover, this precision effect offsets the bias effect so that there is no relation between BM_t and $RMSE_t^T$. On the other hand, EP_t and STD_t^T are uncorrelated. Hence, the negative relation between EP_t and $ABS\_BIAS_t^T$ leads to a negative relation between EP_t and $RMSE_{i,t}^T$, which, in turn, suggests that high prices relative to current fundamentals coincide with time periods when optimism and bias are high and price informativeness is low.

Overall, the results in Table 4 indicate that during our sample period several macro variables are associated with our aggregate metrics of price informativeness. Our findings complement those in BPS and Farboodi, Matray and Veldkamp [2017] who jointly document a broad rise in price informativeness for S&P 500 firms but not for the overall economy. Our analyses show that macro-variables are associated with price informativeness measures for a broad sample of firms, comprising S&P 500 and other firms. We now turn to firm-level analyses to examine the cross-sectional variation in firm-level price informativeness.

6. Firm-level Cross-sectional Analyses

In our second set of analyses we study cross-sectional variation in firm-level price informativeness. Building again on our discussion in Section 3, we consider two firm-level price informativeness variables, $ERR_{i,t}^{T}$ and $ABS\_ERR_{i,t}^{T}$ (see Appendix A for precise definitions). $ERR_{i,t}^{T}$ is our firm-level measure of forecast bias and $ABS\_ERR_{i,t}^{T}$ (i.e., the absolute value of $ERR_{i,t}^{T}$) is our firm-level measure of forecast precision. (Higher values of $ABS\_ERR_{i,t}^{T}$ imply *low* precision.) We evaluate the association between these two variables and a selection of cross-sectional variables that relate to firms' disclosure practices and information environments.

We start by including three proxies for disclosure quality. Our first proxy, $DQ_{i,t}$, is obtained from Chen, Miao and Shevlin [2015]. $DQ_{i,t}$ is a measure of disclosure quality that gauges the level of disaggregation of the financial data in a firm's annual report. The underlying idea is that greater disaggregation leads to greater transparency. Chen et al. [2015] validate this claim by studying the relation between their metric and analyst forecast properties, bid-ask spreads and estimates of cost of equity. Our second metric of disclosure is the fog index, $FOG_{i,t}$, from Li [2008]. This disclosure metric differs from $DQ_{i,t}$ as it measures the "readability" of financial reports and does not simply gauge the level of disaggregation of quantitative items. Li [2008] introduces the measure to the literature and shows how it relates to firm performance and earnings persistence. The latter is important from a forecasting perspective as it implies that readability of annual reports is associated with more sustainable earnings that may be easier to forecast, which, in turn, could affect price informativeness. Recent work by Loughran and McDonald [2014], however, criticizes the fog index as being misspecified and hard to measure. Instead these authors propose a separate readability metric, namely the file size of the 10-K. We use this metric, which we refer to as $SIZE10K_{i,t}$, as our third disclosure proxy. The analysis in Loughran and McDonald [2014] shows that larger 10-K file sizes are associated with larger abnormal return volatility, higher absolute unexpected earnings and higher analyst dispersion. They interpret these results as implying that large 10-Ks lead to "information overload," and thus less informed prices.

Next, we include two variables that measure analyst activity for a given firm. We include these analyst-based variables since "analysts' forecasts have the potential to influence asset prices by conveying information about future cash flows and about the discount rates applied to future cash flows." (Kothari, So and Verdi [2016]). The presence of analyst coverage therefore is likely an important component of the information environment of the firm. Our measure $FOLLOWING_{i,t}$ measures whether a firm is covered by analysts, while $LNNUMFCST_{i,t}$ measures the intensity of the analyst following for a firm.

We also include a number of control variables in the regressions. Per Akbas [2016], we include $INSTITHOLD_{i,t}$ in the regression to control for short-sell constraints. We also include $RDSALES_{i,t}$ to capture the R&D intensity of the firm. We include this variable for two reasons. First, R&D spending is a partial control for truncation bias. In particular, given that R&D expenditures are immediately expensed, as discussed in Zhang [2000] and Monahan [2005], earnings will be low (high) when growth in R&D spending is high (low). Additionally, larger R&D

activity could be an indicator of increased uncertainty about the firm's future.[9] Next, based on the work by Chang et al. [2018], we include the variable $SDFUTROE_{i,t}$, which is a firm-specific forecast of the conditional standard deviation of $ROE_{i,t+1}$. We include this variable because it reflects the level of uncertainty about the firm's future earnings, which should have both a direct effect and indirect effect on price informativeness. Regarding the direct effect, *ceteris paribus*, higher uncertainty implies lower precision and lower price informativeness. However, if management responds to this uncertainty by providing more information, there will be an offsetting indirect effect. By including $SDFUTROE_{i,t}$ in our regressions we partially control for the fact that manager's disclosure choices are endogenously determined.

Finally, we insert four additional control variables. To control for risk, we include the firm's factor loadings on the two Fama-French [1993] risk factors that relate to market to book and size, which we refer to as $HML\_FACT_{i,t}$ and $SMB\_FACT_{i,t}$, respectively. We also control for a firm-specific forecast of the conditional mean of $ROE_{i,t+1}$, per Chang et al. [2018]. We insert this control for expected firm performance in the specification to address the fact that firm performance may be a determinant of firms' disclosure decisions and investors' information acquisition decisions. Our final control variable is $DIRT_{i,t}$, which controls for the extent to which the clean surplus assumption is violated during the five-year horizon over which we measure $ACE^{T}_{i,t+2q}$.

Based on the above discussion, we estimate the following regression:

$$ERR^{T}_{i,t}\ \left(or\ ABS\_ERR^{T}_{i,t}\right) = \alpha_i + \beta_y DISC_{y,i,t} + \sum_{y=1}^{7} \gamma_{y,i,t}\, CONTROL_{y,i,t} + \theta_I + \vartheta_y + \varepsilon_{i,t} \qquad (4)$$

[9] Barth, Kasznik, and McNichols [2001], among others, relate the presence of intangibles (e.g., investing in brands, R&D) to the difficulty of the forecast setting.

In equation (4), $DISC_{y,i,t}$ is one of the five variables of interest (disclosure or information environment) and $CONTROL_{y,i,t}$ is one of the seven control variables. We measure $ERR_{i,t}^{T}$ and $ABS\_ERR_{i,t}^{T}$ *two quarters* after the fiscal-year end for all observations. Our regression specifications also include industry θ (based on the Fama-French 12 industry classification) and year ϑ fixed effects. We calculate standard errors using double-clustering on industry and year.[10]

Tables 5 through 7 present our findings of the cross-sectional analyses. The descriptive statistics in Table 5 show that all variables exhibit considerable variation across the sample, reflecting the broad cross-section of firms we have included. As before, we observe that $ERR_{i,t}^{T}$ is predominantly *positive* in the sample: its mean (median) is 0.81 (0.68) and the 25th percentile is positive. This also implies that there is a large overlap between $ERR_{i,t}^{T}$ and $ABS\_ERR_{i,t}^{T}$. The disclosure variables $DQ_{i,t}$, $FOG_{i,t}$ and $SIZE10K_{i,t}$ show high variation across the sample. Further, more than half the firms in the sample have no analyst following, consistent with our sample representing a broad cross-section of firms. Other notable statistics are that $INSTITHOLD_{i,t}$ is about 34 percent on average and about 25 percent of firms report non-zero R&D spending; and, the forecast of the conditional mean of $ROE_{i,t+1}$, $AVEFUTROE_{i,t}$, is positive on average and for the typical firm (the mean and median are 0.07 and 0.11, respectively).

We show univariate Pearson and Spearman correlations in Table 6. Focusing specifically on the first two columns in the table, we observe that both $ERR_{i,t}^{T}$ and $ABS\_ERR_{i,t}^{T}$ exhibit significant correlations with the variables of interest and the control variables in the regressions. Consistent with the earlier observation in Table 5 that most $ERR_{i,t}^{T}$ observations are positive, we further observe a strong correlation between $ERR_{i,t}^{T}$ and $ABS\_ERR_{i,t}^{T}$. Focusing on the three

[10] We winsorize several variables in order to reduce the effects of outliers. The variables $ERR_{i,t}^{T}$ and $DIRT_{i,t}$ are winsorized at the top and bottom one percentile, and the variable $RDSALES_{i,t}$ is winsorized at the 95th percentile.

disclosure variables, we note first that, perhaps surprisingly, $DQ_{i,t}$ is positively correlated with $ERR_{i,t}^{T}$ and $ABS\_ERR_{i,t}^{T}$. Further, the two "readability" metrics correlate differently with $ERR_{i,t}^{T}$ and $ABS\_ERR_{i,t}^{T}$. A higher FOG index suggests more biased and lower precision but the presence of longer 10-Ks points in the other direction: reduced bias and higher precision. The presence of analysts ($FOLLOWING_{i,t}$) does not correlate with $ERR_{i,t}^{T}$ but is correlated negatively with $ABS\_ERR_{i,t}^{T}$; and, the intensity of analyst following is correlated negatively with both $ERR_{i,t}^{T}$ and $ABS\_ERR_{i,t}^{T}$. In sum, the patterns of the univariate correlations between $ERR_{i,t}^{T}$ or $ABS\_ERR_{i,t}^{T}$ and the main variables of interest present a few surprising results. Of course, these univariate correlations ignore potential confounding influence of other variables. We therefore now turn to the regression tests.

Table 7 presents the results of the regression specifications. Panel A (B) shows the findings for the regressions that focus on $ERR_{i,t}^{T}$ ($ABS\_ERR_{i,t}^{T}$). Given the strong overlap between these two variables, the findings in both panels are similar.[11] We therefore discuss both sets of results simultaneously and highlight differences where they exist. First, there is a significant negative relation between $DQ_{i,t}$ and both $ERR_{i,t}^{T}$ and $ABS\_ERR_{i,t}^{T}$. This implies that forecast bias is lower and forecast precision is higher for firms that provide more-disaggregated financial statement data. These results are consistent with the findings in Chen et al. [2015]. However, the coefficients on both $FOG_{i,t}$ and $SIZE10K_{i,t}$ are insignificant suggesting that "readability" is not associated with price informativeness.

Regarding analyst following, the results on Panel A suggest that it is not associated with forecast bias whereas the results on Panel B suggest that forecast precision is higher for firms that

[11] The overlap creates the concern that $ABS\_ERR_{i,t}^{T}$ does not pick up precision of the forecasts but rather shows bias. We address this concern below.

are followed by analysts. The intensity of analyst following also appears to matter. In particular, the coefficients on $LNNUMFCST_{i,t}$ are significantly negative in both Panels A and B. To the extent that analyst following and the intensity of that following are positively associated with the quality of firms' information environments, these results imply that a better information environment is associated with higher price informativeness (i.e., lower bias and higher precision).

Focusing on the other variables, we observe some additional striking patterns. First, the coefficients on $INSTITHOLD_{i,t}$ are significantly negative in both Panels A and B. These results are consistent with the argument that, when institutional holdings are high, short-sell constraints are low (e.g., Akbas). Consequently, the forecasts embedded in stock prices are less *optimistic* (Panel A) and *more* precise (Panel B). The coefficients on $RDSALES_{i,t}$ are positive and highly significant, consistent with a positive (negative) association between R&D spending and forecast bias (precision). The former finding is consistent with $RDSALES_{i,t}$ reflecting truncation bias in $ERR^{T}_{i,t}$. The positive coefficient on $SDFUTROE_{i,t}$ across specifications suggests that higher earnings uncertainty is positively associated both with higher bias and lower precision.

Finally, regarding the other control variables, we find that the coefficients on the Fama-French factor loadings are generally not significant across specifications. This alleviates the concern that cross-sectional variation in our price informativeness proxies is simply a manifestation of cross-sectional differences in risk. Also, the negative coefficients on $AVEFUTROE_{i,t}$ across specifications is consistent with lower positive bias and higher precision when expected $ROE_{i,t+1}$ is higher. Finally, for completeness, the control variable $DIRT_{i,t}$ tends to be associated with higher bias and lower precision.

Although the findings in Panel A and B of Table 7 suggest that our variables of interest are associated with bias and precision, there is an important caveat. As discussed above, there is a lot of overlap between $ERR_{i,t}^{T}$ and $ABS\_ERR_{i,t}^{T}$. This overlap is likely attributable to two features of our research design: (1) truncation of the forecast horizon to 5 years and (2) our assumption about the equity risk premium – see Appendix B. Truncation bias clearly leads to upwards bias in $ERR_{i,t}^{T}$. Moreover, to the extent our estimate of the equity risk premium is too high, $ERR_{i,t}^{T}$ will be biased upwards. The important implication of the overlap is that our metric $ABS\_ERR_{i,t}^{T}$ may not reflect precision; rather, it may simply be a redundant measure of $ERR_{i,t}^{T}$.

We therefore carry out one additional set of tests to evaluate *precision* of the price forecasts. We follow a two-step process. First, we estimate specification (1) in Table 7 Panel A and obtain the residuals from this regression. Next, we take the absolute values of these residuals and regress them on the specifications in columns (2) through (6) of Table 7 Panel A. This two-step process provides a better assessment of the relation between our variables of interest and the precision of the price forecasts. By taking the absolute values of the residuals from the first regression, we obtain a distribution of firm-specific absolute deviations from our estimate of the firm-specific conditional mean obtained from regression (1). In other words, this distribution captures the relative unsigned magnitude of a measure of $ERR_{i,t}^{T}$ that has been debiased. By regressing these absolute deviations on the treatment and control variables, we evaluate how the variables of interest relate to the level of imprecision.[12] That is, a negative association implies *higher* precision.

We report the descriptive statistics of the residuals, $DMERR_{i,t}^{T}$, and their absolute values, $ABS\_DMERR_{i,t}^{T}$, in Table 5. We observe that more than half of the observations have a *negative* value of $DMERR_{i,t}^{T}$, which implies that $ERR_{i,t}^{T}$ tends to exceed the conditional mean more often

[12] We replicate the analysis by estimating the different specifications (2) through (6) from Table 7 Panel A separately to obtain separate sets of residuals for each regression. We then regress the absolute values of these residuals in the second stage on the same specifications. This approach generates similar results to the ones that we report in the paper.

than it falls below it. (The average value of $DMERR_{i,t}^{T}$ is, by construction, equal to zero.) More importantly, as shown on Table 6. The correlation between $ABS\_DMERR_{i,t}^{T}$ and $ERR_{i,t}^{T}$ is only 0.41; hence, $ABS\_DMERR_{i,t}^{T}$ contains different information than $ERR_{i,t}^{T}$.

In Panel C of Table 7, we show the results from the second-stage regressions. We observe that the coefficient on $DQ_{i,t}$ is statistically insignificant. Taken together with the results in Panel A, this result suggests that the positive relation between disaggregation and price informativeness is solely attributable to a reduction in bias. The coefficient on $FOG_{i,t}$ remains insignificant, but $SIZE10K_{i,t}$ now obtains a significantly negative coefficient. This implies that a longer 10-K file is associated with *more* precise forecasts. This finding may be surprising given the discussion and findings in Loughran and McDonald [2014]. However, they focus on short-term outcome variables such as abnormal return volatility around the publication of the 10-K whereas our measure of price informativeness is based on the level of the equity market value measured well after the date on which the 10-K is published. Consequently, the results are not necessarily contradictory. In particular, as discussed in Loughran and McDonald [2014], longer 10-Ks may lead to short-term information "overload." However, longer 10 Ks may also be more informative, which implies that, to the extent investors eventually "digest" this information, longer 10-Ks are associated with more informative prices. The results on both analyst variables remain unchanged—i.e., both the presence of analysts and the intensity of their forecasts improves the precision of forecasts.

Turning to the other variables, the coefficients on $INSTITHOLD_{i,t}$ are significantly negative. Hence, forecast bias is lower (Panel A) and precision is higher when institutional holdings are high. These results provide an important extension to the results in BPS [2016] and Farboodi et al. [2017]. These authors argue that institutional owners are better at processing information, and thus there is a positive relation between institutional holdings and price informativeness. Our results show that better price informativeness in the presence of higher institutional holdings manifests itself *both* in terms of decreased bias and improved precision. This is consistent with the interpretation that higher institutional holdings lead to lower short-sell constraints, and thus higher price informativeness.

The coefficients on $RDSALES_{i,t}$ become insignificant in Panel C. This suggests that R&D spending is not associated with precision. Moreover, taken together with the rsults in Panel A, which show a positive association between R&D spending and bias, these results suggest that, for our sample of firms, there is a negative association between R&D spending and price informativeness—i.e., higher R&D is associated with higher bias. This is at odds with the results in BPS and Farboodi et al. [2017], who find a positive association between R&D spending and price informativeness for S&P 500 firms.

The coefficients on $SDFUTROE_{i,t}$ are positive and highly significant across all specifications, consistent with firm-specific uncertainty being associated with lower forecast precision. Finally, the coefficients on the Fama-French factor loadings remain insignificant across specifications, higher $AVEFUTROE_{i,t}$ is associated with higher precision and *ex post* dirty surplus accounting is associated with lower *ex ante* precision.

Taken together, the evidence in Table 7 shows significant associations between disclosure variables, the presence of analyst coverage, additional firm-environment variables and our metrics of price informativeness. Importantly, our research design allows us to separately evaluate bias and precision. Broadly speaking, we find that firms that provide more-disaggregated financial data and longer filings have lower forecast bias and higher forecast precision, respectively. Similarly, the presence of analysts and the intensity of their following are also associated with lower bias, higher precision and higher price informativeness.

7. Conclusion

Price informativeness is a central economic phenomenon. When equity prices are more informative, investors pay a fairer price for risk sharing and consumption smoothing, entrepreneurs receive funding that is commensurate with their value-creation potential and economic agents learn more from equity prices, which, in turn, implies that they make more-informed real decisions. Hence, understanding what determines price informativeness is a central issue in accounting, finance and economics.

In this study we shed *some* light on the determinants of price informativeness. To do that we first propose a new measure of price informativeness. Our measure reflects the accuracy of the levels of the expectations embedded in observed equity prices. Hence, it is intuitive yet rigorous. Moreover, it can be used at both the firm- and economy-level and to separately evaluate forecast bias, forecast precision and their combined effect.

Our empirical results show that economy-level price informativeness is high when: (1) there is moderate investor sentiment (either positive or negative); (2) limits to arbitrage are low; (3) uncertainty is low; (3) unemployment is low; and, (4) the aggregate earnings-to-price ratio is high. Our firm-level tests show that firms have more informative prices when: (1) they provide greater transparency in terms of more-disaggregated accounting data and/or longer 10-Ks or (2) they have good information environments in terms of analyst following and the intensity of that following.

Appendix A: Variable Definitions

Model variables:

Variable	Definition	Data Source
$V_{i,t}$	Equity market value of firm *i* at the end of quarter *t* (see App. B)	Compustat
$EARN_{i,t}$	Earnings of firm *i* for quarter *t* (see App. B)	Compustat
$DIV_{i,t}$	Dividend paid by firm *i* in quarter *t* (see App. B)	Compustat
$B_{i,t}$	Book value of firm *i* at the end of quarter *t* (see App. B)	Compustat
$R_{f,t}$	$= \left(1 + r_{f,t}\right)$ where $r_{f,t}$ is the quarterly risk-free rate (see App. B)	US Fed, Compustat and CRSP
$R_{i,t}$	$= \left(1 + r_{i,t}\right)$ where $r_{i,t}$ is firm *i*'s quarterly cost of equity risk (see App. B)	US Fed, Compustat and CRSP
$ACE_{i,t}^{T}$	$= \sum_{\tau=1}^{T}\left\{EARN_{i,t+\tau} + \left(R_{f,t}^{T-\tau} - 1\right) \times DIV_{i,t+\tau}\right\}$ or firm *i*'s aggregate cum-dividend earnings for the time-period spanning quarter *t*+1 through *t*+*T*	Compustat, US Fed, CRSP
$\Delta PREM_{i,t}^{T}$	$= \left(V_{i,t+T} - B_{i,t+T}\right) - \left(V_{i,t} - B_{i,t}\right)$ or the change in premium of equity market value over book value for the time-period spanning quarter *t*+1 through *t*+*T*	Compustat
$ERR_{i,t}^{T}$	Price informativeness for firm *i* at the end of quarter *t*, measured as $\frac{V_{i,t} - \left(\frac{ACE_{i,t}^{T}}{R_{i,t}^{T} - 1}\right)}{V_{i,t}}$ (see App. B)	Compustat, US Fed, CRSP
$ABS\_ERR_{i,t}^{T}$	Absolute value of $ERR_{i,t}^{T}$	Compustat, US Fed, CRSP

Economy-level time-series analyses (time subscripts omitted):

Variable	Definition	Data Source
BIAS	$Bias_t^T = \frac{\sum_{i=1}^{N_t} ERR_{i,t}^{T}}{N_t}$, calculated by quarter (see App. C)	Compustat, US Fed, CRSP
ABS_BIAS	$ABS\_Bias_t^T = \sqrt{\left(\frac{\sum_{i=1}^{N_t} ERR_{i,t}^{T}}{N_t}\right)^2}$ calculated by quarter (see App. C)	Compustat, US Fed, CRSP
STD	$STD_t^T = \sqrt{\frac{\sum_{i=1}^{N_t}\left(ERR_{i,q}^{T} - Bias_{y,q}^{T}\right)^2}{N_t}}$ calculated by quarter (see App. C)	Compustat, US Fed, CRSP
RMSE	$RMSE_t^T = \sqrt{\frac{\sum_{i=1}^{N_t}\left(ERR_{i,t}^{T}\right)^2}{N_t}}$ calculated by quarter (see App. C)	Compustat, US Fed, CRSP
SENT	Sentiment index from Baker and Wurgler (2007)	Baker and Wurgler's website: http://people.stern.nyu.edu/jwurgler/

ABSSENT	Absolute value of *SENT*	Baker and Wurgler's website: http://people.stern.nyu.edu/jwurgler/
NOISE	Monthly average of Hu et al. (2014) Noise index	Jun Pan's website (http://www.mit.edu/~junpan/)
SPVOL	Monthly standard deviation of daily S&P 500 Index returns	CRSP
INDPROD	Industrial production index	Federal Reserve economic data
UNEMP	Monthly unemployment rate	US Dept. of Labor
GDPGROWTH	Quarterly GDP Growth, percent change from the previous period, seasonally adjusted annual rate	Federal Reserve Bank of St. Louis
BM	Aggregate book-to-market ratio for all firms in the sample (see App. B for definition of equity book value and equity market value)	Compustat
EP	Aggregate earnings-to-price ratio for all firms in the sample (see App. B for definition of earnings and equity market value)	Compustat

Firm-level cross-sectional analyses (firm subscripts omitted):

Variable	Definition	Data Source
ERR_t^T	Firm-level measure of model variable $ERR_{i,t}^T$ measured on a quarterly basis. Measured two quarters after the fiscal year end for year t.	Compustat, US Fed, CRSP
$ABS\_ERR_t^T$	Absolute value of $ERR_{i,t}^T$. Measured two quarters after the fiscal year end for year t.	Compustat, US Fed, CRSP
DQ_t	Firm DQ index per Chen et al. (2015).	Authors of Chen et al. (2015)
FOG_t	Fog Index as defined in Li (2008).	Feng Li's website: http://webuser.bus.umich.edu/feng/
$FOLLOWING_t$	Indicator variable that equals one if the firm has analyst following during the year and zero otherwise.	I/B/E/S
$LNNUMFCST_t$	Log of (one plus the number of unique analysts with outstanding forecasts as of the end of the fiscal year).	I/B/E/S
$SIZE10K_t$	Log of the 10K file-size as per Loughran and McDonald (2014).	https://sraf.nd.edu/
$INSTITHOLD_t$	Ratio of total shares held by institutions divided by total firm shares outstanding at fiscal year-end.	Thomson Reuters 13f Holdings
$AVEFUTROE_t$	Forecast of the conditional mean of $ROE_{i,t+t}$ per Chang et al. (2018).	Authors of Chang et al. (2018)
$SDFUTROE_t$	Forecast of the conditional standard deviation of $ROE_{i,t+t}$ per Chang et al. (2018).	Authors of Chang et al. (2018)
$RDSALES_t$	R&D expense scaled by total sales.	Compustat

HML_FACT$_t$	Firm-specific Fama and French HML factor loading, estimated using a 60-months rolling window regression of firms' monthly return on the monthly factors.	CRSP, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
SMB_FACT$_t$	Firm-specific Fama and French SMB factor loading, estimated using a 60-months rolling window regression of firms' monthly return on the monthly factors.	CRSP, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
DIRT$_t$	$(B_{i,t+T} - B_{i,t}) - \sum_{\tau=1}^{T}\{EARN_{i,t+\tau} - DIV_{i,t+\tau}\}$.	Compustat
ABSDIRT$_t$	Absolute value of $DIRT_{i,t}$.	Compustat
ROE$_t$	$4 \times (EARN_t/B_t)$. $EARN_t$ is income and B_t is equity book value.	Compustat
ROA$_{t,}$	$4 \times (EARN_t/AT_t)$. $EARN_t$ is income and AT_t is total assets.	Compustat
MARGIN$_t$	$EARN_t/SALEQ_t$. $EARN_t$ is income and $SALEQ_t$ sales for the quarter.	Compustat
LEVERAGE$_t$	AT_t/B_t. AT_t is total assets and B_t is equity book value.	Compustat
$DMERR_t^T{}_t$	The residuals from the regression of ERR_t^T on a set of control variables, industry fixed effects and year fixed effects.	Compustat, US Fed, CRSP
$ABS\_DMERR_t^T$	The absolute value of $DMERR_t^T$	Compustat, US Fed, CRSP

Appendix B: Calculation of $ERR_{i,t}^T$.

This appendix provides the detail on our calculation of $ERR_{i,t}^T$ for each firm quarter in our sample. $ERR_{i,t}^T = \frac{V_{i,t} - \left(\frac{ACE_{i,t}^T}{R_{i,t}^T - 1}\right)}{V_{i,t}}$. In this equation, $V_{i,t}$ is the equity market value of firm i at the end of quarter t and $ACE_{i,t}^T = \sum_{\tau=1}^{T}\{EARN_{i,t+\tau} + (R_{f,t}^{T-\tau} - 1) \times DIV_{i,t+\tau}\}$ is firm $i's$ aggregate cum-dividend earnings for the time period spanning quarter $t+1$ through $t+T$. $EARN_{i,t+\tau}$ is estimated as firm $i's$ realized earnings for quarter $t+\tau$ and $DIV_{i,t+\tau}$ is estimated as the actual dividend paid by firm i at the end of quarter $t+\tau$. $R_{f,t} = (1 + r_{f,t})$ and $R_{i,t} = (1 + r_{i,t})$; and, $r_{f,t}$ and $r_{i,t}$ are the quarterly risk-free rate and the expected quarterly rate of return on firm $i's$ cost of equity capital, respectively. We use $T = 20$ quarters, which corresponds to 5 years.

$EARN_{i,t+\tau}$ is the quarterly net income and, depending on data availability, we use the one of the following definitions, which are shown in order of preference: Compustat item IBCOMQ (Income Before Extraordinary Items - Available for Common); or, IBQ (Income Before Extraordinary Items) less MIIQ (Noncontrolling Interest - Income Account); or, NIQ (Net Income /Loss) less XIQ (Extraordinary Items). If none of the above three options yields an earnings number and if data is available for the other three quarters of the fiscal year, we impute the income for the missing quarter using the annual income (IBCOM) for the corresponding fiscal year. If IBCOM is also missing, but the income for the trailing three quarters are available, we estimate the income for the current quarter as EPSX12 (Earnings Per Share (Basic) - Excluding Extraordinary Items - 12 Months moving) times CSH12Q (Common Shares Used to Calculate Earnings Per Share - 12 Months Moving) less the cumulative income for the trailing three quarters.

$DIV_{i,t+\tau}$ is the product of DVPSXQ (Div per Share - Exdate – Quarter) and shares outstanding at the beginning of the quarter CSHOQ (Common Shares Outstanding), adjusted for stock splits etc. using AJEXQ (Adjustment Factor (Company) - Cumulative by Ex-Date). In case the above is missing, 1/4th of the annual dividend (DVC) is used. If both are missing, the quarterly dividend is set equal to zero.

We estimate the quarterly risk-free rate $r_{f,t}$ using annual US treasury rates on zero coupon bonds with maturities equal to $T \div 4$ years. We derive the expected quarterly rate of return $r_{i,t}$ for each firm from the annual expected rate of return calculated as follows:

$$Annualr_{i,t}^{T} = Annualr_{f,t}^{T} + beta_{i,t} \times \ MRP$$

We estimate $Annualr_{f,t}$ as described above and maturity matched to the T/4-year treasury rate. We use a market risk premium (MRP) of 5 percent. We estimate $beta_{i,t}$ for each firm in each quarter by re-levering the respective industry un-levered beta. For un-levered betas we use the

Fama-French 30 industries. We estimate the raw industry beta for each industry-quarter using a rolling 60-month window return and unlevered using trailing five-year industry average leverage. We re-lever the un-levered industry beta using trailing five-year average firm leverage. We calculate the equity market value of the firm at the end of each quarter, $V_{i,t}$, from Compustat as PRCCQ (Price Close – Quarter) times CSHOQ (Common Shares Outstanding).

We calculate $ERR_{i,t}^{T}$ for every firm-quarter for which we have a minimum of leading 4 quarters of non-missing *EARN* data and we use up to a maximum of 20 quarters (T/4=5 years). We terminate our $ERR_{i,t}^{T}$ estimation in 2011 as we have full Compustat data only through the fourth calendar quarter of 2016. We identify delisting years from CRSP and all 4 quarters of such years are excluded from the $ERR_{i,t}^{T}$ as well as the *EARN* calculation. This implies that $ERR_{i,t}^{T}$ is not calculated for any of the quarters in the delisting fiscal year and that the last *EARN* values used for any $ERR_{i,t}^{T}$ calculation will be from the quarters one fiscal year prior to the delisting fiscal year. For example, if a firm gets delisted in the fiscal year 2000, $ERR_{i,t}^{T}$ will be calculated for this firm up to the 4th fiscal quarter of the fiscal year 1998. The $ERR_{i,t}^{T}$ estimate for the 4th fiscal quarter of 1998 will use 4 quarters of *EARN* from the fiscal year 1999. For firms which get temporarily delisted but continue to trade subsequently (for example after a bankruptcy / restructuring etc.), $ERR_{i,t}^{T}$ is calculated soon after the delisting year and subject to both income and market value data becoming available.

To account for violations of clean surplus accounting (i.e., "dirty" surplus) we calculate the variable $DIRT_{i,t} = \left(B_{i,t+T} - B_{i,t}\right) - \sum_{\tau=1}^{T}\left\{EARN_{i,t+\tau} - DIV_{i,t+\tau}\right\}$. If clean surplus holds, the difference between $B_{i,t+T}$ and $B_{i,t}$ will equal the cumulative difference between earnings and dividends and $DIRT_{i,t}$ will equal zero. We use $DIRT_{i,t}$ as a control variable in our firm-level cross-sectional regressions. Finally, we drop all observations with one or more of the following variables missing from the final dataset: *ERR*, *SALEQ*, *ATQ*, *LTQ* and *DIRT*.

Appendix C: Calculation of Quarterly Economy-level Price-informativeness Measures

For our economy-level time-series tests, we calculate quarterly-level price informativeness measures by aggregating firm-level values of $ERR_{i,t}^{T}$ (see Appendix B) for each quarter. In particular, we calculate the four statistics shown below:

$$Bias_t^T = \frac{\sum_{i=1}^{N_t} ERR_{i,t}^T}{N_t} \tag{C.1}$$

$$ABS\_Bias_t^T = \sqrt{\left(\frac{\sum_{i=1}^{N_t} ERR_{i,t}^T}{N_t}\right)^2} \tag{C.2}$$

$$STD_t^T = \sqrt{\frac{\sum_{i=1}^{N_t} \left(ERR_{i,t}^T - Bias_t^T\right)^2}{N_t}} \tag{C.3}$$

$$RMSE_t^T = \sqrt{\frac{\sum_{i=1}^{N_t} \left(ERR_{i,t}^T\right)^2}{N_t}} \tag{C.4}$$

N_t is the number of observations for quarter t.

References

AKBAS, F. “The Calm before the Storm.” *Journal of Finance* 71 (2016): 225-266.

ARROW, K. “The Role of Securities in the Optimal Allocation of Risk-bearing.” *Review of Economic Studies* 31 (1964): 91-96.

BAKER, M.; AND J. WURGLER. “Investor Sentiment in the Stock Market.” *Journal of Economic Perspectives* 21 (2007): 129-151.

BAI, J.; T. PHILIPPPON; AND A. SAVOV. “Have Financial Markets Become More Informative?” *Journal of Financial Economics* 122 (2016): 625-654.

BARTH, M.; R. KASZNIK; AND M. MCNICHOLS. “Analyst coverage and intangible assets.” *Journal of Accounting Research* 39 (2001): 1-34.

BASU, S. “The Conservatism Principle and the Asymmetric Timeliness of Earnings.” *Journal of Accounting and Economics* 24 (1997): 3-37.

BEBER, A.; AND M. PAGANO. “Short-Selling Bans Around the World: Evidence from the 2007-09 Crisis”, *The Journal of Finance* 68 (2013): 343-381.

BOND, P.; A. EDMANS; AND I. GOLDSTEIN. “The Real Effects of Financial Markets.” *Annual Review of Financial Economics* 4 (2012): 339-360.

CHANG, W-J.; S. MONAHAN; A. OUAZAD; AND F. VASVARI. “The Higher Moments of Future Earnings.” *Working Paper, INSEAD* (2018).

CHEN, S.; B. MIAO; AND T. SHEVLIN. “A New Measure of Disclosure Quality: The Level of Disaggregation of Accounting Data in Annual Reports.” *Journal of Accounting Research* 53 (2015): 1017-1054.

CHEN, N-F.; R. ROLL; AND S.A. ROSS. “Economic Forces and the Stock Market.” *Journal of Business* 59 (1986): 383-403.

DURNEV, A.; R. MORCK; B. YEUNG; AND P. ZAROWIN. “Does Greater Firm-Specific Return Variation Mean More or Less Informed Stock Pricing?” *Journal of Accounting Research* 41 (2003): 797-836.

EASTON, P.D.; T.S. HARRIS; AND J.A. OHLSON. "Aggregate Accounting Earnings Can Explain Most of Security Returns." *Journal of Accounting and Economics* 15 (1992): 119-142.

FAMA, E.F.; AND K.R. FRENCH. "Common Risk Factors in the Returns on Stocks and Bonds". *Journal of Financial Economics* 33 (1993): 3-56.

FARBOODI, M.; A. MATRAY; AND L. VELDKAMP. "Where Has All the Big Data Gone?" *Working paper, Princeton, NYU* (2017).

GELB D.S.; AND P. ZAROWIN. "Corporate Disclosure Policy and the Informativeness of Stock Prices." *Review of Accounting Studies* 7 (2002): 33-52.

HAYEK, F.A. "The Use of Knowledge in Society." *The American Economic Review* 35 (1945): 519-530.

HU, G.X.; J. PAN; AND J. WANG. "Noise as Information for Illiquidity" *Journal of Finance* 68 (2013): 2341-2382.

HUTTON, A.P.; L.F. LEE; AND S.Z. SHU. "Do Managers Always Know Better? The Relative Accuracy of Management and Analyst Forecasts?" *Journal of Accounting Research* 50 (2012): 1217-1244.

KOEVA, P. "The Facts about Time-to-Build." *IMF Working Paper* (2000).

KOTHARI, S.P.; E. SO; AND R. VERDI. "Analysts' Forecasts and Asset Pricing: A Survey." *Annual Review of Financial Economics* 8 (2016): 197-219.

LI, F. "Annual Report Readability, Current Earnings, and Earnings Persistence." *Journal of Accounting and Economics* 45 (2008): 221-247.

LOUGHRAN, T.; AND B. MCDONALD. "Measuring Readability in Financial Disclosures." *The Journal of Finance* 69 (2014): 1643-1671.

LUNDHOLM R.; AND L.A. MYERS. "Bringing the Future Forward: The Effect of Disclosure on the Return-Earnings Relation." *Journal of Accounting Research* 40 (2002): 809-839.

MILLER, E.M. "Risk, Uncertainty, and Divergence of Opinion." *The Journal of Finance* 32 (1977): 1151-1168.

MILLER, M.H.; AND F. MODGLIANI. "Dividend Policy, Growth, and the Valuation of Shares." *Journal of Business* 34 (1961): 411-433.

MONAHAN, S.J. "Conservatism, growth and the role of accounting numbers in the fundamental analysis process." *Review of Accounting Studies* 10 (2005): 227-260.

MORCK, R.; B. YEUNG; AND W. YU. "The Information Content of Stock Markets: Why Do Emerging Markets Have Synchronous Stock Price Movements?" *Journal of Financial Economics* 58 (2000): 215-260.

PIOTROSKI, J.D.; AND D.T. ROULSTONE. "The Influence of Analysts, Institutional Investors, and Insiders on the Incorporation of Market, Industry, and Firm-Specific Information into Stock Prices." *The Accounting Review* 79 (2004):1119-1151.

ROLL, R. "R^2" *The Journal of Finance* 43 (1988): 541-566.

TOBIN, J. "On the Efficiency of the Financial System." *Lloyds Bank Review* 153 (1984): 1-15.

VUOLTEENAHO, T. "What Drives Firm-Level Stock Returns?" *The Journal of Finance* 57 (2002): 233-2646.

WEST, K.D. "Bubbles, Fads, and Stock Price Volatility Tests: A Partial Evaluation" *The Journal of Finance* 43 (1988): 639-656.

ZHANG, X-J. "Conservate Accounting and Equity Valuation." *Journal of Accounting and Economics* 29 (2000): 125-149.

Figure 1
Time-Series Graph of Biases (Unadjusted)

The figure shows the value of quarterly aggregate level price informativeness measure *BIAS*, *ABS*_BIAS, *STD* and *RMSE*, from 1975Q1 to 2011Q4. See Appendix A for all variable definitions.

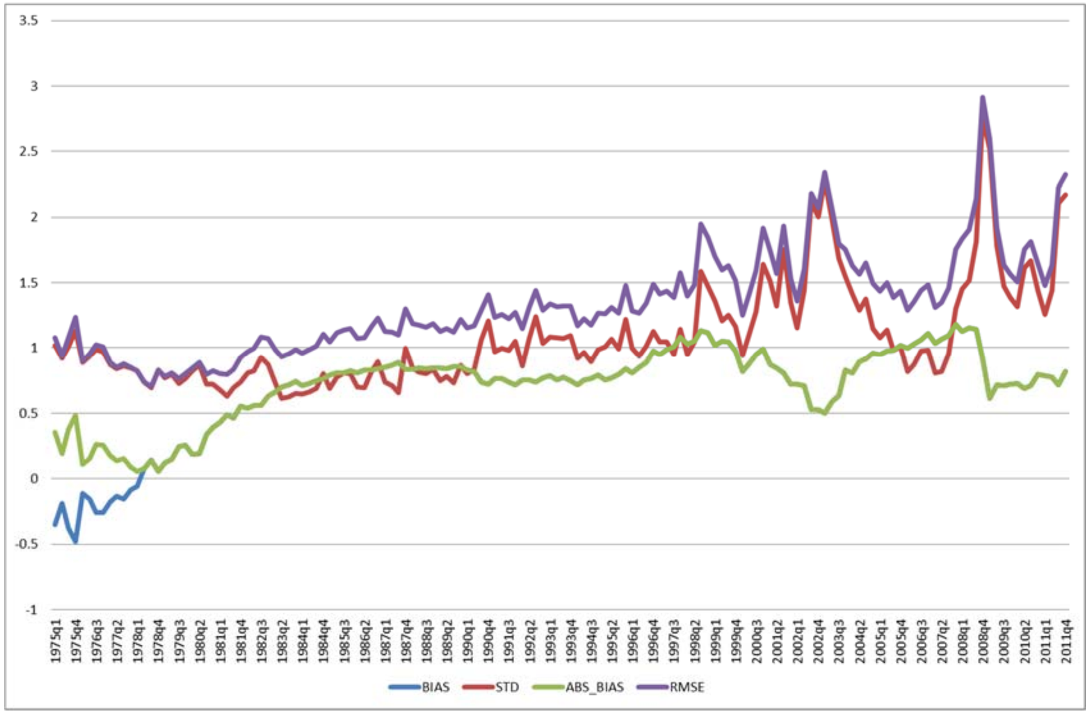

Figure 2
Time-Series Graph of Biases (Detrended)

The left figure shows the value of quarterly aggregate level detrended price informativeness measures *BIAS* and *ABS_BIAS*;
The right figure shows the measures *STD* and *RMSE*, from 1975Q1 to 2011Q4. We detrend all unadjusted variables in this analysis by separately regressing each of them on $TIME\_TREND_t$, and then using the residuals from these regression as our detrended variables of interest. See Appendix A for all variable definitions.

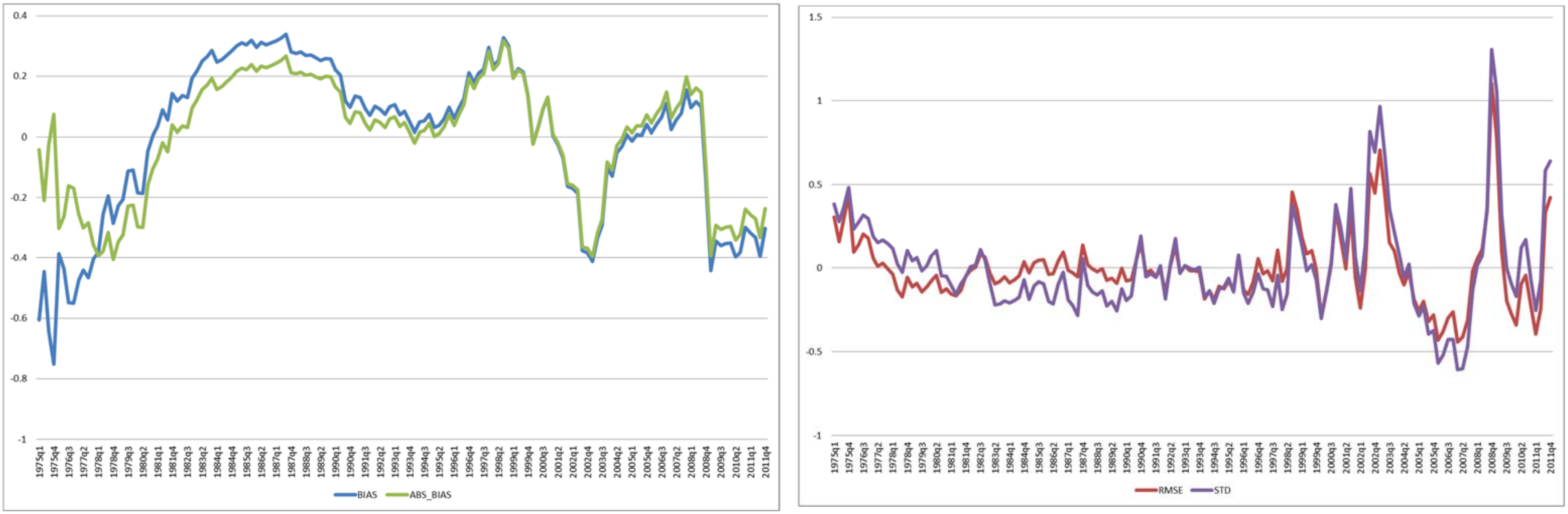

Table 1
Time-Series Analysis: Descriptive Statistics of Quarterly Price Informativeness Measures and Macro Variables

This table shows descriptive statistics for the variables used in the time-series analysis. Panels A and C present statistics for the unadjusted variables; Panels B and D present statistics for detrended variables. We detrend all unadjusted variables in this analysis by separately regressing each of them on $TIME\_TREND_t$, and then using the residuals from these regression as our de-trended variables of interest. See Appendix A for all variable definitions.

Panel A: Price Informativeness Measures (Unadjusted)

Variable	N	mean	sd	min	p1	p5	p10	p25	p50	p75	p90	p95	p99	max
BIAS	148	0.69	0.36	-0.48	-0.38	-0.16	0.07	0.63	0.78	0.88	1.03	1.10	1.15	0.34
ABS_BIAS	148	0.72	0.27	0.06	0.06	0.14	0.19	0.63	0.78	0.88	1.03	1.10	1.15	1.10
STD	148	1.08	0.40	0.61	0.62	0.68	0.71	0.82	0.98	1.24	1.62	1.99	2.52	0.32
RMSE	148	1.33	0.39	0.71	0.74	0.80	0.85	1.08	1.28	1.53	1.85	2.08	2.59	1.31

Panel B: Price Informativeness Measures (Detrended)

Variable	N	mean	sd	min	p1	p5	p10	p25	p50	p75	p90	p95	p99	max
BIAS	148	0.00	0.26	-0.75	-0.64	-0.45	-0.40	-0.19	0.07	0.21	0.29	0.31	0.33	0.34
ABS_BIAS	148	0.00	0.22	-0.44	-0.43	-0.31	-0.25	-0.12	-0.03	0.06	0.31	0.44	0.78	1.10
STD	148	0.00	0.20	-0.41	-0.40	-0.36	-0.32	-0.16	0.04	0.17	0.22	0.24	0.29	0.32
RMSE	148	0.00	0.29	-0.61	-0.60	-0.39	-0.25	-0.17	-0.05	0.11	0.36	0.58	1.06	1.31

Panel C: Macro Variables (Unadjusted)														
Variable	N	mean	sd	min	p1	p5	p10	p25	p50	p75	p90	p95	p99	max
SENT	148	0.11	0.89	-2.20	-2.19	-1.74	-1.17	-0.25	0.15	0.62	0.91	1.26	2.41	2.83
ABSSENT	148	0.65	0.61	0.00	0.01	0.04	0.07	0.21	0.51	0.85	1.70	2.08	2.41	2.83
NOISE	101	3.63	2.16	1.29	1.33	1.45	1.98	2.38	3.21	4.34	5.58	6.02	11.71	18.38
SPVOL	148	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.02	0.03	0.03
INDPROD	148	73.83	19.44	41.61	42.97	48.32	50.18	56.21	68.15	93.77	98.78	102.11	105.09	105.13
UNEMP	148	6.47	1.62	3.90	3.90	4.30	4.50	5.30	6.05	7.40	9.00	9.60	10.30	10.80
GDPGROWTH	148	6.42	4.16	-7.70	-4.50	0.20	2.40	4.45	5.80	8.25	11.70	12.90	20.00	25.20
BM	148	0.56	0.20	0.24	0.24	0.27	0.32	0.39	0.52	0.74	0.87	0.92	1.01	1.03
EP	148	0.02	0.01	-0.03	0.00	0.00	0.01	0.01	0.01	0.02	0.03	0.03	0.04	0.04

Panel D: Macro Variables (Detrended)														
Variable	N	mean	sd	min	p1	p5	p10	p25	p50	p75	p90	p95	p99	max
SENT	148	0.00	0.85	-1.93	-1.93	-1.49	-1.15	-0.42	0.01	0.58	0.99	1.29	2.14	2.57
ABSSENT	148	0.00	0.56	-0.89	-0.82	-0.74	-0.67	-0.36	-0.07	0.26	0.75	1.05	1.92	2.33
NOISE	101	0.00	2.15	-2.08	-2.06	-1.95	-1.66	-1.20	-0.47	0.56	1.76	2.40	8.37	15.03
SPVOL	148	0.00	0.00	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.02	0.02
INDPROD	148	0.00	5.30	-13.75	-11.61	-7.41	-6.62	-3.76	-0.36	4.21	6.70	7.81	10.69	11.18
UNEMP	148	0.00	1.59	-2.37	-2.36	-2.01	-1.66	-1.18	-0.41	0.62	2.75	3.44	3.93	3.97
GDPGROWTH	148	0.00	3.39	-10.81	-10.27	-4.72	-3.64	-1.95	0.05	1.82	3.59	4.36	10.65	15.29
BM	148	0.00	0.14	-0.24	-0.23	-0.21	-0.17	-0.10	-0.01	0.09	0.22	0.26	0.32	0.35
EP	148	0.00	0.01	-0.04	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.02

Table 2
Time-series Analysis: Univariate Correlations between Detrended Price Informativeness Measures

This table shows univariate correlations between detrended price informativeness measures used in the time-series analysis. We detrend all unadjusted variables in this analysis by separately regressing each of them on $TIME\_TREND_t$, and then using the residuals from these regression as our de-trended variables of interest. See Appendix A for all variable definitions. Pearson correlations at the bottom diagonal and Spearman correlations at the upper diagonal. The table shows the correlation coefficients with their corresponding p-values below in brackets. Bold values are significant at the 5% level.

	BIAS	ABS_BIAS	STD	RMSE
BIAS		**0.74**	0.09	**0.03**
		(0.00)	(0.30)	(0.74)
ABS_BIAS	**0.87**		**-0.50**	**-0.49**
	(0.00)		(0.00)	(0.00)
STD	**-0.54**	**-0.49**		**0.93**
	(0.00)	(0.00)		(0.00)
RMSE	**-0.22**	-0.10	**0.88**	
	(0.01)	(0.24)	(0.00)	

Table 3
Time-series Analysis: Univariate Correlations between Detrended Macro Variables

This table shows univariate correlations between detrended macro-variables used in the time-series analysis. We detrend all unadjusted variables in this analysis by separately regressing each of them on $TIME\_TREND_t$, and then using the residuals from these regression as our de-trended variables of interest. See Appendix A for all variable definitions. Pearson correlations at the bottom diagonal and Spearman correlations at the upper diagonal. The table shows the correlation coefficients with their corresponding p-values below in brackets. Bold values are significant at the 5% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)SENT		-0.15	0.02	0.15	-0.02	0.09	0.01	0.08	0.01
		(-0.12)	(-0.83)	(-0.06)	(-0.77)	(-0.27)	(-0.91)	(-0.30)	(-0.86)
(2)ABSSENT	0.07		**0.44**	-0.21	-0.05	0.10	**-0.33**	0.04	**-0.36**
	(0.37)		(0.00)	(-0.03)	(-0.62)	(-0.30)	(0.00)	(-0.68)	(0.00)
(3)NOISE	**-0.20**	0.03		0.08	0.03	0.08	-0.14	**0.18**	-0.11
	(0.04)	(0.75)		(-0.35)	(-0.67)	(-0.34)	(-0.09)	(-0.03)	(-0.17)
(4)SPVOL	-0.01	0.11	**0.64**		0.01	**-0.75**	**0.18**	**-0.28**	0.02
	(0.91)	(0.19)	(0.00)		(-0.91)	(0.00)	(-0.03)	(0.00)	(-0.83)
(5)INDPROD	0.03	**0.21**	**-0.24**	0.01		**-0.19**	**-0.25**	**-0.31**	**-0.29**
	(0.72)	(0.01)	(0.02)	(0.89)		(-0.02)	(0.00)	(0.00)	(0.00)
(6)UNEMP	**-0.21**	-0.01	0.15	0.06	**-0.76**		-0.19	**-0.25**	**-0.31**
	(0.01)	(0.87)	(0.13)	(0.50)	(0.00)		(-0.97)	(0.00)	(-0.01)
(7)GDPGROWTH	**-0.20**	-0.04	**-0.44**	**-0.24**	**0.18**	0.01		0.03	**0.29**
	(0.01)	(0.65)	(0.00)	(0.00)	(0.03)	(0.86)		(-0.68)	(0.00)
(8)BM	**-0.29**	0.03	**0.26**	**0.22**	**-0.39**	**0.68**	-0.05		**0.71**
	(0.00)	(0.75)	(0.01)	(0.01)	(0.00)	(0.00)	(0.57)		(0.00)
(9)EP	**-0.25**	-0.13	**-0.51**	**-0.25**	-0.01	**0.26**	**0.23**	**0.59**	
	(0.00)	(0.11)	(0.00)	(0.00)	(0.92)	(0.00)	(0.00)	(0.00)	

Table 4
Time-Series Analysis:
Univariate Correlations between Price Informativeness Measures and Macro Variables

This table shows univariate correlations between detrended price informativeness measures and macro-variables used in the time-series analysis. We detrend all unadjusted variables in this analysis by separately regressing each of them on $TIME\_TREND_t$, and then using the residuals from these regression as our de-trended variables of interest. See Appendix A for all variable definitions. Pearson correlations are in Panel A; Spearman correlations are in Panel B. The table shows the correlation coefficients with their corresponding p-values below in brackets. Bold values are significant at the 5% level.

Panel A: Pearson Correlations					**Panel B: Spearman Correlations**				
	BIAS	ABS_BIAS	STD	RMSE		BIAS	ABS_BIAS	STD	RMSE
SENT	**0.69**	**0.52**	**-0.40**	**-0.26**	SENT	**0.59**	**0.46**	**-0.41**	**-0.23**
	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.01)
ABSSENT	**-0.38**	**-0.18**	**0.23**	**0.18**	ABSSENT	**-0.39**	**-0.27**	**0.18**	0.10
	(0.00)	(0.03)	(0.00)	(0.03)		(0.00)	(0.00)	(0.03)	(0.23)
NOISE	0.14	0.17	**0.32**	**0.40**	NOISE	**0.32**	**0.25**	**0.28**	**0.41**
	(0.15)	(0.10)	(0.00)	(0.00)		(0.00)	(0.01)	(0.00)	(0.00)
SPVOL	0.05	0.08	**0.28**	**0.36**	SPVOL	0.13	0.11	**0.21**	**0.31**
	(0.54)	(0.35)	(0.00)	(0.00)		(0.12)	(0.17)	(0.01)	(0.00)
INDPROD	-0.02	0.05	-0.15	-0.14	INDPROD	-0.09	0.04	-0.06	-0.09
	(0.79)	(0.55)	(0.07)	(0.08)		(0.28)	(0.66)	(0.44)	(0.28)
UNEMP	**-0.34**	**-0.37**	**0.29**	**0.17**	UNEMP	**-0.28**	**-0.37**	**0.30**	0.15
	(0.00)	(0.00)	(0.00)	(0.04)		(0.00)	(0.00)	(0.00)	(0.06)
GDPGROWTH	**-0.26**	**-0.25**	0.04	-0.04	GDPGROWTH	**-0.26**	**-0.21**	0.05	-0.04
	(0.00)	(0.00)	(0.62)	(0.61)		(0.00)	(0.01)	(0.51)	(0.60)
BM	**-0.43**	**-0.52**	**0.20**	0.05	BM	**-0.41**	**-0.48**	0.15	-0.11
	(0.00)	(0.00)	(0.01)	(0.58)		(0.00)	(0.00)	(0.07)	(0.18)
EP	**-0.38**	**-0.50**	-0.13	**-0.32**	EP	**-0.45**	**-0.49**	-0.08	**-0.39**
	(0.00)	(0.00)	(0.11)	(0.00)		(0.00)	(0.00)	(0.34)	(0.00)

Table 5
Firm-level Cross-sectional Analysis: Descriptive Statistics

This table shows descriptive statistics for the variables used in the firm-level cross-sectional analysis. See Appendix A for all variable definitions.

Variables	**N**	**mean**	**sd**	**min**	**p1**	**p5**	**p10**	**p25**	**p50**	**p75**	**p90**	**p95**	**p99**	**max**
ERR_t	79382	0.81	0.96	-1.70	-1.16	-0.46	-0.12	0.30	0.68	1.13	1.91	2.63	4.40	5.74
ABS_ERR_t	79382	0.93	0.84	0.00	0.02	0.09	0.17	0.39	0.72	1.16	1.91	2.63	4.40	5.74
$DMERR_t$	79382	0.00	0.82	-4.17	-1.89	-1.16	-0.83	-0.40	-0.06	0.28	0.83	1.44	3.04	5.60
ABS_DMERR_t	79382	0.54	0.61	0.00	0.01	0.03	0.06	0.15	0.35	0.70	1.27	1.77	3.07	5.60
DQ_t	65745	0.60	0.11	0.25	0.39	0.43	0.46	0.52	0.58	0.66	0.77	0.80	0.87	0.92
FOG_t	31117	19.47	2.07	0.00	16.24	17.41	17.86	18.57	19.39	20.31	21.36	22.16	24.55	42.04
$SIZE10K_t$	29229	13.58	1.12	6.79	11.55	11.95	12.15	12.62	13.66	14.34	14.91	15.39	16.50	18.77
$FOLLOWING_t$	79382	0.48	0.50	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00
$LNNUMFCST_t$	79382	0.73	0.90	0.00	0.00	0.00	0.00	0.00	0.00	1.39	2.20	2.48	3.00	3.93
$INSTITHOLD_t$	79382	0.34	0.29	0.00	0.00	0.00	0.00	0.06	0.28	0.56	0.78	0.88	1.00	1.00
$RDSALES_t$	79382	0.12	0.26	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.46	0.96	1.02	1.02
$SDFUTROE_t$	79382	0.11	0.11	0.00	0.01	0.01	0.03	0.04	0.07	0.14	0.23	0.32	0.54	1.20
HML_FACT_t	79382	0.00	0.01	-0.13	-0.02	-0.02	-0.01	0.00	0.00	0.01	0.02	0.03	0.03	0.16
SMB_FACT_t	79382	0.01	0.01	-0.11	-0.01	0.00	0.00	0.00	0.01	0.01	0.02	0.02	0.04	0.27
$AVEFUTROE_t$	79382	0.07	0.20	-1.32	-0.66	-0.30	-0.16	0.01	0.11	0.17	0.23	0.29	0.49	2.05
$DIRT_t$	79382	0.28	0.71	-0.72	-0.70	-0.30	-0.17	-0.03	0.06	0.34	0.93	1.58	3.89	4.55

Table 6
Firm-level Cross-sectional Analysis: Univariate Correlations

This table shows univariate correlations between the variables used in the firm-level cross-sectional analysis. See Appendix A for all variable definitions. Pearson correlations at the bottom diagonal and Spearman correlations at the upper diagonal. The table shows the correlation coefficients with their corresponding p-values below in brackets. Bold values are significant at the 5% level.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	ERRt		**0.88**	**0.05**	**0.10**	**0.05**	**-0.08**	**0.02**	**-0.01**	0.00	**0.21**	**0.40**	**0.03**	-0.01	**-0.41**	0.00
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	-(0.30)	(0.00)	(0.00)	(0.00)	-(0.11)	(0.00)	-(0.78)
(2)	ABS_ERRt	**0.90**		**0.22**	**0.07**	**0.05**	**-0.07**	**-0.01**	**-0.05**	**-0.05**	**0.20**	**0.39**	**0.01**	**-0.04**	**-0.43**	**0.06**
		(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	-(0.03)	(0.00)	(0.00)	(0.00)
(3)	ABS_DMERRt	**0.41**	**0.64**		**0.04**	**0.03**	0.00	**-0.06**	**-0.08**	**-0.10**	**0.08**	**0.24**	**-0.01**	**-0.04**	**-0.27**	**0.16**
		(0.00)	(0.00)		(0.00)	(0.00)	-(0.98)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(4)	DQt	**0.11**	**0.09**	**0.06**		**0.13**	**0.56**	**0.32**	**0.35**	**0.45**	**0.38**	**0.29**	**-0.02**	0.00	**-0.13**	**-0.12**
		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	-(0.47)	(0.00)	(0.00)
(5)	FOGt	**0.03**	**0.03**	0.01	**0.07**		**0.28**	**0.06**	**0.08**	**0.05**	**0.04**	**0.09**	**-0.03**	**0.08**	**-0.10**	**0.04**
		(0.00)	(0.00)	-(0.06)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(6)	SIZE10K$_t$	**-0.05**	**-0.05**	-0.01	**0.57**	**0.16**		**0.31**	**0.43**	**0.36**	**-0.03**	**0.02**	**-0.19**	**0.33**	**-0.01**	**-0.06**
		(0.00)	(0.00)	-(0.20)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	-(0.01)	(0.00)	(0.00)	-(0.04)	(0.00)
(7)	FOLLOWING$_t$	0.00	**-0.04**	**-0.07**	**0.36**	**0.05**	**0.35**		**0.75**	**0.51**	**0.17**	**0.09**	0.00	**0.01**	**0.04**	**-0.07**
		-(0.23)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	-(0.24)	-(0.03)	(0.00)	(0.00)
(8)	LNNUMFCST$_t$	**-0.04**	**-0.07**	**-0.08**	**0.37**	**0.08**	**0.46**	**0.85**		**0.59**	**0.16**	**0.06**	**-0.02**	**0.03**	**0.07**	**-0.09**
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(9)	INSTITHOLD$_t$	**-0.04**	**-0.08**	**-0.09**	**0.46**	**0.05**	**0.38**	**0.57**	**0.63**		**0.22**	**0.09**	**0.01**	**0.07**	**0.08**	**-0.20**
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	-(0.04)	(0.00)	(0.00)	(0.00)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(10)	$RDSALES_t$	**0.32**	**0.32**	**0.13**	**0.34**	**0.07**	**-0.03**	**0.14**	**0.12**	**0.12**		**0.28**	**0.06**	**-0.05**	**-0.22**	**0.03**
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(11)	$SDFUTROE_t$	**0.36**	**0.38**	**0.26**	**0.18**	**0.06**	**0.03**	**0.01**	**-0.02**	**-0.01**	**0.36**		**0.04**	**-0.05**	**-0.48**	**0.05**
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)
(12)	HML_FACT_t	**0.01**	-0.01	-0.01	**-0.04**	**-0.03**	**-0.17**	**0.02**	**-0.02**	**-0.01**	**-0.04**	**0.01**		**0.37**	**0.03**	0.00
		(0.00)	-(0.12)	-(0.14)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	-(0.01)	(0.00)	-(0.02)		(0.00)	(0.00)	-(0.41)
(13)	SMB_FACT_t	**-0.02**	**-0.05**	**-0.04**	**-0.06**	**0.02**	**0.34**	**-0.04**	**-0.01**	-0.01	**-0.11**	**-0.06**	**0.25**		**0.04**	**-0.01**
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	-(0.01)	-(0.14)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)
(14)	$AVEFUTROE_t$	**-0.41**	**-0.44**	**-0.27**	**-0.13**	**-0.06**	0.00	**0.05**	**0.09**	**0.10**	**-0.44**	**-0.64**	**0.02**	**0.05**		**-0.13**
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	-(0.94)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)
(15)	$DIRT_t$	0.00	**0.14**	**0.22**	**-0.13**	**0.03**	**-0.05**	**-0.11**	**-0.11**	**-0.19**	**0.06**	**0.08**	**-0.01**	0.00	**-0.12**	
		-(0.21)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	-(0.97)	(0.00)	

Table 7
Firm-Level Cross-sectional Analyses: Regressions

This table shows the results of the estimations of the following regression:

$$ERR_{i,t}\left(or\ ABS_{ERR_{i,t}}\ or\ ABS_{DMERR_{i,t}}\right) = \alpha_i + \beta_y DISC_{y,i,t} + \sum_{y=1}^{7} \gamma_{y,i,t}\, CONTROL_{y,i,t} + \theta_I + \vartheta_y + \varepsilon_{i,t}$$

The dependent variables are $ERR_{i,t}$ in Panel A; $ABS\_ERR_{i,t}$ in Panel B and $ABS\_DMERR_{i,t}$ in Panel C, respectively. *DISC* is a vector of the following 5 variables: *DQ*, *FOG*, *SIZE10K, FOLLOWING*, and *LNNUMFCST*. *CONTROL* is a vector of 7 control variables. θ_I is industry fixed effects, and ϑ_y is year fixed effects. Standard errors are clustered by industry and year. See Appendix A for all variable definitions. The table shows coefficient values and corresponding robust t-statistics between brackets. Significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Dependent variable: ERR_t						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ERR_t	ERR_t	ERR_t	ERR_t	ERR_t	ERR_t
DQ_t		-0.38**				
		(-2.78)				
FOG_t			0.00			
			(0.50)			
$SIZE10K_t$				0.02		
				(0.95)		
$FOLLOWING_t$					-0.00	
					(-0.10)	
$LNNUMFCST_t$						-0.02*
						(-1.86)
$INSTITHOLD_t$	-0.35***	-0.36***	-0.20***	-0.23***	-0.34***	-0.31***
	(-6.03)	(-5.83)	(-3.81)	(-4.19)	(-6.02)	(-6.12)
$RDSALES_t$	0.57***	0.57***	0.52***	0.50***	0.57***	0.57***
	(4.49)	(4.61)	(3.38)	(3.33)	(4.50)	(4.53)
$SDFUTROE_t$	0.83***	0.79***	0.78***	0.79***	0.83***	0.83***
	(5.22)	(4.81)	(6.27)	(6.90)	(5.22)	(5.22)
HML_FACT_t	-1.08	-0.55	-1.88	-0.81	-1.08	-1.08
	(-0.98)	(-0.35)	(-0.81)	(-0.45)	(-0.99)	(-0.98)
SMB_FACT_t	-1.34	-1.22	-3.34	-0.94	-1.34	-1.39
	(-1.65)	(-0.82)	(-0.91)	(-0.45)	(-1.66)	(-1.69)
$AVEFUTROE_t$	-1.14***	-1.10***	-1.13***	-1.19***	-1.14***	-1.14***
	(-17.58)	(-16.00)	(-15.47)	(-14.68)	(-17.78)	(-17.80)
$DIRT_t$	-0.03	-0.02	0.19**	0.21**	-0.03	-0.03
	(-0.51)	(-0.39)	(2.49)	(3.09)	(-0.51)	(-0.50)
Observations	79,382	65,745	31,117	29,229	79,382	79,382
Adj. R-squared	0.265	0.243	0.258	0.261	0.265	0.265

Panel B: Dependent Variable: ABS_ERR_t						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ABS_ERR_t	ABS_ERR_t	ABS_ERR_t	ABS_ERR_t	ABS_ERR_t	ABS_ERR_t
DQ_t		-0.39***				
		(-3.26)				
FOG_t			0.00			
			(0.28)			
$SIZE10K_t$				0.01		
				(0.28)		
$FOLLOWING_t$					-0.03*	
					(-1.87)	
$LNNUMFCST_t$						-0.04***
						(-3.58)
$INSTITHOLD_t$	-0.39***	-0.41***	-0.29***	-0.29***	-0.36***	-0.32***
	(-7.67)	(-7.68)	(-5.36)	(-5.04)	(-6.71)	(-7.00)
$RDSALES_t$	0.45***	0.45***	0.42***	0.40***	0.45***	0.46***
	(3.74)	(3.90)	(3.27)	(3.15)	(3.77)	(3.81)
$SDFUTROE_t$	0.78***	0.71***	0.76***	0.78***	0.77***	0.77***
	(5.21)	(4.65)	(6.78)	(7.46)	(5.21)	(5.23)
HML_FACT_t	-0.49	0.41	-0.51	0.05	-0.50	-0.50
	(-0.53)	(0.33)	(-0.24)	(0.03)	(-0.55)	(-0.54)
SMB_FACT_t	-1.27*	-1.57	-3.83	-2.24	-1.31*	-1.35*
	(-2.05)	(-1.23)	(-1.09)	(-1.35)	(-2.09)	(-2.14)
$AVEFUTROE_t$	-1.05***	-1.03***	-1.05***	-1.10***	-1.05***	-1.04***
	(-18.44)	(-16.58)	(-15.21)	(-15.18)	(-18.91)	(-19.14)
$DIRT_t$	0.13***	0.13***	0.25***	0.26***	0.13***	0.13***
	(3.59)	(3.49)	(3.83)	(4.41)	(3.60)	(3.60)
Observations	79,382	65,745	31,117	29,229	79,382	79,382
Adj.R-squared	0.274	0.251	0.278	0.281	0.274	0.275

Panel C: Dependent variables: ABS_DMERR_t					
	(1)	(2)	(3)	(4)	(5)
VARIABLES	ABS_DMERR_t	ABS_DMERR_t	ABS_DMERR_t	ABS_DMERR_t	ABS_DMERR_t
DQ_t	-0.09				
	(-0.98)				
FOG_t		-0.00			
		(-0.54)			
$SIZE10K_t$			-0.02*		
			(-2.17)		
$FOLLOWING_t$				-0.06***	
				(-6.33)	
$LNNUMFCST_t$					-0.04***
					(-5.59)
$INSTITHOLD_t$	-0.30***	-0.27***	-0.23***	-0.23***	-0.21***
	(-12.41)	(-8.83)	(-6.62)	(-8.61)	(-8.66)
$RDSALES_t$	-0.04	-0.03	-0.04	-0.03	-0.02
	(-1.00)	(-0.89)	(-0.95)	(-0.72)	(-0.66)
$SDFUTROE_t$	0.56***	0.57***	0.52***	0.59***	0.60***
	(5.81)	(4.85)	(4.85)	(6.77)	(6.84)
HML_FACT_t	0.38	-0.04	-0.19	0.09	0.11
	(0.57)	(-0.02)	(-0.12)	(0.20)	(0.24)
SMB_FACT_t	0.42	0.09	-0.06	0.31	0.30
	(0.50)	(0.04)	(-0.06)	(0.75)	(0.74)
$AVEFUTROE_t$	-0.42***	-0.46***	-0.47***	-0.42***	-0.41***
	(-7.88)	(-5.99)	(-6.02)	(-8.59)	(-8.45)
$DIRT_t$	0.19***	0.23***	0.22***	0.18***	0.18***
	(10.35)	(9.28)	(9.03)	(10.00)	(9.97)
Observations	65,745	31,117	29,229	79,382	79,382
Adj. R-squared	0.163	0.170	0.166	0.168	0.168