

THE PRECISION OF INFORMATION IN STOCK  
PRICES, AND ITS RELATION TO DISCLOSURE  
AND COST OF EQUITY

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# **The precision of information in stock prices, and its relation to disclosure and cost of equity**

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## **Abstract**

We estimate the precision of information that prices communicate about firm value, and examine its relation to public disclosure and the cost of equity. We find public disclosure increases the precision of information in prices. For example, stock returns on earnings announcement days reflect the change in the long-term value of the firm more precisely than returns on other days. Similarly, precision of information in prices is higher for firms that voluntarily disclose earnings guidance, and precision has increased for firms that disclose more information following the Sarbanes-Oxley Act. Testing the consequences of higher precision of information in prices, we find it to be associated with a lower cost of equity capital. Our evidence supports the theory that increasing the precision of investor information on the value of the firm will lower its cost of capital.

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## **Abstract**

We estimate the precision of information that prices communicate about firm value, and examine its relation to public disclosure and the cost of equity. We find public disclosure increases the precision of information in prices. For example, stock returns on earnings announcement days reflect the change in the long-term value of the firm more precisely than returns on other days. Similarly, precision of information in prices is higher for firms that voluntarily disclose earnings guidance, and precision has increased for firms that disclose more information following the Sarbanes-Oxley Act. Testing the consequences of higher precision of information in prices, we find it to be associated with a lower cost of equity capital. Our evidence supports the theory that increasing the precision of investor information on the value of the firm will lower its cost of capital.

# **The precision of information in stock prices, and its relation to disclosure and cost of equity**

## **1. Introduction**

The precision of the information that investors have on firm value is an important characteristic of the information environment that can affect the cost of capital (e.g., Admati, 1985; Lambert et al., 2012; Lambert and Verrecchia, 2014). In this paper, we estimate the precision of information that prices communicate about firm value, and examine its relation with public disclosure and the cost of equity capital.

First, we examine the effect of public disclosure on the precision of information in prices. Stock prices aggregate information, and the information that prices eventually communicate can be learned by investors, and coincides with the information commonly known in the market on the value of the firm (e.g., Grossman and Stiglitz, 1980). The precision of this information should increase following disclosures that reduce investor uncertainty about firm value (e.g., Lambert et al., 2012; Lambert and Verrecchia, 2014). Consistent with this hypothesis, we find the precision of information in prices is higher during earnings announcement days than during other days of the quarter. Also, precision during the quarter is higher for firms that provide management earnings guidance than for firms that do not disclose such information during the quarter. Furthermore, we examine the change in precision around the Sarbanes-Oxley (SOX) Act of 2002, and find it has increased for firms that disclose more information following this exogenous change in disclosure requirements. The combined evidence suggests public disclosure increases the precision of information in prices.

The precision of information in prices is expected to increase not only when firms disclose, but also when investors trade their own information into prices. Prices reflect public information and imperfectly reflect private information, and price informativeness increases

as investors trade more on their private information. Investors are expected to trade more aggressively on their private information in liquid stocks, and the precision of information in the prices of these stocks is expected to be higher as a result (Lambert et al., 2012; Lambert and Verrecchia, 2014). Consistent with this argument, we find liquid stocks have higher information precision than illiquid stocks.

The benefit of higher information precision is a lower cost of capital (Lambert et al., 2012; Lambert and Verrecchia, 2014). Consistent with this prediction, we find higher precision of information in stock prices is associated with a lower cost of equity capital.<sup>1</sup> We also find that following the change to the information environment caused by SOX, firms that experienced an increase in the precision of information also experienced a decrease in the cost of equity capital.

Our empirical analyses require a measure of the precision of information in stock prices. To test our hypotheses, we estimate the precision of the information that daily stock returns communicate about the change in firm value. Our methodology is similar to that used by Hodrick (1987) to analyze the information in forward and spot exchange rates, and by Biais et al. (1999) in analyzing information in pre-opening stock prices. Specifically, we regress long-term stock returns (3-13 months around each day) on daily stock returns and use the slope coefficient on the daily stock returns as a measure of precision. Long-term stock returns serve as a proxy for the change in the value of the firm. Imprecise information is information that does not reflect the change in the value of the firm. If daily stock returns contain imprecise information on the change in the long-term value of the firm, the slope (precision) coefficient will be attenuated to 0, and when the precision of information in daily stock returns increases, the slope (precision) coefficient will increase toward 1. We find, for

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<sup>1</sup> As discussed below, we take into account that in theory, the average precision of investors' information is the construct priced, and we introduce controls in our empirical analysis accordingly to test the effect of the precision of information in prices on expected returns.

example, that the precision coefficient is not statistically different from 1 during days around quarterly earnings announcements.

We also construct an alternative measure of precision using a regression of daily stock returns on future earnings surprises. The R-squared of this regression measures the extent to which daily stock returns reflect information on future earnings. This returns-on-earnings precision measure is highly correlated with the returns-on-returns precision measure that we use in our main tests, and both measures are negatively associated with expected returns, supporting the argument that more precise information is associated with a lower cost of equity capital.

Our study contributes to the literature that examines the effect of disclosure on the information in stock prices. Prior literature focuses on the value relevance or timeliness of disclosures (e.g., Lev, 1989; Ball and Shivakumar, 2008). Information is continuously impounded into prices in trading markets, and the periodic accounting disclosures seem to provide a modest amount of incremental information. Prior literature finds, for example, that earnings announcements explain only a small fraction of the variation of stock returns in terms of regression R-squared. Although periodic accounting disclosures lack timeliness, they are subject to more regulation, auditing, and legal scrutiny than other information sources. We find that information impounded into prices on earnings announcement days reflects the change in the long-term value of the stock more accurately than information impounded into prices on other days of the quarter. This result suggests information in quarterly earnings announcements, although not major, is more precise. Similarly, the increase in the precision of information in prices after SOX supports the argument that an increase in required disclosure makes prices a more accurate measure of firm value.

Our study also contributes to the literature that examines the relation between information precision and the cost of equity. Prior studies find a negative relation between

the quality of financial disclosures and the cost of equity (Francis et al., 2005; Leuz and Verrecchia, 2000). If high-quality disclosures are more precise, these prior findings suggest more precise public disclosures decrease the cost of equity. Botosan et al. (2004) examine the relation between the cost of equity capital and the quality of public and private information, using measures derived from analysts' forecasts, and find the precision of public information in analysts' forecasts is negatively associated with the cost of equity capital. On the other hand, the precision of private information in analysts' forecasts is positively associated with the cost of equity, and these effects of private and public information can offset each other. Lambert et al. (2012) and Lambert and Verrecchia (2014), however, argue the precision of both public and private information should be negatively associated with the cost of equity. We find the precision of information in prices, which, according to Lambert et al. (2012) and Lambert and Verrecchia (2014), is an increasing function of the precision of private information and of the precision of public information, is negatively associated with the cost of equity.

## **2. Hypothesis development**

Stock prices aggregate information, reflecting public information and (imperfectly) private information. Because investors learn from prices, the information that can be gleaned from prices reflects the information commonly known to investors (e.g., Grossman and Stiglitz, 1980). The precision of the information that investors have is important because it can affect the pricing of stocks (e.g., Admati, 1985; Lambert et al., 2012; Lambert and Verrecchia, 2014). We estimate the precision of information in stock prices and examine its relation with public disclosure and the cost of equity.

First, we examine the effect of public disclosure on the precision of information in prices. Public disclosures that reduce investor uncertainty about firm value are expected to

increase the precision of information in prices. Prices reflect public information, and the increase in the precision of public information following disclosures will increase the precision of information in prices (Lambert et al., 2012; Lambert and Verrecchia, 2014).<sup>2</sup>

This leads to our first hypothesis:

*H1: Public disclosure increases the precision of information in prices.*

The precision of information in prices is expected to increase also when investors trade their own information into prices. Price informativeness increases as investors trade more on their private information, and investors are expected to trade more aggressively on the basis of their private information, and incorporate more of their information into prices, in liquid stocks. The precision of information in the prices of liquid stocks is expected to be higher as a result (Lambert et al., 2012; Lambert and Verrecchia, 2014).

*H2: The precision of information in prices is higher for more liquid stocks.*

Higher information precision should lead to a lower cost of capital, as argued by Lambert et al. (2012) and Lambert and Verrecchia (2014). Cost of capital, however, should be a function of the average precision across informed and uninformed investors. As discussed above, private information of informed traders is not necessarily impounded in prices, and the precision of information in prices corresponds to the information precision of uninformed traders. Therefore, when testing the relation between cost of capital and the precision of information in prices, we need to control for the precision of private information. To control for the effect of the precision of private information, we use illiquidity. According to Lambert and Verrecchia (2014), illiquidity is associated with the difference between the precision of the information of informed and uninformed investors. That is, when estimating a model of the form

$$\text{Cost of equity}_{it} = \alpha + \beta_1 \text{Precision of information in prices}_{it} + \beta_2 \text{Illiquidity}_{it},$$

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<sup>2</sup> For example, see discussion in Lambert et al. (2012), page 16.



we would expect  $\beta_1$  to be negative.<sup>3</sup> With illiquidity as a control in the regression, the coefficient  $\beta_1$  captures the marginal effect of the precision of information in prices on the cost of equity capital, when holding the difference between the precision of private information and the precision of information in prices constant. In this specification, an increase in the precision of information in prices will increase average precision and is therefore expected to have a negative effect on the cost of equity.

*H3: The precision of information in prices is negatively associated with the cost of equity.*

### 3. Measuring precision of information in prices

To test our hypotheses, we estimate the precision of information in daily stock returns using a methodology similar to that used by Biais et al. (1999). Specifically, we regress long-term stock returns on short-term (daily) stock returns and use the slope coefficient on the daily stock returns as a measure of precision. This measure is linked to the errors-in-variables effect. The dependent variable (long-term returns) serves as a proxy of change in firm value, and the coefficient on daily returns will be attenuated to 0 as daily returns contain less precise information (more measurement error) on change in firm value. Consider the following model:

$$RET_i(t - \tau, t + \tau) = \gamma_0 + \gamma_1 RET(t)_i + \varepsilon_i. \quad (a)$$

The independent (right-hand side) variable is a vector of daily stock returns for firm  $i$ . The dependent (left-hand side) variable is the cumulative return for a window starting  $\tau$  days before and ending  $\tau$  days after day  $t$ , and it serves as a proxy for the change in the fundamental value of the firm. The slope coefficient ( $\gamma_1$ ) is a measure of the precision of the information impounded in the daily stock returns. If information in daily stock returns

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<sup>3</sup> Illiquidity is expected to increase the cost of equity ( $\beta_2 > 0$ ) as argued by Amihud and Mendelson (1986), Amihud (2002), and Lambert and Verrecchia (2014).

accurately reflects the change in the long-term value the stock, the slope coefficient is expected to be 1. However, if daily stock returns contain noise, the slope coefficient will be attenuated toward 0. Consider, for example, a simple case in which  $\tau$  is equal to 1, and the change in the value of the firm over the three trading days is the sum of the information in daily returns:

$$\Delta Value_i(t-1, t+1) = Info(t-1)_i + Info(t)_i + Info(t+1)_i. \quad (b)$$

If the information contents on days  $t-1$ ,  $t$ , and  $t+1$  are uncorrelated, the coefficient  $\gamma_1$  will be exactly 1 when we estimate the following regression, using, for example, the 252 trading days of the stock in one year:

$$\Delta Value_i(t-1, t+1) = \gamma_0 + \gamma_1 Info(t)_i + \varepsilon_i. \quad (c)$$

Following Biais et al. (1999), we use stock returns from time  $t-\tau$  to  $t+\tau$  as a proxy for change in the value of the stock (the dependent variable):

$$Ret_i(t-1, t+1) = \gamma_0 + \gamma_1 Ret(t)_i + \varepsilon_i. \quad (d)$$

If returns on day  $t$  reflect only information, then  $\gamma_1 = 1$ , but if returns also contain noise,  $\gamma_1 < 1$  because the independent variable is measured with error.<sup>4</sup>

We use a return window that starts before  $t$  in the dependent variable, because both the price changes before and after day  $t$  can help determine whether returns on day  $t$  are noisy. For example, returns on day  $t$  can be return reversals due to trade pressures occurring prior to  $t$ , and the inclusion of the returns prior to day  $t$  in the dependent variable will enable us to detect this noise. From an econometric standpoint, using a return window that is centered around  $t$  is not a problem. As long as daily returns are uncorrelated, the precision measure will be unbiased. If returns in the wider return window before or after  $t$  are not relevant, the “cost” will be a greater residual term, and lower R-squared. The slope coefficient, which is

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<sup>4</sup> For an unbiased estimation of (d), the information impounded into prices on different days should be uncorrelated. In our robustness tests below, we estimate our models using a subsample of firms with near-zero autocorrelation in daily stock returns.

the precision measure, is unaffected.<sup>5</sup> Because the use of returns before day  $t$  does not bias the measure, we can simply use monthly returns from CRSP in the dependent variable, which is easier and empirically more tractable.

The empirical equation we estimate here allows the precision coefficient to be different during and outside quarterly earnings announcement days, as follows:

$$RET3M(T)_{it} = \gamma_{0t} + \gamma_{1t}ANND_{it} + \gamma_{2t}RET(T)_{it} + \gamma_{3t}ANND_{it} \times RET(T)_{it} + \varepsilon_{it}. \quad (1)$$

The independent variable,  $RET(T)_{it}$ , is firm  $i$ 's daily stock return on day  $t$  during calendar year  $T$ .  $ANND_{it}$  is an indicator variable that equals 1 in the three-day window around the four quarterly earnings announcements of year  $T$  (12 days in total), and  $ANND_{it} \times RET(T)_{it}$  is a multiplicative variable that allows the slope coefficient to be different for earnings announcement days. The dependent variable,  $RET3M(T)_{it}$ , is the cumulative stock return in the three months surrounding the month containing day  $t$ .

Consider, for example, a company with 252 trading days in calendar year 2012.  $RET(2012)_{it}$  is a vector of 252 daily stock returns in calendar year 2012.  $RET3M(2012)$  is a vector of 252 observations, constructed as follows: for all trading days in June 2012,  $RET3M_{it}$  is the cumulative return from May 1, 2012, through July 31, 2012; for all trading days in July 2012,  $RET3M_{it}$  is the cumulative return from June 1, 2012, through August 31, 2012. The calculation of the returns for the other months of the year follows a similar pattern.  $ANND_{it}$  is a vector of 252 observations in which 12 of the observations corresponding to quarterly earnings announcement days are equal to 1, and the remaining 240 observations are equal to 0.

The coefficient  $\gamma_{2t}$  measures the average precision of non-announcement daily stock returns for company  $i$  in calendar year  $T$ . The coefficient  $\gamma_{3t}$  captures the *incremental*

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<sup>5</sup> In the robustness section below, we show results are similar when we estimate eq. (1) with a forward-looking return window as the dependent variable.

precision of the information released during quarterly earnings announcements by firm  $i$  during calendar year  $T$ . The sum  $[\gamma_{2t} + \gamma_{3t}]$  represents the precision of information released during quarterly earnings announcements by firm  $i$  during calendar year  $T$ .

By estimating eq. (1) for each firm and each year, we obtain a firm-specific annual measure of the precision of information released during non-announcement days, and a measure of the incremental precision of information released during earnings announcement days. Note the slope coefficients in eq. (1) measure the precision of the information, not the information content (often measured by the regression's R-squared).<sup>6</sup> The information in daily returns can be precise but low in information content, so the coefficient  $\gamma_2$  can be close to 1 and, at the same time, the R-squared can be low. For convenience, we label the coefficient  $\gamma_2$  PREC (the precision of information in daily returns); we also label the coefficient  $\gamma_3$  ANNP (the incremental precision of information in returns on earnings announcement days).<sup>7</sup>

We also use an alternative measure of precision based on the association between daily stock returns and subsequent earnings surprises. The R-squared of this regression measures the extent to which daily stock returns reflect information on future earnings, and serves as an alternative precision measure. We find the correlation between this returns-on-earnings precision measure and our returns-on-returns precision measure is 0.30, and both measures yield similar results (see section 5.1 below). We use the returns-on-returns precision measure in our main tests for several reasons. First, the regression of long-term returns on short-term returns, following Biais et al. (1999), yields a robust precision measure. Specifically, we

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<sup>6</sup> Ball and Shivakumar (2008) regress annual stock returns on short-window returns around quarterly earnings announcements, and find returns during announcement days explain only a small fraction of annual returns. Ball and Easton (2013) regress earnings on daily stock returns, and find the coefficient on returns increases significantly on earnings announcement days. They argue that news released on these days signals a more transitory effect than news released on non-earnings announcement days. Both studies focus on timeliness, not precision.

<sup>7</sup> Our results are similar when we use a one-month window, a five-month window, and a seven-month window instead of a three-month window as the dependent variable in eq. (1). Also, as we show later, our results are similar if we replace the symmetric window with a forward-looking return window.

only need daily returns to be serially uncorrelated to get an unbiased precision measure in our setting.<sup>8</sup> On the other hand, the earnings-on-returns measure is based on a regression of returns on future earnings. Whereas returns (dependent variable) are driven by information on all future earnings, the independent variable can include only a limited earnings horizon, and this measurement error biases the estimation. For a similar reason, the earnings-on-returns measure may not coincide as well with the theoretical precision construct. We need to measure the precision of investor information on the change in firm value, and because firm value is the present value of all future cash flows, the long-term returns are a closer proxy than the change in cash flows or earnings over a limited horizon. Lastly, the returns-on-returns measure does not require data on future earnings, allowing larger samples than the returns-on-earnings measure, hence increasing the power of the tests.

## **4. Results**

### *4.1 Increase in precision on earnings announcement days*

The initial sample includes all firm/years for which four quarterly earnings announcement dates are available on COMPUSTAT and at least 200 trading days are available on CRSP. This sample includes 126,762 firm/year observations over the period 1972-2012. Some of our tests require bid-ask spreads, obtained from the TAQ data set. In addition, we adjust stock returns for risk, using Daniel et al.'s (1997) size, book-to-market, and momentum quintile portfolios using data available on Russ Wermers' website. As a result, our sample contains 53,277 firm/years. Table 1 presents details on the sample selection.

(Table 1 about here)

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<sup>8</sup> We present the estimation for a sample of stocks that have zero serial correlation in daily returns (Table 6 below).

Table 2 shows that, consistent with our first hypothesis, the precision of information in returns in the days around earnings announcements is higher than the precision of information in returns during non-announcement days. The table presents average precision coefficients for different long-term return windows. We estimate eq. (1) with firm and time fixed effects, increasing the return window of the dependent variable from 3 months to 13 months. The results show the precision of information in the days around earnings announcements converges to 1 as the return window of the dependent variable increases from 3 to 13 months. When the dependent variable is defined as the surrounding three months, the average precision of information during non-announcement days is 0.674, and the average incremental precision of information released in the days around quarterly earnings announcements is 0.210; that is, the precision of information released in days around quarterly earnings announcements is  $(0.674 + 0.210 =) 0.884$ , higher at the 0.01 level than the precision of information released during non-announcement days. The average precision of returns during non-announcement days remains relatively stable as we increase the return window to 13 months; however, the average precision of information released in the days around quarterly earnings announcements is close to 1.00 for all windows longer than five months. The results in Table 2 suggest the precision of information released during earnings announcement days is higher than that released during non-announcement days, and that this finding is not sensitive to the length of the long-term return window.<sup>9</sup>

(Table 2 about here)

#### 4.2 *The effect of disclosure and liquidity on precision*

To test H1, we use two measures of disclosure: The first measure (labeled NEWS) is the proportion of information released during earnings announcement days. It is measured as

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<sup>9</sup> The intercept has no econometric meaning. It just describes the average long-term returns (which are not explained by daily returns). As described above, the methodology used to estimate the average precision measures is based on the error-in-variables model in econometrics. The intercept can be zero, negative, or positive, depending on return horizon, and it may be different for different subsamples.

the average absolute stock returns in the days around earnings announcements divided by the average absolute daily returns during non-announcement days of the year.<sup>10</sup> The second measure of disclosure is an indicator variable that equals 1 for firms that issued management earnings forecasts (GUID). Firms are using earnings guidance to reduce the uncertainty about their performance (e.g., Houston et al., 2010). Management forecasts are taken from First Call and Capital IQ databases. First Call data end in 2010 and Capital IQ data start in 2001.<sup>11</sup> We create an indicator variable that equals 1 each year for firms with management forecasts available either on First Call or Capital IQ.

To test H2, we use the effective bid-ask spread as a measure of illiquidity. We compute this measure using TAQ data, which are available from 1993, as  $[2 \times (|P_{it} - V_{it}| / V_{it})]$ , where  $P_{it}$  is the trading price and  $V_{it}$  is the security's bid-ask midpoint at the time of the transaction. We calculate the daily effective bid-ask spread by averaging the effective bid-ask spreads of all transactions on that day, and use the average daily effective bid-ask spread for the year as a measure of illiquidity (ILLIQ<sub>it</sub>).<sup>12</sup>

To test the effect of disclosure and illiquidity on precision, we estimate the following pooled regression with firm and year fixed effects:

$$PREC_{it} = \delta_0 + \delta_1 NEWS_{it} + \delta_2 GUID_{it} + \delta_3 ILLIQ_{it} + \delta_4 BM_{it} + \delta_5 MV_{it} + \eta_{it}. \quad (2)$$

The dependent variable in eq. (2) is PREC<sub>it</sub> (the precision of information in daily returns). In addition to the main explanatory variables, NEWS<sub>it</sub>, GUID<sub>it</sub>, and ILLIQ<sub>it</sub>, we control for the book-to-market ratio (BM<sub>it</sub>), measured as the book value of equity divided by the market value of equity at the beginning of each year, and firm size (MV<sub>it</sub>), measured as the natural logarithm of the market value of equity at the beginning of each year. Size and

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<sup>10</sup> For instance, Francis et al. (2002) and Landsman and Maydew (2002) use absolute returns to measure the information content in returns on earnings announcement days.

<sup>11</sup> The coverage of First Call before 1999 is limited. Results with guidance data that start in 1999 are qualitatively similar to those presented in Table 4 below.

<sup>12</sup> We also use price impact as an alternative measure of illiquidity, and report results in Table 6.

book-to-market serve as controls for the general information environment. Smaller firms, for example, may attract less media and analysts coverage (e.g., Atiase, 1985; Collins et al., 1987), and noise trading is more frequent in small firms and is affected by whether the stock is a value or glamour stock (e.g., Barber and Odean, 2000).

Table 3 presents descriptive statistics in panel A, and a correlation matrix in panel B (Pearson above the diagonal and Spearman below the diagonal). The correlations between PREC and ANNP are negative (Pearson = -0.15, Spearman = -0.16), suggesting that when the precision of information on non-announcement days is high, the incremental precision of information on earnings announcement days tends to be lower, and vice versa.

Larger firms release more precise information on non-announcement days, as the positive correlations between PREC and MV reflect (Pearson = 0.08, Spearman = 0.15). Firms with larger book-to-market ratios release less precise information on non-announcement days (Pearson = -0.01, Spearman = -0.07). In addition, earnings news is associated with more precise information released on non-announcement days, as the positive correlations between PREC and NEWS reflect (Pearson = 0.07, Spearman = 0.09). Furthermore, management guidance is positively associated with the precision of information released on non-announcement days, as the positive correlations between PREC and GUID reflect (Pearson = 0.09, Spearman = 0.12). This result is consistent with H1. Consistent with H2, companies with larger bid-ask spreads have less precise stock prices on non-announcement days, as reflected by the negative correlations between PREC and ILLIQ (Pearson = -0.17, Spearman = -0.20).

The correlations between the precision of information in returns on earnings announcement days (PREC+ANNP) and the main research variables are in the same direction, but smaller, probably because our precision measure is noisier for earnings announcement days; it is based on only 12 trading days for each firm-year.



Larger firms disclose more information, as the positive correlation of MV with NEWS (Pearson = 0.18, Spearman = 0.21), and with GUID (Pearson = 0.32, Spearman = 0.34) reflect. Firm size is also highly correlated with illiquidity (Pearson = -0.69, Spearman = -0.89).

(Table 3 about here)

Table 4 presents results of estimating eq. (2), with year and firm fixed effects and with standard errors clustered based on year and firm. The coefficient on earnings guidance is positive (0.019,  $t = 3.26$ , in column 3), as expected under H1, and significant at the 0.01 level. This result means that releasing earnings guidance increases the precision of information on non-announcement days. Also consistent with H1, the magnitude of earnings news (NEWS) is positively associated with the precision of information in returns during the quarter (0.015,  $t = 2.64$ , in column 3). In addition, the coefficient on ILLIQ is negative and significant at the 0.01 level, as expected under H2.

The coefficient on firm size (MV) in the full model (column 3) is unexpectedly negative and significant at the 0.01 level ( $-0.079$ ,  $t = -6.94$ ). Also, the coefficient on the book-to-market ratio (BM) is positive (0.036,  $t = 3.80$ ) and significant at the 0.01 level. When we estimate eq. (2) without the illiquidity variable, which is highly correlated with firm size, and without firm fixed effects (column 1), the coefficient on MV becomes positive and significant at the 0.01 level, and the coefficient on BM is statistically insignificantly different from 0.<sup>13</sup>

Column (6) presents results for estimating eq. (2) with PREC+ANNP as the dependent variable (the precision of information in returns on earnings announcement days). The results suggest the precision of information on earnings announcement days is smaller in large

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<sup>13</sup> The negative coefficient on MV and positive on BM in the regression with firm fixed effects may suggest these variables proxy for noise trading. In a specification with firm fixed effects, the coefficients on MV and BM could capture changes over time. Stocks that recently experienced an increase in MV and decrease in BM are glamour stocks (e.g. Lakonishok et al., 1994). These stocks can attract more noise trading that reduces the precision of information in prices.

firms, as the negative coefficient on MV reflects (-0.102,  $t = -3.75$ ). Also, the coefficient on BM is positive (0.035,  $t = 3.22$ ) and significant at the 0.01 level, suggesting companies with larger book-to-market ratios have more precise information in stock prices on earnings announcements. In addition, the magnitude of earnings news (NEWS) is not associated with the precision of the information impounded into prices on earnings announcement days. Management guidance is also not associated with the precision of the information on earnings announcements, probably because management forecasts are provided outside the earnings announcement windows.

Column (7) provides results of estimating eq. (2), but the dependent variable is ANNP—the *incremental* precision of information in returns on earnings announcement days. Note that positive (negative) coefficients on the independent variables indicate higher (lower) precision relative to non-announcement days. We also added PREC as an independent variable. The purpose of this row is to highlight the substitution between precision of information released outside and within earnings announcements. The coefficient on PREC is negative and significant at the 0.01 level (-0.545,  $t = -15.17$ ), suggesting higher precision on non-announcement days is associated with lower incremental precision of information released in earnings announcements. The results are also consistent with those reported in column (2); that is, the coefficient on firm size is negative (at the 0.01 level), the coefficient on BM is positive (at the 0.10 level), and the coefficient on ILLIQ is negative (at the 0.01 level).

(Table 4 about here)

#### 4.3 Precision and expected returns

To test H3, we estimate the following equation:

$$ABRET_{i,t+1} = \theta_0 + \theta_1 PREC_{it} + \theta_2 ANNP_{it} + \theta_3 ILLIQ_{it} + \omega_{it} \quad (3)$$

$ABRET_{i,t+1}$  is the average monthly risk-adjusted stock returns starting from February of year  $t+1$  through January of year  $t+2$ . We adjust stock returns for risk using Daniel et al.'s (1997) size, book-to-market, and momentum quintile portfolios.  $PREC_{it}$  is the precision of information in daily stock returns,  $ANNP_{it}$  is the incremental precision of information in returns on earnings announcement days, and  $ILLIQ_{it}$  is the effective bid-ask spread as defined above. The model is estimated with firm and year fixed effects, and significance levels are based on errors that are clustered on firm and year.

The results, which are presented in Table 5, show that higher precision of information, both during and outside earnings announcement days, is associated with a lower cost of capital, whereas illiquidity is associated with a higher cost of capital.

The coefficients on  $PREC_{it}$  are negative and significant at the 0.01 level, in all specifications, suggesting precision of information released on non-announcement days reduces the cost of capital. In particular, the coefficient on  $PREC_{it}$  in the first specification is -0.489, which means an increase in precision from the first to the third quartile (from 0.177 to 0.795 according to Table 3) decreases monthly abnormal returns by 0.302%, or about 3.6% annually. After controlling for the effective bid-ask spreads ( $ILLIQ_{it}$ ) in specification 5, the coefficient on  $PREC_{it}$  is -0.385, which means an increase in precision from the first to the third quartile decreases monthly abnormal returns by 0.24%, or about 3% annually. A reduction of 3% in the equity cost of capital is economically significant.

The precision of information in prices on earnings announcement days does not have a different effect on the cost of capital than the precision of information in prices on non-announcement days, as the insignificant coefficient on  $ANNP_{it}$  in specification 5 reflects.

Finally, the coefficient on  $ILLIQ_{it}$  is positive and significant at the 0.01 level (42.48,  $t = 5.94$ ), suggesting illiquidity increases the cost of capital.<sup>14</sup>

(Table 5 about here)

## 5. Sensitivity analyses and robustness tests

We conducted several sensitivity analyses to check whether our results are sensitive to changing the estimation methods, variable definitions, or sample selection. For each setting, we replicated the entire analysis; however, to save space, we report in Table 6 only the results of estimating eq. (3) for each setting.

The main analysis uses the effective bid-ask spread (ILLIQ) as a measure of illiquidity. However, bid-ask spreads may also capture other components of transaction costs, such as inventory risk. We performed our tests using the price impact (PI) instead of the bid-ask spread. PI measures the adverse-selection component of trading costs, and it may be a more accurate measure of information asymmetry. Following Huang and Stoll (1996), we define price impact as  $PI_{it} = 100 \times D_{it} \times (V_{i,t+30} - V_{it}) / V_{it}$ , where  $V_{it}$  is the security's bid-ask midpoint at the time of the transaction, and  $(V_{i,t+30})$  is the bid-ask midpoint 30 minutes after the transaction, or at 4 p.m. for transactions completed during the last half hour of trading.  $D_{it}$  is equal to 1 when a buyer initiated the transaction, and to -1 when a seller initiated it. We use the Lee and Ready (1991) algorithm to determine the direction of the trade. We use TAQ data to estimate the price impact of each transaction.<sup>15</sup> We calculate the daily price impact by

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<sup>14</sup> When using alternatively time-calendar portfolios, and a two-stage cross-sectional regression technique, we also find precision affects expected returns. See section 5.3 below for details.

<sup>15</sup> We delete from the sample trades and quotes with time stamps outside regular trading hours (9:30 a.m. to 4:00 p.m.), as well as a small number of trades and quotes representing possible data errors or with unusual characteristics (Bessembinder, 1999). Specifically, we omit trades if they are indicated in the TAQ database to be coded out of time sequence, or as involving an error or a correction. We also omit trades indicated to be exchange acquisitions or distributions, or that involve nonstandard settlements (TAQ Sale Condition codes A, C, D, N, O, R, and Z), as well as trades that are not preceded by a valid same-day quote. We omit quotes if either the ask or bid price is non-positive, or if the differential between the ask and bid prices exceeds \$5 or is

averaging the price impact of all transactions for each firm during that day, and use the average daily price impact for the year ( $PI_{it}$ ) as a measure of information asymmetry.

Specification (1) of Table 6 reports the results of estimating eq. (3) with PI instead of ILLIQ. The coefficient on PI is positive and significant at the 0.01 level, suggesting illiquidity is positively associated with the cost of capital. Also, after we control for PI, the precision of information released on non-announcement days and the incremental precision of information released on earnings announcement days are both negatively associated with expected stock returns, as expected under H3 (the coefficient on PREC is -0.484 and the coefficient on ANNP is -0.027, both significant at the 0.05 level or better). Hence, using bid-ask spreads as a measure of illiquidity does not drive the results.

In estimating the precision measures in eq. (1), we assume daily stock returns are serially independent; dependence in daily stock returns might lead to a biased slope coefficient. We computed the autocorrelation in daily stock returns for each firm-year and find the autocorrelation is not significantly different from 0 at the 0.05 level for 32,857 firm-year observations (62% of the sample). We re-estimated eq. (3) using only the 32,857 firm-year observations for which the autocorrelation in daily stock returns is close to 0. The results are reported in specification (2) of Table 6. As before, the coefficients on  $PREC_{it}$  are negative and significant at the 0.01 level, and the coefficients on ILLIQ and PI are positive and significant at the 0.01 level. The coefficient on ANNP is negative but not significant at the 0.10 level, suggesting the effect of precision in earnings announcements days is similar to its effect in non-announcement days.

To estimate the precision of information in prices on the firm value, we regress long-term stock returns on daily returns, where long-term returns serve as a proxy for the change in firm value. However, if markets are consistently inefficient, and prices over time do not

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non-positive. We also omit quotes associated with trading halts or designated order imbalances, or that are non-firm (TAQ quote condition codes 4, 7, 9, 11, 13, 14, 15, 19, 20, 27, and 28).

converge to value, this precision measure may be biased. To alleviate the concern that such bias is driving the result, we re-estimated eq. (3) only for large firms, whose prices are usually more efficient, and obtain similar results.<sup>16</sup> In each year, we take the firms with above-median market capitalization, and present the results for this sample in specification (3) of Table 6. The coefficients on  $PREC_{it}$  are negative and significant at least at the 0.01 level, and the coefficients on  $ILLIQ$  and  $PI$  are positive and significant at the 0.01 level.

The precision measures in the main tests use *raw* daily stock returns because we aim to capture all the information in stock returns, both market-wide and firm specific. The precision of information on firm value is expected to affect the cost of capital (Lambert et al., 2012; Lambert and Verrecchia, 2014), and the theory does not distinguish between information that is firm specific and information that pertains to the firm as well as to other firms in the industry or the economy. Regardless, for robustness, we estimate the precision measures in eq. (3) using abnormal returns (based on size, book-to-market, and momentum factors), and redo the analysis using these alternative precision measures (specification 4). The results are similar to those reported in Table 5, suggesting that using raw daily stock returns in constructing the precision measure does not drive our results.

To construct our precision measures, we estimate eq. (1) using symmetric windows around the month containing the daily return. For instance, the three-month window used in eq. (1), as well as the other windows reported in Table 2, include the same number of months before and after the month containing the daily return. As a robustness check, we constructed the precision measures using a forward-looking window—a three-month window that includes the month containing the daily returns and the subsequent two months. Using these forward-looking precision measures, we re-estimate eq. (3) and report the results in

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<sup>16</sup> Furthermore, as discussed above, to alleviate concerns about the validity of long-term returns as a proxy of value, we conduct the tests with different long-term return windows, between 3 and 13 months, and get similar results.

specification (5) of Table 6. The results are similar to those reported in Table 5, suggesting that using symmetric return windows does not drive the results.

(Table 6 about here)

### 5.1 Estimating precision based on future earnings

We also use an alternative measure of precision based on the strength of the association between daily stock returns and subsequent earnings. Specifically, we examine the extent to which daily stock returns reflect information on future earnings, using the R-squared of the following regression:

$$RET_{it} = \delta_0 + \delta_1 \Delta EARN_{i,t+1} + \varepsilon_{it}, \quad (4)$$

where  $RET_{it}$  is firm  $i$ 's daily stock returns, and  $\Delta EARN_{i,t+1}$  is the difference between next year's earnings and analysts' mean forecast ( $actual_{t+1} - forecast_{t-1}$ ; for the daily returns in each month, we use the mean forecast at the end of the previous month).  $\Delta EARN_{i,t+1}$  is divided by the stock price at the beginning of the year. We estimate this regression for each firm and calendar year over the sample period 1993-2012, obtaining an R-squared for each firm-year. This R-squared measures how much of the return variation can be explained by information on future earnings, whereas a higher R-squared means more precise stock returns. To circumvent the bounded nature of R-squared within  $[0, 1]$ , we use a logistic transformation of R-squared. Our returns-on-earnings precision measure is hence

$$RE\_PREC = \log(R^2/(1-R^2)).^{17}$$

We find that correlation between our returns-on-returns precision measure ( $PREC_{it}$ ) and the returns-on-earnings precision measure ( $RE\_PREC_{it}$ ) is 0.30. We also find that using  $RE\_PREC_{it}$  instead of  $PREC_{it}$  yields similar results. That is, higher information precision is associated with lower expected returns.

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<sup>17</sup> Similar log transformation to R-squared is used in the return-synchronicity literature (see, e.g., Gul et al., 2010).

Results are presented in Table 7. When both precision measures are included in the regression (Model 1), the coefficient on the two measures are negative, as expected under H3, but only the returns-on-returns measure (PREC) is statistically significant in explaining expected returns. The lower significance of the earnings-on-returns measure (RE\_PREC) may be attributed to the limited horizon of future earnings that the measure uses. Because the returns-on-earnings precision measure can be practically estimated with only a limited horizon of future earnings, it may be econometrically biased, and it less closely coincides with the theoretical construct of precision than the returns-on-returns precision measure.<sup>18</sup>

(Table 7 about here)

## 5.2 *Change in precision and pricing around SOX*

Disclosure, precision of information in prices, and cost of capital are endogenously determined. In this section, we perform analyses to overcome the endogeneity of the variables, which may bias the estimation results presented above.

First, we perform a changes analysis around the SOX 2002, which is an exogenous increase in disclosure that is expected to increase the precision of investor information. We use this exogenous change to demonstrate the effect of precision on the cost of equity.

We use institutional holdings as a proxy, or an instrumental variable, for the expected change in precision after SOX, because, in addition to the expected exogenous change in precision around SOX, firms can experience an endogenous precision change as in any other period. Therefore, a specification that includes the actual change in precision will not alleviate endogeneity concerns. We therefore use institutional investors as an instrument for the expected change in precision.

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<sup>18</sup> As discussed above, we use the returns-on-returns precision measure for our main tests because it is robust and allows the estimation of precision without bias; it coincides with the theoretical precision construct; and it does not rely on the availability of subsequent earnings, and therefore allows larger samples and increases the power of the tests.



We begin by showing the precision of information in prices increased after SOX more for firms with lower institutional ownership. Information in prices of stocks held by institutional investors is expected to be higher (e.g., Bloomfield, 2002). The presence of sophisticated investors also increases firms' disclosure quality (e.g., Dye, 2001). Therefore, SOX is expected to have a lower effect on the precision of stocks with higher institutional ownership. Bronson et al. (2006), for example, find that before SOX, firms with higher institutional ownership were more likely to voluntarily disclose in their annual report a management report on the effectiveness of internal control, similar to that mandated by SOX Section 404. We use the following regression to test the effect of SOX on the precision of information in prices, conditional on institutional ownership:

$$\Delta PREC_{i,t+1} = \alpha + \beta_1 IO_{i,t-t} + \beta_2 SOX + \beta_3 SOX \times IO_{i,t-t}, \quad (5)$$

where  $\Delta PREC_{i,t+1}$  is the change in the precision of information in prices from a year before  $t$  to a year after  $t$ . For example, for  $t=2002$ ,  $\Delta PREC_{i,t+1} = PREC_{i,2003} - PREC_{i,2001}$ . SOX is an indicator variable that equals 1 in 2002, and 0 in other years, and IO is the percent of outstanding stocks held by institutional investors.

As Model 1 in Table 8 shows, the precision of information in prices increased after SOX (coefficient on SOX is 0.208, significant at the 0.01 level), and the increase was smaller for firms with higher institutional ownership (coefficient on SOX\*IO is -0.137, significant at the 0.05 level).

Next, we test whether SOX had a greater effect on the pricing of stocks with lower institutional ownership. The details of SOX legislation became known and affected stock prices during 2002 (e.g., Li et al., 2008). Because the increase in information precision is higher for stocks with lower institutional ownership, and an increase in precision is expected to decrease the cost of equity, we hypothesize that the prices of stocks with lower

institutional ownership increased more than prices of stocks with higher institutional ownership during 2002, the year SOX was enacted. We use the following methodology:

$$ABRET_{it} = \alpha + \beta_1 IO_{i,t-t} + \beta_2 SOX + \beta_3 SOX \times IO_{i,t-t}, \quad (6)$$

where  $ABRET_{it}$  is the abnormal return in year  $t$  adjusted for size, book-to-market, and momentum factors, and the other variables are similar to those used in equation (6) above. We hypothesize the following:  $\beta_2 > 0$  and  $\beta_3 < 0$ .

As model 2 of Table 8 shows, the price of stocks with lower institutional holdings increased in 2002 (the coefficient on SOX 0.714, significant at the 0.01 level) more than the prices of stocks with higher institutional ownership (coefficient on SOX\*IO is -1.157, significant at the 0.01 level). Together the results in Table 8 suggest the exogenous disclosure shock of SOX had a greater effect on the information precision of stocks with lower institutional ownership, and that the cost of equity of these stocks decreased, and stock prices increased in the year SOX was legislated. This changes analysis around SOX allows us to treat all variables as endogenous, and to test the effect of an exogenous increase in information.

(Table 8 about here)

In addition, we use an instrumental-variable approach, or 2SLS, to estimate the relation between precision and the cost of equity capital. First, we estimate precision as a function of the two proxies of public disclosure. Public disclosure is expected to increase investors' information precision, as discussed above, and we empirically show that two proxies of public disclosure, absolute daily returns on announcement days and an indicator variable for management earnings guidance, are positively associated with precision (Table 4) and therefore can serve as informative instruments. For these instruments to be valid, they should be uncorrelated with the error term in the main regression. Using the Sargan (1958)

test, we find this validity criterion holds for these instruments.<sup>19</sup> Using this 2SLS estimation approach, we find results similar to those presented in the main analysis in Table 5.

Both the instrumental-variable analysis and changes analysis around the exogenous disclosure shock of SOX support the hypothesis that an increase in precision lowers the cost of equity.

Finally, we redo our main analysis with the changes instead of the level of the variables. Specifically, we regress the change in expected returns in year  $t+1$  on the change in precision in year  $t$  and the change in illiquidity in year  $t$ . We get similar results. To the extent that the changes in the variables are less correlated with firm characteristics than levels, and that earlier changes (time  $t$ ) drive subsequent returns (time  $t+1$ ), this result further supports the hypothesis.

### 5.3 *Alternative pricing tests*

To further test the effect of precision on expected returns, we use a time-calendar portfolio approach, which alleviates concerns of cross-sectional dependence in returns (e.g., Fama, 1998; Mitchell and Stafford, 2000). Table 9 presents abnormal returns for quintile portfolios formed based on precision measures and illiquidity. In each year  $t$ , stocks are sorted into quintile portfolios based on the precision of information in daily returns ( $PREC_{it}$ ). In each quintile portfolio, stocks are held from February of year  $t+1$  to January of year  $t+2$ . For each of the five portfolios, we compute average returns for each month, and regress the time series of monthly returns on Fama and French's (1993) three factors (MRKT, SMB, HML). We also create similar quintile time-calendar portfolios for the incremental precision

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<sup>19</sup> Beyond this statistical validity test, it is unclear whether these instruments are ex-ante exogenous (for discussion of instrument validity see, e.g., Murray 2006). For robustness, we redo the analysis with alternative instruments, as the number of analysts, firm size, and book-to-market, and get similar results. Again, whether these instruments are valid/exogenous is unclear.

of information in returns on earnings announcement days ( $ANNP_{it}$ ), the precision of information released in earnings announcements ( $PREC_{it+ANNP_{it}}$ ), and illiquidity ( $ILLIQ_{it}$ ).

As the table shows, firms with larger information precision outside earnings announcements earn lower subsequent abnormal returns, consistent with H3 (larger precision translates into lower cost of capital). We do not find any association between the precision of information released during earnings announcement days and subsequent abnormal stock returns. Firms with larger effective bid-ask spreads (illiquidity) earn larger subsequent abnormal returns, consistent with the argument that more illiquidity increases the cost of capital.

The effect of precision on stock returns in this univariate portfolio analysis is quite large. The quintile portfolio of firms with low precision earns a monthly abnormal return of 0.59%, whereas the quintile portfolio of firms with high precision earns only 0.13%. In annual terms, the difference between the high and low quintiles is 5.5%, which is economically significant. In a multivariate regression analysis, when both precision and illiquidity are included, the incremental effect of precision on expected returns is more modest, as discussed above (Table 5).

(Table 9 about here)

In addition, we examine whether precision is priced, using the two-stage cross-sectional regression technique used, for example, by Core et al. (2008). In the first stage, we estimate multivariate betas from a single time-series regression of excess returns for a firm ( $R_q - R_F$ ) on the contemporaneous returns. We include the three Fama and French (1993) factors (market, size, book-to-market) and a precision factor. To construct the precision factor, we sort stocks based on the precision of their daily returns; the precision factor is the difference between returns of the stocks in the upper three deciles of precision and the returns of the stocks in the lower three deciles of precision. We use the precision on non-

announcement days,  $PREC_{it}$ , because this precision encompasses the majority of trading days during the year. The portfolio is rebalanced every June of year  $t$ , based on the precision estimated during year  $t-1$ , and returns are value weighted. We add the precision factor to the Fama and French (1993) factors and estimate the multivariate betas using the following time-series regression:

$$R_{q,t} - R_{F,t} = b_0 + b_{q,R_M-R_F}(R_{M,t} - R_{F,t}) + b_{q,SMB}SMB_t + b_{q,HML}HML_t + b_{q,Precision}Precision_t + \varepsilon_{q,t}. \quad (7)$$

In the second stage, we estimate a cross-sectional regression of excess returns on the factor betas estimated using eq. (7) as follows:

$$\bar{R}_{q,t} - \bar{R}_{F,t} = \lambda_0 + \lambda_1 b_{q,R_M-R_F} + \lambda_2 b_{q,SMB} + \lambda_3 b_{q,HML} + \lambda_4 b_{q,Precision} + \varepsilon_q, \quad (8)$$

where  $\bar{R}_{q,t} - \bar{R}_{F,t}$  is the mean excess return for asset  $q$ .

If the precision factor carries a positive risk premium, the coefficient ( $\lambda_4$ ) on the precision factor beta will be positive. We compute standard errors from monthly cross-sectional regressions using the Fama and MacBeth (1973) procedure to mitigate concerns about cross-sectional dependence in the data. Also, because betas in the second-stage regressions are not true betas, they may be measured with error. To mitigate this problem, we estimate eq. (7) and eq. (8) using 25 size and book-to-market portfolios, as in Fama and French (1993).

Table 10 presents results for estimating eq. (8). The coefficient on the precision factor beta,  $\lambda_4$ , is positive and significant at the 0.10 level, suggesting precision is priced as a risk factor. The risk premium on the precision factor is 0.513 (0.53% a month). When the model is estimated only with the market and precision factors, the premium on the precision factor is 0.77% a month, and the coefficient is significant at the 0.05 level (t-stat = 2.47). Our pricing results for the three Fama-French factors (Fama and French, 1993) are comparable, for example, to those presented by Core et al. (2008, Table 4).

(Table 10 about here)

#### 5.4 *Relation with other measures of information in prices*

The synchronicity of stock returns with market and industry returns is a measure of information in prices used in the literature (e.g., Morck et al., 2000). Return synchronicity measures the amount of firm-specific information or noise in returns,<sup>20</sup> whereas precision captures uncertainty that investors face regarding firm value. Precision is related to information, as discussed by Lambert and Verrecchia (2014) and Lambert et al. (2012); however, it is related to any information, regardless of whether it is firm specific or pertains to the firm as well as to other firms in the industry or the economy. Therefore, the distinction between firm-specific information and other information is not necessary for our hypothesis testing. Still, the relation between return synchronicity and precision may be descriptively interesting.

Given that the amount of firm-specific information is endogenously determined, the relation between price synchronicity and precision is probably complex. On the one hand, more information will increase precision. We can therefore expect return synchronicity (i.e., less firm-specific information) to be negatively associated with precision. On the other hand, less firm-specific information might be available on firms that face lower uncertainty. In this case, return synchronicity will be positively associated with precision.

Noise trading is another factor that affects both price synchronicity and precision. Noise is expected to lower both price synchronicity and precision, and therefore to create a positive association between the two variables. The noise factor, therefore, yields a straightforward prediction that we can test: stocks with more noisy returns are expected to have more positive correlation between price synchronicity and price precision. Assuming smaller stocks have noisier returns (e.g., Barber and Odean, 2000), we sort the sample each year into

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<sup>20</sup> See, for instance, discussion in Durnev et al. (2003) and Chan and Hameed (2006).

five portfolios based on firm size, and expect correlation between synchronicity and precision to be more positive in smaller stocks.

We estimate the synchronicity in daily returns for each firm and calendar year using the following model (e.g., Gul et al. 2010):

$$RET_{it} = \alpha + \beta_1 MKTR_{it} + \beta_1 MKTR_{i,t-1} + \beta_1 INDR_{it} + \beta_1 INDR_{i,t-1} + \varepsilon_{it}, \quad (9)$$

where, for firm  $i$  and day  $t$ ,  $RET$  denotes the daily return and  $MKTR$  and  $INDR$  denote the value-weighted market return and industry return, respectively. The industry return is created using all firms within the same two-digit SIC industry code with firm  $i$ 's daily return omitted. In eq. (9), lagged industry and market returns are included to alleviate concerns over potential non-synchronous trading biases. To circumvent the bounded nature of R-squared within  $[0, 1]$ , we use a logistic transformation of R-squared and the return synchronicity measure,  $SYNC = \log(R^2/(1 - R^2))$ .

Table 11 shows the results. We sort stocks into five portfolios each calendar year based on their market capitalization at the beginning of the year, and present the correlation between price synchronicity ( $SYNC$ ) and the precision of information in prices ( $PREC$ ) in each size-quintile portfolio. Assuming that within each size quintile, firms face similar uncertainty and the same common information, and the only differences within size groups are firm-specific information and noise, we can explain the results as follows. More firm-specific information leads to a negative correlation between synchronicity and precision. Only in the largest size quintile, where noise is low, this effect of firm-specific information dominates, and the correlation is negative. In smaller stocks, the effect of noise is more dominant, and the correlation between synchronicity and precision is positive for smaller stocks.

(Table 11 about here)

Informational efficiency of prices is another related group of measures used in the literature (see, e.g., Boehmer and Kelley, 2009). The basic idea of these measures is that informationally efficient prices will follow a random walk. Whereas informational efficiency measures gauge the speed or efficiency in which information is impounded into prices, our measure is aimed at gauging the precision of that information. Conceptually, prices of two stocks can be informationally efficient, but the information impounded in one stock is noisy, and in the other, precise. Empirically, we estimate our precision measure for stocks that have zero serial correlation in daily returns, that is, for stocks with similar informational efficiency, and show our hypothesis holds and the variation in precision within that subsample affects the cost of equity (see Panel 2 of Table 6).

## **6. Conclusion**

We estimate the precision of information that prices communicate about firm value, and examine its relation with public disclosure and the cost of equity capital. We find public disclosure increases the precision with which prices reflect the value of the firm. We also find that in liquid stocks, where investors are expected to trade more of their own information into prices, the precision of information is higher than in illiquid stocks, and that the precision of information in prices is negatively associated with the cost of equity. The precision of information in prices is of importance regardless of its cost of capital implications, and the effects of disclosure and liquidity on precision are themselves of interest. Regulators are concerned with increasing the information available to the public of investors (e.g., U.S. Securities and Exchange Commission 2014). Stock prices aggregate information, and less informed investors learn from prices. Therefore, measures that increase the informativeness of prices can increase the information that is available to the public for its investing decisions.



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**Table 1**  
**Sample Selection**

<b>Criterion</b>	<b>Obs.</b>
Firm-years with four quarterly earnings announcement dates on COMPUSTAT and at least 200 trading days on CRSP between 1972 and 2012	126,762
Observations with available risk-adjustment data based on Daniel et al. (1997) for year t+1	101,357
Observations between 1993 and 2012	67,245
Observations with bid-ask-spread data from TAQ	53,277

**Table 2**  
**Precision Measures for Different Time Horizons**

	$\gamma_1$	$\gamma_2$ PREC	$\gamma_3$ ANNP	R-Square	$\gamma_2 + \gamma_3$ PREC+ ANNP
RET3M (3 months)	-0.007***	0.674***	0.210***	3.7%	0.884
RET5M (5 months)	-0.000	0.669***	0.275***	4.7%	0.944
RET7M (7 months)	0.004***	0.672***	0.330***	6.0%	1.002
RET9M (9 months)	0.005***	0.649***	0.373***	7.0%	1.022
RET11M (11 months)	-0.001	0.628***	0.356***	7.8%	0.984
RET13M (13 months)	0.001**	0.631***	0.379***	8.7%	1.010

*Note:* The table presents precision coefficients for non-announcement and announcement days for return windows ranging from 3 to 13 months. We estimate eq. (1) using different return windows, for the entire sample, and with firm fixed effects:

$$RET_{XM}(T)_{it} = \gamma_{0t} + \gamma_{1t}ANND_{it} + \gamma_{2t}RET(T)_{it} + \gamma_{3t}ANND_{it}RET(T)_{it} + \varepsilon_{it},$$

where  $RET_{XM}(T)_{it}$  is the return in the X months surrounding the month containing day t, where X ranges from 3 to 13 months. For example, for the daily returns in June,  $RET_{5M}$  is the cumulative return from April 1 to August 31;  $RET(T)_{it}$  is firm i's daily stock return; and  $ANND_{it}$  is an indicator variable that equals 1 for the 12 days around quarterly earnings announcements during calendar year T, and 0 otherwise. The coefficient  $\gamma_2$  captures the precision of information in daily returns (labeled PREC), and the coefficient  $\gamma_3$  captures the incremental precision of information in returns on earnings announcement days (labeled ANNP). The sample includes 126,762 firm-year observations between 1972 and 2012. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

**Table 3**  
**Determinants of Precision – Descriptive Statistics and Correlations**

Panel A: Descriptive Statistics

Variable	Mean	Std. Dev.	5th Pctl.	25th Pctl.	50th Pctl.	75th Pctl.	95th Pctl.
ANNP	0.177	1.624	-2.411	-0.620	0.132	0.960	2.915
PREC	0.550	0.526	-0.051	0.177	0.432	0.795	1.575
PREC+ANNP	0.727	1.629	-1.625	-0.138	0.543	1.455	3.647
NEWS	1.444	0.528	0.727	1.066	1.358	1.738	2.465
GUID	0.335	0.472	0	0	0	1	1
ILLIQ	0.020	0.026	0.001	0.004	0.011	0.027	0.072
MV	12.42	1.93	9.47	11.03	12.33	13.69	15.77
BM	0.708	0.642	0.135	0.333	0.553	0.868	1.780

Panel B: Correlation Matrix

	ANNP	PREC	PREC +ANNP	NEWS	GUID	ILLIQ	MV	BM
ANNP		-0.15***	0.95***	0.00	0.00	-0.03***	0.03***	0.01*
PREC	-0.16***		0.17***	0.07***	0.09***	-0.17***	0.08***	-0.01***
PREC+ANNP	0.93***	0.15***		0.03***	0.03***	-0.08***	0.05***	0.00
NEWS	0.02***	0.09***	0.07***		0.19***	-0.18***	0.18***	-0.07***
GUID	0.01	0.12***	0.05***	0.19***		-0.26***	0.32***	-0.13***
ILLIQ	-0.04***	-0.20***	-0.11***	-0.27***	-0.34***		-0.69***	0.35***
MV	0.04***	0.15***	0.09***	0.21***	0.34***	-0.89***		-0.39***
BM	0.01**	-0.07***	-0.02***	-0.10***	-0.17***	0.33***	-0.43***	

*Note:* Panel A presents descriptive statistics for the main variables. Panel B presents a Pearson (above the diagonal) and Spearman (below the diagonal) correlation matrix for the main variables. The sample includes 53,277 firm-year observations between 1993 and 2012 (the period over which data on bid-ask spreads and management earnings guidance are available).

*PREC* is the precision of information in daily returns during the year, *ANNP* is the incremental precision of information in returns on earnings announcement days; they are estimated for each firm and calendar year using the following regression:

$$RET3M(T)_{it} = \gamma_{0t} + \gamma_{1t}ANND_{it} + \gamma_{2t}RET(T)_{it} + \gamma_{3t}ANND_{it}RET(T)_{it} + \varepsilon_{it},$$

where  $RET3M_{it}$  is the return in the three months surrounding the month containing day  $t$ . For example, for the daily returns in June,  $RET3M$  is the cumulative return from May 1 to July 31,  $RET(T)_{it}$  is firm  $i$ 's daily stock return, and  $ANND_{it}$  is an indicator variable that equals 1 for the 12 days around quarterly earnings announcements during calendar year  $T$ , and 0 otherwise. The coefficient  $\gamma_2$  captures the precision of information in daily returns during the year (labeled *PREC*), and the coefficient  $\gamma_3$  captures the incremental precision of information in returns on earnings announcement days (labeled, *ANNP*).

*NEWS* is average absolute daily returns on announcement days divided by average daily returns on non-announcement days. *GUID* is an indicator variable that equals 1 for firms that issued management earnings forecasts, and 0 otherwise. *ILLIQ* is the average effective bid-ask spread during the year. *MV* is the natural logarithm market value of equity at the beginning of the year. *BM* is the book-to-market ratio (book value of equity divided by market value of equity) at the beginning of the year. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

**Table 4**  
**Determinants of Precision – Regression Results**

	PREC	PREC	PREC	PREC +ANNP	PREC +ANNP	PREC +ANNP	ANNP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<b>PREC</b>							-0.545 (-15.17) <sup>***</sup>
<b>NEWS</b>	0.053 (7.79) <sup>***</sup>	0.042 (6.53) <sup>***</sup>	0.015 (2.64) <sup>***</sup>	0.035 (1.85) <sup>*</sup>	0.022 (1.17)	-0.023 (-0.84)	-0.030 (-1.24)
<b>GUID</b>	0.056 (5.67) <sup>***</sup>	0.048 (4.82) <sup>***</sup>	0.019 (3.26) <sup>***</sup>	0.047 (2.28) <sup>**</sup>	0.038 (1.90) <sup>*</sup>	0.023 (0.93)	0.014 (0.40)
<b>ILLIQ</b>		-4.488 (-8.41) <sup>***</sup>	-4.746 (-10.52) <sup>***</sup>		-5.483 (-8.12) <sup>***</sup>	-6.302 (-8.15) <sup>***</sup>	-4.144 (-6.10) <sup>***</sup>
<b>MV</b>	0.020 (4.29) <sup>***</sup>	-0.019 (-4.82) <sup>***</sup>	-0.079 (-6.94) <sup>***</sup>	0.046 (5.26) <sup>***</sup>	-0.001 (-0.15)	-0.102 (-3.75) <sup>***</sup>	-0.066 (-2.28) <sup>**</sup>
<b>BM</b>	0.008 (0.69)	0.020 (1.58)	0.036 (3.80) <sup>***</sup>	0.063 (3.72) <sup>***</sup>	0.078 (4.07) <sup>***</sup>	0.035 (3.22) <sup>***</sup>	0.019 (2.39) <sup>**</sup>
<b>Firm effects</b>	NO	NO	YES	NO	NO	YES	YES
<b>Year effects</b>	YES	YES	YES	YES	YES	YES	YES
<b>Observations</b>	53,277	53,277	53,277	53,277	53,277	53,277	53,277
<b>Adj. R<sup>2</sup></b>	3.78%	6.20%	26.90%	0.94%	1.32%	18.07%	19.19%

*Note:* The dependent variables are the precision of information in daily returns during the year (PREC), and the incremental precision of information in returns on earnings announcement days (ANNP), and the precision of information in returns on earnings announcement days (PREC+ANNP). The sample includes 53,277 firm-year observations between 1993 and 2012. For details on the estimation of PREC and ANNP, see Table 3. *NEWS* is the average absolute daily returns on announcement days divided by average absolute daily returns on non-announcement days. *GUID* is an indicator variable that equals 1 for firms that issued management earnings forecasts, and 0 otherwise. *ILLIQ* is the average effective bid-ask spread during the year. *MV* is the natural logarithm market value of equity at the beginning of the year. *BM* is the book-to-market ratio (book value of equity divided by market value of equity) at the beginning of the year. The t-statistics reported in parentheses are based on errors that are clustered by firm and year. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.



**Table 5**  
**Precision and Expected Stock Returns – Regression Analysis**

Model	Dependent Variable	Independent Variables			Obs. Adj-R <sup>2</sup>
		PREC	ANNP	PREC +ANNP	
1	<i>ABRET</i> <sub><i>it+1</i></sub>	-0.489 (-4.92) <sup>***</sup>			53,277 25.36%
2	<i>ABRET</i> <sub><i>it+1</i></sub>		-0.004 (-0.47)		53,277 25.15%
3	<i>ABRET</i> <sub><i>it+1</i></sub>			-0.051 (-3.66) <sup>***</sup>	53,277 25.17%
4	<i>ABRET</i> <sub><i>it+1</i></sub>	-0.504 (-4.97) <sup>***</sup>	-0.029 (-2.32) <sup>**</sup>		53,277 25.37%
5	<i>ABRET</i> <sub><i>it+1</i></sub>	-0.385 (-4.39) <sup>***</sup>	-0.020 (-1.59)		42.48 (5.94) <sup>***</sup> 53,277 26.83%

*Note:* This table presents results of estimating eq. (3) with year and firm fixed effects, and year and firm double-clustered errors:  $ABRET_{i,t+1} = \theta_0 + \theta_1 PREC_{it} + \theta_2 ANNP_{it} + \theta_3 ILLIQ_{it} + \omega_{it}$  (3).

*ABRET*<sub>*i,t+1*</sub> is the average monthly risk-adjusted stock return for year t+1 (from February of year t+1 to January of year t+2) in percentage terms (for instance, 1 is 1% average monthly returns). We adjust monthly returns for size, book-to-market, and momentum quintile portfolios. *PREC* is the precision of information in daily returns during the year; *ANNP* is the incremental precision of information in returns on earnings announcement days (see Table 3 for details); *ILLIQ* is the average bid-ask spread during the year. The sample includes 53,277 firm-years between 1993 and 2012. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

**Table 6**  
**Association between Precision and Expected Stock Returns:**  
**Sensitivity Analysis**

Dependent Variable = $ABRET_{i,t+1}$					
Specification	PREC	ANNP	ILLIQ	PI	Obs. Adj-R <sup>2</sup>
<i>(1) Using PI instead of ILLIQ</i>	-0.484 (-4.89) <sup>***</sup>	-0.027 (-2.20) <sup>**</sup>		0.671 (4.18) <sup>***</sup>	53,277 25.87%
<i>(2) Autocorrelation in daily stock returns is close to zero</i>	-0.254 (-3.26) <sup>***</sup>	-0.015 (-0.96)	56.96 (5.70) <sup>***</sup>		32,857 32.84%
	-0.269 (-3.34) <sup>***</sup>	-0.018 (-1.19)		1.079 (4.32) <sup>***</sup>	32,857 32.21%
<i>(3) Estimation for firms with above median capitalization</i>	-0.164 (-2.63) <sup>***</sup>	-0.022 (-1.58)	106.36 (5.99) <sup>***</sup>		26,643 30.17%
	-0.197 (-3.04) <sup>***</sup>	-0.025 (-1.81) <sup>*</sup>		2.718 (3.12) <sup>***</sup>	26,643 29.75%
<i>(4) Precision measures are obtained using abnormal daily stock returns</i>	-0.261 (-3.47) <sup>***</sup>	-0.048 (-2.69) <sup>***</sup>	41.78 (5.95) <sup>***</sup>		45,327 25.19%
	-0.352 (-4.69) <sup>***</sup>	-0.055 (-3.05) <sup>***</sup>		0.664 (4.41) <sup>***</sup>	45,327 24.13%
<i>(5) Precision measures are obtained using a forward looking return window</i>	-0.937 (-4.49) <sup>***</sup>	-0.022 (-1.56)	41.69 (6.01) <sup>***</sup>		53,277 26.88%
	-1.231 (-5.07) <sup>***</sup>	-0.033 (-2.37) <sup>**</sup>		0.666 (4.22) <sup>***</sup>	53,277 25.98%

*Note:* The table presents results of estimating eq. (3)—the association between precision and expected abnormal stock returns—for different specifications. All regressions include year and firm fixed effects, and year and firm double-clustered errors. See Table 3 for details on the measurement of precision and Table 6 for the equation specification. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

Specification (1): We use price impact (PI) instead of bid-ask spreads (ILLIQ) as an explanatory variable. PI is defined as  $PI_{it} = 100 * D_{it} * (V_{i,t+30} - V_{it}) / V_{it}$ , where  $V_{it}$  is the security's bid-ask midpoint at the time of the transaction and  $V_{i,t+30}$  is the bid-ask midpoint 30 minutes after the transaction (or at 4 p.m. for trades completed during the last half hour of trading).  $D_{it}$  is equal to 1 if the transaction was initiated by a buyer and -1 if it was initiated by a seller.

Specification (2): The analysis is conducted for firm-year observations for which the autocorrelation in daily stock returns is not significantly different from 0 at the 0.05 level (32,857 firm-year observations between 1993 and 2012).

Specification (3): The analysis is performed on firms with above-median market capitalization, (26,643 firm-year observations between 1993 and 2012).

Specification (4): The precision measures are obtained using abnormal stock returns instead of raw returns.

Specification (5): The precision measures are obtained using a forward-looking return window. Specifically, instead of using a symmetric three-month window, we use a window that starts with the first trading day of the month containing the daily return.

**Table 7**  
**Analysis with Alternative Precision Measure**

Model	Dependent Variable	Independent Variables			Obs. Adj-R <sup>2</sup>
		PREC	RE_PREC	ILLIQ	
1	<i>ABRET</i> <sub><i>it+1</i></sub>	-0.227 (-2.64) <sup>***</sup>	-0.015 (-1.55)	60.16 (5.50) <sup>***</sup>	37,214 29.43%
2	<i>ABRET</i> <sub><i>it+1</i></sub>	-0.242 (-2.97) <sup>***</sup>		60.24 (5.51) <sup>***</sup>	37,214 29.43%
3	<i>ABRET</i> <sub><i>it+1</i></sub>		-0.026 (-3.06) <sup>***</sup>	60.75 (5.48) <sup>***</sup>	37,214 29.38%

*Note:* This table presents estimation results with a precision measure that is based on a regression of earnings on returns (RE\_PREC). Specifically, we examine the extent to which daily returns reflect information on future earnings, using the R-squared of the following regression:

$$RET_{it} = \gamma_0 + \gamma_1 \Delta EARN_{i,t+1} + \varepsilon_{it}, \quad (4)$$

where  $RET_{it}$  is firm  $i$ 's daily stock returns and  $\Delta EARN_{i,t+1}$  is the difference between next year's earnings and analysts' mean forecast at time  $t$ , divided by the stock price at  $t$ . The regression is estimated for each firm and calendar year, and a logistic transformation of its R-squared is the earnings-on-returns precision measure,  $RE\_PREC = \log(R^2/(1-R^2))$ .

To test the effect of precision, we estimate the following equation with year and firm fixed effects:

$$ABRET_{i,t+1} = \theta_0 + \theta_1 PREC_{it} + \theta_2 RE\_PREC_{it} + \theta_3 ILLIQ_{it} + \omega_{it}.$$

$ABRET_{i,t+1}$  is the average monthly risk-adjusted stock return for year  $t+1$  (from February of year  $t+1$  to January of year  $t+2$ ) in percentage terms. Thus, for example, 1 is 1% average monthly returns. We adjust monthly returns for size, book-to-market, and momentum quintile portfolios. PREC is the precision of information in daily returns during the year (see Table 3 for details); ILLIQ is the average bid-ask spread during the year. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively, and standard errors are clustered by year and firm.

**Table 8**  
**Changes in Precision and Prices around SOX**

Model	Dependent Variable	Independent Variables			Obs. Adj-R <sup>2</sup>
		IO	SOX	IO*SOX	
1	$\Delta PREC_{i,t+1}$	0.048 (2.95) <sup>***</sup>	0.208 (6.04) <sup>***</sup>	-0.137 (-2.19) <sup>**</sup>	23,539 0.30%
2	$ABRET_{it}$	-0.231 (-2.62) <sup>***</sup>	0.714 (3.73) <sup>***</sup>	-1.157 (-3.42) <sup>***</sup>	23,539 0.11%

*Note:* To test the effect of SOX on precision of information in returns and the cost of equity, we use the following regression:

$$\Delta PREC_{i,t+1} = \alpha + \beta_1 IO_{i,t-t} + \beta_2 SOX + \beta_3 SOX \times IO_{i,t-t} \quad (5)$$

$$ABRET_{it} = \alpha + \beta_1 IO_{i,t-t} + \beta_2 SOX + \beta_3 SOX \times IO_{i,t-t}. \quad (6)$$

PREC is the precision of information in daily returns (see Table 3 for details) and  $\Delta PREC_{i,t+1}$  is the change in our precision of information in daily returns from a year before t to a year after t. For example, for t=2002,  $\Delta PREC_{i,t+1} = PREC_{i,2003} - PREC_{i,2001}$ . SOX is an indicator variable that equals 1 in 2002, and 0 in other years, and IO is the percent of outstanding stocks held by institutional investors.  $ABRET_{i,t+1}$  is the average monthly risk-adjusted stock return for year t+1 (from February of year t+1 to January of year t+2) in percentage terms. Thus, for example, 1 is 1% average monthly returns. We adjust monthly returns for size, book-to-market, and momentum quintile portfolios. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

**Table 9**  
**Precision and Expected Stock Returns - Portfolio Analysis**

Quintile Portfolios	<b>PREC</b> <b>1993-2012</b> (N = 53,277)	<b>ANNP</b> <b>1993-2012</b> (N = 53,277)	<b>PREC+ANNP</b> <b>1993-2012</b> (N = 53,277)	<b>ILLIQ</b> <b>1993-2012</b> (N = 53,277)
<b>Low</b>	0.59% (4.61) <sup>***</sup>	0.28% (2.24) <sup>**</sup>	0.32% (2.61) <sup>**</sup>	0.09% (0.81)
<b>2</b>	0.47% (3.93) <sup>***</sup>	0.30% (2.56) <sup>**</sup>	0.48% (4.03) <sup>***</sup>	0.14% (1.26)
<b>3</b>	0.31% (2.74) <sup>***</sup>	0.48% (4.00) <sup>***</sup>	0.40% (3.31) <sup>***</sup>	0.14% (1.13)
<b>4</b>	0.20% (1.68) <sup>*</sup>	0.39% (3.43) <sup>***</sup>	0.26% (2.36) <sup>**</sup>	0.38% (2.37) <sup>**</sup>
<b>High</b>	0.13% (0.91)	0.25% (2.11) <sup>**</sup>	0.24% (1.93) <sup>*</sup>	0.97% (3.84) <sup>***</sup>

*Note:* The table presents future abnormal stock returns for portfolios formed based on precision measures and illiquidity. In each year  $t$ , stocks are sorted into quintile portfolios based on the precision of information in daily returns during the year (PREC), the incremental precision of information in returns on earnings announcement days (ANNP), and the precision of information in returns on earnings announcement days (PREC+ANNP), and effective bid-ask spreads (ILLIQ). Stocks are held from February of year  $t+1$  to January of year  $t+2$ . For each of the five portfolios, average returns are computed for each month, and the time series of daily returns are regressed on Fama and French's (1997) three factors (MRKT, SMB, HML). <sup>\*</sup>, <sup>\*\*</sup>, and <sup>\*\*\*</sup> denote significance at the 10%, 5%, and 1% levels, respectively.

**Table 10**  
**The Pricing of the Precision Factor**

		Intercept	$b_{R_M-R_F}$	$b_{SMB}$	$b_{HML}$	$b_{precision}$	Adj. R <sup>2</sup>
1	Estimate	1.833	-1.198	0.269	0.370	0.513	77.8%
	FM t-stat	(4.18) <sup>***</sup>	(-3.17) <sup>***</sup>	(1.58)	(2.44) <sup>**</sup>	(1.86) <sup>*</sup>	
2	Estimate	1.683	-0.963	0.218	0.396		72.4%
	FM t-stat	(3.67) <sup>***</sup>	(-2.43) <sup>**</sup>	(1.25)	(2.61) <sup>***</sup>		
3	Estimate	1.226	-0.474			0.772	34.7%
	FM t-stat	(2.50) <sup>**</sup>	(-1.17)			(2.47) <sup>**</sup>	

*Note:* This table presents results on whether the precision factor is priced. We use a two-stage cross-sectional regression that estimates factor betas in the first stage and the factor risk premia in the second stage. The table presents the estimated coefficients of the second stage, the cross-sectional regression (8), using 25 size and book-to-market portfolios and using data from 1972 to 2012. The model is

$$\bar{R}_{q,t} - \bar{R}_{F,t} = \lambda_0 + \lambda_1 b_{q,R_M-R_F} + \lambda_2 b_{q,SMB} + \lambda_3 b_{q,HML} + \lambda_4 b_{q,precision} + \varepsilon_q. \quad (8)$$

$\bar{R}_q - \bar{R}_F$  are the average monthly returns for portfolio q minus the average risk-free monthly rate over the entire sample period. The explanatory variables are full-period factor betas for the 25 size and book-to-market portfolios.  $b_{R_M-R_M}$  is the portfolio beta related to the  $R_M-R_F$  factor.  $b_{SMB}$  is the portfolio beta related to the SMB factor.  $b_{HML}$  is the portfolio beta related to the HML factor.  $b_{precision}$  is the portfolio beta related to precision. Standard errors are computed using the Fama and MacBeth (1973) procedure. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

**Table 11**  
**Relation between Precision and Price Synchronicity**

Size Portfolios	Pearson Corr (SYNC, PREC)	Spearman Corr (SYNC, PREC)
Small stocks	0.179***	0.180***
2	0.145***	0.165***
3	0.040***	0.022**
4	0.009	-0.014
Large stocks	-0.059***	-0.057***

*Note:* The table presents correlations between precision of information in prices ( $PREC_{it}$ ) and price synchronicity by size quintiles. We sort stocks into five portfolios each calendar year based on their market capitalization at the beginning of the year, and compute the Pearson correlation between price synchronicity and the precision of information in prices in each size-quintile portfolio. For details on measuring precision, see Table 3. We estimate price synchronicity for each firm and calendar year using the following model:

$$RET_{it} = \alpha + \beta_1 MKTR_{it} + \beta_1 MKTR_{i,t-1} + \beta_1 INDR_{it} + \beta_1 INDR_{i,t-1} + \varepsilon_{it}, \quad (9)$$

where, for firm  $i$  and day  $t$ ,  $RET$  denotes the daily return and  $MKTR$  and  $INDR$  denote the value-weighted market return and industry return, respectively. The industry return is created using all firms within the same two-digit SIC code, omitting firm  $i$ 's daily returns. The logistic transformation of R-squared,  $SYNC = \log(R^2/(1-R^2))$ , is the return synchronicity measure. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.