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"Illiquidity and Earnings Predictability"

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Abstract

This paper studies the relation between illiquidity and the predictability of fundamental valuation variables. Theory suggests that illiquidity increases during periods of uncertainty about stock value. Consistent with this prediction, we document that during illiquid periods aggregate stock returns contain less information about future aggregate earnings, GNP growth, and industrial production. In addition, a firm-level cross-sectional analysis shows that returns of illiquid stocks contain less information about their future firm earnings compared to those of more liquid stocks. Finally, we document that analyst-forecast error and analyst-forecast dispersion are higher for more illiquid stocks. The results provide further evidence for the impact of illiquidity on fundamental value.

JEL classification: E32, G12, G14, M41

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1 Introduction

Kyle (1985) suggests that illiquidity should be higher when there is more uncertainty about the intrinsic value of a given security. Since much of the uncertainty about a security's value is with respect to its underlying firm's future cash flows, illiquidity should then also be associated with uncertainty about the firm's future performance. Since stock prices are forward-looking and predict future earnings (e.g., Ball and Brown, 1968; Kothari and Sloan, 1992; and Sadka and Sadka, 2009), one would expect that illiquidity will affect the relation between stock returns and future earnings. Specifically, one would expect that stock returns will better reflect future earnings when stocks are more liquid. Kyle (1985) suggests that half of private information about a stock's value is incorporated in its price. Thus, in cases where there is no uncertainty about fundamental value, investors would precisely anticipate future earnings and prices should fully reflect them. Prices reflect expected earnings, but, as the level of uncertainty increases, the ability of investors to predict a firm's future earnings declines. Consequently, the observed relation between stock prices and future actual earnings would weaken.

In this paper, we test whether the relation between a firm's stock return and its future earnings is more significant for liquid stocks than for illiquid stocks. We conduct the test both at the aggregate and at the firm level, employing cross-sectional regressions for the latter. For our illiquidity measure, we use the Amihud (2002) measure, which estimates the average daily price impact per stock. The Amihud measure is a monthly measure and to construct our annual firm-level measures we use the average illiquidity over the twelve-month period. For our aggregate annual illiquidity measure, we use the innovations in the cross-sectional average of firm-level illiquidity.

We begin our empirical analysis by performing tests at the firm level. For the firm-level regressions, we use earnings changes scaled by beginning period prices. We test whether the ability of stock returns in period t to predict earnings in period $t+1$ varies with stock liquidity. First, consistent with prior studies (e.g., Collins, Kothari, and Rayburn, 1987; and Kothari and Sloan, 1992), we find that firm-level stock returns predict earnings for the same firm in the following period. Second, our cross-sectional findings indicate that the stock returns of more liquid firms are better predictors of future firm-level earnings growth than those of illiquid firms.

Next, we focus on aggregate data. For aggregate measures, we use earnings growth, industrial production growth, and real gross national product (GNP) growth, as well as both equal- and value-weighted stock returns. We perform analyses at the aggregate level for two reasons. First, an aggregate analysis focuses on systematic rather than idiosyncratic variations. Second, prior studies suggest that aggregate earnings are predictable (e.g., Sadka, 2007; and Ball, Sadka, and Sadka, 2009). Using aggregate-level data, we show that earnings growth is more predictable using stock returns during periods of relatively favorable liquidity conditions. Specifically, we document that aggregate stock returns in period t are better predictors of aggregate earnings growth in period $t+1$, when aggregate liquidity is high during period t. In addition, we find similar results when using real GNP growth and industrial-production growth in place of earnings growth. These findings are consistent with our hypothesis that liquidity is higher during periods when prices are more informative, as measured by their ability to predict future macroeconomic indicators.

We proceed to expand our cross-sectional analysis using a portfolio approach. First, we sort firms into groups based on illiquidity. We find that marginal increases in illiquidity weakens the relation between returns and future earnings for all illiquidity groups. Second, we also sort firms based on size (market capital) due to the findings of Collins, Kothari, and Rayburn (1987) that stock returns predict earnings growth better for large firms than for small firms. Consistent with their findings, we document that stock returns predict future earnings growth better for large firms than for small firms. This paper complements their findings by showing that marginal increases in illiquidity weakens the relation between returns and future earnings for all size groups.

We further expand our study to employ analyst-forecast properties as alternative measures for predictability. While analyst forecasts provide us with an ex-ante measure of predictability, we note that prior studies find that they do not fully reflect investor expectations (e.g., Lys and Sohn, 1990; and Abarbanell, 1991). Our findings here suggest that analyst-forecast errors are larger in absolute value for more illiquid firms. In addition, we document that illiquid firms also have a higher analyst-forecast dispersion (see also Sadka and Scherbina, 2007). In sum, our findings using analyst-forecast errors and dispersion are consistent with our previous findings employing actual earnings growth and stock returns.

Finally, it is well recognized that liquidity can be measured in various ways and that some measures could produce somewhat different results because they could capture different aspects of liquidity (see Korajczyk and Sadka, 2008). Nevertheless, while the paper mainly utilizes the Amihud measure of illiquidity, an obvious question is whether the main results hold using other measures of liquidity. Therefore, we employ the Pástor and Stambaugh (2003) liquidity measure as well as the fixed and variable components of price impact developed in Sadka (2006). Our main findings about the decline in earnings predictability during illiquid periods hold also when measuring illiquidity both by the Pástor-Stambaugh measure and by Sadka's variable price-impact component. In contrast, Sadka's fixed price-impact component, which theoretically represents a noninformational component of transaction costs, does not show a similar effect on earnings predictability. These results are consistent with our conjecture that liquidity has an impact on the ability of stock prices to predict future earnings, because of the relation of liquidity to the information environment in the marketplace.

Our paper is related to an emerging literature that studies the effects of liquidity in accounting research. Some works in this literature associate illiquidity measures with other contemporaneous measures of uncertainty. For example, Lang and Maffett (2010) find that more transparent firms are also more liquid, while Ng (2010) finds that liquidity beta decreases with transparency. Also, Daske, Hail, Leuz, and Verdi (2008) recently document that the adoption of IFRS improves stock liquidity for the adopting firms. Roulstone (2003) finds that higher analyst-following of a firm provides information to investors resulting in higher liquidity of its stock. While these studies document the relation between illiquidity and other contemporaneous measures of information uncertainty, they do not directly test for the relation between liquidity and uncertainty about the future prospects of the firm.

The remainder of the paper is organized as follows. Section 2 describes our data and its sources. Section 3 describes our empirical methodology and main findings. Section 4 provides an additional analysis using analyst forecasts to test the association between illiquidity and the ability of analysts to forecast, and Section 5 concludes.

2 Data

Our data is gathered from the Compustat, Center for Research in Security Prices (CRSP), Federal Reserve Economic Data (FRED), and Institutional Brokers' Estimate System (IBES) datasets. In this study, we employ both firm-level and aggregate-level tests. Due to data limitations, firm-level regressions include data for the years 1959 to 2007, while the aggregate-level regressions include data for the years 1952 to 2007.

For the firm-level analyses, we eliminate observations that are missing any of the following data items: earnings, returns, volume, and year-end stock price. We also remove all firms which have a fiscal-year end other than December. We then truncate the remaining data at the top and bottom one percentiles to eliminate the possible effects of outliers. Our firm-level illiquidity measure also follows Amihud (2002) and is defined in the following manner. The illiquidity of a firm, $ILLIQ_{i,t}$, is measured as the natural logarithm of the average daily ratio of absolute value of return and dollar volume (multiplied by 10^6) over April of a year through March of the following year..

Table 1 provides descriptive statistics for key variables used in our firm-level regressions, both those which employ forward-looking earnings and analysts' forecasts. The average 12-month return in our sample is 13.4 percent, with a median of 7.2 percent. Descriptive statistics on market value, size, and book-to-market all indicate that our sample is diverse and includes small-, mid-, and large-cap firms. Additionally, the range of -10,537 to 78,262 of operating income further implies a diverse sample and indicates that it includes both highly profitable and unprofitable firms alike.

Our aggregate measures of real GNP growth and growth in industrial production are extracted from Federal Reserve Economic Data. Our aggregate earnings measure is constructed using firm-level earnings from Compustat. Specifically, aggregate earnings are defined as the cross-sectional sum of firm-level operating income. For aggregate stock returns, we employ both the equal-weighted and value-weighted returns of our sample firms. Our analysis includes only firms with December fiscal year-ends.

Our aggregate illiquidity measure, which is defined as an illiquidity shock, $\Delta ILLIQ_t$, is defined following Amihud (2002). Specifically, aggregate illiquidity is the equal-weighted cross-sectional average as, $ILLIQ_t$. Finally, $\Delta ILLIQ_t$ is defined as the error term, ε_t, in the following estimated regression:

$$ILLIQ_t = a + b \times ILLIQ_{t-1} + \xi_t. \tag{1}$$

Finally, for the regressions involving analysts' forecast errors and dispersion, we gather analyst data from the IBES dataset. Due to additional data limitations of the IBES dataset, the firm-level analyst regressions include only the years 1976 to 2007. We define and calculate analysts' forecaset errors as the absolute value of the difference between the actual earnings per share (EPS) and the most recent mean analysts' EPS forecast, scaled by year-end stock price. As our measure of analyst forecast dispersion we use the standard deviation of the most recent analysts' EPS forecast, also scaled by the firm's stock price at year-end.

Table 2 provides both the Spearman and Pearson correlations between variables of interest. In Panel A, we see that Returns are significantly postively correlated with earnings and significantly negatively correlated with illiquidity, both at the 1 percent level. In Panel B we see that illiquidity is negatively correlated with analysts' forecast errors and positively correlated with analysts' forecast dispersion, also both significant at the 1 percent level. These correlations are in the expected directions and reinforce our beliefs and hypotheses.

3 Empirical Analysis

3.1 Empirical Framework

Our empirical analysis follows the framework used in Brown, Griffin, Hagerman, and Zmijewski (1987) and Sadka and Sadka (2009). Under the efficient market hypothesis, realized future earnings growth is an unbiased estimate of expected earnings growth, i.e.,

$$\Delta X_{i,t+1}/P_{i,t} = E_t\left(\Delta X_{i,t+1}/P_{i,t}\right) + \varepsilon_{t+1}, \tag{2}$$

where $\varepsilon_{t+1} \sim (0, \sigma^2)$. The volatility, σ, increases with uncertainty, $\Delta X_{i,t+1}$ is the change in operating income from years t to $t+1$, and $P_{i,t}$ is the stock price of firm i at the end of the fiscal year t.Under complete foresight $\sigma = 0$. Using this property, we use realized earnings growth and stock returns to test for predictability. Specifically, we employ the following model:

$$R_{i,t} = \alpha + \beta \Delta X_{i,t+1}/P_{i,t} + \nu_{i,t}, \tag{3}$$

where $R_{i,t}$ denotes stock returns for firm i in period t. Since unexpected future shocks to earnings do not affect current prices, the relation between stock returns and future earnings growth is due to the expected component, which leads to the following:

$$R_{i,t} = c + d \cdot E_t\left(\Delta X_{i,t+1}/P_{i,t}\right) + \varsigma_{i,t}. \tag{4}$$

When earnings are not entirely predictable, realized earnings measure expected earnings with noise, that is $\sigma > 0$. Therefore, the estimated coefficient, $\widehat{\beta}$, is biased towards zero (errors-in-variables problem). Specifically:

$$plim\widehat{\beta} = \frac{d}{1+\sigma^2}. \tag{5}$$

Thus, a higher estimated coefficient implies more predictability and vice versa.

Note that the relation between earnings and returns can also be affected by illiquidity through its impact on discount rates. Specifically, a higher discount rate would reduce the coefficient as investors would discount the same earnings more significantly. Thus, if illiquidity is associated with discount rates, it may affect the earnings-returns relation independent of predictability. However, the discount rate impact is solely on the slope coefficient. Therefore, in addition to testing differences in the slope, β, we test the implications of illiquidity on the R^2 of the regression presented by Equation (3). A lower R^2 implies less predictability, because it suggests that variations in future earnings explain less of the variation in stock returns.

3.2 Firm-Level Analysis

We begin our empirical analysis by using firm-level cross-sectional regressions (Fama and MacBeth, 1973). Our analysis tests whether more illiquid firms have less informative prices with respect to future earninigs. Using our empirical framework, our first empirical test examines the effect on 12-month stock returns of the forward-looking change in operating earnings, illiquidity, and the two interacted together. Specifically, we test four expanding models with the full model having the following form:

$$R_{i,t} = \alpha_t + \beta_t \Delta X_{i,t+1}/P_{i,t} + \lambda_t \left(\Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ_{i,t}\right) + \delta_t ILLIQ_{i,t} + \nu_{i,t}. \qquad (6)$$

In the above equation $R_{i,t}$ is the cumulative stock return from April of year t until March of year $t+1$, $\Delta X_{i,t+1}$ is the change in operating income from years t to $t+1$, and $P_{i,t}$ is the stock price of firm i at the end of the fiscal year t. The variable $ILLIQ_{i,t}$ is defined following Amihud (2002) and is described above.

The bias towards zero caused by the errors-in-variable problem (discussed above) does not necessarily apply to the regression in Equation (6). This depends on the relation between earnings changes and illiquidity. While the correlation between earnings and illiquidity is relatively low (approximately 7%), this relation may affect our analysis. Therefore, we also use portfolios sorted based on illiquidity, employing univariate regression models presented by Equation (3). In these univariate models, the classical errors-in-variable problem holds and the estimated coefficient, β_t, is biased towards zero.

We estimate the model cross-sectionally for each year t and obtain 49 estimates of the coefficients (corresponding to the 49 years in our sample). Table 3 reports the mean, standard deviation, the 5^{th} percentile, the 25^{th} percentile, median, the 75^{th} percentile, and the 95^{th} percentile. The reported t-statistic is the Fama-MacBeth t-statistic.

In the context of our hypothesis, we expect a negative coefficient on the interaction term, i.e., $\lambda_t<0$. Note, that the overall slope coefficient on $\Delta X_{i,t+1}/P_{i,t}$ is $\beta_t + \lambda_t ILLIQ_{i,t}$. Thus, a negative coefficient, λ_t, implies that earnings are less predictable at higher levels of illiquidity. In other words, $\lambda_t<0$ implies that stock returns contain relatively less information about future earnings as the level of illiquidity increases.

As an initial benchmark for our analysis, we show that changes in forward-looking earnings are associated with current-period returns (e.g., Kothari and Sloan, 1992). Using Fama and Macbeth (1973) regressions, we show a strong, positive coefficient on the change in price-deflated earnings in the first regression of Table 3. In terms of Equation (6), we document that β_t is positive and statistically significant. The average coefficient is 0.429 with a t-statistic of 2.58. The average adjusted-R^2 is 5%.

Next, we build upon the model by including our measure of illiquidity along with the interaction between the illiquidity measure and the change in future earnings. We document a negative coefficient on the interaction term, λ_t. When adding only the interaction term, λ_t has a time-series mean of -0.08 and a t-statistic of -1.38. When estimating the full model, λ_t has a time-series mean of -0.10 and a t-statistic of -2.39. Moreover, in all models, only the 95^{th} percentile of λ_t estimates is positive.

As noted above, we includ our illiquidity measure in our analysis. Consistent with prior studies, the coefficient on illiquidity is negative with a mean of -0.01 with a t-statistic of 2.20 when estimated without the interaction term, and -0.01 with a t-statistic of 1.69 when estimated with it. This implies that illiquidity negatively affects stock returns. In untabulated results, we also run the regresssions using pooled OLS, clustering the error terms by both firm and year to verify the robustness of the results. The results are not significantly different using that alternative specification.

3.3 Aggregate-Level Analysis

Next, we perform aggregate-level analyses. In particular, we perform time-series regressions at the aggregate level and estimate the following regression model:

$$R_t = \alpha + \beta \Delta X_{t+1} + \lambda \Delta X_{t+1} \Delta ILLIQ_t + \nu_t, \tag{7}$$

where R_t is the cumulative equal-weighted and value-weighted stock return from April of year t until March of year t+1, ΔX_{t+1} is the growth in operating income from years t and $t+1$. The variable $\Delta ILLIQ_t$ is the unexpected illquidity shock in period t (following Amihud, 2002) and is described above in Section 2. The results are reported in Table 4. Panel A reports results using equal-weighted stock returns. Panel B reports results using value-weighted stock returns. As with the firm-level analysis above, a negative coefficient λ implies that earnings are less predictable. Due to the short sample period, we did not include illiquidity on its own.

We begin by replicating prior results suggesting that stock returns are positively associated with future earnings growth. Using equal-weighted aggregate returns (Panel A), the coefficient is 0.66, its t-statistic is 3.53 and the adjusted-R^2 is 12%. The results are slightly weaker when using value-weighted stock returns (Panel B). The coefficient is 0.32, the t-statistic is 2.14 and the adjusted-R^2 is 5%. Thses findings imply that aggregate stock returns predict aggregate future earnings growth (e.g., Sadka and Sadka, 2009).

Similar to our firm-level analysis, the interaction term in Equation (7) above is negative as well. Using both equal-weighted and value-weighted returns, the coefficient on the interaction term, λ, is negative and significant. In Panels A and B, the coefficients are -0.17 and -0.08, respectively. The adjusted-R^2 more than doubles when the interaction term is included. For example, in Panel A, the adjusted-R^2 increases from 12% to 33%. These findings are consistent with our hypothesis that earnings growth is less predictable during times of high, aggregate illiquidity.

In addition to using the raw aggregate illiquidity measure, we also employ illiquidity ranks. The results continue to hold when liquidity ranks are used, though they are slightly attenuated. Specifically, when using value-weighted returns (Panel B), the coefficient on the interaction term has a t-statistic of -1.95, compared to -2.88 when using illiquidity values. Similarly, the adjusted-R^2 is lower when using ranks. For example, in Panel A, the adjusted-R^2 is 24% when the interaction term is based on illiquidity ranks, compared to 33% when using the actual illiquidity values.

Finally, we partition the sample into two time periods, where one partition contains the 23 most illiquid periods and the other contains the 22 most liquid time periods. The advantage of this approach is that the R^2 is the correlation squared. When comparing the two results, we find that during periods of high liquidity, earnings growth is more predictable using stock returns. Using equal-weighted returns, the coefficient on earnings is 0.75 and is significant at the 10 percent level. However, during periods of high illiquidity, the effect disappears and the coefficient on earnings becomes insignificantly different from zero. The results are slightly weaker using value-weighted returns, as displayed in Panel B, but the inferences are similar.

Using the two separate time periods is useful to identify the effects of illiquidity on the earnings-returns regression. Theoretically, the coefficient λ above can be negative simply because the discount rate increases in periods of illiquidity (see e.g., Collins and Kothari, 1989). In other words, the response to changes in cash flows is less pronounced when the discount rates are higher. However, unlike the regression coefficient, if predictability remains the same the adjusted-R^2 should remain the same in both periods. A change in the discount rate will lower the response (negative λ), but should not affect the association (R^2). As we note above, our findings, that the R^2 declines in periods of illiquidity, suggest that the relation between earnings and lagged-stock returns declines partly due to to less predictability.

3.3.1 Aggregate Stock Returns, Illiquidity, and Macroeconomic Indicators

In addition to aggregate earnings, we also study the effects of liquidity on other macroeconomic indicators. Specifically, we test whether illiquidity affects the ability of stock returns to predict real growth in GNP (denoted by ΔGNP_{t+1}) and growth in industrial production (denoted by $\Delta PROD_{t+1}$).[1] We employ the same empirical methodology as presented in Equation (7). In this section, we replace the earnings growth measure with one of our other macroeconomic indicators. The results of these aggregate-level regressions are reported in Table 5. Following the same format as in Table 4, Panel A of Table 5 reports results using equal-weighted stock returns and Panel B reports results using value-weighted stock returns. Also, similar to the analysis in Table 4, we use both illiquidity values and illiquidity ranks to generate our interaction term.

We begin our analysis by replicating prior evidence that stock returns predict future GNP growth and future industrial production (e.g., Fama, 1990). The coefficient on ΔGNP_{t+1} is both positive and statistically significant in all models. The coefficient varies from 2.40 to 6.76 and the t-statistic varies from 2.91 to 5.28. Similarly, the coefficient on $\Delta PROD_{t+1}$ is positive and statistically significant in all models. The coefficient varies from 1.11 to 1.58 and the t-statistic varies from 3.08 to 5.21.

Overall, the results in Table 5 are consistent with those in Table 4 and our hypothesis. We find that higher illiquidity is associated with less predictable fundamentals. For example, when using equal-weighted aggregate returns and real GNP growth, the interaction term, λ, is -4.13 with a t-statistic of -2.84. When the interaction term is included, the adjusted-R^2 increases from 13% to 27%. These findings suggest that aggregate illiquidity in part reflects uncertainty about future economic prospects.

Also consistent with our findings in Table 4, the results are weaker when we employ value-weighted returns. In particular, when using illiquidity ranks, the interaction term of illiquidity and GNP growth becomes statistically insignificant. However, all interaction

[1] Fama (1990) and Schwert (1990) document a robust relation between stock returns and current and future industrial production.

terms using illiquidity ranks, illiquidity values, GNP and industrial production are negative. In addition, apart from the above-mentioned model, the interaction term is significant at the 10% level or lower.

3.4 Aggregate Illiquidity and the Effects of Firm-Level Illiquidity

Prior studies document that firm-level illiquidity is affected by aggregate-level illiquidity (e.g., Lang and Maffett, 2010). In addition, these studies document that firm-level characteristics modify this relation. In the same vein, we test whether aggregate illiquidity modifies the effects of firm-level illiquidity on predictability. Specifically, we regress the time-series of cross-sectional estimates of Equation (6) above on aggregate illiquidity

$$\begin{aligned} FMINT_t &= a_1 + b_1 \Delta ILLIQ_t + \mu_{1,t}, \\ FMEARN_t &= a_2 + b_2 \Delta ILLIQ_t + \mu_{2,t}. \end{aligned} \tag{8}$$

where $FMINT_t$ denotes the yearly coefficients on the interaction term from the firm-level Fama and Macbeth (1973) regressions, $\widehat{\lambda}_t$ in Equation (6). $FMEARN_t$ denotes the yearly coefficients on earnings growth from that same regression, $\widehat{\beta}_t$ in Equation (6).

In unreported results, we find little evidence of a statistical relationship between aggregate illiquidity and the cross-sectional association between illiquidity and predictability. Although the coefficient b_1 is positive and b_2 is negative, both coefficients are insignificantly different from zero.

3.5 Portfolio Analysis

In addition to our aggregate-level and firm-level analyses, we also include a within-portfolio analysis. In particular, we sort firms into portfolios/groups. We then estimate firm-level cross-sectional regressions similar to Equation (6) within the different portfolios/groups of securities. First, we sort firms based on illiquidity. This sort helps us test whether the marginal effect of illiquidity is dependent on the level of illiquidity. Second, we sort firms based on size (defined as the market capitalization at the beginning of the period). We sort on size because prior studies, e.g., Collins, Kothari, and Rayburn (1987), document that the stock prices of large firms contain more information about future earnings than those of small firms.

The results in Table 6 are consistent with those reported in Table 3. We find that stock returns contain more information about future earnings in more liquid stocks. When estimating the model only with future earnings, the coefficient declines from 1.085 for the most liquid group to 0.069 for the most illiquid group. Consistently, the average adjusted-R^2 also declines from 6% for the most liquid group to 1% for the most illiquid group. As we note above, the decline in adjusted-R^2 implies that the decline in the earnings-returns relation is not simply due to higher discount rates. The results imply that illiquid firms have less predictable earnings.

The findings in Table 6 imply that the marginal effect of illiquidity on predictability is aparent in all illiquidity groups. The coefficient on the interaction term, λ_t, is negative and is highest in absolute value for the second most illiquid stocks (rank=2). For example, in the full model, the coefficient is -0.184 for the most liquid group and is -0.109 for the most illiquid group. The highest magnitude of the coefficient is in the second most liquid group (rank = 2), where the coefficient is -0.460. However, our findings are statistically insignificant.

The test results for the portfolios sorted on size are reported in Table 7. Our findings are consistent with prior studies (e.g., Collins, Kothari, and Rayburn, 1987; and Sadka and Sadka, 2009) insofar that stock returns are better predictors of future earnings for larger firms. The average coefficient, β_t, increases from 0.067 to 1.084. Consistently, the average adjusted-R^2 increases monotonically from 1% to 5%.

The results in Table 7 imply that the marginal effect of illiquidity on predictability pronounced in all size groups. The coefficient on the interaction term, λ_t, is negative and is statistically significant. For example, in the full model the coefficient is -0.101 for the smallest firm group and is -0.193 for the largest firm group. In the middle size group (rank = 3), the coefficient is -0.475. The t-statistic varies from -2.59 to -4.72.

4 Analyst Forecasts

Our analyses thus far employ ex-post realizations to test our hypothesis. We now turn to analysts' forecasts as an ex-ante measure of predictability. We should note that while Brown and Rozeff (1978) document that analysts' forecasts are better estimates of future earnings than time-series forecasts using prior earnings, the literature has long debated whether analysts' forecasts reflect investor expectations. In fact, several studies (such as Abarbanell, 1991; Lys and Sohn, 1991; Abarbanell and Lehavy, 2003; Hughes, Liu, and Su, 2008; and Konchitchki, Lou, Sadka, and Sadka, 2010) document that stock returns predict forecast errors. Nevertheless, we believe that testing our hypothesis using analyst forecasts can strengthen our understanding of the relation between illiquidity and predictability.

In our analysis, we employ two measures of predictability using analysts' forecast: forecast errors and forecast dispersion. $|ERROR|_{i,t}$ is our measure of forecast error and is defined as the absolute value of the difference between the actual EPS and the most recent mean analysts' EPS forecast that is available prior to the actual EPS announcement, scaled by year-end stock price. $DISPERS_{i,t}$ is our measure of analysts' forecast dispersion and is defined as the standard deviation of the most recent analysts' EPS forecast, scaled by the firm's stock price at the end of the year. We also include standard controls from the analyst forecast literature, including size, book-to-market, and the sign of earnings.

We first test the effect of analysts' forecast errors by employing a parsimonious model without any additional controls and then we test a full model that includes all relevant controls. Specifically, the full model we test is of the following form:

$$|ERROR|_{i,t} = \gamma_0 + \gamma_1 ILLIQ_{i,t} + \gamma_2 SIZE_{i,t} + \gamma_3 BM_{i,t} + \gamma_4 SIGN_{i,t} + \upsilon_{i,t}, \tag{9}$$

where $ILLIQ_{i,t}$ is defined the same as above, $SIZE_{i,t}$ is the natural logarithm of the balance of firm year-end assets, $BM_{i,t}$ is the year-end book-to-market value of equity ratio, and $SIGN_{i,t}$ is an indicator variable equal to one when firm-level earnings in the period are positive, and zero otherwise. We employ both Fama and MacBeth (1973) regressions as well as pooled regressions with two-way clustered standard errors. The results of these regressions are reported in Table 8.

The coefficient on illiquidity, γ_1, is significantly positive regardless of the model or test procedure utilized. The coefficient ranges from 0.0095 to 0.0098, and is always highly significant at the one percent level. This suggests that analysts' forecast errors are larger in absolute value for more illiquid firms and supports our hypothesis that illiquidity reduces the predictability of earnings.

With respect to our control variables, all coefficients are positive except for γ_4, which is negative. These findings imply that forecast errors are larger in absolute value for large firms and high book-to-market firms. The negative coefficient on the sign of earnings suggests that forecast errors are smaller when earnings are positive.

We proceed to test our hypothesis using analysts' forecast dispersion. To do so, we again begin with a parsimonious model and then expand it to its full form, which is the following:

$$DISPERS_{i,t} = \alpha_i + \beta_i ILLIQ_{i,t} + \lambda_i SIZE_{i,t} + \delta_i BM_{i,t} + \eta_i SIGN_{i,t} + \upsilon_{i,t}. \tag{10}$$

For this series of tests, we also employ both Fama and MacBeth (1973) regressions as well as pooled regressions with two-way clustered standard errors. The results of the test using analysts' forecast dispersion are reported in Table 9.

Similar to the results in Table 8, the coefficient on illiquidity is again significant regardless of the level of controls or regression type and ranges from 0.0012 to 0.0017. These findings suggest that analysts' forecast dispersion is larger for more illiquid firms, implying that forecasts are less accurate the higher the illiquidity of the firm. This further supports our hypothesis that illiquidity reduces the predictability of earnings, in this case by increasing the ex-ante prediction errors made by analysts.

5 Alternative Measures of Illiquidity

Our main analysis employs the Amihud (2002) illiquidity measure. This is because this measure is available on a firm-year basis for a relatively long time series. However, the literature includes several additional measures of illiquidity. We test the robustness of our findings by including such additional measures. Specifically, we employ the Pástor and Stambaugh (2003) liquidity measure (PS) as well as the Sadka (2006) measures, that are available from 1962 and 1984, respectively.

The aggregate Pástor-Stambaugh measure is available on a monthly basis. To construct an annual series, we average the monthly levels of liquidity each year. Also, since this measure signifies liquidity, we add a negative sign to the time series to arrive with a time series of market illiquidity. Finally, similar to the case of the Amihud measure, we use Equation (1) to compute aggregate illiquidity shocks. As for the Sadka measures, we utilize both the Variable Permanent (VP) and the Fixed Transitory (FT) components of price impact. Similar to the Pástor-Stambaugh measure, we average the monthly aggregate levels of illiquidity each year to create an annual series, and then use These measures are availalbe on a monthly basis and then apply Equation (1) to compute aggregate illiquidity shocks.

While PS and VP are measures that may be associated with information asymmetry, the FT component represents a noninformational part of transaction costs, because it is represents a transitory trade-to-trade price effect. Therefore, we do not expect to find a relation between FT and the ability of stock returns to predict earnings.

We conduct the aggregate-level regressions as described in Equation (7) using the alternative illiquidity measures. The results are reported in Table 10. The results are consistent with the findings in Section 3.3. When using the PS and VP illiquidity measures, the interaction term is consistently negative and statistically significant. The coefficient varies from -3.15 to -15.56 and the t-statistic varies from -1.97 to -5.95. Note that the sample size declines significantly. Using the Sadka (2006) measures, the sample size is reduced to 24 observations. Using PS measures, the sample size is reduced to 46 observations.

In contrast, when using the FT component of price impact to proxy for illiquidity, the interaction term is negative but statistically insignificant. These findings are consistent with our hypothesis because the FT component of price impact should not be affected by uncertainty with respect to the stock's underlying value. Our study helps validate the illiquidity measures as capturing uncertainty about the fundamental value of stocks.

6 Conclusion

This paper studies the association between illiquidity and the predictability of fundamental valuation variables, such as earnings. We document that illiquidity is associated with less informed prices with respect to future earnings, and find evidence in both aggregate- and firm-level analyses. We also find consistent evidence using analyst-forecast error and analyst-forecast dispersion. The results complement those in other recent studies that document an association between measures of illiquidity and contemporaneous measures of uncertainty.

We study several measures of illiquidity and find that the measure of illiquidity capturing the noninformational cost does not affect predictability. In contrast, our effects are associated with the informational cost of illiquidity. These findings are consistent with theory suggesting that a part of illiquidity is associated with uncertainty about fundamental value.

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Table 1
Descriptive Statistics

This table presents the descriptive statistics of key variables. RET is the cumulative return from April of year *t* until March of year *t*+1. EARN denotes the change in operating income from years *t* and *t*-1, scaled by the stock price of firm *i* at the end of the fiscal year *t*-1. The illiquidity of a firm, $ILLIQ_{i,t}$, is measured as the natural logarithm of the average daily ratio of absolute value of return and dollar volume (multiplied by 10^6) over April of year *t* through March year *t*+1. OPEARN is the unscaled operating income after depreciation in year *t*. MV is the market value of the firm. FORERR is defined as the absolute value of the difference between the actual EPS and the most recent mean analysts' EPS forecast, scaled by year-end stock price. DISPERS is the standard deviation of the most recent analysts' EPS forecasts, scaled by year-end stock price. SIZE is the natural logarithm of total assets, and BM is the book-to-market value of equity ratio. The descriptive statistics for RET, EARN, ILLIQ, OPEARN, and MV are based upon 98,139 observations from 1959 to 2007, while the descriptive statistics for FORERR, DISPERS, SIZE, and BM are based upon 37,309 observations from 1976 to 2007.

	Mean	Std	Min	25 Pctile	Median	75 Pctile	Max
RET	0.134	0.484	-0.805	-0.162	0.072	0.337	2.742
EARN	0.018	0.123	-0.590	-0.018	0.012	0.047	0.871
ILLIQ	2.537	2.608	-3.815	0.680	2.655	4.423	8.763
OPEARN	184.522	936.984	-10,537.000	2.324	17.837	90.835	78,262.400
MV	1,506.733	6,276.956	0.357	43.388	180.196	789.368	348,034.300
FORERR	-0.046	5.056	-445.170	-0.050	0.010	0.043	688.500
DISPERS	0.114	2.271	0.010	0.020	0.040	0.090	352.670
SIZE	6.932	1.962	0.521	5.496	6.867	8.202	14.897
BM	0.652	0.644	-31.929	0.328	0.543	0.836	27.494

Table 2
Correlation Matrix

This table reports correlations among the variables of interest. Panel A reports the correlations between variables used in the firm-level earnings-based regressions as seen in Table 3, whereas Panel B reports the correlations between variables used in the firm-level analyst- based regressions as seen in Tables 8 and 9. RET is the cumulative return from April of year t until March of year t+1. $EARN_t$ denotes the change in operating income from years t and t-1, scaled by the stock price of firm i at the end of the fiscal year t-1. The illiquidity of a firm, $ILLIQ_{i,t}$, is measured as the natural logarithm of the average daily ratio of absolute value of return and dollar volume (multiplied by 10^6) over April of year t through March year t+1. MV is the market value of the firm. SIZE is the natural logarithm of total assets. BM is the book-to-marke value of equityt ratio. FORERR is defined as the absolute value of the difference between the actual EPS and the most recent mean analysts' EPS forecast, scaled by year-end stock price, and DISPERS is the standard deviation of the most recent analysts' EPS forecasts, scaled by year-end stock price. Spearman correlations are above the diagonal, while Pearson correlations are below. The correlations in Panel A are based on 98,193 firm-year observations for the period 1959 to 2007, while those in Panel B are based on 37,309 firm-year observations for the period 1976 to 2007. ***, **, * represent significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Firm-level using earnings

	RET	EARN	ILLIQ	MV
RET		0.1407 ***	-0.1179 ***	0.1585 ***
$EARN_{t+1}$	0.0723 ***		0.061 ***	-0.0474 ***
ILLIQ	-0.0699 ***	0.0785 ***		-0.9079 ***
MV	0.033 ***	-0.0123 ***	-0.3472 ***	

Panel B: Firm-level using analyst models

	RET	ILLIQ	SIZE	BM	FORERR	DISPERS
RET		-0.0898 ***	0.0834 ***	-0.2084 ***	0.1895 ***	-0.0817 ***
ILLIQ	-0.0371 ***		-0.6447 ***	0.2874 ***	-0.1283 ***	0.0383 ***
SIZE	-0.0157 ***	-0.6437 ***		0.1838 ***	0.0574 ***	0.1661 ***
BM	-0.162 ***	0.2394 ***	0.1132 ***		-0.0935 ***	0.2546 ***
FORERR	0.0076	-0.0164 ***	0.0097 *	-0.0092 *		-0.1203 ***
DISPERS	-0.0051	-0.0159 ***	0.0401 ***	0.0099 *	-0.2133 ***	

Table 3

Firm-Level Regressions

This table reports the results of the time-series of firm-level cross-sectional regressions. The annual returns of firm *i* at year *t*, $R_{i,t}$, is the cumulative return from April of year *t* until March of year *t*+1. $\Delta X_{i,t}$ denotes the change in operating income from years *t* and *t*-1. The stock price of firm *i* at the end of the fiscal year *t*-1 are denoted $P_{i,t-1}$. The illiquidity of a firm, $ILLIQ_{i,t}$, is measured as the natural logarithm of the average daily ratio of absolute value of return and dollar volume (multiplied by 10^6) over April of year *t* through March year *t*+1. The data includes NYSE, AMEX, and NASDAQ December fiscal year-end firms for the period 1959 to 2007.

$$R_{i,t} = \alpha_i + \beta_i \cdot \Delta X_{i,t+1}/P_{i,t} + \upsilon_{i,t}$$

	Mean	Std	5%	25%	Median	75%	95%	*t*-stat
β_i	0.429	1.161	-0.529	-0.032	0.157	0.451	3.062	2.58
R^2	0.05	0.15	0.00	0.00	0.01	0.03	0.30	
Adj-R^2	0.05	0.14	0.00	0.00	0.01	0.03	0.30	

$$R_{i,t} = \alpha_i + \beta_i \cdot \Delta X_{i,t+1}/P_{i,t} + \lambda_i \cdot \Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ_{i,t} + \upsilon_{i,t}$$

	Mean	Std	5%	25%	Median	75%	95%	*t*-stat
β_i	0.28	1.38	-1.06	-0.09	0.08	0.31	1.96	1.45
λi	-0.08	0.39	-0.42	-0.16	-0.06	-0.02	0.10	-1.38
R^2	0.11	0.15	0.00	0.01	0.02	0.04	0.31	
Adj-R^2	0.11	0.15	0.00	0.01	0.02	0.04	0.30	

$$R_{i,t} = \alpha_i + \beta_i \cdot \Delta X_{i,t+1}/P_{i,t} + \lambda_i \cdot \Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ_{i,t} + \delta_i \cdot ILLIQ_{i,t} + \upsilon_{i,t}$$

	Mean	Std	5%	25%	Median	75%	95%	*t*-stat
β_i	0.29	1.40	-0.95	-0.01	0.09	0.31	2.21	1.43
λi	-0.10	0.28	-0.50	-0.13	-0.06	-0.02	0.07	-2.39
δi	-0.01	0.04	-0.06	-0.02	-0.02	0.01	0.04	-1.69
R^2	0.09	0.16	0.01	0.02	0.05	0.08	0.31	
Adj-R^2	0.09	0.15	0.01	0.02	0.05	0.08	0.29	

$$R_{i,t} = \alpha_i + \beta_i \cdot \Delta X_{i,t+1}/P_{i,t} + \delta_i \cdot ILLIQ_{i,t} + \upsilon_{i,t}$$

	Mean	Std	5%	25%	Median	75%	95%	*t*-stat
β_i	0.45	1.24	-0.53	0.01	0.15	0.43	2.97	2.54
δi	-0.01	0.03	-0.06	-0.03	-0.02	0.01	0.04	-2.20
R^2	0.08	0.15	0.01	0.02	0.03	0.08	0.31	
Adj-R^2	0.08	0.15	0.01	0.02	0.03	0.08	0.30	

Table 4
Aggregate-Level Regressions

This table reports time-series regression results at the aggregate level. The annual market return at year t, R_t, is the cumulative value- or equal-weighted return from April of year t until March of year t+1 (value weights are based on beginning-of-period market capitalization). ΔX_t denotes the growth in the cross-sectional sum of operating income from years t and t-1. The illiquidity of a firm, $ILLIQ_{i,t}$, is measured as the natural logarithm of the average daily ratio of absolute value of return and dollar volume (multiplied by 10^6) over April of year t through March year t+1. Aggregate illiquidity, $ILLIQ_t$, is measured as the cross-sectional average of firm-level annual estimates. Finally, $\Delta ILLIQ_t$ is defined as the error term in the following estimated regression: $ILLIQ_t = a + b \cdot ILLIQ_{t-1} + \zeta_t$. In addition, the table includes regressions based upon liquidity ranks where each year is ranked based upon $ILLIQ_t$ for that year. Further, the table shows the results of regressions which include only the 23 most illiquid periods, as well as the results of regressions which only include the 22 most liquid periods. The t-statistics are reported in square brackets. The data includes NYSE, AMEX, and NASDAQ December fiscal year-end firms for the period 1959 to 2007.

Panel A: Equal-weighted returns

Dependent variable	Intercept	Independent variables ΔX_{t+1}	$\Delta X_{t+1} \cdot \Delta ILLIQ_{,t}$	R^2	Adj-R^2
R_t	-0.56	0.66		0.14	0.12
	[-2.93]	[3.53]			
R_t	-0.35	0.45	-0.17	0.35	0.33
	[-2.10]	[2.98]	[-3.45]		
R_t	-0.36	0.62	-0.05	0.27	0.24
Using liquidity ranks	[-2.03]	[3.68]	[-2.99]		
R_t	-0.12	0.17		0.02	-0.03
23 most illiquid periods	[-0.47]	[0.71]			
R_t	-0.62	0.75		0.11	0.06
22 most liquid periods	[-1.25]	[1.69]			

Panel B: Value-weighted returns

Dependent variable	Intercept	Independent variables ΔX_{t+1}	$\Delta X_{t+1} \cdot \Delta ILLIQ_{,t}$	R^2	Adj-R^2
R_t	-0.23	0.32		0.07	0.05
	[-1.38]	[2.14]			
R_t	-0.15	0.24	-0.08	0.19	0.16
	[-1.01]	[1.84]	[-2.88]		
R_t	-0.15	0.33	-0.03	0.15	0.12
Using liquidity ranks	[-0.95]	[2.39]	[-1.95]		
R_t	0.01	0.07		0.00	-0.04
23 most illiquid periods	[0.03]	[0.30]			
R_t	-0.24	0.34		0.07	0.02
22 most liquid periods	[-0.61]	[1.00]			

Table 5

Aggregate-Level Regressions Predicting Real GNP Growth and Industrial Production

This table reports time-series regression results at the aggregate level. The annual market returns at year *t*, R_t, is the cumulative value- or equal-weighted returns from April of year *t* until March of year *t*+1 (value weights are based on beginning-of-period market capitalization). ΔGNP_t denotes the real growth in the gross national product from years *t* and *t*-1. $\Delta PROD_t$ denotes the growth in industrial production from years *t* and *t*-1. The illiquidity of a firm, $ILLIQ_{i,t}$, is measured as the natural logarithm of the average daily ratio of absolute value of return and dollar volume (multiplied by 10^6) over April of year *t* through March year *t*+1. Aggregate illiquidity, $ILLIQ_t$, is measured as the cross-sectional average of firm-level annual estimates. Finally, $\Delta ILLIQ_t$ is defined as the error term in the following estimated regression: $ILLIQ_t = a + b \cdot ILLIQ_{t-1} + \zeta_t$. The *t*-statistics are reported in square brackets. The data includes December fiscal year-end firms for the period 1952 to 2007.

Panel A: Equal-weighted returns					
Dependent variable	Independent variables: Intercept	ΔGNP_{t+1}	$\Delta GNP_{t+1} \cdot \Delta ILLIQ_t$	R^2	Adj-R^2
R_t	0.03	3.99		0.15	0.13
	[1.00]	[5.28]			
R_t	0.04	3.03	-4.13	0.29	0.27
	[1.41]	[4.57]	[-2.84]		
R_t	0.04	6.76	-1.17	0.22	0.19
Using liquidity ranks	[1.37]	[5.17]	[-3.01]		

Panel B: Value-weighted returns					
Dependent variable	Independent variables: Intercept	ΔGNP_{t+1}	$\Delta GNP_{t+1} \cdot \Delta ILLIQ_t$	R^2	Adj-R^2
R_t	0.03	2.75		0.15	0.13
	[0.94]	[3.06]			
R_t	0.04	2.40	-1.44	0.18	0.15
	[-1.01]	[3.61]	[-1.74]		
R_t	-0.15	3.44	-0.30	0.16	0.12
	[0.04]	[2.91]	[-0.90]		

Panel A: Equal-weighted returns					
Dependent variable	Independent variables: Intercept	$\Delta PROD_{t+1}$	$\Delta PROD_{t+1} \cdot \Delta ILLIQ_t$	R^2	Adj-R^2
R_t	-1.47	1.58		0.13	0.12
	[-4.28]	[4.74]			
R_t	-1.02	1.14	-0.19	0.36	0.33
	[-2.68]	[3.08]	[-3.82]		
R_t	-1.07	1.37	-0.06	0.27	0.24
Using liquidity ranks	[-2.86]	[3.87]	[-4.10]		

Panel B: Value-weighted returns					
Dependent variable	Independent variables: Intercept	$\Delta PROD_{t+1}$	$\Delta PROD_{t+1} \cdot \Delta ILLIQ_t$	R^2	Adj-R^2
R_t	-1.25	1.33		0.19	0.18
	[0.94]	[5.21]			
R_t	-1.02	1.11	-0.08	0.27	0.25
	[-4.29]	[4.74]	[-2.63]		
R_t	-1.05	1.21	-0.03	0.24	0.21
	[-4.39]	[5.09]	[-1.84]		

Table 6

Illiquidity Sorts

This table reports the result of the time-series of firm-level cross-sectional regressions when firms are sorted based upon illiquidity ranks. The annual returns of firm *i* at year *t*, $R_{i,t}$, is the cumulative return from April of year *t* until March of year *t*+1. $\Delta X_{i,t}$ denotes the change in operating income from years *t* and *t*-1. The stock price of firm *i* at the end of the fiscal year *t*-1 are denoted $P_{i,t-1}$. The illiquidity of a firm, $ILLIQ_{i,t}$, is measured as the natural logarithm of the average daily ratio of absolute value of return and dollar volume (multiplied by 10^6) over April of year *t* through March year *t*+1. For each period firms are sorted into five groups based on illiquidity at the beginning of year *t*. The *t*-statistics are reported in square brackets. The data includes NYSE, AMEX, and NASDAQ December fiscal year-end firms for the period 1959 to 2007.

$R_{i,t} = \alpha_i + \beta_i \cdot \Delta X_{i,t+1}/P_{i,t} + \upsilon_{i,t}$					
	Illiquidity Rank				
	1	2	3	4	5
β_i	1.085	0.958	0.652	0.210	0.069
	[7.19]	[7.85]	[5.41]	[5.28]	[1.50]
Adj-R^2	0.06	0.05	0.03	0.01	0.01
$R_{i,t} = \alpha_i + \beta_i \cdot \Delta X_{i,t+1}/P_{i,t} + \lambda_i \cdot \Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ_{i,t} + \upsilon_{i,t}$					
	Illiquidity Rank				
	1	2	3	4	5
β_i	1.251	2.021	1.577	0.981	0.756
	[4.45]	[2.83]	[2.04]	[1.33]	[2.70]
λi	-0.213	-0.325	-0.288	-0.150	-0.113
	[-1.66]	[-1.22]	[-1.37]	[-0.87]	[-2.40]
Adj-R^2	0.07	0.05	0.04	0.02	0.02
$R_{i,t} = \alpha_i + \beta_i \cdot \Delta X_{i,t+1}/P_{i,t} + \lambda_i \cdot \Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ_{i,t} + \delta_i \cdot ILLIQ_{i,t} + \upsilon_{i,t}$					
	Illiquidity Rank				
	1	2	3	4	5
β_i	1.151	2.337	1.641	1.044	0.739
	[4.40]	[2.74]	[1.84]	[1.51]	[2.59]
λi	-0.184	-0.460	-0.311	-0.169	-0.109
	[-1.51]	[-1.47]	[-1.30]	[-1.05]	[-2.30]
δi	0.000	0.035	-0.016	-0.008	-0.006
	[0.06]	[2.52]	[-1.45]	[-0.68]	[-0.85]
Adj-R^2	0.07	0.06	0.04	0.02	0.02

Table 7
Size Sorts

This table reports the results of the time-series of firm-level cross-sectional regressions when firms are sorted based upon size ranks. The annual returns of firm *i* at year *t*, $R_{i,t}$, is the cumulative return from April of year *t* until March of year *t*+1. $\Delta X_{i,t}$ denotes the change in operating income from years *t* and *t*-1. The stock price of firm *i* at the end of the fiscal year *t*-1 are denoted $P_{i,t-1}$. The illiquidity of a firm, $ILLIQ_{i,t}$, is measured as the natural logarithm of the average daily ratio of absolute value of return and dollar volume (multiplied by 10^6) over April of year *t* through March year *t*+1. Fore each period firms are sorted into five groups based on the market capitalization at the beginning of year *t*. The *t*-statistics are reported in square brackets. The data includes NYSE, AMEX, and NASDAQ December fiscal year-end firms for the period 1959 to 2007.

$R_{i,t} = \alpha_i + \beta_i \cdot \Delta X_{i,t+1}/P_{i,t} + \upsilon_{i,t}$					
	Size Rank				
	1	2	3	4	5
β_i	0.067	0.247	0.581	0.789	1.084
	[1.41]	[4.84]	[8.49]	[6.46]	[6.02]
Adj-R^2	0.01	0.01	0.03	0.05	0.05
$R_{i,t} = \alpha_i + \beta_i \cdot \Delta X_{i,t+1}/P_{i,t} + \lambda_i \cdot \Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ_{i,t} + \upsilon_{i,t}$					
	Size Rank				
	1	2	3	4	5
β_i	1.386	2.278	2.451	1.704	1.415
	[6.52]	[6.73]	[7.49]	[4.39]	[4.72]
λi	-0.219	-0.459	-0.589	-0.422	-0.247
	[-6.57]	[-6.19]	[-6.83]	[-3.79]	[-2.44]
Adj-R^2	0.02	0.03	0.05	0.06	0.06
$R_{i,t} = \alpha_i + \beta_i \cdot \Delta X_{i,t+1}/P_{i,t} + \lambda_i \cdot \Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ_{i,t} + \delta_i \cdot ILLIQ_{i,t} + \upsilon_{i,t}$					
	Size Rank				
	1	2	3	4	5
β_i	0.717	1.599	2.090	1.402	1.332
	[3.89]	[5.51]	[5.68]	[5.15]	[5.42]
λi	-0.101	-0.299	-0.475	-0.308	-0.193
	[-3.48]	[-4.72]	[-4.54]	[-4.03]	[-2.59]
δi	-0.084	-0.117	-0.081	-0.056	-0.011
	[-13.04]	[-16.60]	[-10.52]	[-7.31]	[-3.04]
Adj-R^2	0.06	0.11	0.11	0.10	0.07

Table 8

Analysts' Forecast Errors

This table reports results for regressions employing analysts' forecast errors. $|ERROR|_{i,t}$ is defined as the absolute value of the difference between the actual EPS and the most recent mean analysts' EPS forecast, scaled by year-end stock price. The illiquidity of a firm, $ILLIQ_{i,t}$, is measured as the natural logarithm of the average daily ratio of absolute value of return and dollar volume (multiplied by 10^6) over April of year t through March year t+1. $SIZE_{i,t}$ is defined as the natural logarithm of the balance of firm year-end assets. $BM_{i,t}$ is defined as the year-end book-to-market value of equity ratio. $SIGN_{i,t}$ is an indicator variable equal to one when firm earnings are positive for the year, and zero otherwise. Panels A and C report the results for Fama and MacBeth (1973) regressions. Panels B and D report the results for panel regressions where standard errors are clustered by firm and year. The data includes December fiscal year-end firms for the period 1976 to 2007.

$$|ERROR|_{i,t} = \alpha_i + \beta_i \cdot ILLIQ_{i,t} + \upsilon_{i,t}$$

Panel A: Cross-sectional regressions				Panel B: Panel regressions			
	Mean	*t*-stat	Avg. R^2		Coefficient	*t*-stat	R^2
α_i	0.0077	9.62	0.0589	α_i	0.01017	7.84	0.0630
β_i	0.0096	16.1		β_i	0.0095	12.43	

$$|ERROR|_{i,t} = \alpha_i + \beta_i \cdot ILLIQ_{i,t} + \lambda_i \cdot SIZE_{i,t} + \delta_i \cdot BM_{i,t} + \eta_i \cdot SIGN_{i,t} + \upsilon_{i,t}$$

Panel C: Cross-sectional Regresssion				Panel D: Panel regressions			
	Mean	*t*-stat	Avg. R^2		Coefficient	*t*-stat	R^2
α_i	0.0432	6.46	0.1601	α_i	0.0245	4.81	0.0799
β_i	0.0097	9.85		β_i	0.0098	11.68	
λ_i	0.0047	5.32		λ_i	0.0051	7.29	
δ_i	0.0068	2.20		δ_i	0.0091	3.26	
η_i	-0.0801	-9.28		η_i	-0.0629	-10.25	

Table 9

Analysts' Forecast Dispersion

This table reports results for regressions employing analysts' forecast dispersion. $DISPERS_{i,t}$ is defined as the standard deviation of the most recent analysts' EPS forecasts, scaled by year-end stock price. The illiquidity of a firm, $ILLIQ_{i,t}$, is measured as the natural logarithm of the average daily ratio of absolute value of return and dollar volume (multiplied by 10^6) over April of year t through March year t+1. $SIZE_{i,t}$ is defined as the natural logarithm of the balance of firm year-end assets. $BM_{i,t}$ is defined as the year-end book-to-market value of equity ratio. $SIGN_{i,t}$ is an indicator variable equal to one when firm earnings are positive for the year, and zero otherwise. Panels A and C report the results for Fama and MacBeth (1973) regressions. Panels B and D report the results for panel regressions where standard errors are clustered by firm and year. The data includes December fiscal year-end firms for the period 1976 to 2007.

$DISPERS_{i,t} = \alpha_i + \beta_i \cdot ILLIQ_{i,t} + \upsilon_{i,t}$

Panel A: Cross-sectional regressions				Panel B: Panel regressions			
	Mean	*t*-stat	Avg. R^2		Coefficient	*t*-stat	R^2
α_i	0.0042	21.02	0.0528	α_i	0.0045	20.45	0.0134
β_i	0.0017	16.37		β_i	0.0017	14.13	

$DISPERS_{i,t} = \alpha_i + \beta_i \cdot ILLIQ_{i,t} + \lambda_i \cdot SIZE_{i,t} + \delta_i \cdot BM_{i,t} + \eta_i \cdot SIGN_{i,t} + \upsilon_{i,t}$

Panel C: Cross-sectional regressions				Panel D: Panel regressions			
	Mean	*t*-stat	Avg. R^2		Coefficient	*t*-stat	R^2
α_i	0.0134	5.7	0.2052	α_i	0.0062	4.50	0.0124
β_i	0.0012	6.27		β_i	0.0017	7.84	
λ_i	0.0004	2.07		λ_i	0.0010	5.57	
δ_i	0.0044	7.06		δ_i	0.0032	3.53	
η_i	-0.0163	-9.46		η_i	-0.0121	-11.49	

Table 10

Alternative Measures of Illiquidity

This table reports time-series regression results at the aggregate level. The annual market returns at year *t*, R_t, is the cumulative value- or equal-weighted returns from April of year *t* until March of year *t*+1 (value weights are based on beginning-of-period market capitalization). ΔX_t denotes the growth in the sum of operating income from years *t* and *t*-1. This table shows the results of regressions using annual changes in the Sadka (2006) Variable Permanent component (VP_t) and Fixed Transitory (FT_t) components of price impacts. In addition, it also shows the results of regressions using the Pástor and Stambaugh (2003) liquidity measure (PS_t), with a negative sign added to create a measure of illiquidity. The *t*-statistics employ Newey-West standard errors with four lags and are reported in square brackets. The sample period for the Pástor and Stambaugh (2003) measure is 1962 to 2007, while that for the Sadka (2006) measures is 1984 to 2007. The data includes December fiscal year-end firms.

Panel A: Equal-weighted returns

Dependent variable	Independent variables: Intercept	ΔX_{t+1}	$\Delta X_{t+1}\cdot\Delta PS_t$	R^2	Adj-R^2
R_t	-0.51	0.70	-3.15	0.31	0.28
	[-2.88]	[3.78]	[-5.43]		

Panel B: Value-weighted returns

Dependent variable	Independent variables: Intercept	ΔX_{t+1}	$\Delta X_{t+1}\cdot\Delta PS_t$	R^2	Adj-R^2
Rt	-0.15	0.32	-2.49	0.34	0.31
	[-1.30]	[2.99]	[-5.95]		

Panel C: Equal-weighted returns

Dependent variable	Independent variables: Intercept	ΔX_{t+1}	$\Delta X_{t+1}\cdot\Delta FT_t$	R^2	Adj-R^2
R_t	-0.65	0.74	-2.83	0.14	0.06
	[-1.60]	[1.83]	[-0.52]		

Panel D: Value-weighted returns

Dependent variable	Independent variables: Intercept	ΔX_{t+1}	$\Delta X_{t+1}\cdot\Delta FT_t$	R^2	Adj-R^2
R_t	-0.17	0.27	-0.65	0.05	-0.04
	[-0.60]	[-0.11]	[-0.11]		

Panel E: Equal-weighted returns

Dependent variable	Independent variables: Intercept	ΔX_{t+1}	$\Delta X_{t+1}\cdot\Delta VP_t$	R^2	Adj-R^2
R_t	-0.50	0.59	-15.56	0.26	0.19
	[-1.87]	[2.22]	[-1.97]		

Panel F: Value-weighted returns

Dependent variable	Independent variables: Intercept	ΔX_{t+1}	$\Delta X_{t+1}\cdot\Delta VP_t$	R^2	Adj-R^2
Rt	-0.07	0.17	-9.22	0.18	0.15
	[-0.33]	[0.93]	[-2.58]		