Illiquidity and Earnings Predictability*

Jon Kerr, Gil Sadka, and Ronnie Sadka†

1st August 2012

Abstract

This paper studies the relation between illiquidity and the predictability of fundamental valuation variables. Theory suggests that illiquidity is associated with uncertainty about stock value. Consistent with this, 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. A natural experiment utilizing an exogenous variation in liquidity amid the reduction of tick size on the NYSE indicates that improvement in liquidity increases earnings predictability. The results provide further evidence for the usefulness of illiquidity in fundamental forecasting models.

JEL classification: E32, G12, G14, M41

Keywords: stock prices; aggregate earnings; illiquidity; expected returns; expected earnings

*We would like to thank an anonymous referee, Doron Nissim, Yuan Zhang, and workshop participants at Columbia University, London Business School Doctoral Consortium, and Brigham Young University for helpful comments and suggestions. Any errors are our own.

†Jon and Gil are from Columbia Business School, New York, NY 10027, USA, e-mail addresses: *jkerr13@gsb.columbia.edu*, *gs2235@columbia.edu*. Ronnie is from Carroll School of Management, Boston College, Boston, MA 02467, USA, e-mail address: *sadka@bc.edu*.

1 Introduction

The literature has long documented that stock prices are forward-looking and predict future earnings (e.g., Ball and Brown, 1968; Beaver, Clarke and Wright, 1979; and Beaver, Lambert and Morse, 1980). Although the predictability of earnings may hold on average, this paper shows that the ability of stock prices to predict future earnings is contingent on the ex-ante degree of stock liquidity.

There are several hypotheses, based on the economic drivers of liquidity, that would generate such a relation. Market-microstructure models demonstrate that stock illiquidity can arise endogenously in equilibrium, and that illiquidity can be modeled as proportionate to the degree of uncertainty of information asymmetry among market participants. For example, a risk-neutral and competitive market maker charges a trading fee/cost to protect herself against adverse selection. This cost increases with the degree of information asymmetry and decreases with the amount of noise trading. Glosten and Milgrom (1985) model this cost as a bid-ask spread, building on earlier work by Copeland and Galai (1983). Kyle (1985) models this cost as a price impact of trade: $\Delta P = \lambda V$, where V is the number of shares traded and λ, commonly referred to as Kyle's Lambda, is the price impact per unit of trade. Kyle (1985) shows that λ is proportional to the standard deviation of the distribution of possible fair values of the security, σ, and inversely proportional to the standard deviation of the distribution of trades by noise traders, σ_u, that is, $\lambda = \frac{2\sigma}{\sigma_u}$.

Under the assumption that the stock's value is proportional to earnings, Kyle's Lambda will also be proportional to the standard deviation of the distribution of possible earnings outcomes, as captured by the uncertainty about future earnings, that is, $\lambda \sim \frac{2\sigma_{EPS}}{\sigma_u}$. (For other models see, Admati and Pfliederer, 1988, and Easley and O'Hara, 1992.) Most models assume that the amount of non-information-driven or noise-trading activity is fairly constant, while the amount of uncertainty or information asymmetry about fundamental value may change over time. Therefore, under these assumptions, the liquidity of a stock can proxy for ex-ante uncertainty about the future earnings of its firm.

While illiquidity is likely associated with uncertainty about stock value, future earnings is not be the only source of information asymmetry affecting the value of a stock. There are other relevant uncertainties pertaining to other fundamental sources including the discount rate and the systematic risk exposures of the stock (which would also affect discount rates), as well as non-fundamental sources such as future trading costs (see, e.g., Amihud and Mendelson, 1986). Thus, the relation between illiquidity and earnings predictability is not completely straightforward. However, even absent uncertainty about fundamental value, that is, even if all investors agree on the correct price of an asset, some non-informational frictions, such as pure market-making costs (inventory or search costs), may cause the price of the asset to deviate from the asset's intrinsic value. For example, the tick sizes used for trading on the stock exchanges can distort pricing, and may inhibit arbitrageurs from trading a stock to its fundamental value. Therefore, in sum, we hypothesize that liquidity can be used to assess the degree of informativeness of prices about future earnings.

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 firm level, employing both pooled and cross-sectional regressions for the latter. For the most part, we use the Amihud (2002) measure of illiquidity, which estimates the average daily price impact per stock. This measure is consistent with the notion of Kyle's Lambda measure and therefore can be used to proxy for uncertainty. Notwithstanding the Amihud measure relying on daily data, which allows us to utilize a long time series, research shows this measure to be highly correlated with more precise, intradaily measures (see, e.g., Hasbrouck, 2009; and Goyenko, Holden, and Trzcinka, 2009). The Amihud measure is estimated monthly 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 market values. We test whether the ability of stock returns in period t to predict earnings growth from period t to period $t+1$ varies with stock liquidity. Consistent with prior studies (e.g., Beaver, Lambert and Morse, 1980; Collins, Kothari, and Rayburn, 1987; and Kothari and Sloan, 1992), we first confirm that firm-level stock returns predict earnings changes for the same firm in the following period. Then, we further show that the stock returns of more liquid firms are better predictors of future firm-level earnings growth than those of illiquid firms.

Although the analysis above documents an association between illiquidity and earnings predictability, the direction of causality remains unclear. On the one hand, as argued above, illiquidity can reduce the ability of prices to predict earnings. On the other hand, the lack of predictability itself may signify an increase in the information asymmetry environment of the stock, which in turn would reduce its liquidity. While we cannot rule out the latter, we present some supporting evidence for the former channel. Specifically, we exploit an exogenous, non-informational shock to the liquidity of NYSE-listed firms. On June 24, 1997, the NYSE reduced the tick size from one eighth to one sixteenth of a dollar. This event resulted in a drop in the bid/ask spreads and thus improvement in stock liquidity (**CITES...**). We employ a difference in difference approach which compares the ability of stock prices to predict earnings before and after 1997 across firms listed on NYSE versus unaffected firms traded on AMEX and NASDAQ. The findings indicate that the improvement in liquidity, for NYSE firms, improved the ability of stock returns to predict earnings, compared with stock returns of our control group. These findings suggest that liquidity causally affects earnings predictability.

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. It is useful to perform analyses at the aggregate level in addition to the firm level for two reasons. First, prior studies (e.g., Kothari, Lewellen and Warner, 2006) show that the earnings-returns relation differs at the aggregate versus the firm level. Second, prior studies also suggest that earnings are more predictable at the aggregate level than at the firm level (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 prices are more informative, in terms of their ability to predict future macroeconomic indicators, during periods of increased liquidity.

Recent research about liquidity and accounting information highlight the importance of second moment measures of liquidity in accounting research (see, e.g., Lang and Maffett, 2011; Ng, 2011; and Sadka, 2011). We therefore decompose firm earnings growth and liquidity into their systematic and idiosyncratic components. The decomposition can answer the following two questions: (1) Does the relation between illiquidity and predictability stem from the idiosyncratic or systematic component of earnings? (2) Is the relation between illiquidity and predictability driven by the idiosyncratic or systematic component of illiquidity? The results indicate that the information in firm-level returns largely pertains to future idiosyncratic earnings changes, while the quality of such information is determined by both components of illiquidity. These results suggest that the uncertainty about individual-firm earnings specifically pertains to idiosyncratic variations in earnings, not to information about systematic earnings risk (or earnings beta), and that not only liquidity level but also liquidity beta determines predictability.

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 growth for all illiquidity groups. Second, in untabulated results, 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 also employ analyst-forecast properties as alternative measures for predictability. While analyst forecasts provide us with an ex-ante measure of predictability, which, in contrast to illiquidity, is unlikely related to discount rates, 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 tend to have a high analyst-forecast dispersion (see also Sadka and Scherbina, 2007). These findings lend further support for the hypothesis that higher illiquidity is associated with higher uncertainty about future earnings.

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, we find that our main result about the relation of illiquidity and earnings predictability is robust to employing alternative measures of illiquidity, such as the Pástor and Stambaugh (2003) liquidity measure as well as the fixed and variable components of price impact developed in Sadka (2006).

The results of this paper have several practical implications. Portfolio managers can use firm liquidity not only as a measure of transaction costs, but also as an ex-ante measure of model uncertainty. For example, per the results in the paper regarding the ability of past return to predict future earnings and other macroeconomic indicators, it is plausible to use past return to form expectations of these future indicators. Nevertheless, the results of this paper suggest that the accuracy of such expectation models decreases with illiquidity, and therefore these models should be underweighted or overweighted in the investment process contingent on the illiquidity of the asset in question. Furthermore, our findings imply that investors should reduce their reliance on analyst forecasts to form earnings expectations for firms with illiquid securities because analyst forecasts tend to be less accurate for these firms.

This paper is related to a growing literature that studies the effects of liquidity in accounting research. Diamond and Verrechia (1991) argue that the disclosure of accounting information can reduce information asymmetry thereby improving stock liquidity. Consequently, many studies in the literature relate accounting information events, such as earnings announcements, to stock liquidity. Lee, Mucklow, and Ready (1993), Kim and Verrechia (1994), Krinsky and Lee (1996), and Affleck-Graves, Callahan, and Chipalkatti (2002) study measures of liquidity around earnings announcements. More recently, Vega (2006) and Francis, Lafond, Olsson and Schipper (2007) find that the post-earnings-announcement drift is related to the amount of private information. Several other works discuss the relation between disclosure policy and liquidity (e.g., Welker (1995), Brown, Hillegeist, and Lo (2004), and Brown and Hillegeist (2007)). Finally, some works associate illiquidity measures with other contemporaneous measures of uncertainty. For example, Lang and Maffett (2011) find that more transparent firms are also more liquid, while Ng (2011) 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, while 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 framework, while Section 4 includes the main findings. Section 5 studies predictability using the systematic and idiosyncratic components of firm earnings and illiquidity. Section 6 uses analyst forecasts to test the association between illiquidity and the ability of analysts to predict earnings. Additional tests are included in Section 7, and Section 8 concludes.

2 Data

The 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. This study employs both firm-level and aggregate-level tests. The sample period is 1952–2010.

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. To ensure that return windows cover the same time period, we also remove all firms which have a fiscal-year end other than December. We then winsorize the remaining data at the top and bottom one percentiles to reduce the possible effects of outliers. Our firm-level illiquidity measure, $ILLIQ_{i,t}$, follows Amihud (2002) and is defined 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. The average 12-month return in our sample is 13.1 percent, with a median of 8.0 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.

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, we use the growth in aggregate earnings from period t to period $t+1$, where aggregate earnings is 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. Similar to our firm-level analysis, we include only firms with December fiscal year-ends in the aggregation.

Our aggregate illiquidity measure, which is defined as an illiquidity shock, $\Delta ILLIQ_t$, is calculated following Amihud (2002).[1] Specifically, aggregate illiquidity is the equal-weighted cross-sectional average, $ILLIQ_t$.[2] The shock $\Delta ILLIQ_t$ is defined as the error term, ξ_t, in the following estimated regression:

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

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,

[1] While our firm-level analyses utilize liquidity levels for cross-sectional comparisons, we use liquidity shocks for our aggregate measure. This is because of the non-stationarity (time trend) of liquidity in the aggregate. In contrast, our cross-sectional analyses are unaffected by aggregate time trends. A similar approach is applied in Acharya and Pedersen (2005) and Sadka (2006) who form portfolios using the level of liquidity, while regressing these portfolio returns on changes in aggregate liquidity.

[2] The results in the paper are robust to using value weights to calculate aggregate illiquidity.

the firm-level analyst regressions include only the years 1976 to 2010. We calculate analyst-forecast errors as the absolute value of the difference between the actual EPS and the most recent mean analyst EPS forecast that is available prior to the actual EPS announcement, both taken from IBES. We then scale this difference by the firm-specific stock price as of the end of the return window for year $t-1$. As our measure of analyst-forecast dispersion we use the standard deviation of the most recent analyst EPS forecast for year t, also scaled by the firms' stock price as of the end of the return window for year $t-1$.

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

3 Empirical Framework

3.1 Estimating the Effects of illiquidity on Predictability

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

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

where $\varepsilon_{t+1} \sim (0, \sigma^2)$. The volatility, σ, increases with uncertainty, $\Delta X_{i,t+1}$ is the change in net 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:

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

where $R_{i,t}$ denotes stock returns for firm i in period t. We employ the previous period market value as a deflator for earnings growth so that the deflator for both earnings changes and changes in market values is the same. 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:

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

When earnings growth is not entirely predictable, realized earnings changes measure expected earnings changes with noise, that is $\sigma > 0$. Therefore, the estimated coefficient in Equation(3), $\widehat{\beta}$, 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.

Our analysis tests whether more illiquid firms have less informative prices with respect to future earnings growth. Using the empirical framework above, our first empirical test examines the effect of the forward-looking change in earnings, illiquidity, and the two interacted together on 12-month stock returns . Specifically, we test four expanding models with the full model having the following form:

$$R_{i,t} = \alpha_t + \beta_t \cdot \Delta X_{i,t+1}/P_{i,t-1} + \gamma_t \cdot (\Delta X_{i,t+1}/P_{i,t-1} \cdot ILLIQ_{i,t}) + \delta_t \cdot ILLIQ_{i,t} + \nu_{i,t}. \tag{6}$$

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 forward-looking change in net 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. Note that since illiquidity could be related to expected returns (through the discount rate), it is necessary to control for illiquidity as a separate variable in the regression.

The bias towards zero caused by the errors-in-variable problem (discussed above) does not necessarily apply to the regression in Equation (6) depending on the relation between earnings changes and illiquidity. While the correlation between the change in 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.

Following Easton and Harris (1991), we also estimate the model with earnings levels scaled by stock price, instead of earnings changes (scaled by stock price). Our findings are qualitatively similar. In addition, we employ two-period ahead earnings growth. The results are significantly weaker when we employ long-horizon earnings growth. For brevity, we only report results using scaled earnings changes.

3.2 Nonparametric Approach

The model above tests whether illiquidity is associated with the ability of stock returns to predict future earnings. In this section, we apply a simple nonparametric approach to test for earnings predictability, which is based on a similar intuition to the one used in Equation (3).

Specifically, every year, we double sort firms independently into five groups based on their returns that year and their earnings growth the following year. For example, if the firm's stock return in a given year t is in the top (bottom) 20%, the firm is allocated into the highest (lowest) returns group $RANK_{i,t,R} = 5$ ($RANK_{i,t,R} = 1$). Similarly, if the firm's earnings growth in a given year $t+1$ is in the top 20% then $RANK_{i,t+1,X} = 5$. We compute a firm-year measure of earnings predictability, $DIFF_{i,t}$, which is defined as the absolute value of the difference between the two quintile ranks:

$$DIFF_{i,t} = |RANK_{i,t+1,X} - RANK_{i,t,R}| \tag{7}$$

This measure is based on the intuition that higher expected future earnings should be associated with higher contemporaneous returns. Thus, if a firm is in the highest 20^{th} percentile of earnings growth in the following year, and earnings are predictable, its contemporaneous return is more likely to be among the highest 20^{th} percentile as well. If $RANK_{i,t+1,X} = RANK_{i,t,R}$, it implies that investors correctly anticipate the growth in earnings. This relation is consistent with a positive slope coefficient in Equation (3) above. Therefore, the variable $DIFF_{i,t}$ measures the extent to which investors correctly predict future earnings changes; a higher $DIFF_{i,t}$ implies that stock returns for firm i in period t do not correctly anticipate the earnings growth at period $t+1$.

4 Main Findings

4.1 Firm-Level Analysis

We estimate the model in Equation (6) using both cross-sectional and pooled regressions (with the standard errors of the pooled regressions clustered at both the firm and year levels). We estimate the cross-sectional regressions for each year t and obtain 57 estimates of the coefficients (corresponding to the 57 years in our sample). Table 3 Panel A reports results for the Fama-MacBeth regressions where reported coefficient is the mean coefficients, and the reported t-statistic is the Fama-MacBeth t-statistic. Table 3 Panel B reports results for the pooled estimation.

In the context of our hypothesis, we expect a negative coefficient on the interaction term, i.e., γ_t<0. Note, that the overall slope coefficient on $\Delta X_{i,t+1}/P_{i,t}$ is $\beta_t + \gamma_t ILLIQ_{i,t}$. Thus, a negative coefficient, γ_t, implies that earnings are less predictable at higher levels of illiquidity. In other words, γ_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. Using Fama and MacBeth (1973) regressions, we show a strong, positive coefficient on the change in price-deflated earnings growth 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 0.341 with a t-statistic of 5.07. The average adjusted-R^2 is 1.8%. The pooled results are similar, the coefficient is positive (0.181) and statistically significant (t-statistic of 2.97).

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, γ_t. When adding only the interaction term to the Fama-MacBeth regressions, γ_t has a time-series mean of -0.153 and a t-statistic of -5.85. When estimating the full model, γ_t has a time-series mean of -0.152 and a t-statistic of -5.87. We find similar results when we estimate a pooled model (Table 3, Panel B). The coefficient, γ_t, is negative and statistically significant in all our models.

As noted above, we include the illiquidity measure in the analysis. Consistent with prior studies, the coefficient on illiquidity is negative and statistically significant. This implies that illiquidity negatively affects contemporaneous stock returns. In our Fama-MacBeth regressions, the coefficient δ_t takes a value of either -0.019 or -0.021. In the pooled models, the coefficient is slightly higher in absolute value (-0.027).

In addition to the regression analysis in Equation (6), we test whether $DIFF$ is explained by variations in illiquidity. Specifically, we estimate the following model using both pooled and cross-sectional regressions:

$$DIFF_{i,t} = \phi_0 + \phi_1 \cdot ILLIQ_{i,t} + \varrho_{i,t}. \tag{8}$$

The results are reported in Table 4. Panel A reports results using the Fama-MacBeth approach and Panel B reports results using a pooled estimation approach.

We begin our analysis using univariate regression models. The findings are consistent with the hypothesis that higher stock illiquidity is associated with lower earnings predictability.

The coefficient on $ILLIQ_{i,t}$, ϕ_1, is positive and statistically significant. For example, using the pooled regression the coefficient is 0.054 and the t-statistic is 14.27. In our multivariate test, we add size, book-to-market, and an indicator variable for profitable firms. After adding these controls, our measure of predictability remains positive and significantly associated with stock illiquidity and the adjusted-R^2 increases considerably. In sum, the coefficient on $ILLIQ_{i,t}$ is positive and statistically significant in all models, the t-statistic is above 7 in all of our estimated models.

4.2 Do Changes in Liquidity Affect Predictability?

The results in Table 3 highlight the difficulty in determining the direction of causality between illiquidity and earnings predictability. On the one hand, illiquidity can reduce the ability of prices to predict earnings as prices can vary in a window around the "true" price. On the other hand, however, the lack of predictability itself may signify an increase in the information asymmetry environment of the stock, which, in turn, reduces its liquidity. While we cannot rule out the latter, we present some supporting evidence for the former channel using a non-informational, exogenous shock to the liquidity of NYSE-listed firms.

On June 24, 1997, the NYSE reduced the tick size from one eighth to one sixteenth of a dollar. This event resulted in a drop in the bid/ask spreads and thus improvement in stock liquidity.[3] The reduction of NYSE tick size in 1997 coincided with similar tick reductions for both AMEX and NASDAQ. However, while the reduction in tick sizes for NYSE was near-uniform in 1997, AMEX and NASDAQ had phased in the tick-size reductions with previous reductions that occurred in 1992 and 1995.[4] Thus, we exploit the earlier tick reductions in AMEX and NASDAQ and retain only the AMEX- and NASDAQ-listed firms that did

[3] In January 2001, NYSE reduced the tick size to one cent. However, although decimalization reduced the bid/ask spreads, price impacts have increased (see Sadka, 2006). We therefore do not use this event for our causality tests.

[4] Starting in 1995, NASDAQ instituted a policy by which stocks trading at prices less than ten dollars would have a tick size of 1/32 of a dollar, as opposed to a tick size of 1/8 of a dollar for stocks trading at prices above or equal to ten dollars. AMEX phased in the tick reduction in 1992 and then again in 1995. In 1992, AMEX reduced the tick size to 1/16 of a dollar for stocks trading below five dollars, and then changed that to include stocks trading below ten dollars in 1995.

not experience a tick reduction in 1997 as the control group. Our control group, therefore, includes stocks trading below ten dollars for AMEX and stocks trading below ten dollars both at the start and the end of the year for NASDAQ, as NASDAQ still had a policy of stocks trading at prices of below ten dollars as having a tick size of 1/32 of a dollar.[5]

To identify the effects of the shock to liquidity, we employ a difference-in-difference approach. We identify our treatment group as firms traded on the NYSE post the regime change in 1997. If liquidity affects predictability, we expect the stock returns of our treatment group to have an increase in association between current stock returns and future earnings growth, compared with firms in other exchanges. Accordingly, $Shock$ is a dummy variable that receives the value of 1 if the firm is traded on the NYSE during 1997. The analysis employs the following regression model:

$$\begin{aligned} R_{i,t} \quad = \quad & \alpha + \theta \cdot Shock + \beta_1 \cdot \Delta X_{i,t+1}/P_{i,t-1} + \beta_2 \cdot (\Delta X_{i,t+1}/P_{i,t-1} \cdot Shock) \\ & + \delta_1 \cdot ILLIQ_{i,t} + \delta_2 \cdot (ILLIQ_{i,t} \cdot Shock) + \nu_{i,t}. \end{aligned} \tag{9}$$

If liquidity affects predictability, we expect a positive coefficient for β_2. The results are reported in Table 5. Panel A reports results excluding controls for illiquidity and Panel B reports the results for the full model.

Our findings indicate that the stock returns of our treatment group, NYSE-listed firms, better reflect future earnings in 1997 compared with 1996. This improvement is in comparison to firms traded on other exchanges (AMEX and NASDAQ), which were not affected by the change in liquidity. In particular, excluding illiquidity, the coefficient is positive (0.187) and the t-statistic is 1.80. In Panel B, which reports the results for the full model, the coefficient is 0.215 with a t-statistic of 2.09. The coefficient is economically significant in comparison to β_1, which is 0.135. These findings imply that liquidity causally affects earnings predictability.

Note, there were additional shocks to liquidity during our sample period. AMEX-listed

[5]Restricting the NASDAQ sample excludes firms whose stock prices cross the ten-dollar threshold and thus incurring either tick increases or decreases during 1997.

firms underwent a phased tick reduction starting in August 1992 and then again in February 1995. The 1992 reduction reduced the tick size from 1/8 of a dollar to 1/16 of a dollar for AMEX-listed stocks priced between one dollar and five dollars, while the 1995 reduction reduced the tick size from 1/8 of a dollar to 1/16 of a dollar for all stocks priced below ten dollars. Also, starting in 1995, it was the convention of NASDAQ to reduce the tick sizes of listed stocks with bid-price quotations of below ten dollars to 1/32 of a dollar, while listed stocks with bid-price quotations at or above ten dollars retained the tick size of 1/8 of a dollar. Using these events as exogenous shocks to liquidity is problematic for a multitude of reasons. First, the sample sizes of affected stocks are usually less than a couple hundred and make generalization to the larger body of stocks somewhat unclear. Second, since tick-size reductions are tied to stock prices, the potential variation in liquidity is not viewed as exogenous since stocks can use stock splits and other means to achieve a desired tick size. In addition, higher priced stocks are often associated with higher performance measures and thus induce a mechanical relation between the independent and dependent variables. Lastly, stocks can move between tick thresholds multiple times in a given year, making it difficult if not impossible to conduct meaningful tests with earnings growth and still be able to draw clear inferences from the results. For these reasons, none of the above listed events form a basis for a natural experiment for our causality tests.

4.3 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:

$$R_t = \alpha + \beta \cdot \Delta X_{t+1} + \gamma \cdot \Delta X_{t+1} \cdot \Delta ILLIQ_t + \nu_t, \tag{10}$$

where R_t is the cumulative equal-weighted or value-weighted stock return from April of year t until March of year t+1, and ΔX_{t+1} is the growth in operating income from years t and $t+1$. We use operating instead of net income for the aggregate-level analysis to avoid the effects of the goodwill write-offs during 2001–2002 (see Jorgensen, Li and Sadka, 2010).

4.3.1 The Amihud measure

In this subsection, the variable $\Delta ILLIQ_t$ is the unexpected illquidity shock in period t (following Amihud, 2002) and is described in Section 2. The results are reported in Table 6. 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 on the interaction between earnings changes and illiquidty implies that earnings are less predictable. Due to the small number of observations (a constraint of the relatively short sample period), we do not include aggregate illiquidity on its own. In unreported results, we find that when illiquidity is included in the regression, all of the coefficients are statistically insignificant. As robustness, we also use the equal-weighted and value-weighted firm earnings (net income) changes scaled by beginning of period stock prices to estimate the regression in Equation (10). Our findings do not change significantly.

We begin by replicating prior results suggesting that stock returns are positively associated with future earnings growth. Using equal-weighted aggregate returns (Table 6, Panel A), the coefficient is 0.645, its t-statistic is 2.46 and the adjusted-R^2 is 11%. The results are slightly weaker when using value-weighted stock returns (Panel B). The coefficient is 0.433, the t-statistic is 1.96 and the adjusted-R^2 is 7%. These 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 (10) above is negative as well. Using both equal-weighted and value-weighted returns, the coefficient on the interaction term, γ, is negative and significant. In Panels A and B, the coefficients are -0.301 and -0.192, respectively. The adjusted-R^2 increases significantly when the interaction term is included. For example, in Panel A, the adjusted-R^2 increases from 11% to 48%. These findings are consistent with our hypothesis that earnings growth is less predictable during periods of high aggregate illiquidity.

In addition to using the raw aggregate illiquidity measure, we also employ illiquidity ranks, where each year in the sample period is assigned one of five ranks based on $\Delta ILLIQ_t$ for that year. 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 -4.40, compared to -5.02 when using illiquidity values. Similarly, the adjusted-R^2 is lower when using ranks. For example, in Panel A, the adjusted-R^2 is 44% when the interaction term is based on illiquidity ranks, compared to 48% when using the actual illiquidity values.

Finally, we partition the sample into two time periods, where one partition contains the 29 most illiquid periods and the other contains the 28 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 changes is 0.869 and is statistically significant. However, during periods of high illiquidity, the effect disappears and the coefficient on earnings changes becomes insignificantly different from zero. The results are weaker using value-weighted returns, as displayed in Panel B.

4.3.2 Alternative Measures of Illiquidity

The analyses above employ 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, which are available from 1962 and 1984, respectively.

The aggregate Pástor-Stambaugh measure is available on a monthly basis.[6] To construct an annual series, we average the monthly levels of liquidity each year. Also, since this measure signifies liquidity rather than illiquidity, 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

[6] We thank Ľubo¨ Pástor for providing this aggregate measure on his website: http://faculty.chicagobooth.edu/lubos.pastor/research/.

price impact. Similar to the Pástor-Stambaugh measure, we average the monthly aggregate levels of illiquidity each year to create annual time series.

We conduct the aggregate-level regressions as described in Equation (10) using the alternative illiquidity measures. The results are reported in Table 7 Panels A and B. When using the PS and VP illiquidity measures, the interaction term is consistently negative and statistically significant. The coefficient varies from -1.86 to -14.90 and the t-statistic varies from -2.60 to -7.40. 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. When using the FT component of price impact to proxy for illiquidity, the interaction term is negative but statistically insignificant from zero. These analyses therefore provide further evidence for the robustness of the main results about illiquidity and earnings predictability to different measures of illiquidity.

4.3.3 Macroeconomic Indicators

In addition to aggregate earnings growth, we also study the effects of liquidity on other macroeconomic indicators. In the macroeconomics literature, stock market return is shown a leading indicator of economic activity. Therefore, we test whether illiquidity affects the ability of stock returns to predict growth in real GNP (denoted by ΔGNP_{t+1}) and growth in industrial production (denoted by $\Delta PROD_{t+1}$). We employ the same empirical methodology as presented in Equation (10). 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 8. Following the same format as in Tables 6 and 7, Panel A of Table 8 reports results using equal-weighted stock returns and Panel B reports results using value-weighted stock returns. Also, similar to the analysis in Table 6, we use both illiquidity values and illiquidity ranks to generate interaction terms.

We begin our analysis by replicating prior evidence that stock returns predict future GNP growth and future industrial production (e.g., Fama, 1990; and Schwert, 1990). The coefficient on ΔGNP_{t+1} is both positive and statistically significant in all models. The coefficient varies from 3.31 to 7.96 and the t-statistic varies from 3.09 to 6.21. Similarly, the coefficient on $\Delta PROD_{t+1}$ is positive and statistically significant in all models. The coefficient varies from 1.50 to 3.26 and the t-statistic varies from 3.23 to 4.21.

Overall, the results in Table 8 are consistent with those in Table 6 and the hypothesized relation between illiquidity and predictability. 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, $\Delta GNP_{t+1} \cdot \Delta ILLIQ_t$, is -6.17 with a t-statistic of -2.76. When the interaction term is included, the adjusted-R^2 increases from 21% to 36%. These findings suggest that aggregate illiquidity in part reflects uncertainty about future economic prospects.

5 A Decomposition of Illiquidity and Earnings

Prior studies document that firm-level illiquidity is affected by aggregate-level illiquidity (e.g., Acharya and Pedersen, 2005). In addition, Ball, Sadka and Sadka (2009) document that firm-level earnings have a significant systematic components. Therefore, we decompose firm-level earnings growth and firm-level illiquidity into their respective systematic and idiosyncratic components. This decomposition can better identify the determinants of the relation between illiquidity and the predictability of earnings at the firm level.

Following Chordia, Roll, Subrahmanyam (2000) and Korajczyk and Sadka (2008), we decompose our illiquidity measure into idiosyncratic and systematic components using the model

$$ILLIQ_{i,d} = \alpha_{L,i,t} + \beta_{L,i,t} \cdot ILLIQ_{m,d} + \omega_d, \tag{11}$$

where d denotes day. We estimate the model by firm each year using all available days for the firm during the year. The model employs daily variation in illiquidity to generate annual measures of idiosyncratic and systematic components of illiquidity. The annual measure of idiosyncratic illiquidity is the estimate of $\alpha_{L,i,t}$. Similarly, we define the systematic component of illiquidity as the estimate of $\beta_{L,i,t}$. To ease the notation, we denote $\alpha_{L,i,t}$ as $ILLIQ\_Idio_{i,t}$ and $\beta_{L,i,t}$ as $ILLIQ\_Beta_{i,t}$.

To test the implication of systematic and idiosyncratic illiquidity on earnings predictability. We use the decomposition above and estimate the following model

$$\begin{aligned} R_{i,t} &= \alpha_1 + \beta_1 \cdot \Delta X_{i,t+1}/P_{i,t-1} + \delta_1 \cdot ILLIQ\_Idio_{i,t} + \delta_2 \cdot ILLIQ\_Beta_{i,t} \\ &\quad + \gamma_1 \cdot (\Delta X_{i,t+1}/P_{i,t-1} \cdot ILLIQ\_Idio_{i,t}) + \gamma_2 \cdot (\Delta X_{i,t+1}/P_{i,t-1} \cdot ILLIQ\_Beta_{i,t}) + \nu_{i,t}. \end{aligned} \tag{12}$$

Table 9 estimates the model in Equation (12) using the Fama-MacBeth approach in Panel A, while Panel B estimates a pooled regression.

The results indicate that both the idiosyncratic and systematic components of illiquidity are associated with lower earnings predictability. The coefficient on the interaction terms are negative ($\gamma_1 < 0$ and $\gamma_2 < 0$). In Panel A (Fama-MacBeth regressions), the coefficient on γ_2 is negative and statistically significant at the 10% level, suggesting that the systematic component of illiquidity is associated with less earnings predictability. In contrast, the idiosyncratic component of illiquidity is negative, but statistically insignificant. Our pooled regressions find that both the idiosyncratic and systematic components are associated with less earnings predictability ($\gamma_1 < 0$ and $\gamma_2 < 0$ and they are statistically significant). The difference between the pooled regressions and the Fama-MacBeth regressions is the time-series variation in earnings and returns. The increased significance in our pooled regressions suggest that the effects of illiquidity on predictability are present both in the cross-section and the time series.

Irrespective of earnings predictability, both the systematic and idiosyncratic components of illiquidity are negatively related to stock returns. The coefficients δ_1 and δ_2 are significantly negative in all models and all specifications. Also, consistent with our findings in Table 3, stock returns are positively related to future earnings growth. The coefficient β_1 is positive and statistically significant in all models.

In addition to the systematic and idiosyncratic components of illiquidity, we test whether illiquidity affects the predictability of the systematic and idiosyncratic components of earnings. Similar to illiquidity, earnings growth includes both a firm-level (idiosyncratic) component and a market-wide (systematic) component (e.g., Brown and Ball, 1967; Ball, Sadka, and Sadka, 2009). We therefore decompose earnings growth using the model

$$\Delta X_{p,t}/P_{i,t-1} = \alpha_{X,p,t} + \beta_{X,p,t} \cdot \Delta X_t + \omega_d. \tag{13}$$

Since we use annual firm earnings, it is difficult to obtain precise estimates of the regression above per firm. We therefore follow a portfolio approach to calculate firms' idiosyncratic and systematic components. We first sort firms each year into 20 portfolios based on beginning of period market values. For each portfolio, we define earnings growth as the value-weighted average of firm-level earnings growth. We then estimate the regression model for each portfolio over the entire sample period. For each firm-year observation, the annual measure of idiosyncratic illiquidity is the estimate of $\alpha_{X,p,t}$. In other words, each firm i, in each period t assumes the systematic and idiosyncratic earnings of the portfolio to which it belongs. Similarly, we define the systematic component of illiquidity as the estimate of $\beta_{X,p,t}$. Since the portfolio allocation changes over time, the firm-year estimates of idiosyncratic and systematic earnings change over time as well. To ease the notation, we denote $\alpha_{X,p,t}$ as $EARN\_Idio_{i,t}$ and $\beta_{L,i,t}$ as $EARN\_Beta_{i,t}$.

To examine the implications of both the systematic and idiosyncratic components of illiquidity and earnings we estimate the model:

$$\begin{aligned} R_{i,t} \quad = \quad & \alpha_1 + \delta_1 \cdot ILLIQ\_Idio_{i,t} + \delta_2 \cdot ILLIQ\_Beta_{i,t} + \delta_3 \cdot EARN\_Idio_{i,t} + +\delta_4 \cdot EARN\_Beta_{i,t} \\ & +\gamma_1 \cdot (EARN\_Idio_{i,t} \cdot ILLIQ\_Idio_{i,t}) + \gamma_2 \cdot (EARN\_Idio_{i,t} \cdot ILLIQ\_Beta_{i,t}) \qquad (14) \\ & +\gamma_3 \cdot (EARN\_Beta_{i,t} \cdot ILLIQ\_Idio_{i,t}) + \gamma_4 \cdot (EARN\_Beta_{i,t} \cdot ILLIQ\_Beta_{i,t}) + \nu_{i,t}. \end{aligned}$$

Table 9 reports the results. We employ both Fama-MacBeth regressions and pooled regressions.

We begin our analysis using the idiosyncratic and systematic components of both earnings growth and returns, excluding interaction terms. The evidence suggests that firm-level stock returns reflect information about both the idiosyncratic component and the systematic component of earnings. However, the findings imply that firm-level stock returns contain more information with respect to the idiosyncratic component of earnings. While $EARN\_Beta_{i,t}$ loads positively and significant in the Fama-MacBeth regressions (coefficient of 0.014 with a t-statistic of 5.77), it is statistically insignificant in the pooled regressions (coefficient of 0.002 with a t-statistic of 0.75). In sum, our findings suggest that firm-level returns contain more information about future idiosyncratic earnings compared to the systematic component of earnings.

When we estimate the full model in Equation (14), our findings further support our findings that firm-level returns are affected significantly by idiosyncratic earnings. The interaction terms $EARN\_Idio_{i,t} \cdot ILLIQ\_Idio_{i,t}$ and $EARN\_Idio_{i,t} \cdot ILLIQ\_Beta_{i,t}$ load consistently negatively in all our models. The statistical significance is lower than the 10% level only for the estimate of γ_1 in the equation above when we estimate the regression using the Fama-MacBeth approach. In contrast, the interaction terms $EARN\_Beta_{i,t} \cdot ILLIQ\_Idio_{i,t}$ and $EARN\_Beta_{i,t} \cdot ILLIQ\_Beta_{i,t}$ are all positive, though mostly not significantly different from zero.

In sum, while our 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, the decomposition shows that the information in returns pertains to future idiosyncratic earnings, while the quality of such information is determined by both components of illiquidity. The results in Table 9 suggest that the uncertainty about individual-firm earnings specifically pertains to idiosyncratic variations in earnings, not to information about systematic earnings risk (or earnings beta). They also highlight that not only liquidity level but also liquidity beta determines predictability.

6 Analyst Forecasts

We now turn to analyst forecasts as an ex-ante measure of predictability. Specifically, we use analyst-forecast error and dispersion as measures of earnings predictability. There are two reasons for using analyst forecasts. First, any effect of illiquidity on discount rates should not affect analyst forecasts of earnings (although discount rates may affect the buy/sell/hold recommendations). Second, the ability of analysts to predict earnings accurately is an additional measure of earnings predictability.

We note that while Brown and Rozeff (1978) document that analyst forecasts are better estimates of future earnings than time-series forecasts using prior earnings, the literature has long debated whether analyst 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 analyst-forecast errors are predictable by prior stock returns. Nevertheless, we believe that testing our hypothesis using analyst forecasts can strengthen the understanding of the relation between illiquidity and predictability.

In our analysis, we employ two measures of predictability using analyst forecasts: forecast error and forecast dispersion. The variable $|ERROR|_{i,t}$ is our measure of forecast error and is defined as the absolute value of the difference between the actual EPS for year t and the most recent mean analyst EPS forecast that is available prior to the actual EPS announcement, both taken from IBES, scaled by stock price as of the end of the return window for year $t-1$. $DISPERS_{i,t}$ is our measure of analyst forecast dispersion and is defined as the standard deviation of the most recent analyst EPS forecast for year t, scaled by the firms' stock price as of the end of the return window for year $t-1$. We also include standard controls used in the analyst-forecast literature, including size, book-to-market, and the sign of earnings.

We first test the effect of analyst-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:

$$|ERROR|_{i,t} = \gamma_0 + \gamma_1 ILLIQ_{i,t} + \gamma_2 SIZE_{i,t} + \gamma_3 BM_{i,t} + \gamma_4 SIGN_{i,t} + \upsilon_{i,t}, \tag{15}$$

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 for profitable firms equal to one when firm-level operating income in the period is positive, and zero otherwise. We employ both Fama and MacBeth (1973) regressions as well as pooled regressions. The results of these regressions are reported in Table 10, Panels A and B.

The coefficient on illiquidity, γ_1, is significantly positive regardless of the model or test procedure utilized. The coefficient ranges from 0.657 to 1.093, and is always highly significant at the one percent level. This suggests that analyst-forecast errors are larger in absolute value for more illiquid firms and supports our hypothesis that illiquidity reduces the predictability of earnings.

As for the 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 analyst-forecast dispersion. To do so, we again begin with a parsimonious model and then expand it to its full form, which is the following:

$$DISPERS_{i,t} = \alpha_i + \beta_i ILLIQ_{i,t} + \nu_i SIZE_{i,t} + \delta_i BM_{i,t} + \eta_i SIGN_{i,t} + \upsilon_{i,t}. \tag{16}$$

For this series of tests, we also employ both Fama and MacBeth (1973) regressions as well as pooled regressions. The results of the test using analysts-forecast dispersion are reported in Table 10, Panels C and D.

Similar to the results using the absolute values of forecast errors, the coefficient on illiquidity is again significant regardless of the level of controls or regression type, and ranges from 0.120 to 0.187. These findings suggest that analyst-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.

In addition to our analysis with illiquidity, we employ the same analysis for idiosyncratic and systematic illiquidity as described in Equation (11) above. The results are reported in Table 11. Panel A employs Fama-MacBeth regressions, while Panel B employs pooled regressions. Our findings imply that both the systematic and idiosyncratic components of illiquidity are associated with lower earnings predictability. Specifically, we document that firm-years with higher firm-level illiquidity and higher illiquidity betas have higher absolute forecast errors and higher forecast dispersions. When regressing absolute forecast errors on $ILLIQ\_Beta_{i,t}$, the coefficient varies from 0.034 to 0.947 and the t-statistic varies between 3.69 and 4.30. When regressing absolute forecast errors on $ILLIQ\_Idio_{i,t}$, the coefficient varies from 0.019 to 0.168 and the t-statistic varies between 3.04 and 5.02.

7 Additional Tests

In addition to the 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. We sort firms based on illiquidity. This sort helps us test whether the marginal effect of illiquidity is dependent on the level of illiquidity.

The results in Table 12 are consistent with those reported in Table 3. We find that stock returns contain more information about forward-looking earnings changes in more liquid stocks. When estimating the model only with earnings growth, the coefficient declines from 0.980 for the most liquid group to 0.214 for the most illiquid group. Consistently, the average adjusted-R^2 also declines from 5% for the most liquid group to 2% for the most illiquid group. The decline in adjusted-R^2 implies that illiquid firms have less predictable earnings.

The findings in Table 12 imply that the marginal effect of illiquidity on predictability is apparent in all illiquidity groups. The coefficient on the interaction term, γ_t, is negative and statistically significant. For example, in the full model, the coefficient is -0.487 for the most liquid group and is -0.143 for the most illiquid group. The highest magnitude of the coefficient is in the middle group (rank = 3), where the coefficient is -0.942. However, this coefficient is statistically insignificant.

We also test results for the portfolios sorted on size. For brevity, these results are not tabulated. Our findings are consistent with prior studies (e.g., Collins, Kothari, and Rayburn, 1987; and Sadka and Sadka, 2009) insofar as stock returns are better predictors of earnings changes for larger firms. The results also imply that the marginal effect of illiquidity on predictability is pronounced in all size groups.

8 Conclusion

This paper studies the association between illiquidity and the predictability of fundamental valuation variables, such as firm earnings growth. We document that illiquidity is associated with less informed prices with respect to forward-looking earnings changes, and find evidence in both aggregate- and firm-level analyses. We provide further evidence suggesting that an improvement in stock liquidity (exogenously) can improve earnings predictability. 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.

To better identify the determinants of the relation between illiquidity and the predictability of earnings we decompose firm earnings changes and liquidity into their systematic and idiosyncratic components. The results suggest that the uncertainty about individual-firm earnings specifically pertains to idiosyncratic variations in earnings growth, not to information about systematic earnings risk, and that not only liquidity level but also liquidity beta affects predictability.

There are several practical implications. For example, asset managers can use firm liquidity not only as a measure of transaction costs, but also as an ex-ante measure of the accuracy of models used to predict earnings changes. Similarly, investors should reduce their reliance on analyst forecasts to form earnings expectations for firms with illiquid securities because analyst forecasts tend to be less precise for these firms.

References

Abarbanell, Jeffrey S., 1991, Do analysts' earnings forecasts incorporate information in prior stock price changes? *Journal of Accounting and Economics* 14, 147–165.

Abarbanell, Jeffrey S., and Reuven Lehavy, 2003, Biased forecasts or biased earnings? The role of reported earnings in explaining apparent bias and over/underreaction in analysts' earnings forecasts, *Journal of Accounting and Economics* 36, 105–146.

Acharya, Viral V., and Lasse Heje Pedersen, 2005, Asset pricing with liquidity risk, *Journal of Financial Economics*, 77, 375–410.

Admati, Anat, and Paul Pfleiderer, 1988, A theory of intraday patterns: Volume and price variability, *Review of Financial Studies* 1, 3–40.

Affleck-Graves, J., Callahan, C.M., Chipalkatti, N., 2002, Earnings predictability, information asymmetry, and market liquidity, *Journal of Accounting Research* 40, 561–583.

Amihud, Yakov, 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Amihud, Yakov, and Haim Mendelson, 1986, Asset pricing and the bid-ask spread, *Journal of Financial Economics* 17, 223–249.

Ball, Ray, and Philip Brown, 1968, An empirical evaluation of accounting income numbers, *Journal of Accounting Research* 6, 159–178.

Ball, Ray, Gil Sadka, and Ronnie Sadka, 2009, Aggregate earnings and stock prices, *Journal of Accounting Research* 47, 1097–1133.

Beaver, William H, Roger Clarke, and William F. Wright, 1979, The association between unsystematic security returns and the magnitude of earnings forecast errors, *Journal of Accounting Research* 17, 316–340.

Beaver, William H., Richard lambert, and Dale Morse, 1980, The information content of security prices, *Journal of Accounting and Economics* 2, 3–28.

Brown, Lawrence D., Paul A. Griffin, Robert L. Hagerman, and Mark E. Zmijewski, 1987, An evaluation of alternative proxies for the market's assessment of unexpected earnings, *Journal of Accounting and Economics* 9, 159–193.

Brown, Lawrence D., and Michael S. Rozeff, 1978, The superiority of analyst forecasts as measures of expectations: Evidence from earnings, *Journal of Finance* 33, 1–16.

Brown, Philip, and Ray Ball, 1967, Some perliminary findings on the association between the earnings of a firm, its industry, and the economy, *Journal of Accounting Research* 5, 55–77.

Brown, S., Hillegeist, S.A., 2007, How disclosure quality affects the level of information asymmetry, *Review of Accounting Studies* 12, 443–477.

Brown, S., Hillegeist, S.A., Lo, K., 2004, Conference calls and information asymmetry, *Journal of Accounting and Economics* 37, 343–366.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2000, Commonality in liquidity, *Journal of Financial Economics* 56, 3–28.

Collins, Daniel W., S.P. Kothari, and Judy D. Rayburn, 1987, Firm size and the information content of prices with respect to earnings, *Journal of Accounting and Economics* 9, 111–138.

Collins, Daniel W., and S.P. Kothari, 1989, An analysis of intertemporal and cross-sectional determinants of earnings response coefficients, *Journal of Accounting and Economics* 11, 143–181.

Copeland, Thomas, and Dan Galai, 1983, Information effects on the bid-ask spread, *Journal of Finance* 38, 1457–1469.

Daske, Holger, Luzi Hail, Christian Leuz, and Rodrigo Verdi, 2008, Mandatory IFRS reporting around the world: Early evidence on the economic consequences, *Journal of Accounting Research* 46, 1085–1142.

Diamond, D.W., Verrecchia, R.E., 1991, Disclosure, liquidity, and the cost of capital, *Journal of Finance* 46, 1325–1359.

Easley, David, and Maureen O'Hara, 1992, Time and the process of security price adjustment, *Journal of Finance* 47, 576–605.

Easton, Peter D., and Trevor S. Harris, 1991, Earnings as an explanatory variable for returns, *Journal of Accounting Research* 29, 19–36.

Fama, Eugene F., 1990, Stock returns, expected returns, and real activity, *Journal of Finance* 45, 1089–1108.

Fama, Eugene F., and James MacBeth, 1973, Risk, return and equilibrium: empirical tests, *Journal of Political Economy* 81, 607–636.

Francis, J., Lafond, R., Olsson, P., Schipper, K., 2007, Information uncertainty and post-earnings-announcement-drift, *Journal of Business, Finance and Accounting* 34, 403–433.

Glosten, Lawrence R., Milgrom, Paul R., 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics* 14, 71–100.

Goyenko, Ruslan Y., Holden, Craig W., and Trzcinka, Charles A., 2009, Do liquidity measures measure liquidity? *Journal of financial Economics* 92, 153–181.

Hasbrouck, Joel, 2009, Trading costs and returns for US equities: Estimating effective costs from daily data, *Journal of Finance* 64, 1445–1477.

Hughes, John, Jing Liu, and Wei Su, 2008, On the relation between predictable market returns and predictable analyst forecast errors, *Review of Accounting Studies* 13, 266–291.

Jorgensen, Bjorn N, Jing Li, and Gil Sadka, 2010, Are accounting standards diversifiable? Evidence on the valuation effects of standards, working paper.

Kim, O., Verrecchia, R.E., 1994, Market liquidity and volume around earnings announcements, *Journal of Accounting and Economics* 17, 41–67.

Konchitchki, Yaniv, Xiaoxia Lou, Gil Sadka, and Ronnie Sadka, 2011, Underreaction or risk? Expected earnings and the post-earnings-announcement drift, working paper.

Korajczyk, Robert A., and Ronnie Sadka, 2008, Pricing the commonality across alternative measures of liquidity, *Journal of Financial Economics* 87, 45–72.

Kothari, S.P., and Richard G. Sloan, 1992, Information in prices about future earnings: Implications for earnings response coefficients, *Journal of Accounting and Economics* 15, 143–171.

Krinsky, I., Lee, J., 1996. Earnings announcement and the components of the bid-ask spread, *Journal of Finance* 51, 1523–1535.

Kyle, Albert S., 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315–1335.

Lang, Mark, and Mark Maffett, 2011, Transparency and liquidity uncertainty in crisis periods, *Journal of Accounting and Economics* 52, 101–125.

Lee, C.M.C., Mucklow, B., Ready, M.J., 1993, Spreads, depths, and the impact of earnings information: An intraday analysis, *Review of Financial Studies* 6, 345–374.

Lys, Thomas, and Sungkyu Sohn, 1990, The association between revisions of financial analysts' earnings forecasts and security-price changes, *Journal of Accounting and Economics* 13, 341–363.

Ng, Jeffrey, 2011, The effect of information quality on liquidity risk, *Journal of Accounting and Economics* 52, 126–143.

Pástor, Ľubos, and Robert F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642–685.

Roulstone, Darren T., 2003, Analysts following and market liquidity, *Contemporary Accounting Research* 20 552–578.

Sadka, Gil, 2007, Understanding stock price volatility: The role of earnings, *Journal of Accounting Research* 48, 199–228.

Sadka, Gil, and Ronnie Sadka, 2009, Predictability and the earnings-returns relation, *Journal of Financial Economics* 94, 87–106.

Sadka, Ronnie, 2006, Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk, *Journal of Financial Economics*, 80 309–349.

Sadka, Ronnie, 2011, Liquidity risk and accounting information, *Journal of Accounting and Economics* 52, 144–152.

Sadka, Ronnie, and Anna Scherbina, 2007, Analyst disagreement, mispricing, and liquidity, *Journal of Finance* 62, 2367–2403.

Schwert, W., 1990, Stock returns and real activity: A century of evidence, *Journal of Finance* 45, 1237–1257.

Vega, C., 2006, Stock price reaction to public and private information, *Journal of Financial Economics* 82, 103–133.

Welker, M., 1995, Disclosure policy, information asymmetry, and liquidity in equity markets, *Contemporary Accounting Research* 11, 801–827.

Table 1
Descriptive Statistics

This table presents the descriptive statistics of key variables. All descriptive statistics are time-series averages of cross-sectional averages. $R_{i,t}$ is the cumulative return from April of year *t* until March of year *t*+1. $\Delta X_{i,t+1}/P_{i,t}$ denotes the change in net income from years *t* and *t*+1, scaled by the market value of firm *i* at the end of the return window for 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. $|ERROR|_{i,t}$ is defined as the absolute value of the difference between the actual EPS for year *t* and the most recent mean analysts' EPS forecast prior to the actual (both taken from I/B/E/S), scaled by the stock price of firm *i* at the end of the return window for year *t*-1. $DISPERS_{i,t}$ is the standard deviation of the most recent analysts' EPS forecasts for year *t*, scaled by the stock price of firm *i* at the end of the return window for year *t*-1. $SIZE_{i,t}$ is the natural logarithm of total assets, and $BM_{i,t}$ is the book-to-market value of equity ratio, both for year *t*. The descriptive statistics for $R_{i,t}$, $\Delta X_{i,t+1}/P_{i,t}$, $ILLIQ_{i,t}$, and $MV_{i,t}$ are based upon 99,369 observations from 1952 to 2009 and are restricted to only include stocks with at least 100 daily return observations and a prior day closing price of at least 2, while the descriptive statistics for $|ERROR|_{i,t}$, $SIZE_{i,t}$, and $BM_{i,t}$ are based upon 47,727 observations from 1976 to 2010 and $DISPERS_{i,t}$ is based upon 39,105 observations from data spanning 1976 to 2010. Only December fiscal year-end firms are included and all continuous variables used in tests are winsorized at the 1 and 99 percentiles.

Variable	Mean	Std Dev	Min	10 Pctile	25 Pctile	Median	75 Pctile	90 Pctile	Max
$R_{i,t}$	0.131	0.408	-0.712	-0.304	-0.120	0.080	0.301	0.600	2.466
$\Delta X_{i,t+1}/P_{i,t}$	0.014	0.167	-0.806	-0.086	-0.019	0.008	0.037	0.108	1.112
$ILLIQ_{i,t}$	0.285	2.325	-5.407	-2.774	-1.465	0.278	1.979	3.402	6.148
$MV_{i,t}$	1,114.8	4,703.9	2.0	20.1	50.1	164.6	620.5	2,012.7	113,170.9
$\|ERROR\|_{i,t}$	0.00244	0.00777	0	0.000003	0.00003	0.00017	0.00103	0.00522	0.05696
$DISPERS_{i,t}$	0.00046	0.00113	0	0.000001	0.00002	0.00009	0.00034	0.00109	0.00808
$SIZE_{i,t}$	6.439	1.914	2.456	4.027	5.012	6.302	7.767	9.002	11.586
$BM_{i,t}$	0.753	0.489	-0.100	0.243	0.411	0.666	0.978	1.371	3.005

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 changes-based regressions, whereas Panel B reports the correlations between variables used in the firm-level analyst-based regressions. $R_{i,t}$ is the cumulative return from April of year *t* until March of year *t*+1. $\Delta X_{i,t+1}/P_{i,t}$ denotes the change in net income from years *t* and *t*+1, scaled by the market value of firm *i* at the end of the return window for 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. To calculate $EARN\_Beta_{i,t+1}$, firms are first placed into 20 portfolios formed on market value at the end of year *t*-1. The value-weighted average of $\Delta X_{i,t+1}/P_{i,t}$ is computed for each portfolio and regressed on the value-weighted average of $\Delta X_{i,t+1}/P_{i,t}$ for the market (EARN_MAR) and the coefficient on EARN_MAR is taken. $EARN\_Idio_{i,t+1}$ is defined at the firm level as $\Delta X_{i,t+1}/P_{i,t}$ - $EARN\_Beta_{i,t+1}$ * EARN_MAR. $ILLIQ\_Beta_{i,t}$ is defined as the coefficient on the market-level illiquidity (multiplied below by 10^7) from a regression of the daily firm-level illiquidity as defined above on the daily market-level illiquidity defined as the value-weighted average of the daily firm-level illiquidities. $ILLIQ\_Idio_{i,t}$ is defined as the intercept of the previous regression. $|ERROR|_{i,t}$ is defined as the absolute value of the difference between the actual EPS for year *t* and the most recent mean analysts' EPS forecast prior to the actual (both taken from I/B/E/S), scaled by the stock price of firm *i* at the end of the return window for year *t*-1. $DISPERS_{i,t}$ is the standard deviation of the most recent analysts' EPS forecasts for year *t*, scaled by the stock price of firm *i* at the end of the return window for year *t*-1. $SIZE_{i,t}$ is the natural logarithm of total assets, and $BM_{i,t}$ is the book-to-market value of equity ratio, both for year *t*. The correlations in Panel A are based upon 99,369 observations from 1952 to 2010 and are restricted to only include stocks with at least 100 daily return observations and a prior day closing price of at least 2, while the correlations in Panel B are based upon 47,727 observations from 1976 to 2010 for the top and 39,105 observations also from 1976 to 2010 for the bottom. All continuous variables used in tests are winsorized at the 1 and 99 percentiles and include only December fiscal year-end firms. ***, **, * represent significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Firm-level using earnings

Variable	$R_{i,t}$	$\Delta X_{i,t+1}/P_{i,t}$	$ILLIQ_{i,t}$	$EARN\_Beta_{i,t+1}$	$EARN\_Idio_{i,t+1}$	$ILLIQ\_Beta_{i,t}$	$ILLIQ\_Idio_{i,t}$
$R_{i,t}$		0.1733 *	-0.185 ***	-0.0862 ***	0.0979 ***	-0.0592 ***	-0.0465 ***
$\Delta X_{i,t+1}/P_{i,t}$	0.0721 ***		0.0228 ***	0.0204 ***	0.7468 ***	0.0196 ***	-0.0194 ***
$ILLIQ_{i,t}$	-0.1477 ***	0.0166 ***		0.7452 ***	-0.0703 ***	0.5686 ***	-0.051 ***
$EARN\_Beta_{i,t+1}$	-0.0268 ***	0.0235 ***	0.5896 ***		-0.0988 ***	0.4972 ***	-0.0371 ***
$EARN\_Idio_{i,t+1}$	0.0407 ***	0.9414 ***	-0.0294 ***	-0.0444 ***		-0.0463 ***	-0.0084 ***
$ILLIQ\_Beta_{i,t}$	-0.0665 ***	0.0056 *	0.263 ***	0.2568 ***	-0.0003		-0.5709 ***
$ILLIQ\_Idio_{i,t}$	-0.04 ***	0.0047	0.0172 ***	0.0221 ***	-0.0031	-0.5571 ***	

Panel B: Firm-level using analyst models

	$R_{i,t}$	$ILLIQ_{i,t}$	$SIZE_{i,t}$	$B2M_{i,t}$	$\|ERROR\|_{i,t}$	$DISPERS_{i,t}$
$R_{i,t}$		-0.1211 ***	0.0995 ***	-0.2308 ***	-0.0901 ***	
$ILLIQ_{i,t}$	-0.0945 ***		-0.6977 ***	0.3292 ***	0.637 ***	
$SIZE_{i,t}$	0.016 ***	-0.7036 ***		0.0971 ***	-0.4577 ***	
$BM_{i,t}$	-0.2545 ***	0.331 ***	0.0555 ***		0.3322 ***	
$\|ERROR\|_{i,t}$	-0.0708 ***	0.3215 ***	-0.214 ***	0.2077 ***		
$R_{i,t}$		-0.079 ***	-0.079 ***	-0.079 ***		-0.0645 ***
$ILLIQ_{i,t}$	-0.0571 ***		-0.6761 ***	0.3025 ***		0.5723 ***
$SIZE_{i,t}$	-0.0102 **	-0.6838 ***		0.1574 ***		-0.3687 ***
$BM_{i,t}$	-0.2471 ***	0.3022 ***	0.1168 ***			0.3314 ***
$DISPERS_{i,t}$	-0.0284 ***	0.352 ***	-0.2114 ***	0.2278 ***		

Table 3

Firm-Level Regressions

This table reports the results of both the time-series of firm-level cross-sectional regressions, or Fama-Macbeth (1973), (Panel A) and pooled regressions (Panel B) with 2-way clustering by firm and year. 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. $\Delta X_{i,t+1}/P_{i,t}$ denotes the change in net income from years *t* and *t*+1, scaled by the market value of firm *i* at the end of the return window for 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. The data includes 99,369 firm-year observations of NYSE, AMEX, and NASDAQ firms with a December fiscal year-end for the period 1952 to 2010. The sample is restricted to include only those stocks with at least 100 daily return observations and a prior day closing price of at least 2. All continuous variables used in tests are winsorized at the 1 and 99 percentiles.

Panel A: Fama-Macbeth (1973)			Panel B: Pooled		
Variable	Mean Coeff.	*t*-stat	Variable	Coefficient	*t*-stat
$R_{i,t} = \alpha_i + \beta_i \cdot \Delta X_{i,t+1}/P_{i,t} + \upsilon_{i,t}$					
$\Delta X_{i,t+1}/P_{i,t}$	0.341	5.07	$\Delta X_{i,t+1}/P_{i,t}$	0.181	2.97
Avg. Adj-R^2	0.018		Adj-R^2	0.005	
$R_{i,t} = \alpha_i + \beta_i \cdot \Delta X_{i,t+1}/P_{i,t} + \gamma_i \cdot \Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ_{i,t} + \upsilon_{i,t}$					
$\Delta X_{i,t+1}/P_{i,t}$	0.642	5.82	$\Delta X_{i,t+1}/P_{i,t}$	0.216	3.29
$\Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ_{i,t}$	-0.153	-5.85	$\Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ_{i,t}$	-0.050	-3.33
Avg. Adj-R^2	0.028		Adj-R^2	0.008	
$R_{i,t} = \alpha_i + \beta_i \cdot \Delta X_{i,t+1}/P_{i,t} + \gamma_i \cdot \Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ_{i,t} + \delta_i \cdot ILLIQ_{i,t} + \upsilon_{i,t}$					
$\Delta X_{i,t+1}/P_{i,t}$	0.638	5.80	$\Delta X_{i,t+1}/P_{i,t}$	0.217	3.34
$\Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ_{i,t}$	-0.152	-5.87	$\Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ_{i,t}$	-0.042	-3.25
$ILLIQ_{i,t}$	-0.019	-5.73	$ILLIQ_{i,t}$	-0.027	-4.45
Avg. Adj-R^2	0.061		Adj-R^2	0.030	
$R_{i,t} = \alpha_i + \beta_i \cdot \Delta X_{i,t+1}/P_{i,t} + \delta_i \cdot ILLIQ_{i,t} + \upsilon_{i,t}$					
$\Delta X_{i,t+1}/P_{i,t}$	0.346	5.19	$\Delta X_{i,t+1}/P_{i,t}$	0.187	3.08
$ILLIQ_{i,t}$	-0.021	-6.59	$ILLIQ_{i,t}$	-0.027	-4.40
Avg. Adj-R^2	0.052		Adj-R^2	0.027	

Table 4

Firm-Level Regressions with Earnings-Returns Quintile Difference

This table reports the results of both the time-series of firm-level cross-sectional regressions, or Fama-Macbeth (1973), (Panel A) and pooled regressions (Panel B) with two-way clustering by firm and year. Every year firms are double sorted independently into quintiles based on their annual returns that year and the change in their net income the following year. 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. The change in net income of firm *i* from year *t* to *t*+1, $\Delta X_{i,t+1}/P_{i,t}$ is defined as the change in net income scaled by the market value of firm *i* at the end of the return window for year *t*-1. The absolute value of the difference between a firm's return quintile rank and its change in net income quintile rank is defined as $DIFF_{i,t}$. 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 the natural logarithm of total assets. $BM_{i,t}$ is the book-to-market value of equity ratio. $SIGN_{i,t}$ is an indicator variable equal to one when firm operating income is positive for year *t*, and zero otherwise. The first model includes 99,369 firm-year observations of NYSE, AMEX, and NASDAQ firms with a December fiscal year-end for the period 1952 to 2010 while the second model has 86,713 observations due to more stringent data requirements. The sample is restricted to include only those stocks with at least 100 daily return observations and a prior day closing price of at least 2. All continuous variables used in tests are winsorized at the 1 and 99 percentiles.

Panel A: Fama-Macbeth (1973)			Panel B: Pooled		
Variable	Mean Coeff.	*t*-stat	Variable	Coefficient	*t*-stat
$DIFF_{i,t} = \phi_0 + \phi_1 \cdot ILLIQ_{i,t} + \varrho_{i,t}$					
$ILLIQ_{i,t}$	0.081	17.48	$ILLIQ_{i,t}$	0.054	14.27
Avg. Adj-R^2	0.025		Adj-R^2	0.017	
$DIFF_{i,t} = \phi_0 + \phi_1 \cdot ILLIQ_{i,t} + \phi_2 \cdot SIZE_{i,t} + \phi_3 \cdot BM_{i,t} + \phi_4 \cdot SIGN_{i,t} + \varrho_{i,t}$					
$ILLIQ_{i,t}$	0.052	8.87	$ILLIQ_{i,t}$	0.046	7.07
$SIZE_{i,t}$	0.004	0.52	$SIZE_{i,t}$	0.010	1.21
$BM_{i,t}$	0.022	2.24	$BM_{i,t}$	0.000	0.23
$SIGN_{i,t}$	-0.623	-14.57	$SIGN_{i,t}$	-0.582	-21.47
Avg. Adj-R^2	0.056		Adj-R^2	0.048	

Table 5

Firm-Level Regressions with Exogenous Shock to Illiquidity

This table reports the results of pooled regressions using the reduction of tick size from $1/8 to $1/16 on June 24, 1997, by the NYSE as an exogenous shock to liquidity. Standard errors are clustered by firm. 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. The change in net income of firm *i* from year *t* to *t*+1, $\Delta X_{i,t+1}/P_{i,t}$ is defined as the change in net income scaled by the market value of firm *i* at the end of the return window for 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. The variable *Shock* is equal to one if the firm traded on the NYSE during 1997, and zero otherwise. The test includes 4,334 firm-year observations of NYSE, AMEX, and NASDAQ firms with a December fiscal year-end for the period 1996 and 1997. All NYSE stocks are included while stocks listed on AMEX and NASDAQ that did not experience tick changes during 1997 are used as a control group. The sample is restricted to stocks with at least 100 daily return observations and a prior day closing price of at least 2. All continuous variables used in tests are winsorized at the 1 and 99 percentiles.

Panel A

Variable	Coefficient	*t*-stat
$R_{i,t} = \alpha + \theta \bullet Shock + \beta_1 \bullet \Delta X_{i,t+1}/P_{i,t} + \beta_2 \bullet Shock \bullet \Delta X_{i,t+1}/P_{i,t} + \upsilon_{i,t}$		
Shock	0.154	2.84
$\Delta X_{i,t+1}/P_{i,t}$	0.397	27.38
Shock • $\Delta X_{i,t+1}/P_{i,t}$	0.187	1.80
Adj-R^2	0.143	

Panel B

Variable	Coefficient	*t*-stat
$R_{i,t} = \alpha + \theta \bullet Shock + \beta_1 \bullet \Delta X_{i,t+1}/P_{i,t} + \beta_2 \bullet Shock \bullet \Delta X_{i,t+1}/P_{i,t} + \delta_1 \cdot ILLIQi,t + \delta_2 \bullet Shock \bullet ILLIQ_{i,t} + \upsilon_{i,t}$		
Shock	0.340	15.46
$\Delta X_{i,t+1}/P_{i,t}$	0.135	2.50
Shock • $\Delta X_{i,t+1}/P_{i,t}$	0.215	2.09
$ILLIQ_{i,t}$	-0.046	-16.83
Shock • $ILLIQ_{i,t}$	0.025	3.87
Adj-R^2	0.197	

Table 6
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+1} 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 into five ranks based upon $ILLIQ_t$ for that year. Further, the table shows the results of regressions which include only the 29 most illiquid periods, as well as the results of regressions which only include the 28 most liquid periods. The *t*-statistics are reported in square brackets. The data includes NYSE, AMEX, and NASDAQ December fiscal year-end firms with data for the period 1952 to 2010.

Panel A: Equal-weighted returns

Dependent variable	Intercept	ΔX_{t+1}	$\Delta X_{t+1} \cdot \Delta ILLIQ_t$	R^2	Adj-R^2
R_t	-0.566	0.645		0.13	0.11
	[-2.06]	[2.46]			
R_t	-0.220	0.322	-0.301	0.50	0.48
	[-1.17]	[1.83]	[-6.45]		
R_t	-0.222	0.528	-0.007	0.46	0.44
Using liquidity ranks	[-1.13]	[2.95]	[-5.81]		
R_t	-0.211	0.217		0.03	-0.01
29 most illiquid periods	[-0.80]	[0.87]			
R_t	-0.710	0.869		0.23	0.20
28 most liquid periods	[-2.31]	[3.07]			

Panel B: Value-weighted returns

Dependent variable	Intercept	ΔX_{t+1}	$\Delta X_{t+1} \cdot \Delta ILLIQ_t$	R^2	Adj-R^2
R_t	-0.356	0.433		0.09	0.07
	[-1.48]	[1.96]			
R_t	-0.135	0.227	-0.192	0.32	0.30
	[-0.73]	[1.35]	[-5.02]		
R_t	-0.139	0.360	-0.004	0.30	0.27
Using liquidity ranks	[-0.70]	[2.06]	[-4.40]		
R_t	-0.32	0.33		0.08	0.04
29 most illiquid periods	[-1.13]	[1.24]			
R_t	-0.10	0.27		0.04	0.00
28 most liquid periods	[-0.32]	[0.97]			

Table 7

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+1} denotes the growth in the sum of cross-sectional 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 2009, while that for the Sadka (2006) measures is 1984 to 2009. The data includes December fiscal year-end firms.

Panel A: Equal-weighted returns

Dependent variable	Intercept	Independent variables		R^2	Adj-R^2
		ΔX_{t+1}	$\Delta X_{t+1} \cdot \Delta PS_t$		
R_t	-0.35	0.44	-2.96	0.45	0.43
	[-1.48]	[2.03]	[-7.40]		
		ΔX_{t+1}	$\Delta X_{t+1} \cdot \Delta FT_t$		
R_t	-0.37	0.47	-3.05	0.07	-0.02
	[-0.67]	[0.89]	[-0.67]		
		ΔX_{t+1}	$\Delta X_{t+1} \cdot \Delta VP_t$		
R_t	-0.27	0.36	-14.90	0.24	0.17
	[-0.97]	[1.36]	[-2.60]		

Panel B: Value-weighted returns

Dependent variable	Intercept	Independent variables		R^2	Adj-R^2
		ΔX_{t+1}	$\Delta X_{t+1} \cdot \Delta PS_t$		
R_t	-0.23	0.31	-1.86	0.30	0.26
	[-1.01]	[1.54]	[-4.19]		
		ΔX_{t+1}	$\Delta X_{t+1} \cdot \Delta FT_t$		
R_t	0.10	0.02	-1.92	0.01	-0.09
	[0.25]	[0.06]	[-0.37]		
		ΔX_{t+1}	$\Delta X_{t+1} \cdot \Delta VP_t$		
R_t	0.17	-0.04	-9.35	0.13	0.05
	[0.67]	[-0.20]	[-3.03]		

Table 8

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+1} denotes the real growth in the gross national product from years *t* and *t*+1. $\Delta PROD_{t+1}$ 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 table also includes regressions based upon liquidity ranks, using five ranks. The *t*-statistics are reported in square brackets. The data includes December fiscal year-end firms with data for the period 1952 to 2010.

Panel A: Equal-weighted returns

Dependent variable	Intercept	ΔGNP_{t+1}	$\Delta GNP_{t+1} \cdot \Delta ILLIQ_{,t}$	R^2	Adj-R^2
R_t	0.00	4.25		0.22	0.21
	[0.00]	[4.31]			
R_t	-0.02	3.90	-6.17	0.38	0.36
	[-0.38]	[3.19]	[-2.76]		
R_t	-0.01	7.96	-0.14	0.39	0.37
Using liquidity ranks	[-0.27]	[6.21]	[-3.46]		

Dependent variable	Intercept	$\Delta PROD_{t+1}$	$\Delta PROD_{t+1} \cdot \Delta ILLIQ_{,t}$	R^2	Adj-R^2
R_t	0.08	1.72		0.18	0.16
	[2.93]	[4.11]			
R_t	0.07	1.74	-2.15	0.23	0.20
	[2.45]	[3.87]	[-1.81]		
R_t	0.07	3.26	-0.05	0.24	0.21
Using liquidity ranks	[2.43]	[3.53]	[-2.10]		

Panel B: Value-weighted returns

Dependent variable	Intercept	ΔGNP_{t+1}	$\Delta GNP_{t+1} \cdot \Delta ILLIQ_{,t}$	R^2	Adj-R^2
R_t	0.01	3.46		0.23	0.21
	[0.16]	[3.75]			
R_t	0.00	3.31	-2.53	0.27	0.24
	[-0.02]	[3.09]	[-1.59]		
R_t	0.00	5.19	-0.07	0.28	0.26
	[0.02]	[5.08]	[-2.14]		

Dependent variable	Intercept	$\Delta PROD_{t+1}$	$\Delta PROD_{t+1} \cdot \Delta ILLIQ_{,t}$	R^2	Adj-R^2
R_t	0.07	1.50		0.21	0.19
	[2.97]	[4.21]			
R_t	0.07	1.51	-0.84	0.22	0.19
	[2.69]	[4.11]	[-1.02]		
R_t	0.07	2.17	-0.02	0.22	0.20
	[2.64]	[3.23]	[-1.29]		

Table 9

Firm-Level Illiquidity and Earnings Disaggregation Regressions

This table reports the results of both the time-series of firm-level cross-sectional regressions, or Fama-Macbeth (1973), (Panel A) and pooled regressions (Panel B) with 2-way clustering by firm and year. 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. $\Delta X_{i,t+1}/P_{i,t}$ denotes the change in net income from years *t* and *t*+1, scaled by the market value of firm *i* at the end of the return window for 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. Illiquidity is then disaggregated into its systematic and idiosyncratic components, $ILLIQ\_Beta_{i,t}$ and $ILLIQ\_Idio_{i,t}$, respectively. $ILLIQ\_Beta_{i,t}$ is defined as the coefficient on the market-level illiquidity from a regression of the daily firm-level illiquidity (as defined above) on the daily market-level illiquidity (defined as the value-weighted average of the daily firm-level illiquidity). $ILLIQ\_Idio_{i,t}$ is defined as the intercept of the previous regression. To make the coefficients on the regressions below more tractable, $ILLIQ\_Beta_{i,t}$ is multiplied by 10^2 and $ILLIQ\_Idio_{i,t}$ is multiplied by 10^{-5}. Additionally, earnings growth is also disaggregated into its systematic and idiosyncratic components, $EARN\_Beta_{i,t+1}$ and $EARN\_Idio_{i,t+1}$, respectively. To calculate $EARN\_Beta_{i,t+1}$, firms are first placed into 20 portfolios formed on market value at the end of return window for year *t*-1. The value-weighted average of $\Delta X_{i,t+1}/P_{i,t}$ is computed for each portfolio and regressed on the value-weighted average of $\Delta X_{i,t+1}/P_{i,t}$ for the market ($EARN\_MAR_t$) and the coefficient on $EARN\_MAR_t$ is taken. $EARN\_Idio_{i,t+1}$ is defined at the firm level as $\Delta X_{i,t+1}/P_{i,t}$ - $EARN\_Beta_{i,t+1}$ * $EARN\_MAR_t$. The data includes 99,369 firm-year observations of NYSE, AMEX, and NASDAQ firms with a December fiscal year-end for the period 1952 to 2010. The sample is restricted to include only those stocks with at least 100 daily return observations and a prior day closing price of at least 2. All continuous variables used in tests are winsorized at the 1 and 99 percentiles.

Panel A: Fama-Macbeth (1973)			Panel B: Pooled		
Variable	Mean Coeff.	*t*-stat	Variable	Coefficient	*t*-stat
$R_{i,t} = \alpha_1 + \beta_1 \cdot \Delta X_{i,t+1}/P_{i,t} + \delta_1 \cdot ILLIQ\_Idio_{i,t} + \delta_2 \cdot ILLIQ\_Beta_{i,t} + \upsilon_{i,t}$					
$\Delta X_{i,t+1}/P_{i,t}$	0.361	5.26	$\Delta X_{i,t+1}/P_{i,t}$	0.184	3.02
$ILLIQ\_Idio_{i,t}$	-2.248	-4.93	$ILLIQ\_Idio_{i,t}$	-0.986	-5.02
$ILLIQ\_Beta_{i,t}$	-1.121	-3.40	$ILLIQ\_Beta_{i,t}$	-0.171	-4.80
Avg. Adj-R^2	0.064		Adj-R^2	0.018	
$R_{i,t} = \alpha_1 + \beta_1 \cdot \Delta X_{i,t+1}/P_{i,t} + \delta_1 \cdot ILLIQ\_Idio_{i,t} + \delta_2 \cdot ILLIQ\_Beta_{i,t} + \gamma_1 \cdot \Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ\_Idio_{i,t} + \gamma_2 \cdot \Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ\_Beta_{i,t} + \upsilon_{i,t}$					
$\Delta X_{i,t+1}/P_{i,t}$	0.467	5.44	$\Delta X_{i,t+1}/P_{i,t}$	0.207	3.47
$ILLIQ\_Idio_{i,t}$	-2.245	-3.97	$ILLIQ\_Idio_{i,t}$	-0.971	-4.96
$ILLIQ\_Beta_{i,t}$	-1.031	-2.72	$ILLIQ\_Beta_{i,t}$	-0.167	-4.66
$\Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ\_Idio_{i,t}$	-5.968	-1.10	$\Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ\_Idio_{i,t}$	-0.916	-3.30
$\Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ\_Beta_{i,t}$	-8.454	-1.83	$\Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ\_Beta_{i,t}$	-0.252	-3.23
Avg. Adj-R^2	0.072		Adj-R^2	0.019	
$R_{i,t} = \alpha_1 + \beta_1 \cdot EARN\_Idio_{i,t+1} + \beta_2 \cdot EARN\_Beta_{i,t+1} + \delta_1 \cdot ILLIQ\_Idio_{i,t} + \delta_2 \cdot ILLIQ\_Beta_{i,t} + \upsilon_{i,t}$					
$EARN\_Idio_{i,t+1}$	0.353	5.38	$EARN\_Idio_{i,t+1}$	0.099	2.96
$EARN\_Beta_{i,t+1}$	0.014	5.77	$EARN\_Beta_{i,t+1}$	0.002	0.75
$ILLIQ\_Idio_{i,t}$	-3.006	-5.11	$ILLIQ\_Idio_{i,t}$	-1.002	-4.80
$ILLIQ\_Beta_{i,t}$	-1.929	-4.75	$ILLIQ\_Beta_{i,t}$	-0.175	-4.33
Avg. Adj-R^2	0.076		Adj-R^2	0.015	
$R_{i,t} = \alpha_1 + \beta_1 \cdot EARN\_Idio_{i,t+1} + \beta_2 \cdot EARN\_Beta_{i,t+1} + \beta_3 \cdot ILLIQ\_Idio_{i,t} + \beta_4 \cdot ILLIQ\_Beta_{i,t} + \gamma_1 \cdot EARN\_Idio_{i,t+1} \cdot ILLIQ\_Idio_{i,t} + \gamma_2 \cdot EARN\_Idio_{i,t+1} \cdot ILLIQ\_Beta_{i,t} + \gamma_3 \cdot EARN\_Beta_{i,t+1} \cdot ILLIQ\_Idio_{i,t} + \gamma_4 \cdot EARN\_Beta_{i,t+1} \cdot ILLIQ\_Beta_{i,t} + \upsilon_{i,t}$					
$EARN\_Idio_{i,t+1}$	0.438	5.67	$EARN\_Idio_{i,t+1}$	0.128	3.39
$EARN\_Beta_{i,t+1}$	0.014	5.09	$EARN\_Beta_{i,t+1}$	0.001	0.44
$ILLIQ\_Idio_{i,t}$	-5.083	-3.78	$ILLIQ\_Idio_{i,t}$	-1.245	-3.05
$ILLIQ\_Beta_{i,t}$	-3.698	-3.81	$ILLIQ\_Beta_{i,t}$	-0.300	-3.73
$EARN\_Beta_{i,t+1} \cdot ILLIQ\_Idio_{i,t}$	0.121	1.31	$EARN\_Beta_{i,t+1} \cdot ILLIQ\_Idio_{i,t}$	0.028	0.89
$EARN\_Beta_{i,t+1} \cdot ILLIQ\_Beta_{i,t}$	0.097	1.31	$EARN\_Beta_{i,t+1} \cdot ILLIQ\_Beta_{i,t}$	0.015	2.44
$EARN\_Idio_{i,t+1} \cdot ILLIQ\_Idio_{i,t}$	-5.650	-1.28	$EARN\_Idio_{i,t+1} \cdot ILLIQ\_Idio_{i,t}$	-0.759	-2.22
$EARN\_Idio_{i,t+1} \cdot ILLIQ\_Beta_{i,t}$	-6.469	-1.68	$EARN\_Idio_{i,t+1} \cdot ILLIQ\_Beta_{i,t}$	-0.250	-2.25
Avg. Adj-R^2	0.094		Adj-R^2	0.017	

Table 10

Analysts' Forecast Errors and Dispersion

This table reports the results of both the time-series of firm-level cross-sectional regressions, or Fama-Macbeth (1973), (Panel A) and pooled regressions (Panel B) with 2-way clustering by firm and year. $|ERROR|_{i,t}$ is defined as the absolute value of the difference between the actual EPS for year *t* and the most recent mean analysts' EPS forecast prior to the actual (both taken from I/B/E/S), scaled by the stock price of firm *i* at the end of the return window for year *t*-1. $DISPERS_{i,t}$ is the standard deviation of the most recent analysts' EPS forecasts for year *t*, scaled by the stock price of firm *i* at the end of the return window for 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 and is limited to firms with more than 100 daily observations in a year and beginning price for the year greater than 2. $SIZE_{i,t}$ is the natural logarithm of total assets, and $BM_{i,t}$ is the book-to-market value of equity ratio, both for year *t*. $SIGN_{i,t}$ is an indicator variable equal to one when firm operating income is positive for year *t*, and zero otherwise. To make the coefficients in the tables below more tractable, all variables are multiplied by 10^2. The data includes 47,727 firm-year observations and includes December fiscal year-end firms for the period 1976 to 2010. All continuous variables used in tests are winsorized at the 1 and 99 percentiles.

Panel A: Fama-Macbeth (1973)			Panel B: Pooled		
Variable	Mean	*t*-stat	Variable	Coefficient	*t*-stat
$\|ERROR\|_{i,t} = \gamma_0 + \gamma_1 \cdot ILLIQ_{i,t} + \upsilon_{i,t}$					
$ILLIQ_{i,t}$	1.093	10.36	$ILLIQ_{i,t}$	0.806	11.70
Avg. Adj-R^2	0.109		Adj-R^2	0.103	
$\|ERROR\|_{i,t} = \gamma_0 + \gamma_1 \cdot ILLIQ_{i,t} + \gamma_2 \cdot SIZE_{i,t} + \gamma_3 \cdot BM_{i,t} + \gamma_4 \cdot SIGN_{i,t} + \upsilon_{i,t}$					
$ILLIQ_{i,t}$	0.771	11.01	$ILLIQ_{i,t}$	0.657	11.41
$SIZE_{i,t}$	-0.115	-1.24	$SIZE_{i,t}$	0.027	0.37
$BM_{i,t}$	1.935	8.42	$BM_{i,t}$	1.615	4.57
$SIGN_{i,t}$	-5.213	-6.34	$SIGN_{i,t}$	-2.812	-5.41
Avg. Adj-R^2	0.165		Adj-R^2	0.134	
Panel C: Fama-Macbeth (1973)			Panel D: Pooled		
$DISPERS_{i,t} = \alpha_i + \beta_i \cdot ILLIQ_{i,t} + \upsilon_{i,t}$					
$ILLIQ_{i,t}$	0.187	10.55	$ILLIQ_{i,t}$	0.149	11.71
Avg. Adj-R^2	0.118		Adj-R^2	0.124	
$DISPERS_{i,t} = \alpha_i + \beta_i \cdot ILLIQ_{i,t} + \nu_i \cdot SIZE_{i,t} + \delta_i \cdot BM_{i,t} + \eta_i \cdot SIGN_{i,t} + \upsilon_{i,t}$					
$ILLIQ_{i,t}$	0.120	11.10	$ILLIQ_{i,t}$	0.129	12.28
$SIZE_{i,t}$	-0.045	-2.13	$SIZE_{i,t}$	0.012	0.81
$BM_{i,t}$	0.434	6.72	$BM_{i,t}$	0.308	3.61
$SIGN_{i,t}$	-0.950	-7.14	$SIGN_{i,t}$	-0.467	-4.78
Avg. Adj-R^2	0.198		Adj-R^2	0.159	

Table 11

Illiquidity Disaggregation and Analysts' Forecasts

This table reports the results of both the time-series of firm-level cross-sectional regressions, or Fama-Macbeth (1973), (Panel A) and pooled regressions (Panel B) with 2-way clustering by firm and year. In the regressions below, $Y_{i,t}$ takes on the value of either $|ERROR|_{i,t}$ or $DISPERS_{i,t}$. $|ERROR|_{i,t}$ is defined as the absolute value of the difference between the actual EPS for year *t* and the most recent mean analysts' EPS forecast prior to the actual (both taken from I/B/E/S), scaled by the stock price of firm *i* at the end of the return window for year *t*-1. $DISPERS_{i,t}$ is the standard deviation of the most recent analysts' EPS forecasts for year *t*, scaled by the stock price of firm *i* at the end of the return window for year *t*-1. The illiquidity of a firm is then disaggregated into systematic and idiosyncratic components, $ILLIQ\_Beta_{i,t}$ and $ILLIQ\_Idio_{i,t}$, respectively. $ILLIQ\_Beta_{i,t}$ is defined as the coefficient on the market-level illiquidity from a regression of the daily firm-level illiquidity (as defined above) on the daily market-level illiquidity (defined as the value-weighted average of the daily firm-level illiquidity). $ILLIQ\_Idio_{i,t}$ is defined as the intercept of the previous regression. To make the coefficients on the regressions below more tractable, $ILLIQ\_Beta_{i,t}$ is multiplied by 10^3 and $ILLIQ\_Idio_{i,t}$ is multiplied by 10^{-5}. $SIZE_{i,t}$ is the natural logarithm of total assets, and $BM_{i,t}$ is the book-to-market value of equity ratio, both for year *t*. $SIGN_{i,t}$ is an indicator variable equal to one when firm operating income is positive for year *t*, and zero otherwise. To make the coefficients in the tables below more tractable, $SIZE_{i,t}$ $BM_{i,t}$, and $SIGN_{i,t}$ are multiplied by 10^2. Regression where $Y_{i,t,}$ is $|ERROR|_{i,t}$ include 47,727 firm-year observations from 1976 to 2010 while those regressions where $Y_{i,t}$ is $DISPERS_{i,t}$ include 39,105 observations for the same time period. Regressions include only those firms with a December fiscal year-end. All continuous variables used in tests are winsorized at the 1 and 99 percentiles. The *t*-statistics are reported in square brackets.

Panel A: Fama-Macbeth (1973)			Panel B: Pooled		
	Independent Variables			Independent Variables	
	$\|ERROR\|_{i,t}$	$DISPERS_{i,t}$		$\|ERROR\|_{i,t}$	$DISPERS_{i,t}$
$Y_{i,t} = \alpha_1 + \delta_1 \cdot ILLIQ\_Idio_{i,t} + \delta_2 \cdot ILLIQ\_Beta_{i,t} + \upsilon_{i,t}$					
$ILLIQ\_Idio_{i,t}$	0.168	0.064	$ILLIQ\_Idio_{i,t}$	0.027	0.004
	[5.02]	[4.10]		[3.59]	[2.87]
$ILLIQ\_Beta_{i,t}$	0.947	0.342	$ILLIQ\_Beta_{i,t}$	0.056	0.008
	[3.81]	[3.52]		[4.30]	[2.50]
Avg. Adj-R^2	0.113	0.082	Adj-R^2	0.029	0.008
$Y_{i,t} = \alpha_1 + \delta_1 \cdot ILLIQ\_Idio_{i,t} + \delta_2 \cdot ILLIQ\_Beta_{i,t} + \lambda_i \cdot SIZE_{i,t} + \delta_i \cdot BM_{i,t} + \eta_i \cdot SIGN_{i,t} + \upsilon_{i,t}$					
$ILLIQ\_Idio_{i,t}$	0.117	0.034	$ILLIQ\_Idio_{i,t}$	0.019	0.003
	[4.90]	[3.32]		[3.04]	[1.41]
$ILLIQ\_Beta_{i,t}$	0.540	0.167	$ILLIQ\_Beta_{i,t}$	0.034	0.003
	[3.71]	[2.83]		[3.69]	[2.32]
$SIZE_{i,t}$	-0.612	-0.122	$SIZE_{i,t}$	-0.607	-0.113
	[-6.97]	[-7.33]		[-7.93]	[-7.90]
$BM_{i,t}$	2.572	0.584	$BM_{i,t}$	2.726	0.573
	[12.37]	[9.68]		[6.96]	[6.57]
$SIGN_{i,t}$	-4.516	-0.920	$SIGN_{i,t}$	-2.415	-0.406
	[-6.72]	[-6.92]		[-4.75]	[-4.25]
Avg. Adj-R^2	0.190	0.197	Adj-R^2	0.119	0.126

Table 12
Firm-Level 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. $\Delta X_{i,t+1}/P_{i,t}$ denotes the change in net income from years *t* and *t*+1, scaled by the market value of firm *i* at the end of the return window for 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. 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 1952 to 2010. The sample is restricted to include only those stocks with at least 100 daily return observations and a prior day closing price of at least 2. All continuous variables used in tests are winsorized at the 1 and 99 percentiles.

Variable	Illiquidity Rank				
	1	2	3	4	5
$R_{i,t} = \alpha_i + \beta_i \cdot \Delta X_{i,t+1}/P_{i,t} + \upsilon_{i,t}$					
$\Delta X_{i,t+1}/P_{i,t}$	0.980	0.604	0.671	0.329	0.214
	[5.21]	[4.55]	[4.79]	[4.32]	[2.48]
Avg. Adj-R^2	0.05	0.04	0.04	0.03	0.02
$R_{i,t} = \alpha_i + \beta_i \cdot \Delta X_{i,t+1}/P_{i,t} + \lambda_i \cdot \Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ_{i,t} + \upsilon_{i,t}$					
$\Delta X_{i,t+1}/P_{i,t}$	0.293	0.513	1.197	1.578	1.075
	[0.84]	[3.29]	[3.79]	[4.75]	[3.53]
$\Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ_{i,t}$	-0.544	-0.910	-0.501	-0.599	-0.261
	[-2.21]	[-3.67]	[-2.02]	[-3.91]	[-2.67]
Avg. Adj-R^2	0.08	0.07	0.08	0.06	0.04
$R_{i,t} = \alpha_i + \beta_i \cdot \Delta X_{i,t+1}/P_{i,t} + \lambda_i \cdot \Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ_{i,t} + \delta_i \cdot ILLIQ_{i,t} + \upsilon_{i,t}$					
$\Delta X_{i,t+1}/P_{i,t}$	0.384	0.492	0.942	1.134	0.752
	[1.07]	[3.11]	[3.65]	[4.22]	[3.22]
$\Delta X_{i,t+1}/P_{i,t} \cdot ILLIQ_{i,t}$	-0.487	-0.686	0.942	-0.368	-0.143
	[-2.05]	[-3.13]	[-1.30]	[-3.22]	[-2.21]
$ILLIQ_{i,t}$	-0.038	-0.150	-0.182	-0.186	-0.171
	[-5.30]	[-14.84]	[-22.62]	[-20.51]	[-18.04]
Avg. Adj-R^2	0.11	0.17	0.21	0.21	0.18