Analyst Disagreement, Mispricing and Liquidity

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Abstract

We document a close link between mispricing and liquidity by investigating stocks with high analyst disagreement. Previous research finds that these stocks tend to be overpriced, but prices correct down as uncertainty about earnings is resolved. We conjecture that one reason mispricing has persisted is that analyst disagreement coincides with high trading costs. Indeed, we show that in the cross-section the less liquid stocks tend to be more severely overpriced. Additionally, increases in aggregate market liquidity accelerate convergence of prices to fundamentals. As a result, returns of the initially overpriced stocks are negatively correlated with the time series of innovations in aggregate market liquidity.

I. Introduction

We investigate the relation between mispricing and liquidity. We conjecture that when mispricing is bound to be short-lived trading costs make up a large fraction of the costs of arbitrage and therefore the magnitude of mispricing should be closely related to the asset's liquidity. Mispricing of stocks with high analyst disagreement about future earnings provides an ideal setting for investigating this hypothesis because it tends to be corrected within a short time frame, as the earnings uncertainty is resolved.

There has been some debate about the cause of future underperformance of high-dispersion stocks. Johnson (2004) argues that it is a rational phenomenon and is not indicative of initial mispricing. In that case, there should be no relation between liquidity and returns. On the other hand, Scherbina (2004) argues that it is caused by mispricing. She shows that analyst disagreement coincides with an upward bias in the mean forecast, which ends up being reflected in the stock price. Prices correct down as information about future earnings becomes public. In that case, liquidity should be related to returns.

We conjecture that one reason the mispricing has persisted over the years is that analyst disagreement tends to coincide with high trading costs.[1] The empirical relation between analyst disagreement and trading costs is consistent with the predictions of Kyle (1985) and Glosten and Milgrom (1985) models, which demonstrate that trading costs should increase in the degree of the potential information asymmetry between the market maker and informed investors. As analysts' skills and incentives vary, so does the precision of their earnings forecasts. The market maker might believe a subset of investors to be better informed about specific analysts' incentives and, hence, to have superior knowledge about how to aggregate analysts' opinions. The potential information asymmetry is more pronounced the higher the analyst disagreement. The market maker protects himself against adverse selection by raising the cost of trade. We show that the

[1] Initially, Diether, Malloy, and Scherbina (2002) and Scherbina (2004) conjectured that the anomaly has persisted because of high short-sale costs.

strategy of selling short high-dispersion stocks becomes considerably less profitable after taking into account trading costs.

Informed investors will trade on their knowledge only if potential profit exceeds costs. This insight is discussed by Shleifer (2000), who points out that prices must lie within the "no-arbitrage" bounds around the fair value. Arbitrage is achieved through a so-called convergence trade that involves finding two groups of fundamentally similar assets that currently diverge in price. An arbitrageur would buy the cheaper and sell short the more expensive group of assets, holding the position until prices converge. There are several costs involved in a convergence trade. Transaction costs need to be paid twice – when getting in and out of the position. Besides that, short-selling costs can be nontrivial, as demonstrated by Mitchell, Pulvino, and Stafford (2002). Moreover, Xiong (2001) and Gromb and Vayanos (2002) show that in imperfect capital markets a further divergence in prices might trigger additional demand for capital and thus force arbitrageurs to abandon potentially profitable positions. Abreu and Brunnermeier (2002) and Abreu and Brunnermeier (2003) establish that in a world in which two similar assets might differ in price indefinitely, arbitrageurs will not only forgo a convergence trade but instead establish a long position in the overpriced asset anticipating a further price run-up. Brunnermeier and Nagel (2004) provide empirical evidence for this having occurred during the "tech bubble," when hedge funds held long positions in technology stocks they considered to be overpriced.

When convergence is instantaneous all costs of a convergence trade, save transaction costs, go to zero. Because it happens immediately, convergence is riskless and smooth, and short selling is costless since the interest forgone on the margin account in an instant of time is zero. Following this logic, as the time commitment of an arbitrage strategy keeps shrinking, so do all the costs of arbitrage except the transaction costs, which remain unchanged.[2] The mispricing we consider here is fairly short-lived; Diether, Malloy, and Scherbina (2002) show that it goes away within

[2]The Kyle (1985) model implies that informativeness of prices is independent of the securities' liquidity because the informed investor will strategically adjust the size of trade to hide them among the trades of noise traders. However, his model also implies that the informed investor's expected profits decline with liquidity. One can imagine that the costs omitted from the Kyle (1985) setup could offset the potential profits on the illiquid stocks, in which case illiquid stocks will end up mispriced. This point is discussed in more detail later in the paper.

six months, on average, as the uncertainty about annual earnings is gradually resolved. Thus, the "no-arbitrage bounds" should thus be determined largely by assets' liquidity.

Indeed, we document a close relation between mispricing and liquidity. We show that in the cross-section of high-dispersion stocks, the less liquid ones tend to be the most mispriced. They end up earning substantially lower future returns than the relatively liquid high-dispersion stocks.

In the time series, changes in aggregate liquidity are negatively related to the magnitude of mispricing.[3] Increases in liquidity reduce the costs of arbitrage, and accelerate convergence of prices to fundamentals. We show that stocks with high levels of forecast dispersion earn substantially more negative returns in months in which aggregate liquidity has increased relative to the previous month. As a result, returns on high-dispersion stocks are negatively correlated with time series of innovations in aggregate market liquidity, which explains about 30% of the cross-sectional variation of expected returns of portfolios sorted on dispersion and size. This finding complements the line of research started by Pástor and Stambaugh (2003), as well as Acharya and Pedersen (2004) and Sadka (2004) that documents sensitivity of stock prices to changes in aggregate liquidity.

Evidence presented in this paper of the relation between mispricing and liquidity augments a growing body of empirical literature on costly arbitrage. Lesmond, Schill, and Zhou (2004), Korajczyk and Sadka (2004), and Chen, Stanzl, and Watanabe (2002) find that price momentum could be largely eliminated by a small capital investment. Sadka (2001) reaches a similar conclusion about the January effect. Mitchell, Pulvino, and Stafford (2002) and Baker and Savasoglu (2002) find that accounting for arbitrage costs greatly reduces potential profits in merger arbitrage. Gabaix, Krishnamurthy, and Vigneron (2004) document a relationship between mispricing and arbitrage costs in the mortgage-backed securities market, and Pontiff (1996) presents evidence that the mispricing of closed-end funds is closely related to the cost of arbitrage. In a setting where the costs of arbitrage are closely approximated by the costs of trade, we show

[3] See Chordia, Roll, and Subrahmanyam (2000), Acharya and Pedersen (2004), Amihud (2002), Pástor and Stambaugh (2003), and Sadka (2004) for evidence of fluctuations in aggregate liquidity. Vayanos (2004) presents a model of how exogenous shocks to market-wide volatility can lead to fluctuations in liquidity.

that liquidity is a significant determinant of the amount of mispricing. This suggests that market microstructure considerations have important implications for asset pricing.

We thus argue that changes in liquidity are related to returns of the initially mispriced stocks because they determine the fluctuations in the “no-arbitrage” bounds. This observation should also hold true for other types of mispricing. For example, if both price momentum (Jegadeesh and Titman (1993)) and post-earnings announcement drift (Ball and Brown (1968)) are caused by marginal investor’s underreaction to new information, then increases in liquidity help lower arbitrage costs and push prices closer to fundamentals, making the returns of these phenomena more pronounced. Consistently, Sadka (2004) documents that changes in aggregate liquidity are correlated with momentum portfolio returns, and Sadka and Sadka (2004) show that aggregate liquidity shocks are significant determinants of the magnitude of the post-earnings announcement drift. This evidence as well as the results in this paper contribute to the literature that shows the importance of aggregate liquidity in asset pricing (Pástor and Stambaugh (2003) and Acharya and Pedersen (2004)).

The rest of the paper is organized as follows. Section II discusses the relationship between mispricing and liquidity when analysts disagree about future earnings and articulates three testable hypotheses. Section III tests these hypotheses. Section IV discusses the results, alternative explanations and related findings. Section V concludes.

II. Hypotheses Development

Analyst disagreement about future earnings creates a unique situation in which mistaken beliefs coincide with unusually high transaction costs. The mistaken beliefs are corrected in the near future, ensuring that the mispricing is fairly short-lived. Because of the short horizon of the potential arbitrage strategy, trading costs constitute a large fraction of arbitrage costs, providing an easy opportunity to detect the relation between mispricing and liquidity.

A. Analyst disagreement and optimistic beliefs

Analyst disagree more following bad news (Ciccone (2003)). Evidence indicates that stock prices do not reflect the full extent of bad news. One reason could be that prices are slow to adjust to new information. Another is that the marginal investor is fooled by the tendency of analysts to be more optimistic when the disagreement is high, which could be explained by analysts' incentives. Lim (2001) hypothesizes that when earnings are highly uncertain, analysts are willing to add a higher optimistic bias to their estimates in exchange for inside information from management about the firm's future earnings. Scherbina (2004) and Jackson (2004) conjecture that analysts, who derive monetary benefits from issuing optimistic forecasts, add a higher bias to their private estimates knowing that they will be penalized less for being wrong when earnings are uncertain. Moreover, if analysts with extremely negative views choose not to reveal them the mean of the reported forecast distribution will be upwardly biased, more so the more negative the withheld opinions. This is likely to be the case when analyst disagreement is high overall (Scherbina (2004)). Because the marginal investor fails to fully account for the correlation between analyst disagreement and forecast bias, high-dispersion stocks are likely to be overvalued and to underperform otherwise similar stocks in the future.[4]

B. Costs of arbitrage

Since stocks with high analyst disagreement tend to be overpriced, an arbitrageur would sell them short until prices converge down to the fundamentals.[5] There are several costs associated with this trade. We will argue that because the mispricing is short-lived, trading costs will compose a large fraction of the total costs.

A short position is generally costly because it requires setting aside cash in a margin account to ensure against default on the stock loan. A margin account usually pays an interest rate below

[4]See Diether, Malloy, and Scherbina (2002) and Scherbina (2004) for empirical evidence of this phenomenon.

[5]It is common to minimize the risk of the short position by holding a long position in stocks with otherwise similar characteristics.

the risk-free rate that is determined by the availability and demand for borrowing and varies across borrowers.[6] Additionally, an arbitrageur faces the risk that prices will not converge.[7] The possibility that prices will diverge even further before converging to fundamentals creates the risk that a trade will have to be terminated prematurely. A further price divergence will reduce an arbitrageur's current wealth and, if wealth has been used as collateral, require commitment of additional funds. It might also generate margin calls. When capital constraints bind, arbitrageurs might be forced to close their positions before any profits are realized.[8] Finally, an arbitrageur will pay trading costs when opening and closing the short position. These costs are determined by market microstructure considerations.

Mistaken beliefs associated with analysts' disagreement are bound to be corrected soon. Initially optimistic investors revise down their beliefs as they continuously learn about the state of earnings for the current year through news releases and quarterly earnings announcements. Diether, Malloy, and Scherbina (2002) find that mispricing is corrected in, on average, six months. Shortening arbitrage horizons reduces all arbitrage costs except trading costs. Hence, arbitrage costs will be closely approximated by the costs of trade and the equilibrium magnitude of mispricing will be strongly related to the stock's liquidity.

Market microstructure models predict that trading costs should increase in the degree of information asymmetry in the market.[9] It is reasonable to expect that information symmetry is increasing in analyst disagreement. Analysts' skills and incentives differ. Better information about specific analysts affords insight into how to aggregate analysts' views. The information asymmetry between investors who possess this knowledge and the market maker is increasing in the level of analyst disagreement. Asymmetric information about earnings will lead to asymmetric information about stock valuations. The market maker will protect himself against adverse selection by raising trading costs, which would in turn make it costly to trade against mispricing.

[6]See D'Avolio (2002) for a description of the market for borrowing equity.

[7]Mitchell, Pulvino, and Stafford (2002) find that 30% of 82 potential arbitrage opportunities in which a company is trading at a price different than its parts terminate without converging.

[8]See Xiong (2001) and Gromb and Vayanos (2002) for the model.

[9]See, for example, Kyle (1985) and Glosten and Milgrom (1985).

Given our conjecture that the market maker knows little about analyst-specific incentives, it is also natural to assume that neither does he know that analyst disagreement on average results in optimistic forecasts and valuations.[10]

While a wider spread of possible equity values worsens the informational disadvantage of the market maker, noise trading alleviates it. The trading cost that risk-neutral and competitive market maker charges to protect himself against adverse selection is increasing in the potential information asymmetry and decreasing in the amount of noise trading. Glosten and Milgrom (1985) model this cost as a bid-ask spread, and Kyle (1985) 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, the price impact per unit of trade. Kyle (1985) shows λ to be proportional to the standard deviation of the distribution of the possible fair values of the security, σ, and inversely proportional to the standard deviation of the distribution of trades by noise traders, σ_u: $\lambda = \frac{2\sigma}{\sigma_u}$. Under the assumption that the stock value is proportional to earnings, Kyle's Lambda will also be proportional to the standard deviation of the distribution of possible earnings outcomes, captured by the standard deviation of analysts' earnings forecasts: $\lambda \sim \frac{2\sigma_{EPS}}{\sigma_u}$.[11]

Suppose that the current price of a high-dispersion stock is P and it is higher than its fair value, P^{Fair}. According to Kyle (1985), the maximized profit of a monopolistic arbitrageur is equal to $\left(P - P^{Fair}\right)^2/4\lambda$ in a simplified setup where everyone trades just once (and twice as high in a world with continuous trading). Suppose that C captures other costs of a short position (such as short-sale costs and risks and transitory costs of trade). The arbitrageur will trade as long as the profit exceeds the costs: $\left(P - P^{Fair}\right)^2/4\lambda \geq C$. This implies an upper bound on the amount of mispricing that could persist in equilibrium: $P - P^{Fair} = 2\sqrt{\lambda C}$. Thus, the equilibrium mispricing

[10] Alternatively, one could argue that analyst disagreement only proxies for the earnings uncertainty, and the market maker charges high trading costs as a precaution against potential adverse selection.

[11] An alternative explanation for the positive correlation between forecast dispersion and the price impact of trade has been suggested to us by Tuomo Vuolteenaho. If forecast dispersion captures the differences of opinion among investors about the value of a security, it implies that the demand schedule for the security will be steep, and the price impact of trade might be simply measuring the local steepness of the demand curve rather than the informational cost of trade.

is increasing in the stock's liquidity and in other costs of a short position.[12] Given that in the cross-section the current equilibrium level of mispricing is increasing in λ, future returns will be decreasing in λ: $\frac{\partial Ret}{\partial \lambda} \equiv \frac{\partial \left[\left(P^{Fair} - P \right) / P \right]}{\partial \lambda} < 0$. Additionally, the time-series increases in liquidity will contemporaneously accelerate the convergence of prices to fundamentals: $\frac{\partial}{\partial t} \left(P - P^{Fair} \right) = \dot{P} = \dot{\lambda} \sqrt{\frac{C}{\lambda}} < 0$ if $\dot{\lambda} < 0$.

We would like to test the time series prediction by using the component of liquidity that is unrelated to the resolution of firm-specific uncertainty. It has been documented that liquidity has a common component (see, for example, Chordia, Roll, and Subrahmanyam (2000)). We assume that the common component in liquidity is related to the relative number of liquidity traders trading in the stock market, with the increase in the number of liquidity traders reducing the severity of the adverse selection and lowering the price impact of trade. We obtain changes in the common component of liquidity by averaging the price impact across stocks and calculating unexpected changes in the resulting time series of aggregate liquidity (as in Sadka (2004)).

C. Testable hypotheses

Consistent with the discussion above, we test the following three hypotheses.

Hypothesis 1: Trading costs are increasing in analyst disagreement.

Hypothesis 2: Controlling for the level of analyst disagreement, the stocks with the highest price impact of trade will be the most overpriced and earn the lowest future returns.

Hypothesis 3: Initially overpriced high-dispersion stocks should exhibit the highest downward price adjustment during months of increasing aggregate market liquidity. Returns on a portfolio of high-dispersion stocks should thus be negatively correlated with changes in market-wide liquidity.

[12]Consistently, Boheme, Danielsen, and Sorescu (2005) show that future returns on high-dispersion stocks are decreasing in short-sale costs, which the authors proxy by the amount of short interest.

III. Empirical Results

These section describes the test of the hypotheses above. The data are described in the appendix and summarized in Table 1.

A. Estimating price impact

We use the price impact of a trade as a measure of liquidity throughout this paper. This measure is inspired by the Kyle (1985) model in the sense that it is designed to capture the cost of trade as a function of information asymmetry and is closely related to Kyle's Lambda. Yet, the market microstructure literature documents that price impact induced by actual trading contains both informational and non-informational effects on prices. Theoretical studies include Copeland and Galai (1983), Glosten and Milgrom (1985), Kyle (1985), Admati and Pfleiderer (1988), Easley and O'Hara (1987) and Easley and O'Hara (1992), and empirical evidence is provided in Glosten and Harris (1988), Hasbrouck (1991a), Hasbrouck (1991b), Keim and Madhavan (1996), Kraus and Stoll (1972), and Madhavan and Smidt (1991), among others. The informational price impact is associated with information asymmetry and the amount of noise trading (see Kyle (1985)), while the non-informational price impact is often thought to capture market making costs (such as inventory and search costs). Each component can be further decomposed into fixed and variable cost (the variable component capturing the cost per share – for example, the Lambda in the Kyle (1985) model can be represented by the informational variable component of price impact).

Using the empirical model of Glosten and Harris (1988), Sadka (2004) estimates the four components of price impact for a large cross-section of stocks at the monthly frequency (for summary statistics see Tables 1 in Sadka (2004)). In our empirical analysis we use the variable informational component of price impact as a proxy for the informational cost of a unit of trade because we are interested in a standardized measure of the cost of information asymmetry. From now on we will refer to it simply as price impact. Please see the Appendix for further discussion and details of estimation.

It is important to note that we will be using price impact and not the actual cost of trade for the analysis of Hypotheses 2 and 3. The theoretical reason is that it directly captures the trading costs due to information asymmetry (see Kyle (1985)). Since we claim that these are the costs responsible for the persistence of mispricing, it allows us to focus on them directly.[13]

B. Analyst disagreement and liquidity

To see how the costs of trade are related to analyst disagreement we sort stocks into portfolios based on dispersion in analysts' earnings per share forecasts. Following Diether, Malloy, and Scherbina (2002) and Johnson (2004), we define dispersion as the standard deviation of all outstanding earnings per share forecasts for the current fiscal year scaled by the absolute value of the mean outstanding earnings forecast (with the observations where the mean forecast is zero excluded from the sample). To make observations of dispersion comparable in the cross-section of stocks, we only consider December fiscal year end firms (unless otherwise noted). Finally, following Jegadeesh and Titman (1993) we eliminate stocks priced lower than $5 per share to minimize the bid-ask bounce in returns.

We begin by documenting the existing result that stocks with high analyst dispersion underperform otherwise similar stocks in the future, presented in Table 2. The table shows average portfolio returns for February 1983 to August 2001 time period for different assets pricing models. The first two columns of each panel present the average excess returns and the corresponding *t*-statistics, the next two columns – the CAPM alphas and their *t*-statistics, the two columns after that – the alphas and the *t*-statistics of the Fama-French three-factor model, and the last two columns – the alphas and *t*-statistics of the three-factor model plus momentum. Panel A shows the result for 25 dispersion-sorted portfolios. Panel B sorts stocks first into five size groups and

[13] Alternative measures of the cost of trade, such as bid-ask spread and effective spread are noisy estimates of the information-related costs. Bid-ask spread mainly captures the market making costs for small trades (George, Kaul, and Nimalendran (1991)). Effective spread captures all the costs and is likely increasing in the size of the trade. If some stocks were traded in larger blocks than others, the observed effective spreads will be high, whereas, in all likelihood, the price impact was low. Price impact being measured on a per-unit basis, it can be compared across stocks. If the fixed costs of trade do not vary systematically across stocks, the variation in price impact will be a good indication of the variations in total trading costs.

then into five dispersion groups within each size quintile. It can be seen from both panels that the average portfolio returns decline with dispersion and the risk-adjusted returns are significantly negative for high-dispersion portfolios.

Hypothesis 1 states that it is not easy to take advantage of the return predictability because of high trading costs of high-dispersion stocks. Table 3 illustrates that this is indeed the case. It presents the average trading costs for 25 dispersion-sorted portfolios. Portfolios are formed monthly based on dispersion as of that month. The average informational component of the price impact of trade and the average effective spread of a stock are calculated as of the same month.[14] Both measures are expressed in per cent of price, and price impact is calculated based on a trade of 1,000 shares. Effective spread is considerably higher than price impact because it is not normalized to be per 1,000 shares because it also includes transitory costs of trade.[15]

As can be seen from the table, both the price impact and the effective spread are increasing in analyst disagreement, which is consistent with Hypothesis 1. The last raw of the table reports that the differences in price impact and the effective spread between the high- and low-dispersion portfolios are highly statistically significant. The average difference in the effective spread is 0.24%. Short-sale costs of a median stock are small in comparison. Geczy, Musto, and Reed (2002) estimate that the average monthly cost of a short position for 90% to 95% of stocks at any given time is only about 0.017%.

In order to see how changes in analyst disagreement influence changes in stock's liquidity, we also run a series of firm-by-firm regressions of monthly price impact on dispersion (with both price impact and dispersion expressed in percentiles based on the monthly cross-sectional rankings):

$$PI_{it} = \beta_i disp_{it} + \varepsilon_{it} \tag{1}$$

[14]Effective spread is equal to the difference between the execution price and immediately preceding price (measured as the midpoint of the bid-ask spread) as a fraction of the preceding price.

[15]It is interesting to note that stocks in the lowest-dispersion portfolio also appear relatively illiquid. A possible explanation is that analysts tend to herd in highly uncertain environments when the potential for information asymmetry is also high.

We require each firm in the regression to have at least 60 months of data. Coefficients β_i are then averaged across firms. The average coefficient is 0.066 (t-statistic = 10.01). The average regression R^2 is 3.62%, which is on the low side because price impact tends to be more volatile than dispersion. The result implies that for each firm, a one per cent increase in the cross-sectional dispersion ranking increases the price impact ranking by on average 0.066%, and the average increase is significantly positive.

A corollary of Hypothesis 1 is that potential arbitrage profits from selling short high-dispersion stocks will fall dramatically after taking into account trading costs. In the appendix, we provide a rough estimate of the costs of trade that shows that this is indeed the case.

C. Mispricing and price impact in the cross-section

We test Hypothesis 2 that the cross-sectional variation in price impact determines the magnitude of mispricing. In the previous section we have shown that costs of trade increase with analyst disagreement. But as Table 3 indicates, there is still enough heterogeneity in the costs of trade among high-dispersion stocks to test the cross-sectional implications of liquidity. There two explanation for this heterogeneity. First, dispersion in analysts' forecasts is not always an indicator of information asymmetry. In some cases analyst disagreement does not coincide with information asymmetry in the market, as would be the case if an analyst would issue an overly optimistic forecast in an attempt to secure investment banking business. In this case, analyst disagreement will not lead to a high price impact, and using price impact will afford an additional level of screen as to whether analyst disagreement is in fact indicative of asymmetric information or simply driven by an irrelevant outlier. Second, two stocks could systematically attract different amounts of noise trading, perhaps due to the different levels of investor awareness (Frieder and Subrahmanyam (2004)). The stock with more noise trading will be more liquid even if both stocks have the same level of analyst disagreement.

Some may argue that we should expect to find the opposite result of Hypothesis 2 because when the price impact is high, the price should be closer to the fundamentals because the market is "learning." This is not necessarily the case because the market maker could set up high trading costs preemptively following a news event, in anticipation of informed trading. Moreover, if prices were already close to the fundamentals, it is unlikely that informational costs of trading would be high in the first place.

We perform two tests of Hypothesis 2. First, we sort stocks based on dispersion and price impact to show that it is illiquid stocks that are more prone to being mispriced. We show that by documenting that they end up earning lower subsequent returns than the relatively liquid stocks. It is important to follow stocks' performance for some time into the future to allow the uncertainty to be resolved and prices to adjust down. Table 4 presents the results. In Panel A, stocks are first sorted by analyst forecast dispersion and then by price impact. It can be seen that it is the illiquid high-dispersion stocks that end up earnings significantly negative returns in the future. Panel B presents the results for stocks sorted by price impact first and then by dispersion. Once again, it is clear that the relatively liquid stocks do not become mispriced. It is the illiquid stocks that are in higher danger to deviate from their fundamentals.

Figure 1 provides a visual illustration of Table 4. It plots cumulative returns of the low- and high-liquidity portfolios. Top figure uses the sorting of Panel A bottom figure – of panel B. Stocks are held in the portfolio for three month, and the future performance is tracked up to six months from the formation period t. Cumulative portfolio returns are formed from the alphas of the Fama-French three-factor model. As can be seen from the figure, the less liquid stocks subsequently earn considerably lower risk-adjusted return that the more liquid securities.

We further quantify these liquidity-related differences in performance of high-dispersion stocks by running a set of cross-sectional regressions. Table 5 presents results of the Fama and MacBeth (1973) regressions of three-month cumulative stock returns on various predictors. Only stocks in the highest dispersion quintile are considered. Once again, we limit our sample to only December fiscal year end stocks. We use non-overlapping returns formed in June and September of each year. All the right-hand-side variables are known before the returns are calculated. *Liq* is the informational component of price impact. Various control variables are considered. *Mom* is the cumulative return over the past 12 months. *Lev* is the firm leverage, which along with the leverage and dispersion interaction term was shown to be significant by Johnson (2004). As can be seen from the table, dispersion tends to be a negative and significant predictor of returns. The inclusion of controls reduces the significance of dispersion. When the liquidity and dispersion interaction term is not included, *Liq* is a negative and significant predictor of returns, indicating that illiquid stocks tend to be initially more overpriced. Momentum is highly statistically significant, which indicates that the underperformance of high-dispersion stocks is strongly related to the momentum phenomenon. The Johnson (2004) leverage variables tend to be negative and significant, but the liquidity variables dominate them in significance when included in the regression specification. This implies that at least part of the future underperformance of high-dispersion stocks is related to the initial mispricing and the difficulty in arbitraging it away. Overall, the significance of the interaction term of liquidity and dispersion indicates that it is the illiquid stocks that end up the most mispriced. Thus, the results in this subsection support Hypothesis 2, which states that the least liquid high-dispersion stocks tend to be the most mispriced.

D. Portfolio returns and aggregate liquidity changes

Hypothesis 3 states that unexpected time series increases in liquidity reduce mispricing. We use the Sadka (2004) time series of unexpected changes in aggregate liquidity rather than changes in liquidity for individual stocks. By using the aggregate measure we are focusing on the common component of liquidity that is not likely to be closely related to firm-specific information events. Sadka (2004) computes aggregate change in liquidity by first averaging price impact across stocks every month and then calculating the unexpected month-to-month changes in this aggregate measure.

A decrease in price impact can be caused by either a decrease in information asymmetry or an increase in noise trading. Since the average level of analyst disagreement about the stocks in the high-dispersion portfolio remains steady over time (albeit slightly decreasing towards the end of the calendar year because most firms have a December fiscal year end), we interpret an increase in aggregate market liquidity to signify that more uninformed traders have entered the market.[16] Given a drop in transaction costs, prices of high-dispersion stock will converge down to fundamentals. This is when high-dispersion stocks will experience the most pronounced price corrections and lowest returns.

If high-dispersion stocks earn lower returns when liquidity increases, their returns will be negatively correlated with the time series of aggregate liquidity changes. To the extent that the market on average earns higher returns when liquidity increases (Baker and Stein (2003)), returns on low-dispersion stocks will be positively correlated with the changes in liquidity. Figure 2 presents alphas of the Fama-French three-factor model (as bars) and regression coefficients on the time series of changes in aggregate liquidity when the Fama-French three factors are also included in the regression (as dots) for 25 dispersion-based portfolios. The figure indicates that regression coefficients become more negative as dispersion increases, meaning that returns of high-dispersion portfolios tend to be negatively correlated with changes in aggregate liquidity. This is consistent with Hypothesis 3.

Since high- and low-dispersion stocks have an opposite relationship with aggregate liquidity changes, the performance of an arbitrage strategy that involves selling short overpriced high-dispersion stocks and holding a long position in low-dispersion stocks will be positively related to the changes in market liquidity, earning the highest returns when liquidity increases. The results reported in Table 6 suggest that a large portion of the variation in the mean returns of dispersion-sorted portfolios can be explained by their correlation with the time series of changes in aggregate liquidity. Results for this table are computed in two steps. First, portfolio returns are regressed on the times series of factors in each specification. Second, average portfolio returns are regressed on the factor regression coefficients to see whether the differences in the coefficients

[16]Of course, it is possible that some liquidity changes could be related to common information events not reflected immediately in analyst forecast dispersion. For example, an earnings announcement of one firm could shed light on the earnings prospects of other firms in the industry.

could explain the differences in average returns across portfolios. As can be seen from the table, the coefficient on liquidity is always negative and significant, meaning that high-dispersion stocks that earn low future returns also have substantially lower liquidity betas than other portfolios. For the portfolios sorted on size and dispersion, adding the time series of changes in aggregate liquidity as an additional explanatory factor increases the R^2 of the regressions by up to 24% as compared to the Fama and French three factors and momentum. The additional explanatory power of liquidity is lower for the 25 dispersion-only-sorted portfolios, indicating that size and liquidity are closely related.

It is interesting to point out that the liquidity changes alone (not reported) have little explanatory power for the returns of dispersion-sorted portfolios (the regression R^2 are no higher than 4%). The time series of liquidity changes works well only in conjunction with other factors. The reason is that it explains returns on high-dispersion stocks, which are unexplained by the Fama-French three-factor model. These stocks have high market betas (because analyst tend to disagree more about stocks with high systematic risk), but tend to earn lower returns when market-wide liquidity goes up, as opposed to the market portfolio. So, these are the stocks whose returns should be highly correlated with market returns, but they in fact go in the opposite direction when market-wide liquidity improves. The reason why the regression R^2 increase dramatically with the addition of the changes in aggregate liquidity variable rather than going up by less than the R^2 of the regression on this variable alone is because the two-step nature of the regression allows factor loadings to change and form a better model fit in the first step regression.[17]

All the evidence presented in this section supports Hypothesis 3, which states that increases in aggregate liquidity coincide with more rapid convergence of prices to fundamentals.

[17]We thank Ken French for inviting us to think more about this point.

IV. Discussion

We present evidence that liquidity affects the magnitude of mispricing because it is directly related to the costs of arbitrage. In particular, we show that (1) the most illiquid high-dispersion stocks are most severely mispriced and (2) returns on high-dispersion stocks are negatively correlated with changes in aggregate liquidity. These results can, however, be consistent with an alternative explanation that is unrelated to mispricing. In a recent paper, Johnson (2004) argues that stocks with high analyst dispersion are in fact fairly priced: If a firm is levered, equity is a call option, and uncertainty about future earnings increases the value of the call option. If high price impact serves as another indication, in addition to analyst forecast dispersion, that the market perceives earnings to be uncertain, then in fact the stocks with high analyst disagreement in combination with high price impact of trade should command a higher price and earn lower future returns. Moreover, if changes in aggregate liquidity are purely information-driven, then increases in liquidity would imply the resolution of aggregate uncertainty and lead to the decline in the value of equity as a call option.

A little distinct in flavor but similar in spirit is another alternative explanation that liquidity is a priced risk factor. If the marginal investor has a preference for liquidity, then high-dispersion stocks, whose returns are negatively correlated with changes in liquidity, will earn lower returns in equilibrium. The view of liquidity as a risk factor has been advanced by Pástor and Stambaugh (2003), Acharya and Pedersen (2004), Sadka (2004) and Sadka and Sadka (2004).

V. Conclusion

In this paper we empirically investigate the relationship between liquidity and equilibrium mispricing. We argue that when mispricing is bound to be short-lived, liquidity should be closely associated with the costs of arbitrage. In this case, the time-series and cross-sectional variations in liquidity should coincide with the time series and cross-sectional variations in the equilibrium mispricing. This is precisely what we document in the paper.

One of the basic predictions of the market microstructure literature is that the costs of trade are determined endogenously, based on the degree of information asymmetry faced by the market maker. In our case, the source of the information asymmetry is clear. Because the stocks under investigation have high analyst disagreement about future earnings, the information asymmetry is related to the uncertainty about future earnings to the extent that it affects the firm value. In support of this view, we show that high-dispersion stocks have unusually high costs of trade, and that at least in part explains why the mispricing has persisted for the past 20 years.

However, the connection between mispricing and the costs of trade should not be limited only to stocks with high analyst disagreement about future earnings. Any news related to firm's value could potentially lead to an increase in information-related trading costs that the market maker would change in order to protect himself against adverse selection of potentially better informed market participants. It is therefore not surprising that changes in aggregate liquidity are also closely related to other information-based anomalies, such as price and earnings momentum (Sadka (2004) and Sadka and Sadka (2004)). In the future, the relation between mispricing and information-related trading costs should be explored further since it suggests a very natural link between asset pricing and market microstructure considerations. This line of research may shed light on the slow reaction to news and other asset-pricing anomalies that may persist due to endogenously high information-related trading costs.

Appendix

A. Data description

Analysts' earnings forecasts are taken from the Institutional Brokers Estimate System (I/B/E/S) U.S. Detail History and Summary History datasets. The latter contains summary statistics for analyst forecasts, including forecast mean, median, and standard deviation as well as information about the number of analysts making forecasts and the number of upward and downward revisions. These variables are calculated on (ordinarily) the third Thursday of each month. The Detail History file records individual analyst forecasts and dates of issue. Each record also contains a revision date on which the forecast was last confirmed to be accurate.

The standard-issue Summary and Detail files have a data problem that makes them unsuitable for the purposes of this paper.[18] In these datasets, I/B/E/S adjusts earnings per share for stock splits and stock dividends since the date of the forecast to smooth the forecast time series. The adjusted number is then rounded to the nearest cent. For firms with large numbers of stock splits or stock dividends earnings per share forecasts (and the summary statistics associated with earnings) will be reported as zero. But these tend also to be the firms that did well ex-post. Observations with the standard deviation of zero (and/or mean forecast of zero) will thus include firms that have earned high future returns (which is what is actually observed in the data). To avoid inadvertently using this ex-post information, we rely on forecasts not adjusted for stock splits produced by I/B/E/S at our request.

Data on stock returns, prices, and shares outstanding are from the daily and monthly stock files of the Center for Research in Security Prices (CRSP). The accounting data are from the merged CRSP/Compustat database, extended through fiscal year 2002. If less than three months has elapsed since the latest fiscal-year-end date, accounting data for the preceding year is used.

Book value of equity is calculated using Compustat annual data (including the Research file). We use total common equity, if available, plus balance sheet deferred taxes and investment tax credit. If total common equity is not available, we use shareholder's equity minus the value of preferred stock. For preferred stock we use redemption value, liquidating value, or carrying value in that order, as available. The book-to-market ratio is defined as the ratio of book value to market value of equity. The latter is calculated as the product of month-end share price and the number of shares outstanding.

[18]This problem was first reported in Diether, Malloy, and Scherbina (2002).

To minimize the problem of bid-ask bounce, we use stocks priced at no less than $5 per share. Because we are interested in dispersion in analysts' earnings per share forecasts, we consider only stocks in the I/B/E/S database that are followed by at least two analysts. As of January 1981 the number of stocks priced above $5 per share and followed by at least two analysts at the intersection of I/B/E/S and CRSP was 1,239. Of these, 858 were in the lowest nine NYSE market-capitalization deciles. As of January 1983 the number of stocks at the intersection of I/B/E/S and CRSP priced above $5 per share and followed by at least two analysts grew to 1,401, of which 962 were ranked in the lowest nine NYSE market-capitalization deciles. At the end of 1999, the respective numbers were 3,466 and 2,525. At the intersection of the I/B/E/S, CRSP, and Compustat datasets the pattern is similar, although the total number of available observations is lower because Compustat contains only a subset of the stocks in CRSP. The number of stocks at this intersection priced above $5 per share and followed by at least two analysts grew from 1,178 in January 1983 to 1,979 in December 1999. A more complete sample description is available in Table I of Diether, Malloy, and Scherbina (2002). I/B/E/S data go back to 1976, but the number of stocks in the cross-section increases more than threefold between 1976 and 1983. We use data from January 1983 through December 2000 to allow for a larger cross-section of stocks, and to be on par with the availability of intraday data.

Intraday data for calculating trading costs are obtained from two databases. The Institute for the Study of Securities Markets (ISSM) database includes tick-by-tick data for trades and quotes of NYSE- and AMEX-listed firms for the period January 1983 through December 1992 (as well as NASDAQ-listed stocks for part of the sample). The New York Stock Exchange Trades and Automated Quotes (TAQ) database includes data for NYSE, AMEX, and NASDAQ for the period January 1993 through August 2001.

Table 1 reports detailed statistics for our data sample. As can be seen from the table, stocks with high dispersion tend to be smaller, possibly because smaller stocks are more opaque. Diether, Malloy, and Scherbina (2002) report that after controlling for size, stocks with high dispersion tend to have higher analyst coverage, possibly because there is more demand for expert opinion when it is difficult to interpret available information.

B. Estimating permanent price impact

This appendix summarizes the estimation procedure developed in Sadka (2004). Let m_t denote the market maker's expected value of the security, conditional on the information set available at time t (t represents the event time of a trade)

$$m_t = E_t\left[\widetilde{m}_{t+1} | D_t, V_t, y_t\right] \tag{2}$$

where V_t is the order flow, D_t an indicator variable that receives a value of (+1) for a buyer-initiated and (-1) for seller-initiated trade, and y_t a public information signal. To determine the sign of a trade we follow the classification scheme proposed by Lee and Ready (1991), which classifies trades priced above the midpoint of the quoted bid and ask as buyer-initiated and those priced below the midpoint as seller-initiated (trades priced exactly at midpoint are discarded from the estimation).

The literature distinguishes between two main effects, permanent and transitory, that trades exert on prices. Permanent effects are attributed to the possibility of insiders trading on private information, transitory effects associated with costs of making market, such as inventory and order processing. Sadka (2004) assumes that price impacts have linear functional forms and, therefore, distinguishes between fixed costs per total trade, which are independent of the order flow, and variable costs per share traded, which depend on the order flow. There are thus four components of price impacts, denoted as follows. Fixed effects are Ψ and $\overline{\Psi}$ (permanent and transitory, respectively), variable costs λ and $\overline{\lambda}$ (permanent and transitory, respectively).

To estimate the permanent price effects we follow the formulation proposed by Glosten and Harris (1988) and assume that m_t takes a linear form such that

$$m_t = m_{t-1} + D_t\left[\Psi + \lambda V_t\right] + y_t \tag{3}$$

where Ψ and λ are the fixed and variable permanent price-impact costs, respectively. Equation (3) describes the innovation in the conditional expectation of the security value through new information, both private (D_t, V_t) and public (y_t). Notice that information exerts a permanent impact on expected value.

Assuming competitive risk-neutral market makers, the (observed) transaction price, p_t, can be written as

$$p_t = m_t + D_t \left[\overline{\Psi} + \bar{\lambda} V_t \right] \tag{4}$$

Notice that $\overline{\Psi}$ and $\bar{\lambda}$ are temporary effects, as they affect only p_t, and are not carried on to p_{t+1}. Taking first differences of p_t (Equation (4)) and substituting Δm_t from Equation (3) we have

$$\Delta p_t = \Psi D_t + \lambda D_t V_t + \overline{\Psi} \Delta D_t + \bar{\lambda} \Delta D_t V_t + y_t \tag{5}$$

where y_t is the unobservable pricing error.

The formulation in Equation (5) assumes that the market maker revises expectations according to the total order flow observed at time t. However, the literature has documented predictability in the order flow (see, for example, Hasbrouck (1991a), Hasbrouck (1991b), and Foster and Viswanathan (1993)). For example, to reduce price impact costs traders might decide to break up large trades into smaller trades, which would create an autocorrelation in the order flow. Thus, following Brennan and Subrahmanyam (1996), Madhavan, Richardson, and Roomans (1997), and Huang and Stoll (1997), Equation (5) is adjusted to account for the predictability in the order flow. In particular, the market maker is assumed to revise the conditional expectation of the security value only according to the *unanticipated* order flow rather than to the entire order flow at time t. The unanticipated order flow, denoted by $\varepsilon_{\lambda,t}$, is calculated as the fitted error term from a five-lag autocorrelation regression of the order flow $D_t V_t$ (after computing $\varepsilon_{\lambda,t}$, the unanticipated sign of the order flow, $\varepsilon_{\Psi,t}$, is calculated while imposing normality of the error $\varepsilon_{\lambda,t}$—see Sadka (2004) for more details). Equation (5) thus translates to

$$\Delta p_t = \Psi \varepsilon_{\Psi,t} + \lambda \varepsilon_{\lambda,t} + \overline{\Psi} \Delta D_t + \bar{\lambda} \Delta D_t V_t + y_t \tag{6}$$

Lastly, the literature documents different price effects induced by block trades (see, for example, Madhavan and Smidt (1991), Keim and Madhavan (1996), Nelling (1996) and Huang and Stoll (1997)). In light of this, large or block trades, generally considered to be trades in excess of 10,000 shares, are separated from smaller trades in the estimation using dummy variables. The model in Equation (6) is estimated separately for each stock every month using OLS (including an intercept) with corrections for serial correlation in the error term.

C. Arbitrage profits after trading costs

We estimate the profitability of dispersion-based trading strategies after accounting for transaction costs. This type of analysis is in the spirit of recent work that focuses on the profitability of different trading strategies after considering transaction costs (see, for example, Mitchell and Pulvino (2001) and Lesmond, Schill, and Zhou (2004)). Some studies use cost measures that increase with the amount of investment (e.g., the price impact of trades) to calculate the investment size that would eliminate apparent profit opportunities (e.g., Sadka (2001), Chen, Stanzl, and Watanabe (2002), and Korajczyk and Sadka (2004)).

We proxy transaction costs by the percentage effective spread measured for each transaction as the absolute value of the transaction price and midpoint of quoted bid and ask, divided by the bid-ask midpoint. Monthly estimates for each stock are obtained as simple averages using the trades and quotes throughout each month. Effective spread is a noisy measure of the cost of trade faced by the arbitrageur. It usually increases with the size of the trade. Ideally, we would like to use the cost of a dollar of trade.

We try to get a rough idea by how much trading costs will reduce the profits of the convergence strategy of short-selling high-dispersion stocks and buying low-dispersion stocks (in this calculation, we ignore short-selling costs). We value-weight stocks in the portfolio to minimize the amount of trade. We assume that trading costs are incurred only when a stock enters or exits the portfolio. Because portfolios are rebalanced at the end of each month, we proxy a stock's trading costs by its average effective spread over that month.

By using the average monthly effective spread in our calculations, are are no doubt capturing the upper bound of the trading costs being faced by a savvy arbitrageur. A smart market player will be able to trade at the times when the trading costs are below the monthly average and spread trades strategically to minimize the price impact.

Table A1 reports the average returns in excess of the risk-free rate, Fama-French alphas (measured as risk-adjusted return relative to the Fama and French (1993) three factor model), and effective spreads for the stocks in each portfolio. Portfolios in the left panel are equally-weighted, in the right panel value-weighted. Value-weighting reduces the average effective spread for the stocks in the portfolio because it underweights smaller stocks that are likely to be less liquid. Actual Cost is the average monthly trading cost for a portfolio. For example, the small high-dispersion portfolio (portfolio 55) has the average value-weighted effective spread of 0.70%. That the actual monthly cost of trade is only 0.46% indicates that a stock stays in the portfolio for an average of three months ($\frac{2}{3}0.70 \approx 0.46$). Net Alpha is the post-transaction-cost performance for the value-weighted portfolios. It is computed by differencing the monthly portfolio return and trading costs (only negative returns for short positions and positive returns for long positions are reported). We add trading costs to the negative alphas of high-dispersion portfolios because an arbitrage strategy would involve selling these portfolios short.

Panel A reports the results for portfolios formed by sorting stocks into 25 dispersion portfolios, based on beginning-of-month numbers. Panel B 5x5 portfolios sorted first on size (measured by market capitalization) and then dispersion, also based on beginning-of-month numbers. As can be seen from the tables, even though value-weighted returns are significantly negative for some high-dispersion portfolios, they are never significant after adjusting for trading costs. For example, the smallest high-dispersion portfolio has earned on average a significantly negative risk-adjusted return of -0.74% per month (with the t-statistic -2.75), but after subtracting for the transaction costs incurred when a stock enters or exits the portfolio, the return becomes an insignificant -0.29% per month, with the t-statistic -1.06.

Given that the transaction costs in this calculation are likely to be overstated (see the discussion above), we cannot make a claim that there are no profits to by made by an experienced arbitrageur. However, it is clear, that making a profit is not easy, and the profits are likely to be much smaller after accounting for the transaction costs.

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Table 1
Summary Statistics

This table reports summary statistics for five groups sorted on dispersion in analysts' forecasts. Dispersion is measured as the standard deviation of the outstanding earnings forecasts scaled by the mean forecast. The groups are re-formed each month. The statistics are computed from the pooled time-series and cross-section of firms in each group. The sample includes stocks available at the intersection of the CRSP and I/B/E/S databases for the period January 1983 to August 2001. Stock with share price below five dollars are omitted from the sample.

Characteristic	Portfolio	Mean	Standard deviation	Percentile 25	Median	Percentile 75
Number of analysts	Low dispersion	9.09	8.11	3	6	13
		10.42	8.09	4	8	15
		9.93	7.89	4	7	14
		9.19	7.62	4	7	12
	High dispersion	7.65	6.65	3	5	10
	All	9.26	7.75	3	6	13
Market capitalization (billions of dollars)	Low dispersion	2.55	11.40	0.15	0.44	1.49
		2.89	11.85	0.19	0.57	1.80
		2.66	12.00	0.16	0.46	1.50
		2.19	11.20	0.13	0.35	1.12
	High dispersion	1.15	5.74	0.08	0.21	0.65
	All	2.29	10.72	0.13	0.38	1.27
Book-to-market ratio	Low dispersion	0.73	0.48	0.41	0.64	0.94
		0.69	0.45	0.38	0.60	0.89
		0.68	0.47	0.37	0.58	0.88
		0.69	0.53	0.36	0.59	0.88
	High dispersion	0.72	0.70	0.34	0.57	0.90
	All	0.70	0.53	0.37	0.59	0.90
Dispersion of opinion (multiplied by 100)	Low dispersion	0.16	0.11	0.10	0.16	0.23
		0.38	0.13	0.27	0.36	0.48
		0.64	0.19	0.49	0.62	0.78
		1.11	0.31	0.88	1.09	1.31
	High dispersion	3.69	4.15	1.90	2.53	3.90
	All	1.20	2.26	0.31	0.63	1.29

Table 2
Risk-Adjusted Returns of Portfolios Based on Dispersion in Analysts' Forecasts

This table reports average returns (excess of risk-free rate) and risk-adjusted returns (relative to CAPM, Fama-French (1993) three factors (FF3), and Fama-French factors and a momentum factor (FF4)) for portfolios based on dispersion in analysts' forecasts. Two sets of portfolios are analyzed: 25 portfolios sorted on dispersion in analysts' forecasts, and 5 x 5 dependent sorts of size (market capitalization) and dispersion. The results are reported for the period February 1983 to August 2001 and for all stocks of December fiscal year-end that available at the intersection of the CRSP and I/B/E/S databases. Stocks are equal-weighted in each portfolio (and the portfolios rebalanced monthly). Stocks with share price lower than five dollars are omitted from the sample.

Panel A: 25 Dispersion-based Portfolios

Disp.	Excess Return	T of Alpha	CAPM Alpha	T of Alpha	FF3 Alpha	T of Alpha	FF4 Alpha	T of Alpha
1 (low)	1.09	3.26	0.42	2.36	0.36	2.65	0.44	3.16
	1.18	3.97	0.59	3.66	0.33	2.20	0.33	2.16
	0.95	3.14	0.33	2.16	0.07	0.49	0.11	0.81
	0.93	3.04	0.29	2.04	0.11	0.83	0.17	1.26
5	0.90	3.07	0.28	2.13	0.12	1.02	0.23	2.03
	0.92	2.98	0.26	1.93	0.06	0.52	0.19	1.54
	0.88	2.87	0.24	1.68	0.10	0.77	0.17	1.32
	0.91	2.91	0.24	1.78	0.14	1.26	0.22	1.97
	0.89	2.88	0.23	1.70	0.12	1.00	0.25	2.20
10	0.70	2.07	-0.02	-0.12	-0.06	-0.53	0.01	0.06
	0.88	2.72	0.19	1.35	0.11	0.95	0.26	2.41
	0.66	1.96	-0.06	-0.42	-0.10	-0.82	-0.04	-0.36
	0.86	2.52	0.13	0.89	0.04	0.35	0.24	2.03
	0.85	2.44	0.11	0.70	0.07	0.69	0.13	1.17
15	0.63	1.78	-0.12	-0.82	-0.12	-1.13	-0.01	-0.10
	0.79	2.17	0.01	0.09	-0.01	-0.05	0.07	0.63
	0.92	2.42	0.12	0.68	0.17	1.49	0.34	3.18
	0.42	1.12	-0.36	-2.03	-0.37	-2.91	-0.22	-1.79
	0.51	1.34	-0.26	-1.37	-0.29	-2.38	-0.23	-1.82
20	0.30	0.74	-0.53	-2.65	-0.51	-3.58	-0.31	-2.35
	0.36	0.88	-0.47	-2.16	-0.41	-2.67	-0.25	-1.68
	0.33	0.81	-0.50	-2.35	-0.46	-3.21	-0.29	-2.09
	0.37	0.85	-0.49	-2.03	-0.48	-3.11	-0.31	-2.04
	0.12	0.26	-0.76	-2.82	-0.72	-4.01	-0.53	-3.02
25 (high)	-0.32	-0.70	-1.18	-4.36	-1.10	-6.01	-0.89	-4.98
25 - 1	-1.40	-5.50	-1.60	-6.56	-1.47	-6.30	-1.33	-5.62

Panel B: Controlling for Size

Size	Disp.	Excess Return	T of Alpha	CAPM Alpha	T of Alpha	FF3 Alpha	T of Alpha	FF4 Alpha	T of Alpha
1	1 (low)	1.18	3.44	0.55	2.53	0.38	2.13	0.58	3.42
(small)		0.81	2.31	0.17	0.76	0.07	0.41	0.28	1.77
		0.66	1.81	-0.03	-0.11	-0.09	-0.49	0.18	1.08
		0.24	0.60	-0.52	-2.13	-0.56	-3.09	-0.26	-1.60
	5 (high)	-0.35	-0.85	-1.08	-3.83	-1.14	-6.01	-0.87	-4.87
2	1	0.94	2.73	0.27	1.37	0.15	1.02	0.28	1.85
		1.04	2.73	0.29	1.37	0.31	2.08	0.47	3.18
		0.80	2.03	0.01	0.06	0.04	0.30	0.24	1.95
		0.64	1.49	-0.20	-0.83	-0.15	-1.02	0.03	0.20
	5	0.04	0.10	-0.85	-3.08	-0.77	-4.52	-0.57	-3.45
3	1	1.08	3.42	0.44	2.67	0.32	2.28	0.39	2.82
		1.01	3.02	0.32	1.96	0.26	2.00	0.35	2.68
		0.87	2.35	0.09	0.53	0.09	0.69	0.25	1.91
		0.65	1.62	-0.18	-0.95	-0.09	-0.76	-0.04	-0.32
	5	0.32	0.67	-0.63	-2.49	-0.52	-3.24	-0.36	-2.26
4	1	0.91	2.94	0.26	1.84	0.05	0.41	0.12	0.88
		0.71	2.36	0.07	0.51	-0.08	-0.64	-0.04	-0.28
		0.57	1.72	-0.16	-1.22	-0.19	-1.66	-0.11	-0.92
		0.65	1.77	-0.14	-0.87	-0.15	-1.27	-0.11	-0.89
	5	0.43	0.99	-0.44	-1.89	-0.38	-2.12	-0.35	-1.88
5	1	0.94	3.25	0.36	2.36	0.11	0.93	0.07	0.60
(large)		0.76	2.72	0.16	1.36	-0.07	-0.72	-0.05	-0.52
		0.75	2.56	0.09	1.00	-0.07	-0.89	-0.08	-0.94
		0.72	2.25	0.00	0.03	-0.13	-1.34	-0.15	-1.49
	5	0.63	1.66	-0.18	-1.12	-0.18	-1.18	-0.13	-0.82
1	5-1	-1.53	-6.74	-1.63	-7.18	-1.52	-7.08	-1.45	-6.62
5	5-1	-0.31	-1.08	-0.54	-1.95	-0.29	-1.23	-0.20	-0.83
5-1	1	-0.24	-0.90	-0.19	-0.71	-0.27	-1.48	-0.51	-2.99
5-1	5	0.98	3.54	0.89	3.22	0.96	3.94	0.74	3.05

Table 3
Analysts' Dispersion and Liquidity

Each month stocks are sorted into 25 portfolios according to analysts' dispersion. The price impacts reported below are the permanent-variable components of total price impact induced by trades. They are estimated using the Glosten and Harris (1988) model with dummy variables for trades above 10,000 shares. In addition, the estimation is corrected for unanticipated trade sign and signed volume (see Sadka (2004)). Price impacts are estimated on a monthly basis for every stock. The effective percentage spread is measured for each transaction as the absolute value of the transaction price and midpoint of quoted bid and ask, divided by the bid-ask midpoint. Monthly estimates of effective spread are obtained as simple averages using the trades and quotes throughout each month. Time-series means of monthly cross-sectional statistics are calculated below for 25 portfolios sorted on dispersion. The results are reported for the period February 1983 to December 2000 and for all NYSE-listed stocks of December fiscal year-end (with available intra-day data) at the intersection of the CRSP and I/B/E/S databases. Stocks are equal-weighted in each portfolio (and the portfolios rebalanced monthly). Stocks with share price lower than five dollars are omitted from the sample.

	Price Impact (%, per trade of 1,000 shares)					Effective Spread (%)				
Disp.	Mean	Std	25%	Median	75%	Mean	Std	25%	Median	75%
1 (low)	0.032	0.050	0.008	0.017	0.041	0.28	0.18	0.14	0.23	0.35
	0.022	0.030	0.008	0.014	0.027	0.23	0.17	0.14	0.19	0.27
	0.024	0.036	0.008	0.016	0.030	0.24	0.14	0.15	0.21	0.29
	0.023	0.032	0.008	0.016	0.029	0.24	0.13	0.16	0.21	0.29
5	0.024	0.029	0.009	0.017	0.031	0.25	0.14	0.16	0.22	0.30
	0.023	0.029	0.008	0.017	0.031	0.25	0.13	0.17	0.23	0.30
	0.026	0.047	0.008	0.017	0.032	0.25	0.13	0.17	0.23	0.30
	0.025	0.032	0.009	0.018	0.033	0.26	0.13	0.17	0.23	0.31
	0.025	0.031	0.009	0.017	0.033	0.26	0.13	0.17	0.23	0.32
10	0.026	0.038	0.008	0.017	0.033	0.27	0.16	0.17	0.24	0.32
	0.025	0.041	0.009	0.018	0.034	0.29	0.20	0.18	0.24	0.33
	0.026	0.038	0.008	0.017	0.033	0.27	0.15	0.17	0.24	0.33
	0.026	0.039	0.009	0.018	0.034	0.28	0.16	0.18	0.25	0.34
	0.027	0.038	0.009	0.018	0.035	0.28	0.16	0.17	0.24	0.34
15	0.028	0.040	0.009	0.018	0.035	0.30	0.19	0.18	0.25	0.36
	0.028	0.040	0.009	0.018	0.036	0.30	0.19	0.18	0.25	0.36
	0.029	0.040	0.009	0.019	0.038	0.33	0.28	0.19	0.27	0.38
	0.028	0.066	0.009	0.020	0.040	0.33	0.22	0.19	0.28	0.40
	0.031	0.043	0.009	0.020	0.041	0.34	0.21	0.19	0.29	0.42
20	0.031	0.048	0.009	0.021	0.043	0.36	0.26	0.20	0.30	0.45
	0.032	0.052	0.010	0.022	0.043	0.37	0.23	0.21	0.31	0.46
	0.033	0.047	0.010	0.023	0.045	0.39	0.24	0.22	0.33	0.50
	0.035	0.051	0.011	0.024	0.049	0.42	0.27	0.23	0.36	0.53
	0.039	0.055	0.012	0.027	0.053	0.58	1.01	0.26	0.40	0.59
25 (high)	0.040	0.065	0.013	0.028	0.057	0.53	0.28	0.32	0.47	0.70
25 - 1 (*)	0.008	0.015	0.005	0.011	0.016	0.25	0.10	0.18	0.24	0.34

(*) All the differences are statistically significant at the 1% level

Table 4

Performance of Portfolios Sorted on Dispersion and Price Impact

This table reports the performance of two sets of 5x5 equal-weighted portfolios. In Panel A portfolios are sorted first on dispersion and then on price impact, while in Panel B the portfolios are sorted first on price impact and then on dispersion. The tables report the average performance of the portfolios, the stocks being kept in the portfolio for six months and twelve months after formation. For each strategy the table reports the average return (excess of risk-free rate) and Alpha (measured as risk-adjusted return relative to Fama-French (1993) and a momentum factor). The *t*-statistics are corrected for autocorrelation and heteroskedasticity. Returns are reported in percentages. The results are reported for the period February 1983 to December 2000 for all stocks at the intersection of the CRSP and I/B/E/S databases (with available intraday data). Stocks with share price lower than five dollars are omitted from the sample.

Panel A: 5 x 5 Dispersion/Price impact Portfolios

		Six months				Twelve months			
Dispersion	Price impact	Return	Tstat	Alpha	Tstat	Return	Tstat	Alpha	Tstat
1	1 (low)	0.97	3.62	0.17	1.44	0.94	3.56	0.15	1.42
(low)		0.95	3.53	0.06	0.50	0.93	3.48	0.05	0.45
		0.89	3.23	0.03	0.27	0.86	3.13	-0.02	-0.16
		0.88	3.03	0.01	0.10	0.85	2.88	-0.01	-0.09
	5 (high)	0.90	2.86	0.16	1.15	0.83	2.68	0.07	0.55
	5 -1	-0.07	-0.50	0.00	-0.03	-0.11	-0.90	-0.08	-0.92
5	1	0.72	2.00	-0.03	-0.20	0.74	2.01	-0.04	-0.27
(high)		0.66	1.85	-0.12	-0.74	0.71	1.98	-0.09	-0.61
		0.57	1.50	-0.17	-1.14	0.55	1.47	-0.20	-1.29
		0.51	1.26	-0.23	-1.52	0.56	1.42	-0.19	-1.25
	5	0.24	0.57	-0.32	-1.90	0.34	0.83	-0.28	-1.81
	5 - 1	-0.48	-3.05	-0.29	-2.21	-0.40	-2.83	-0.24	-2.11

Panel B: 5 x 5 Price impact/Dispersion Portfolios

		Six months				Twelve months			
Price Impact	Dispersion	Return	Tstat	Alpha	Tstat	Return	Tstat	Alpha	Tstat
1	1 (low)	0.97	3.65	0.18	1.59	0.95	3.59	0.16	1.50
(low)		0.91	3.25	0.12	1.26	0.87	3.24	0.10	1.14
		0.87	3.06	0.06	0.86	0.83	2.94	0.04	0.50
		0.85	2.80	0.10	1.24	0.86	2.84	0.09	1.16
	5 (high)	0.76	2.11	0.01	0.08	0.76	2.07	-0.01	-0.04
	5 -1	-0.21	-0.77	-0.17	-0.72	-0.19	-0.71	-0.16	-0.76
5	1	0.90	2.88	0.16	1.15	0.82	2.71	0.08	0.64
(high)		0.85	2.84	0.13	1.05	0.81	2.69	0.06	0.59
		0.76	2.31	0.08	0.75	0.79	2.41	0.08	0.73
		0.62	1.71	-0.03	-0.23	0.66	1.81	-0.04	-0.37
	5	0.21	0.49	-0.39	-2.04	0.33	0.78	-0.35	-2.00
	5 - 1	-0.68	-2.64	-0.55	-2.23	-0.49	-2.10	-0.43	-2.01

Table 5
Fama-MacBeth Regressions

This table reports the results of Fama-MacBeth (1973) cross-sectional regressions on individual firms. The independent variable is the natural logarithm of the three-month cumulative returns. The independent variables are dispersion in analysts' forecasts and price impact (PI). Control variables are size (measured as the natural logarithm of total market capitalization), book-to-market ratio (also measured in logs), momentum (measured as past 12-month cumulative returns) and leverage (LEV). The dependent variables are measured at the end of the month prior to the return accumulation. Only December fiscal-year end firms in the highest quintile of dispersion are utilized, and the regressions include non-overlapping three-month returns measured at the end of June and September of each year. The *t*-statistics (two-digit numbers) are corrected for autocorrelation and heteroskedasticity. The results are reported for the period February 1983 to December 2000 for all stocks at the intersection of the CRSP and I/B/E/S databases (with available intraday data). Stocks with share price lower than five dollars are omitted from the sample.

Disp	PI	Disp x PI	Size	BM	Mom	Lev	Disp x Lev
-0.0108							
-2.66							
-0.0087			0.0111	0.0124	0.0475	-0.0406	
-2.60			3.62	1.27	5.31	-2.24	
-0.0042			0.0113	0.0131	0.0483	-0.0388	-0.0194
-0.42			3.59	1.36	5.21	-1.81	-0.81
	-0.2593						
	-2.57						
	-0.0931		0.0112	0.0111	0.0499	-0.0411	
	-0.87		3.27	1.11	5.46	-2.18	
	-0.1145		0.0112	0.0128	0.0488	-0.0343	-0.0207
	-0.98		3.17	1.29	5.29	-1.77	-2.15
-0.0111	-0.2624						
-2.75	-2.59						
-0.0094	-0.1013		0.0110	0.0126	0.0484	-0.0403	
-2.66	-0.91		3.19	1.28	5.19	-2.06	
-0.0044	-0.1223		0.0109	0.0133	0.0491	-0.0384	-0.0200
-0.45	-1.00		3.03	1.37	5.10	-1.71	-0.87
-0.0050	-0.1877	-0.2031					
-0.97	-1.63	-2.64					
-0.0024	-0.0212	-0.2032	0.0109	0.0123	0.0482	-0.0422	
-0.51	-0.15	-2.03	2.98	1.23	5.11	-2.04	
0.0007	-0.0280	-0.2475	0.0108	0.0132	0.0490	-0.0390	-0.0166
0.07	-0.23	-2.97	2.93	1.36	5.03	-1.79	-0.66

Table 6
Cross-Sectional Regressions of Mispricing and Sensitivity to Aggregate Liquidity Changes

This table reports the results of cross-sectional regressions of alternative factor models using different portfolios based on dispersion in analysts' forecasts. The models are of the form $E(R_{i,t}) = \gamma_0 + \gamma`\beta_{i,}$ where $R_{i,t}$ are the returns of portfolio i, β_i is a vector of factor loadings, and γ are the estimated coefficients. The loadings are computed through a time-series multiple regression of portfolio returns (excess of risk-free rate) on the factors tested (over the entire sample period). The factors considered are the Fama-French three factors (MKT, SMB, and HML), a momentum factor (MOM), and the non-traded liquidity factor (LIQ). Fama-MacBeth *t*-statistics adjusted for Shanken (1992) correction are reported below the estimated coefficients (two digit numbers) together with the adjusted R^2. Two sets of portfolios are analyzed: 25 portfolios sorted on dispersion in analysts' forecasts, and 5 x 5 dependent sorts of size (market capitalization) and dispersion. The results are reported for the period February 1983 to August 2001 and for all stocks (with December fiscal year-end) at the intersection of the CRSP and I/B/E/S databases. The stocks are equal-weighted in each portfolio (and the portfolios rebalanced monthly). Stocks with share price lower than five dollars are omitted from the sample.

Panel A: 25 Analysts' Dispersion Portfolios

Intercept	MKT	SMB	HML	MOM	LIQ	Adjusted R^2
3.16	-1.94	-0.76	0.05			0.72
4.35	-2.58	-1.93	0.11			
2.92	-1.61	-0.73	-0.08	0.87		0.72
4.19	-2.18	-1.87	-0.15	1.71		
2.81	-1.76	-0.49	0.10		0.37	0.75
3.86	-2.36	-1.20	0.19		2.81	
2.73	-1.62	-0.51	0.03	0.73	0.34	0.74
3.87	-2.19	-1.22	0.06	1.42	2.50	

Panel B: 5 x 5 Size and Analysts' Dispersion Portfolios

Intercept	MKT	SMB	HML	MOM	LIQ	Adjusted R^2
4.38	-3.07	-0.19	-1.27			0.33
4.12	-3.15	-0.75	-2.39			
4.61	-3.37	0.18	-0.98	1.80		0.34
4.35	-3.45	0.81	-1.85	3.16		
3.92	-2.58	-0.10	-1.82		0.75	0.49
3.99	-2.91	-0.38	-3.33		4.17	
4.11	-2.81	0.15	-1.59	2.07	0.73	0.48
4.25	-3.23	0.66	-2.89	3.64	3.95	

Table A1
Post-Transaction Cost Performance of Portfolios Sorted on Dispersion

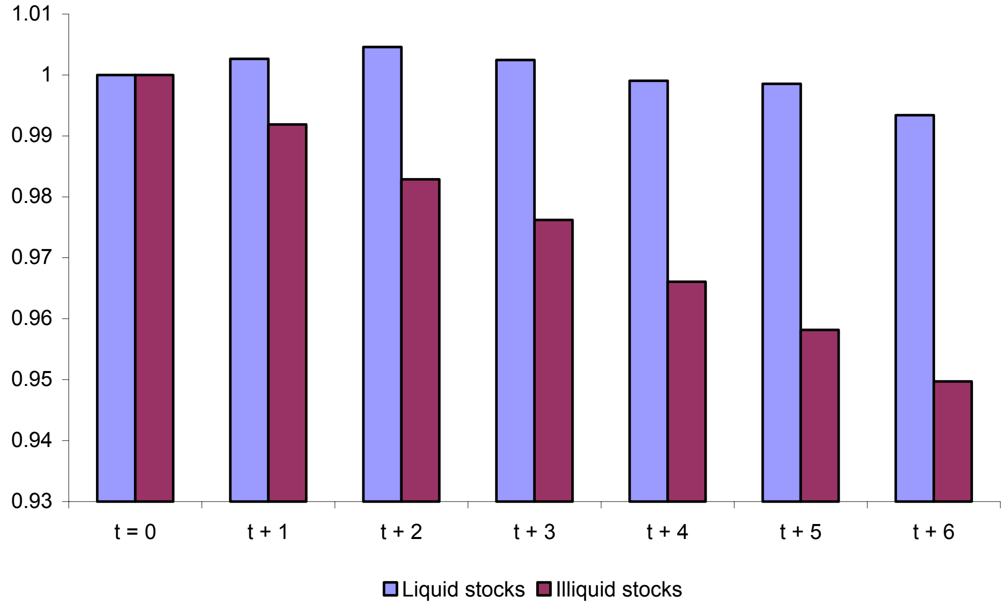
This table reports the post-transaction cost performance of different trading strategies based on dispersion in analysts' forecasts. Two sets of portfolio strategies are examined: 25 portfolios sorted on dispersion and 5x5 portfolios based on dependent sorts on size (measured by market capitalization as of previous end-of-month) and then on dispersion. Both equal- and value-weighted portfolios are rebalanced at the beginning of each month. Trading costs are computed as the percentage effective spread of the specific stock during the previous month prior to entering/exiting the portfolio. The effective percentage spread is measured for each transaction as the absolute value of the transaction price and midpoint of quoted bid and ask, divided by the bid-ask midpoint. Monthly estimates are obtained as simple averages using the trades and quotes throughout each month. For each strategy the table reports the average pre-transaction cost return (excess of risk-free rate), the Alpha (measured as risk-adjusted return relative to Fama-French (1993) three factors), the *t*-statistic of Alpha, and the average effective spread of the stocks in each portfolio. For value-weighted strategies the table also reports actual average monthly trading costs, which take into account only costs incurred if stocks enter/exit the portfolio, as well as the net Alpha and its *t*-statistic, which are computed by differencing the monthly return and the actual trading costs (only negative returns for short positions and positive returns for long positions are reported). Numbers are reported in percentages. The results are reported for the period February 1983 to December 2000 and for all stocks at the intersection of the CRSP and I/B/E/S databases.

Panel A: Dispersion-based Portfolios

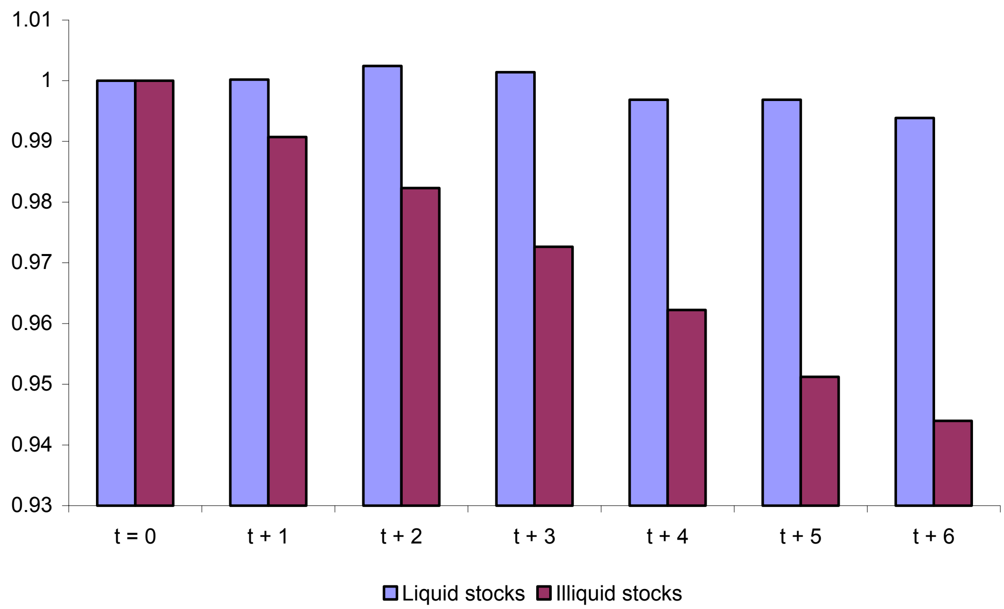
	Equal-weighted				Value-weighted						
Disp.	Excess Return	FF Alpha	T of Alpha	Effective Spread	Excess Return	FF Alpha	T of Alpha	Effective Spread	Actual Cost	Net Alpha	T Net Alpha
1 (low)	1.10	0.24	1.57	0.37	1.00	0.17	0.92	0.19	0.13	0.03	0.18
	0.90	0.04	0.28	0.28	0.92	0.13	0.73	0.17	0.17	.	.
	0.98	0.09	0.63	0.27	0.97	0.10	0.58	0.18	0.21	.	.
	0.86	-0.06	-0.41	0.27	0.71	-0.14	-0.85	0.19	0.23	.	.
5	1.03	0.10	0.69	0.28	1.03	0.17	1.00	0.18	0.25	.	.
	0.97	0.09	0.74	0.28	1.06	0.23	1.47	0.18	0.25	.	.
	0.79	-0.12	-0.85	0.28	1.15	0.34	1.81	0.17	0.26	0.09	0.46
	1.03	0.07	0.47	0.28	0.86	-0.05	-0.29	0.18	0.26	.	.
	0.73	-0.22	-1.61	0.29	0.51	-0.45	-2.96	0.18	0.28	-0.18	-1.16
10	0.94	-0.06	-0.40	0.29	0.87	-0.05	-0.26	0.18	0.28	.	.
	1.02	0.10	0.69	0.29	0.95	0.09	0.53	0.19	0.30	.	.
	0.84	-0.11	-0.77	0.30	1.07	0.16	0.82	0.19	0.29	.	.
	0.78	-0.25	-1.70	0.30	0.75	-0.13	-0.72	0.20	0.30	.	.
	0.75	-0.19	-1.29	0.31	1.07	0.22	1.26	0.20	0.30	.	.
15	0.95	-0.03	-0.19	0.33	0.88	0.00	0.02	0.19	0.29	.	.
	0.69	-0.29	-1.81	0.33	1.00	0.03	0.12	0.20	0.30	.	.
	0.78	-0.21	-1.37	0.34	0.60	-0.35	-1.94	0.20	0.31	-0.05	-0.25
	0.76	-0.28	-1.83	0.34	0.82	-0.12	-0.64	0.20	0.30	.	.
	0.68	-0.39	-2.25	0.36	0.83	-0.18	-0.88	0.21	0.30	.	.
20	0.71	-0.26	-1.46	0.38	0.30	-0.73	-3.64	0.21	0.29	-0.44	-2.21
	1.11	0.03	0.14	0.39	1.16	0.09	0.40	0.21	0.31	.	.
	0.59	-0.47	-2.44	0.43	0.64	-0.36	-1.47	0.24	0.32	-0.05	-0.20
	0.60	-0.44	-2.20	0.45	0.59	-0.40	-1.62	0.29	0.31	-0.10	-0.41
	0.62	-0.50	-2.38	0.50	0.76	-0.27	-1.18	0.28	0.27	-0.01	-0.03
25 (high)	0.11	-0.95	-3.47	0.67	0.34	-0.61	-1.91	0.33	0.19	-0.43	-1.33

		Equal-weighted				Value-weighted						
Size	Disp.	Excess Return	FF Alpha	T of Alpha	Effective Spread	Excess Return	FF Alpha	T of Alpha	Effective Spread	Actual Cost	Net Alpha	T Net Alpha
1	1 (low)	0.92	-0.05	-0.29	0.55	0.91	-0.07	-0.39	0.49	0.40	.	.
(small)		0.87	-0.07	-0.31	0.56	0.92	-0.04	-0.19	0.51	0.49	.	.
		0.75	-0.18	-0.80	0.62	0.69	-0.29	-1.32	0.55	0.57	.	.
		0.85	-0.15	-0.70	0.68	0.84	-0.19	-0.84	0.59	0.58	.	.
	5 (high)	0.15	-0.90	-3.19	0.85	0.31	-0.74	-2.75	0.70	0.46	-0.29	-1.06
2	1	1.08	0.30	1.97	0.34	1.08	0.31	2.07	0.33	0.23	0.07	0.51
		0.98	0.10	0.64	0.35	1.01	0.13	0.81	0.34	0.33	.	.
		0.70	-0.24	-1.32	0.37	0.71	-0.22	-1.23	0.36	0.37	.	.
		0.78	-0.27	-1.48	0.39	0.79	-0.26	-1.37	0.38	0.36	.	.
	5	0.57	-0.49	-2.42	0.46	0.58	-0.47	-2.33	0.45	0.28	-0.19	-0.95
3	1	1.02	0.11	0.64	0.29	0.97	0.04	0.26	0.29	0.21	.	.
		0.63	-0.32	-2.18	0.28	0.61	-0.35	-2.36	0.28	0.27	-0.08	-0.55
		0.72	-0.27	-1.68	0.29	0.73	-0.28	-1.77	0.28	0.29	.	.
		0.93	-0.10	-0.60	0.30	0.95	-0.10	-0.59	0.29	0.27	.	.
	5	0.72	-0.42	-2.23	0.33	0.72	-0.41	-2.16	0.33	0.20	-0.22	-1.14
4	1	1.00	0.09	0.60	0.22	0.97	0.05	0.38	0.22	0.13	.	.
		1.05	0.02	0.17	0.22	1.08	0.03	0.25	0.21	0.19	.	.
		1.01	-0.03	-0.19	0.22	0.99	-0.04	-0.32	0.22	0.21	.	.
		0.67	-0.42	-3.01	0.22	0.70	-0.38	-2.74	0.22	0.20	-0.19	-1.35
	5	0.59	-0.51	-2.40	0.25	0.66	-0.44	-2.05	0.24	0.14	-0.31	-1.44
5	1	1.02	0.13	1.04	0.17	1.04	0.20	1.62	0.15	0.07	0.13	1.08
(large)		1.02	0.17	1.54	0.17	0.95	0.13	1.04	0.15	0.12	0.01	0.05
		0.77	-0.15	-1.40	0.16	0.81	-0.03	-0.28	0.16	0.13	.	.
		0.88	-0.07	-0.65	0.17	0.91	0.12	0.97	0.17	0.12	.	.
	5	0.66	-0.33	-2.62	0.19	0.72	-0.25	-1.83	0.17	0.08	-0.17	-1.26

Panel B: Controlling for Size



Panel A: High-dispersion stocks of dispersion/liquidity sorted portfolios



Panel B: High-dispersion stocks of liquidity/dispersion sorted portfolios

Figure 1. Cumulative abnormal returns (in event time) of high-dispersion stocks. This figure plots the average cumulative abnormal returns of portfolios sorted on analysts' dispersion and liquidity. In Panel A stocks are sorted into five groups according to the dispersion in their analysts' earnings forecasts six months and three months prior to the fiscal year-end of each stock. Within each group stocks are sorted into five groups according to the price impact of their trades during the month of June. Price impacts are calculated using tick-by-tick data (see Sadka (2004)). Similarly, in Panel B stocks are sorted into five liquidity groups and then five dispersion groups. Each of the figures plots the cumulative abnormal returns of two portfolios: the portfolio of stocks in the highest dispersion quintile and in the lowest price-impact quintile (denoted "Liquid stocks"), and the portfolio of stocks in the highest dispersion quintile and in the highest price-impact quintile (denoted "Illiquid stocks"). Abnormal returns are calculated using a four-factor model including the Fama and French (1993) three factors and a momentum factor. The results are reported for the period February 1983 through December 2000 for all stocks at the intersection of NYSE-listed stocks with available intraday data and the I/B/E/S database. The stocks are equal-weighted in each portfolio (and the portfolios rebalanced monthly). Stocks with share price less than five dollars have been omitted from the sample.

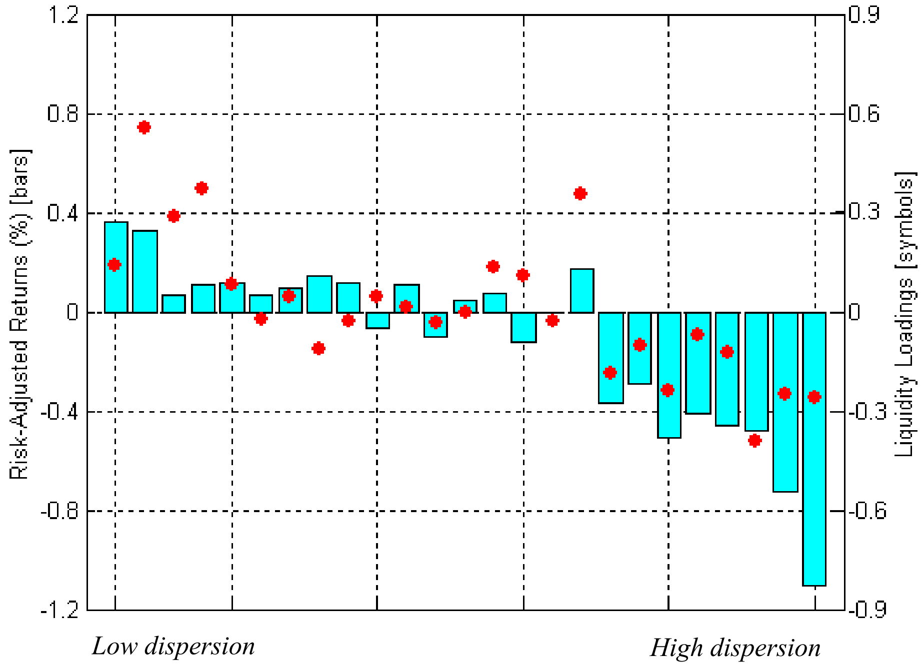


Figure 2. Risk-adjusted returns and liquidity loadings of dispersion portfolios. Stocks are sorted at the beginning of each month into 25 groups according to the dispersion in their analysts' earnings forecasts available up to that month. The liquidity loadings are calculated using time-series regressions of portfolio returns on the Fama-French three factors, MKT, SMB, HML, and the non-traded liquidity factor LIQ. Risk-adjusted returns are calculated using similar time-series regressions, but without the non-traded factor. The results are reported for the period February 1983 through August 2001 for all at the intersection of the CRSP and I/B/E/S databases. The stocks are equal-weighted in each portfolio (and the portfolios rebalanced monthly). Stocks with share price lower than five dollars are omitted from the sample.