Analyst Disagreement, Mispricing and Liquidity

Ronnie Sadka and Anna Scherbina*

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*Sadka is at the University of Washington Business School (rsadka@u.washington.edu). Scherbina is at the Harvard Business School (ascherbina@hbs.edu). We thank Malcolm Baker, Shlomo Baruch, Ken French, Alan Hess, Ravi Jagannathan, Li Jin, Avi Kamara, Jennifer Koski, Ed Rice, Gil Sadka, Michael Schwarz, Erik Stafford, Tuomo Vuolteenaho, seminar participants at the University of Washington Business School, Harvard Business School, NBER Market Microstructure Meeting (Summer 2004), Notre Dame Behavioral Finance Conference and our discussants, Paul Irvine (NBER) and Rick Mendenhall (Notre Dame), for helpful suggestions. We would also like to thank I/B/E/S for making its dataset available for our research. We are responsible for any errors.

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Abstract

Examining returns of stocks with high levels of analyst disagreement about future earnings reveals a close link between mispricing and liquidity. Previous research finds these stocks often to be overpriced, but prices to correct down within a fiscal year as uncertainty about earnings is resolved. We conjecture that one reason mispricing has persisted is that these stocks have higher trading costs than otherwise similar stocks, possibly because some investors are better informed than the market maker about how to aggregate analysts' opinions. As analyst disagreement increases so does the informational disadvantage of the marker maker, and trading costs rise. In the cross-section, less liquid stocks are, on average, more severely mispriced. Moreover, increases in aggregate market liquidity accelerate convergence of prices to fundamentals. As a result, returns of 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 liquidity is closely related to the cost of arbitrage. Such a setting is provided by the mispricing of stocks with high analyst disagreement about future earnings. Analysts usually disagree about the extent of bad news about the firm (see, e.g., Ciccone (2003)). Diether, Malloy, and Scherbina (2002) and Scherbina (2004) show that the full extent of bad news is not initially reflected in market prices, and, as a result, these stocks tend to be overpriced.[1] However, the true earnings are revealed within a fiscal year and the mispricing goes away.

We conjecture that one reason that the mispricing has persisted over the years is that stocks with high analyst disagreement tend to have high trading costs.[2] The empirical correlation between analyst disagreement and trading costs is consistent with the predictions of the 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 after taking into account transaction costs the profitability of the strategy of selling short high-dispersion stocks significantly decreases.

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. A number of costs involved in setting up a convergence strategy to take advantage of a potential mispricing make up the "no-arbitrage" bounds. Conver-

[1] Johnson (2004) provides a rational explanation of why these stocks earn low future returns. We will come back to it later in the paper.

[2] This is distinct from the conjecture of the earlier papers that pointed to high short-sale costs as the reason the anomaly persisted.

gence strategy involves finding two groups of assets that, though they are similar in characteristics and should have similar values, currently diverge in price, and holding a zero-cost portfolio with the long position in the cheaper and the short position in the more expensive group of assets until the prices converge. Convergence trades are shown to be costly and risky. Mitchell, Pulvino, and Stafford (2002) demonstrate that the cost of the short side of the trade can be non-trivial. Xiong (2001) and Gromb and Vayanos (2002) show that in imperfect capital markets a further price divergence of the assets involved in the convergence trade 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.

In the limit, when convergence is instantaneous all costs of a convergence trade, save transaction costs, which are unaffected, go to zero. Since convergence happens immediately it is riskless and smooth. Short selling is costless because the interest forgone on the margin account in an instant of time is zero. Therefore, as the time commitment of an arbitrage strategy shrinks to zero, so do all the costs associated with arbitrage, but transaction costs involved in setting up the portfolio remain unchanged.[3] The mispricing we consider here is fairly short-lived.[4] The "no-arbitrage bounds" should thus be determined largely by trading costs.

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. The

[3]Whereas the Kyle (1985) model implies that the informativeness of prices is independent of the securities' liquidity because informed investors will strategically spread their trades, we assume that fixed costs of trade (which are not part of the Kyle (1985) setup) prevent arbitrageurs from spreading their trades too thin; thus illiquid stocks will be persistently mispriced.

[4]Diether, Malloy, and Scherbina (2002) show that it goes away within six months, on average, as the uncertainty about annual earnings is gradually resolved.

interaction term of forecast dispersion and liquidity is shown to dominate forecast dispersion alone as a negative predictor of future returns.

In the time series, changes in aggregate liquidity are negatively related to the magnitude of mispricing.[5] 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) who study the profitability of momentum trading strategies after accounting for transaction costs find that the momentum effect, as documented in the literature, 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 that liquidity is a significant determinant of the amount of mis-

[5] 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.

pricing. 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 the price momentum (Jegadeesh and Titman (1993)) and the 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 a number of 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. Because these mistaken beliefs are corrected in the near future, the costs of trading on this information are captured mainly by transaction costs. This setting creates a suitable opportunity to study the empirical relationship between mispricing and liquidity as related to the costs of arbitrage.

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 a 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. (See Diether, Malloy, and Scherbina (2002) for empirical documentation of this result.)

B. Analyst disagreement and the cost of trade

Mistaken beliefs of a subset of investors are not arbitraged away if arbitrage is costly. We show that there exists a strong positive relationship between analyst disagreement and trading costs, which is consistent with Kyle (1985) and Glosten and Milgrom (1985) models.

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 will be increasing in analyst disagreement, making it costly to trade against mispricing. Given our assumption 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, generates a higher than usual bias in the mean outstanding forecast.[6]

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: $\lambda \sim \frac{2\sigma_{EPS}}{\sigma_u}$.[7]

C. Costs of arbitrage when mistaken beliefs will be corrected soon

Although trading costs are not the only costs associated with exploiting mispricing, we argue that they are the most significant costs associated with arbitrage in this setting. To minimize risk exposure a mispricing is usually exploited via a convergence trade, which, as noted earlier, involves finding two groups of assets with similar characteristics such that they should, but currently do

[6] 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.

[7] 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.

not, have similar prices. The relatively underpriced group of assets is sold short and the proceeds invested in a long position in the cheaper group of assets. This zero-cost portfolio is held until the prices converge.

A short position is generally costly because it requires setting aside cash in the margin account to ensure against default on the stock loan. A margin account usually pays an interest rate below the risk-free rate that is determined by the availability and demand for borrowing and varies across borrowers.[8] Additionally, an arbitrageur faces the risk that prices will not converge.[9] The possibility that prices will diverge even further before converging 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 the commitment of additional funds. It might also generate margin calls on the short side of the trade. When capital constraints bind, arbitrageurs might be forced to close their positions before any profits are realized.[10] Finally, an arbitrageur incurs trading costs associated with opening and closing an arbitrage 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. Because in this setting the time commitment of a convergence trade is relatively short, arbitrage costs will be closely approximated by the costs of trade. Hence, mispricing will be strongly related to the stock's liquidity.

That said, we must acknowledge that classical market microstructure models vary in their predictions of whether liquidity will have an impact on the informativeness of prices. A key

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

[9] 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.

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

feature seems to be whether informed traders are allowed to cooperate and trade strategically. The Kyle (1985) model with one strategic informed investor implies that the amount of noise trading has no impact of the informativeness of prices because the informed trader adjusts the optimal size of trade to conceal his information among the trades of noise traders. However, Kyle (1985) omits the fixed component of the costs of trade. If in addition to variable component λV each trader were also charged the fixed cost to enable the market maker to make a positive profit, very small trades would become unprofitable. The very illiquid stocks would then have a higher likelihood of being mispriced. On the other hand, Glosten and Milgrom (1985) model does not allow informed investors to strategically choose the size of trade, and one of their implications is that prices of the less liquid stocks are less informative.

If the informativeness of prices indeed depends on stocks' liquidity, increases in the number of noise traders make prices more informative. i.e. closer to fundamentals. It has been shown that there is a common component in liquidity (see, for example, Chordia, Roll, and Subrahmanyam (2000)). This common component is likely related to the relative number of noise traders in the stock market rather than the commonality in the information environment. Because we would like to investigate how exogenous changes in liquidity affect mispricing, we look at the price reaction to the changes in aggregate rather than stock-specific liquidity. And by looking at changes in liquidity of individual securities we would be much more likely to pick up information related events that will simultaneously affect prices and trading costs. If mispricing is smaller when trading costs are lower, then increases in aggregate liquidity will speed the convergence to fundamentals of initially mispriced individual securities.

D. Testable hypotheses

Consistent with the discussion above, we put forth four hypotheses. The first two are specific to the mispricing of high-dispersion stocks and suggest why it has persisted. The last two hypotheses are applicable to any type of mispricing and indicate where in the cross-section it will be more severe and when in the time series convergence to fundamentals will be accelerated.

Hypothesis 1: Trading costs are increasing in dispersion in analysts' earnings forecasts.

Hypothesis 2: After controlling for trading costs, the profits of the strategy of buying low-dispersion and selling short high-dispersion stocks decline considerably.

Hypothesis 3: 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 4: Initially overpriced high-dispersion stocks should exhibit the highest downward price adjustment during increases in aggregate market liquidity. Returns on a portfolio of high-dispersion stocks should thus be negatively correlated with changes in market-wide liquidity.

III. Empirical Results

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.[11] 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.

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

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.

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. Analyst disagreement, costs of trade and arbitrage profits

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. Dispersion is defined as the standard deviation of all outstanding earnings per share forecasts for the current fiscal year, scaled by the book value of equity. Analyst disagreement declines through the fiscal year, as quarterly earnings numbers come out and uncertainty about annual earnings is gradually resolved. To make comparisons across firms with different fiscal year ends we scale dispersion by the square root of the number of quarters remaining until the month in which the annual earnings number will be announced. This methodology assumes that an equal amount of uncertainty is resolved each quarter until the fiscal year end. We exclude all firm-month observations with fewer than three outstanding forecasts, book equity value of less than $3 per share, and share price less than $5. We form portfolios every month.

Table 2, Panel A reports average monthly portfolio returns for 25 dispersion-sorted portfolios. Panel B of the table sorts stocks first into five size and momentum groups and then into five dispersion groups. Momentum sorting is based on the cumulative returns for the past 12 months. High-dispersion stocks underperform otherwise similar stocks in terms of raw returns, CAPM-adjusted returns, and Fama-French adjusted returns. The trading strategy of holding low-dispersion stocks and short-selling high-dispersion stocks generates significant profit due mainly to the underperformance (negative alphas) of the high-dispersion portfolios.

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 estimate the cost per unit of trade. If one were to take Kyle (1985) as a description of reality, basing the estimate of the effective spread on the trades that were larger/smaller than the optimal size would lead us to overestimate/underestimate the cost of trade.

The noisiness of our proxy notwithstanding, Table 3 shows that effective spread increases steadily with dispersion. The highest dispersion-based portfolio in Panel A has the average effective spread of 0.33% of the share price, the lowest only 0.19%. The same pattern holds when stocks are sorted into size quintiles first and then into dispersion quintiles (Panel B). The difference is most remarkable among the smallest quintile of stocks. The high-dispersion small-stock portfolio has the average effective spread of 0.70%. This evidence supports Hypothesis 1 that trading costs increase with dispersion. Short-sale costs are small in comparison. The average monthly cost of a short position for 90% to 95% of stocks at any given time is only about 0.017% (Geczy, Musto, and Reed (2002)).

We then 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). Since portfolios are rebalanced monthly we simulate the performance of a trading strategy, incurring trading costs only if a stock enters or exits the portfolio. When a stock enters or exits the portfolio at the beginning of the month we assume the cost of trading the stock to be the effective spread estimated during the previous month (so that the cost of the investment strategy is adapted to the information process). The portfolios being value-weighted, there is no additional cost of portfolio rebalancing.

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 3 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, consistent with Hypothesis 2.

C. 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 3 and 4. 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.[12]

[12] 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.

D. Mispricing and price impact in the cross-section

Here we test Hypothesis 3 that cross-sectional variations in price impact determine the magnitude of mispricing. The rationale for this is that high price impact will force arbitrageurs to trade very small amounts of stock at a time, but the fixed costs of trade will make such thin trading forbiddingly costly. As a result, the stocks with the high price impact of trade will likely be mispriced.

An important question is why would two stocks with similar levels of analyst disagreement have different informational costs of trade. There could be two reasons. First, dispersion in analysts' forecasts is not always an indicator of information asymmetry. In some cases, as when an analyst, perhaps driven by the desire to secure investment banking business, issues an overly optimistic forecast, the market maker might be aware of this incentive and ignore the forecast. 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, the two stocks could systematically attract different amounts of noise trading, perhaps due to the different levels of investor awareness (Frieder and Subrahmanyam (2004)).

Additionally, some may argue that 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 3. First, we sort stocks into portfolios first by dispersion in the outstanding earnings forecasts and then by the measure of liquidity based on the permanent price impact of trades (Sadka (2004)). Consistent with Hypothesis 3, we find that among the stocks in the fourth and fifth dispersion-based quintiles the least liquid stocks are the most overpriced. This is indicated by the fact that they earn a lower risk-adjusted return after they enter the portfolio. If stocks are held in the portfolio for three months or longer, the less liquid high-dispersion stocks significantly underperform the more liquid high-dispersion stocks. It is clear why portfolios need to be held for several months to see the difference in performance. If a stock is mispriced and arbitrage is costly, prices will be corrected only after information about mispricing will become public (for example, through corporate news releases or earnings announcements). Thus, the longer an overpriced stock remains in the portfolio, the higher the probability that the price will be adjusted down based on newly available information. For example, when stocks in the highest dispersion quintile are held in the portfolio for six months, those in the most liquid quintile earn an average risk-adjusted monthly return of -0.22% (with a t-statistic of -1.50), those in the least liquid quintile — a significantly lower return of -0.56% (with a t-statistic of -2.69). These results are reported in Table 4.

Figure 1 provides a visual illustration of Table 4. It plots cumulative returns of the low- and high-liquidity portfolios formed of the stocks in the highest quintile of forecast dispersion. Returns are calculated by cumulating monthly risk-adjusted returns. As can be seen from the figure, the less liquid stocks earn considerably lower risk-adjusted return that the more liquid securities over the next year.

We further quantify these liquidity-related differences in performance 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. We use non-overlapping returns formed in January, April, July and October of each year. *Disp* is the standard deviation in analysts' earnings forecasts scaled by the book value of equity. *Size* is the natural logarithm of the market capitalization. *PI* is the price impact of trade, calculated as the permanent price impact of trade using the Sadka (2004) regression specifications. *Disp* x *Size* and *Disp* x *PI* are the cross-products of these variables. All the right-hand-side variables are known before the returns are calculated. We do not report any regression specifications with the cross-product *Size* x *PI* because it is never significant. As can be seen from the table, dispersion is negative and significant in all specifications but those where the cross-product of dispersion and price impact is included, in which case, the cross-product absorbs all the statistical significance. This suggests that it is high-dispersion stocks with a high degree of information asymmetry, and, hence, low liquidity that become overpriced. High price impact is itself is not significant because it is not necessarily accompanied by mistaken beliefs of a particular direction. *Disp* x *Size* is negative, but not significant. It is negative because smaller stocks tend to be less liquid, and so the future underperformance of high-dispersion stocks is more pronounced for smaller stocks.

These results support Hypothesis 3, which states that the least liquid high-dispersion stocks tend to be the most mispriced.

E. Portfolio returns and aggregate liquidity changes

Hypothesis 4 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 focusing on changes in liquidity for individual stocks.[13] The monthly time series of aggregate liquidity is constructed by averaging the monthly price impact estimates 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.

To test the time-series relationship between mispricing and liquidity we subdivide our sample into months of increased and decreased aggregate liquidity. A month is classified as a month of increased liquidity if the average permanent price impact of trade in the market has fallen from the previous month. It is classified as a month of decreased liquidity if the average permanent price impact of trade has risen from the month before. Over the sample period of 1983-1999 we have roughly the same number of months of increased and decreased liquidity.

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

[13]As explained earlier, we use the variable informational component of price impact.

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.[14] 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.

This is, indeed, what the data reveal. Table 6 reports the risk-adjusted returns on dispersion-sorted stock portfolios in the months of increased and decreased liquidity. Panel A presents average returns for the 25 dispersion-sorted portfolios. Panel B presents results for portfolios formed through independent sorts on size and dispersion. As can be seen from the table, high-dispersion stocks perform more poorly in months of increased liquidity than in months of decreased liquidity. For example, the first panel of the table shows the risk-adjusted return of the 25th dispersion-sorted portfolio to be -1.24% per month (with a t-statistic of -4.41) in the months of increased liquidity and -0.74% per month (with a t-statistic of -2.03) in the months of decreased liquidity. This finding supports Hypothesis 4, which states that prices converge to fundamentals more quickly when liquidity increases.

We proceed to further quantify the significance of the relationship between returns on high-dispersion stocks and changes in aggregate liquidity. 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. The results of regressing portfolio returns on the time series of changes in aggregate liquidity are reported in Table 7. We find that low-dispersion stock returns have a positive, high-dispersion stocks have a negative, correlation with the aggregate liquidity factor, the difference being statistically significant. For example, the coefficient on changes in liquidity factor is -0.63 (with the t-statistic of -1.89) for the highest-dispersion portfolio based

[14] 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.

on 1x25 sorting. Differences in the coefficients on the liquidity time series between the low-dispersion and high-dispersion portfolios are also statistically significant (the difference is -0.88, with a *t*-statistic of -2.74, between the first and 25th dispersion-based portfolio). The average coefficients of regression of dispersion-based portfolio returns on the innovations in the time series of aggregate liquidity are presented in Figure 2 as a line, along with the average risk-adjusted portfolio returns, presented as vertical bars. It is clear from the graph that the regression coefficients become reliably more negative as dispersion increases. This implies that high-dispersion stocks earn significantly lower returns when liquidity increases.

Since high- and low-dispersion stocks have an opposite relationship with aggregate liquidity changes, the performance of the 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. One could interpret uncertainty about liquidity as adding to the risk of the arbitrage strategy. The results reported in Table 8 suggest that a large fraction of the monthly return variation between the low- and high-dispersion portfolios is explained by the monthly variation in aggregate liquidity. For the portfolios sorted on size and dispersion, the addition of aggregate liquidity adds 33% to explaining the variation of the portfolio returns. 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 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.[15]

All the evidence presented in this section supports Hypothesis 4, which states that increases in aggregate liquidity coincide with more rapid convergence of prices to fundamentals.

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

[15] We thank Ken French for making us think more about this point.

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

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)

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

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

$$m_t = m_{t-1} + D_t\left[\Psi + \lambda V_t\right] + y_t \tag{2}$$

where Ψ and λ are the fixed and variable permanent price-impact costs, respectively. Equation (2) 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

$$p_t = m_t + D_t \left[\overline{\Psi} + \overline{\lambda} V_t \right] \tag{3}$$

Notice that $\overline{\Psi}$ and $\overline{\lambda}$ 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 (3)) and substituting Δm_t from Equation (2) we have

$$\Delta p_t = \Psi D_t + \lambda D_t V_t + \overline{\Psi} \Delta D_t + \overline{\lambda} \Delta D_t V_t + y_t \tag{4}$$

where y_t is the unobservable pricing error.

The formulation in Equation (4) 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 (4) 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 (4) thus translates to

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

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 (5) is estimated separately for each stock every month using OLS (including an intercept) with corrections for serial correlation in the error term.

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Table 1
Summary Statistics

This table reports summary statistics for different groups sorted on dispersion in analysts' forecasts. 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.

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 and Fama-French (1993) three factors) 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. T-statistics are reported below each return (two digit numbers). The results are reported for the period February 1983 to August 2001 and for all stocks 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).

Panel A: 25 Dispersion-based Portfolios

Disp.	Excess Return	T of Alpha	CAPM Alpha	T of Alpha	FF Alpha	T of Alpha
1 (low)	1.01	2.76	0.28	1.42	0.29	2.06
	1.08	3.49	0.45	2.87	0.21	1.46
	1.01	3.16	0.34	2.32	0.16	1.23
	0.94	2.97	0.27	1.92	0.14	1.08
5	0.9	2.81	0.21	1.59	0.1	0.87
	0.87	2.65	0.17	1.21	0.07	0.63
	0.81	2.41	0.09	0.62	0.06	0.50
	0.91	2.65	0.18	1.19	0.11	0.93
	0.87	2.55	0.15	0.96	0.14	1.36
10	0.76	2.19	0.02	0.14	0.01	0.10
	0.75	2.11	-0.01	-0.04	0.03	0.21
	0.72	1.95	-0.07	-0.42	-0.03	-0.26
	0.85	2.32	0.08	0.48	0.09	0.77
	0.66	1.77	-0.13	-0.81	-0.08	-0.70
15	0.8	2.08	0	0.02	0.09	0.73
	0.68	1.73	-0.13	-0.71	-0.05	-0.43
	0.73	1.84	-0.09	-0.45	-0.06	-0.49
	0.34	0.85	-0.49	-2.42	-0.43	-3.62
	0.53	1.29	-0.3	-1.35	-0.2	-1.38
20	0.35	0.81	-0.5	-2.18	-0.42	-2.76
	0.34	0.80	-0.5	-2.03	-0.39	-2.63
	0.36	0.80	-0.52	-1.98	-0.42	-2.28
	0.17	0.37	-0.72	-2.52	-0.58	-3.07
	-0.13	-0.26	-1.03	-3.19	-0.93	-4.19
25 (high)	-0.31	-0.63	-1.18	-3.71	-1.05	-4.65
25 - 1	-1.31	-5.53	-1.46	-6.32	-1.34	-6.13

Panel B: Controlling for Size

Size	Disp.	Excess Return	T of Alpha	CAPM Alpha	T of Alpha	FF Alpha	T of Alpha
1	1 (low)	0.94	2.40	0.24	0.93	0.16	0.76
(small)		0.7	1.59	-0.05	-0.14	0.01	0.03
		0.31	0.73	-0.42	-1.41	-0.38	-1.62
		0.15	0.31	-0.63	-1.81	-0.55	-1.90
	5 (high)	-0.42	-0.80	-1.24	-3.09	-1.14	-3.50
2	1	1.07	2.82	0.34	1.53	0.26	1.49
		1.01	2.51	0.23	1.00	0.27	1.75
		0.72	1.77	-0.07	-0.32	-0.03	-0.20
		0.53	1.18	-0.34	-1.29	-0.25	-1.49
	5	-0.11	-0.22	-1.02	-3.31	-0.88	-4.52
3	1	1.02	2.94	0.31	1.76	0.23	1.63
		0.87	2.38	0.11	0.64	0.14	1.10
		0.9	2.33	0.1	0.55	0.18	1.42
		0.67	1.57	-0.2	-0.91	-0.09	-0.70
	5	0.27	0.58	-0.66	-2.51	-0.52	-3.62
4	1	1.04	3.22	0.36	2.47	0.23	1.71
		0.68	2.10	-0.01	-0.10	-0.14	-1.15
		0.69	1.95	-0.08	-0.53	-0.06	-0.52
		0.68	1.77	-0.15	-0.93	-0.1	-1.06
	5	0.44	0.98	-0.48	-2.14	-0.37	-2.50
5	1	0.93	3.13	0.29	2.32	0.12	1.10
(large)		0.79	2.76	0.15	1.62	0.02	0.25
		0.78	2.45	0.05	0.66	0	-0.03
		0.72	2.07	-0.07	-0.67	-0.07	-0.76
	5	0.65	1.62	-0.2	-1.17	-0.11	-0.74
1	5-1	-1.36	-5.37	-1.48	-5.90	-1.31	-5.49
5	5-1	-0.28	-0.97	-0.5	-1.81	-0.23	-1.00
5-1	1	-0.02	-0.05	0.05	0.16	-0.04	-0.18
5-1	5	1.07	2.95	1.03	2.83	1.04	3.01

Table 3
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						
		Panel B: Controlling for Size										
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

Table 4
Performance of Portfolios Sorted on Dispersion and Price Impact

This table reports the performance of 5x5 portfolios (equal-weighted) sorted first on dispersion and then on price impact. The tables report the average performance of the portfolios, the stocks being kept in the portfolio for three months, six months, nine 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) three factors). 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).

	Price	Three months				Six months				Nine months				Twelve months			
Dispersion	impact	Return	Tstat	Alpha	Tstat	Return	Tstat	Alpha	Tstat	Return	Tstat	Alpha	Tstat	Return	Tstat	Alpha	Tstat
1	1 (low)	0.95	3.90	0.11	0.77	0.99	4.12	0.15	1.18	0.94	3.96	0.10	0.77	0.94	4.00	0.10	0.78
(low)		0.99	3.92	0.06	0.43	0.96	3.96	0.05	0.38	0.96	3.87	0.05	0.32	0.94	3.80	0.03	0.18
		1.05	4.24	0.15	1.06	1.05	4.27	0.13	0.95	1.01	4.15	0.10	0.70	0.97	3.95	0.05	0.33
		1.00	3.68	0.08	0.48	0.96	3.57	0.04	0.28	0.92	3.44	0.01	0.06	0.90	3.41	-0.01	-0.06
	5 (high)	0.95	3.23	0.07	0.38	0.95	3.31	0.07	0.41	0.89	3.19	0.03	0.18	0.87	3.11	0.01	0.05
	5 -1	-0.01	-0.06	-0.03	-0.25	-0.05	-0.42	-0.08	-0.83	-0.05	-0.49	-0.07	-0.75	-0.08	-0.74	-0.09	-1.02
2	1	0.91	3.55	0.05	0.42	0.93	3.59	0.05	0.44	0.93	3.64	0.05	0.47	0.92	3.65	0.04	0.38
		0.94	3.69	-0.01	-0.11	0.92	3.51	-0.06	-0.45	0.94	3.55	-0.05	-0.36	0.95	3.66	-0.03	-0.22
		0.93	3.39	-0.07	-0.52	0.96	3.56	-0.03	-0.24	0.94	3.49	-0.05	-0.39	0.96	3.60	-0.02	-0.19
		0.95	3.44	-0.02	-0.17	0.93	3.38	-0.04	-0.27	0.91	3.32	-0.06	-0.41	0.90	3.25	-0.07	-0.50
	5	0.91	3.34	0.02	0.15	0.87	3.06	-0.01	-0.10	0.84	3.02	-0.04	-0.28	0.85	3.08	-0.03	-0.25
	5 -1	0.00	0.02	-0.03	-0.20	-0.06	-0.55	-0.06	-0.58	-0.09	-0.82	-0.09	-0.96	-0.07	-0.71	-0.08	-0.91
3	1	1.05	3.66	0.12	1.07	1.01	3.54	0.07	0.79	0.98	3.44	0.04	0.45	0.97	3.42	0.04	0.39
		0.94	3.36	-0.05	-0.35	0.95	3.46	-0.05	-0.46	0.97	3.56	-0.03	-0.33	0.95	3.43	-0.06	-0.56
		0.83	3.04	-0.16	-1.36	0.83	2.97	-0.19	-1.69	0.87	3.10	-0.16	-1.44	0.88	3.12	-0.15	-1.33
		0.91	3.10	-0.08	-0.56	0.84	2.91	-0.16	-1.13	0.85	2.94	-0.16	-1.22	0.87	2.98	-0.15	-1.12
	5	0.72	2.17	-0.24	-1.36	0.77	2.40	-0.18	-1.12	0.84	2.63	-0.13	-0.88	0.83	2.61	-0.15	-1.03
	5 -1	-0.33	-2.25	-0.36	-2.80	-0.24	-1.79	-0.26	-2.11	-0.14	-1.11	-0.18	-1.57	-0.14	-1.24	-0.18	-1.90
4	1	0.83	2.63	-0.15	-1.19	0.93	2.98	-0.03	-0.23	0.93	3.02	-0.03	-0.28	0.94	3.03	-0.03	-0.30
		0.84	2.86	-0.21	-1.66	0.84	2.84	-0.21	-1.85	0.86	2.86	-0.20	-1.80	0.86	2.82	-0.21	-1.77
		0.87	2.72	-0.22	-1.60	0.86	2.76	-0.23	-1.78	0.88	2.83	-0.22	-1.74	0.89	2.87	-0.21	-1.73
		0.77	2.36	-0.28	-1.71	0.76	2.32	-0.31	-2.15	0.78	2.40	-0.29	-2.09	0.80	2.46	-0.27	-2.00
	5	0.68	1.86	-0.27	-1.36	0.68	1.91	-0.29	-1.65	0.72	2.06	-0.26	-1.53	0.74	2.10	-0.26	-1.63
	5 -1	-0.14	-0.92	-0.12	-0.89	-0.26	-1.91	-0.26	-2.36	-0.21	-1.73	-0.22	-2.22	-0.20	-1.67	-0.23	-2.42
5	1	0.79	2.17	-0.26	-1.69	0.81	2.25	-0.22	-1.50	0.81	2.22	-0.24	-1.61	0.83	2.29	-0.22	-1.46
(high)		0.66	1.91	-0.42	-2.68	0.65	1.87	-0.46	-3.17	0.68	1.95	-0.44	-3.02	0.68	1.95	-0.44	-2.91
		0.53	1.44	-0.68	-3.92	0.51	1.39	-0.69	-3.78	0.58	1.56	-0.61	-3.50	0.60	1.63	-0.58	-3.27
		0.55	1.34	-0.58	-3.19	0.51	1.31	-0.60	-3.29	0.57	1.49	-0.53	-2.82	0.60	1.56	-0.50	-2.67
	5	0.43	1.03	-0.60	-2.74	0.47	1.15	-0.56	-2.69	0.46	1.15	-0.55	-2.78	0.51	1.27	-0.51	-2.61
	5 - 1	-0.35	-1.85	-0.35	-1.92	-0.34	-2.04	-0.33	-2.25	-0.35	-2.25	-0.32	-2.29	-0.32	-2.17	-0.29	-2.35

Table 5
Fama-MacBeth Regressions

This table reports the results of Fama-MacBeth (1973) cross-sectional regressions on individual firms. The independent variable is three-month cumulative returns. The dependent variables are dispersion in analysts' forecasts, size measured as the natural logarithm of total market capitalization, and price impact. The dependent variables are measured at the end of the month prior to the return accumulation. The regressions utilize non-overlapping returns only from portfolios formed at the beginning of the months January, April, July, and October. The regression coefficients are reported in percentages. The *t*-statistics are corrected for autocorrelation and heteroskedasticity (the Bartlett kernel of five lags). 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).

Disp	Size	PI	Disp x Size	Disp x PI
-39.52				
-3.30				
-38.53	-0.15			
-3.44	-0.93			
-25.57	-0.08		-7.68	
-1.95	-0.45		-1.43	
-38.14		-0.55		
-3.22		-2.41		
-24.25		-0.21		-25.74
-1.55		-0.75		-2.00
-38.37	-0.11	-0.27		
-3.45	-0.72	-1.28		
-25.91	-0.06	-0.21	-7.20	
-1.97	-0.33	-1.00	-1.33	
-24.18	-0.12	0.10		-25.65
-1.63	-0.76	0.47		-2.09
-18.58	-0.11	0.12	-1.42	-29.16
-1.23	-0.59	0.56	-0.23	-2.21

Table 6
Performance and Market Liquidity

This table reports the performance of different portfolios based on dispersion in analysts' forecasts during liquid and illiquid months. Performance is measured by risk-adjusted returns relative to Fama-French (1993) three factors. 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. T-statistics are reported below each return (two digit numbers). The results are reported for the period February 1983 to August 2001 for all stocks 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).

Panel A: Dispersion-based Portfolios

Disp.	All Months	Months of Liquidity Change Positive	Months of Liquidity Change Negative
1 (low)	0.0029	0.0030	0.0032
	2.04	1.52	1.55
5	0.0010	0.0002	0.0015
	0.87	0.10	0.97
21	-0.0039	-0.0040	-0.0025
	-2.60	-2.28	-1.05
25 (high)	-0.0105	-0.0124	-0.0074
	-4.61	-4.41	-2.03
25-1	-0.0134	-0.0154	-0.0106
	-6.07	-5.24	-3.05

Panel B: Controlling for Size

Size	Disp.	All Months	Months of Liquidity Change Positive	Months of Liquidity Change Negative
1	1 (low)	0.0016	0.0007	0.0032
(small)		0.75	0.29	0.91
	5 (high)	-0.0114	-0.0155	-0.0064
		-3.47	-4.53	-1.14
5	1	0.0012	0.0027	-0.0003
(large)		1.09	1.73	-0.20
	5	-0.0011	-0.0024	0.0013
		-0.73	-1.27	0.57
1	5-1	-0.0131	-0.0162	-0.0095
		-5.44	-5.20	-2.49
5	5-1	-0.0023	-0.0051	0.0017
		-0.99	-1.71	0.46
5-1	1	-0.0004	0.0020	-0.0035
		-0.17	0.77	-0.89
5-1	5	0.0104	0.0130	0.0077
		2.98	3.27	1.34

Table 7
Liquidity Loadings of Portfolios Based on Dispersion in Analysts' Forecasts

This table reports the loadings of different portfolios based on dispersion in analysts' forecasts on a non-traded liquidity factor (Sadka (2004)). The loadings are calculated through a time-series regression of portfolio returns (excess of risk-free rate) on the Fama and French three factors and the liquidity factor LIQ. Three sets of portfolios are analyzed: 25 portfolios sorted on dispersion in analysts' forecasts, 5 x 5 dependent sorts of size (market capitalization) and dispersion, and 5 x 5 dependent sorts of momentum (past 11-month cumulative returns, skipped one month) and dispersion. T-statistics are reported below each liquidity loading. The results are reported for the period February 1983 to August 2001 for all stocks 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).

Panel A: 25 Dispersion-based Portfolios

Disp.	Liquidity Loading	T of Loading
1 (low)	0.25	1.18
	0.62	2.96
	0.36	1.79
	0.37	1.96
5	0.11	0.63
	0.06	0.33
	-0.12	-0.71
	-0.01	-0.07
	0.02	0.13
10	0.09	0.53
	0.04	0.20
	0.01	0.08
	0.08	0.44
	0.23	1.38
15	0.01	0.07
	0.13	0.67
	-0.19	-0.97
	-0.23	-1.30
	-0.13	-0.58
20	-0.09	-0.40
	-0.04	-0.20
	-0.32	-1.20
	-0.42	-1.48
	-0.53	-1.60
25 (high)	-0.63	-1.89
25 - 1	-0.88	-2.74

Panel B: Controlling for Size

Size	Disp.	Liquidity Loading	T of Loading
1	1 (low)	0.14	0.44
(small)		-0.08	-0.21
		-0.05	-0.14
		-0.10	-0.23
	5 (high)	-0.76	-1.56
2	1	0.25	0.93
		-0.05	-0.20
		0.21	0.90
		-0.37	-1.49
	5	-0.47	-1.62
3	1	0.42	1.96
		0.01	0.08
		0.21	1.17
		-0.07	-0.40
	5	-0.19	-0.90
4	1	0.23	1.15
		0.19	1.04
		0.03	0.15
		-0.05	-0.33
	5	-0.20	-0.90
5	1	0.42	2.60
(large)		-0.01	-0.11
		0.02	0.16
		0.16	1.12
	5	-0.33	-1.54
1	5-1	-0.90	-2.57
5	5-1	-0.76	-2.24
5-1	1	0.28	0.80
5-1	5	0.42	0.82

Table 8
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) and the non-traded liquidity factor (LIQ). Fama-MacBeth *t*-statistics 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 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).

Panel A: 25 Analysts' Dispersion Portoflios

Intercept	MKT	SMB	HML	LIQ	Adjusted R^2
0.0387	-0.029				0.76
4.40	-3.16				
0.0305	-0.0228			0.0041	0.79
3.47	-2.50			3.06	
0.0404	-0.0262	-0.0083	-0.0014		0.81
5.08	-3.17	-2.23	-0.31		
0.0314	-0.0191	-0.0057	-0.0029	0.0036	0.84
3.82	-2.27	-1.55	-0.66	2.68	

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

Intercept	MKT	SMB	HML	LIQ	Adjusted R^2
0.0256	-0.0172				0.27
3.88	-2.36				
0.0175	-0.0118			0.0072	0.44
2.72	-1.63			3.73	
0.0074	0.0008	-0.006	0.0123		0.33
0.68	0.07	-1.67	2.11		
0.0055	0.002	-0.0016	-0.0006	0.0101	0.63
0.49	0.19	-0.51	-0.12	4.55	

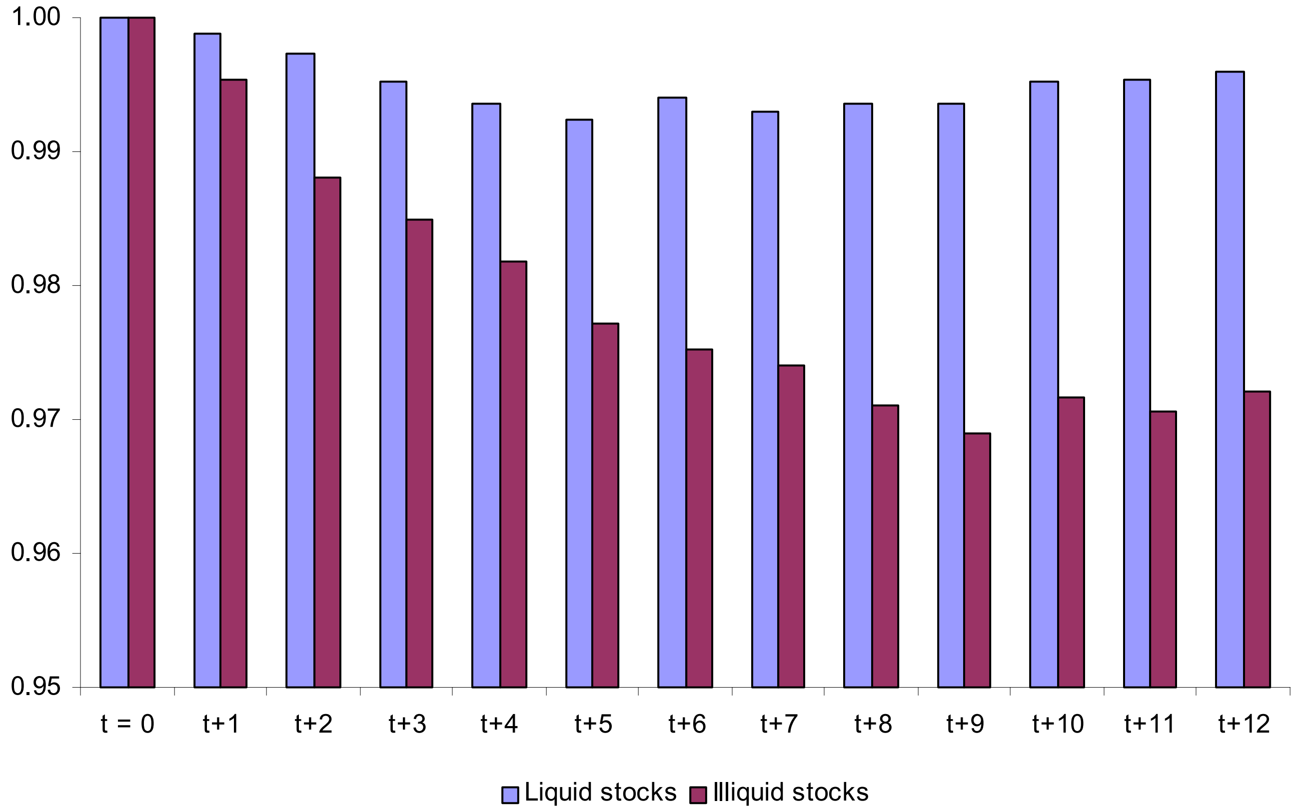

Figure 1. Cumulative abnormal returns (in event time) of high-dispersion stocks. This figure plots the average cumulative returns of two dispersion-based trading strategies. At the beginning of each month stocks are sorted into five groups according to the dispersion in their analysts' earnings forecasts available up to that month. Within each group stocks are sorted into five groups according to the price impact of their trades during the previous month (calculated using tick-by-tick data (see Sadka (2004))). The figure analyzes the cumulative abnormal returns of two of the above-described 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 the Fama and French (1993) three-factor model. The results are reported for the period February 1983 through December 1999 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).

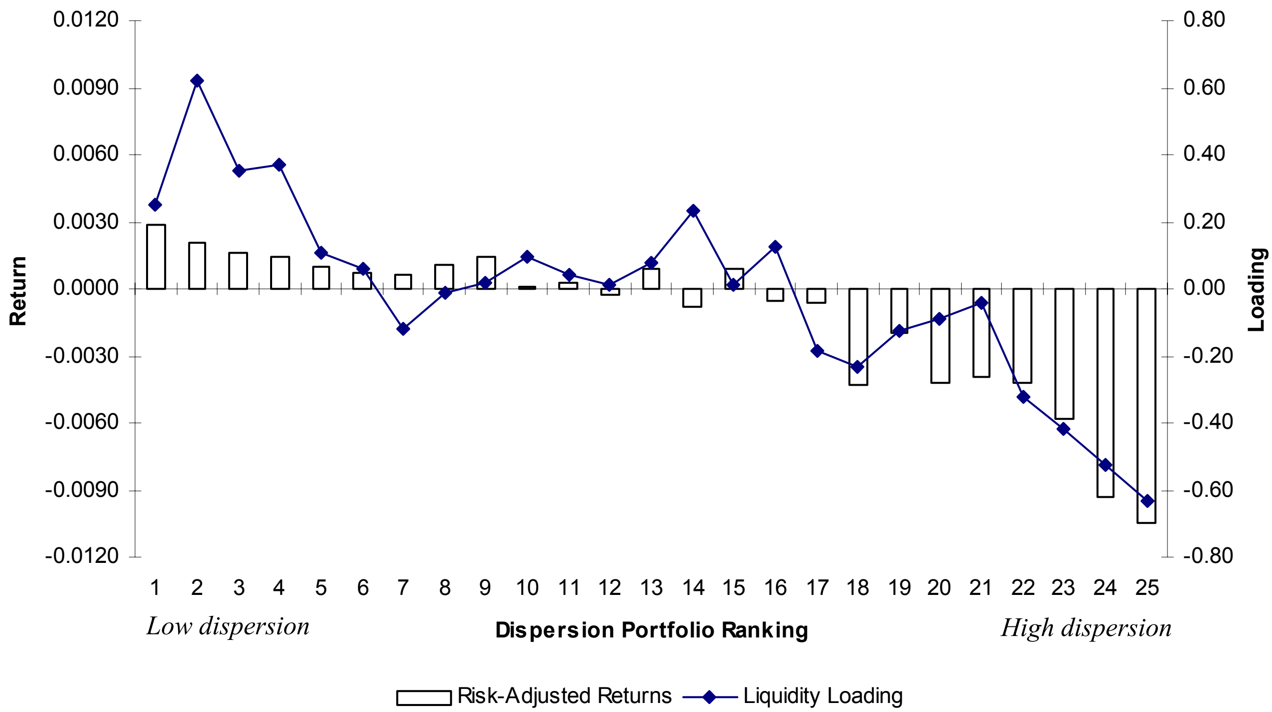

Figure 2. Risk-adjusted returns and liquidity loadings of dispersion portfolios. At the beginning of each month stocks are sorted into 25 groups according to the dispersion in their analysts' earnings forecasts available up to that month. The liquidity loadings are calculated using time-series regressions 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 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).