Analyst Disagreement, Mispricing and Liquidity

Ronnie Sadka and Anna Scherbina[*]

June 18, 2004

Abstract

Examining mispricing 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 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. The apparent mispricing arises because analyst disagreement coincides with an unusually high optimistic bias in the earnings forecasts that is not fully discounted by the boundedly rational investors (Scherbina (2004)). 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. 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 becomes insignificant.

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. Convergence strategy involves finding two groups of assets that, though they are similar in characteristics and should have similar values, currently diverge in price, and forming and holding until the prices converge a zero-cost portfolio with the long position in the cheaper and the short

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position in the more expensive group of assets. 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 in 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.[1] The mispricing we consider here is fairly short-lived.[2] 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 interaction term of forecast dispersion and liquidity is shown to be the most significant negative predictor of future returns.

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

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

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.

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 taking into account 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. We show that in a setting that produces a relatively noiseless link between liquidity and the costs of arbitrage, liquidity is a significant determinant in the amount of mispricing, which suggests that market microstructure considerations have important implications for asset prices.

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 (see Jegadeesh and Titman (1993)) and the post-earnings announcement drift (see Ball and Brown

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[3]See Chordia, Roll, and Subrahmanyam (2000), Acharya and Pedersen (2003), 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.

(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. Alternatively, the view advanced by Sadka (2004) and Sadka and Sadka (2004) that changes in aggregate liquidity represent a risk factor, could explain the correlation between changes in aggregate liquidity and the dispersion-sorted portfolios studied in this paper.

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 supports a study of the empirical relationship between mispricing and liquidity as related to the costs of arbitrage.

A. Analyst disagreement and optimistic beliefs

Analyst disagreement about future earnings leads to a more optimistic than usual bias in the mean outstanding forecast. This relationship might 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) conjectures 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 highly 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.

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

One reason the mistaken beliefs of a subset of investors are not arbitraged away is that to do so would be costly. The positive relationship between analyst disagreement and trading costs follows from the 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.

While analyst disagreement leads worsens the informational disadvantage of the market maker, noise trading alleviates it. The trading cost that risk-neutral and competitive market maker

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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 potential information asymmetry about stock valuations is proportional to the information asymmetry about earnings, Kyle's Lambda will also be proportional to the standard deviation of analysts' earnings forecasts: $\lambda \sim \frac{2\sigma_{EPS}}{\sigma_u}$. One can also show that under similar assumptions the bid-ask spread in the Glosten and Milgrom (1985) model will also be proportional to analyst disagreement about earnings.[4]

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 only 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 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

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[4] An alternative explanation for the positive correlation between forecast dispersion and the price impact of trade has been suggested in a seminar 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.

the risk-free rate that is determined by the availability and demand for borrowing and usually varies across borrowers.[5] Additionally, an arbitrageur faces the risk that prices will not converge.[6] 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.[7] 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. In the limit, when convergence is instantaneous the probability that a trade will have to be terminated prematurely is zero and the short position is costless. Only trading costs are unaffected. 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. Arbitrage costs and, hence, mispricing will be closely related to a stock's liquidity.

D. Testable hypotheses

Unlike short-sale costs, trading costs affect optimistic and pessimistic investors to the same extent. Trading costs will be related to mispricing if shocks to a firm's fundamentals are impeded by some form of irrationality from being fully incorporated into stock valuations. Analyst disagree-

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

[6]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.

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

ment is usually caused by bad news.[8] Prices do not adjust down sufficiently, however, because the full extent of bad news is not reflected in analysts' forecasts. Rational arbitrageurs who realize that analyst disagreement coincides with overvaluation and would like to sell overpriced stocks are often impeded from doing so by the unusually high costs of trade, occasioned by analyst disagreement generating a high degree of information asymmetry between the market maker and informed investors. The component of the cost of trade due to information asymmetry is increasing in potential information asymmetry, captured by the magnitude of analyst disagreement, and decreasing in the degree of noise trading.

Market microstructure models differ in their predictions of whether liquidity will have an impact on the informativeness of prices. A key 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. Kyle (1985) also omits the fixed component of the costs of trade. If in addition to λV each trader is also charged the fixed cost to enable the market maker to make a profit, very small trades would become unprofitable, and the informed investor would stay away from illiquid stocks altogether. Illiquid stocks would thus have a higher likelihood of being mispriced. The 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.

According to this view, increases in the number of noise traders make prices more informative, meaning they will be closer to fundamentals. There being a high common component in liquidity, individual stock liquidity can be aggregated to the market level. The time series implication is that increases in aggregate liquidity will thus speed the convergence to fundamentals of initially mispriced individual securities. We can therefore articulate four hypotheses. The first two are specific to the mispricing of high-dispersion stocks and suggest why it has persisted. The

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[8]See Ciccone (2003) for empirical documentation of this fact.

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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 should be increasing with dispersion in analysts' earnings forecasts.

Hypothesis 2: After controlling for trading costs, the strategy of buying low-dispersion and selling short high-dispersion stocks should be unprofitable.

Hypothesis 3: After controlling for the level of analyst disagreement, the stocks perceived by the market maker to have a higher degree of information asymmetry 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.[9] 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.

Stocks with high dispersion tend to be smaller, possibly because smaller stocks are more opaque. 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. High-dispersion stocks tend to be value stocks that have done poorly in the past and have higher systematic risk (Ciccone (2003)).

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[9]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.

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, effective spread increases steadily with dispersion, as can be see from Table 3. 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. For 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 see whether the convergence strategy of short-selling high-dispersion stocks and buying low-dispersion stocks generates profit after accounting for transaction costs (and ignoring, for now, the 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.

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 ef-

fective 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 are based first on dependent sorts on size (measured by market capitalization) and then on 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. This implies that the profits of an arbitrage strategy that calls for a long position in low-dispersion stocks and a short position in high-dispersion stocks will be insignificant after accounting for transaction costs. In support of Hypothesis 2, these findings suggest that the convergence strategy does not generate a significant profit after taking into account trading costs.

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C. Estimating price impact

We use price impact of trade as a measure of liquidity throughout the paper. This is inspired by the Kyle (1985) model in the sense that it is designed to capture the cost of trade due to information asymmetry and is closely related to Kyle's Lambda. The details and motivations of our measure of price impact are presented below.

Measures of liquidity used in this paper rely on microstructure models of the price impact of trades. The market microstructure literature documents that actual trading induces both permanent and transitory effects on prices. Theoretical studies include those 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). 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 permanent price impact is associated with information asymmetry and the amount of noise trading (see Kyle (1985)), the temporary price impact often considered to be driven by the inventory costs of the market maker. Each component can be further decomposed into fixed and variable costs as a function of the number of shares traded (for example, the Lambda in the Kyle (1985) model represents the permanent variable cost function).

It is important to clarify the different economic interpretations associated with the various liquidity measures used in this literature. Following Copeland and Galai (1983) and Glosten and Milgrom (1985), many studies use the bid-ask spread as a measure of information asymmetry (see, for example, Lee, Mucklow, and Ready (1993), Leuz and Verrecchia (2000), and Affleck-Graves, Callahan, and Chipalkatti (2002)). But empirical studies have shown most of the bid-ask spread to be transitory and, hence, likely to be associated with market making costs rather than information asymmetry (see, for example, George, Kaul, and Nimalendran (1991) and Huang and Stoll (1997)).

In general, one could view the bid-ask spread as the fixed component of a more general price-impact function that includes as well a component that varies with (signed) volume as suggested by the empirical model of Glosten and Harris (1988). Sadka (2004) estimates these four components of price impact (fixed/variable for both permanent/transitory) for a large sample (for summary statistics see Tables 1 in Sadka (2004)). The results support previous evidence that the fixed part of price impact (i.e., the bid-ask spread) is mostly transitory (i.e., market making costs), the variable component mostly permanent (i.e., information asymmetry). In our empirical analysis we use the variable/permanent components of price impact as a proxy for the information environment of different stocks. See the Appendix for further discussion and details of estimation.

Permanent and transitory price impacts are correlated for the following reason. Unlike the permanent price impact, which is related to the degree of information asymmetry between the market maker and investors, the temporary price impact of trade is related to how costly it is for the market maker to maintain the market in a particular stock. One might think of it as compensation the market maker charges traders to break even. Since "buy" and "sell" orders rarely balance at any given time, the market maker is forced to keep an inventory of the stock. Given that the market maker trades in just a few stocks, the inventory portfolio is not diversified and the market maker demands a premium not just for the systematic, but also for the idiosyncratic risk of the portfolio. When uncertainty about its value is high, so is a stock's idiosyncratic risk. For this reason, when the permanent price impact of trades is high the temporary price impact is high as well.

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 and make arbitrage unprofitable after taking into account the fixed costs of trade.

One obvious question is why we use price impact and not the actual costs of trade for this analysis. The answer is that it is difficult to know what trading costs an arbitrageur would have had to pay. Although one can observe bid-ask spreads and effective spreads from past trades, these magnitudes are increasing in the size of the trade, and we would like measures on the per unit of trade basis. Moreover, if some stocks are 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 we assume that the fixed costs of trade do not vary in systematic ways across stocks, it gives us a good idea of the stocks' cost of trade.

Even though dispersion and price impact are correlated, we still observe some cross-sectional variation in the price impact of trade across high-dispersion stocks. Dispersion in analysts' forecasts does not always lead to information asymmetry. In some cases, as when an analyst, perhaps driven by the desire to secure investment banking business, issues an overly optimistic forecasts, , 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. 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. Another reason for the heterogeneity in price impact across high-dispersion stocks is the variation in the amount of noise trading across stocks.

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 higher risk-adjusted return after they enter the portfolio. If stocks are held in the portfolio for three months or longer, the more liquid high-dispersion stocks will significantly outperform the less liquid high-dispersion stocks. Why stocks must be held in the portfolio for several months in order to see the difference in performance is clear. If a stock is mispriced and arbitrage is costly, the market marker must wait for the signals about the true value of the stock

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(e.g. corporate news releases or earnings announcements) to become public in order to correct the price. 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 20% will have earned an average risk-adjusted monthly return of -0.22% (with a t-statistic of -1.50), those in the least liquid 20% a significantly lower return of -0.56% (with a t-statistic of -2.69).

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.

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. We did not report regression specifications with the cross-product *Size* x *PI* because it was never significant. As can be seen from the table, dispersion is negative and significant in all specifications, unless 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. *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.

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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 will 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. 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.

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 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. Given a drop in transaction costs, arbitrageurs will start selling shares of high-dispersion stock and reduce the overpricing. 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.[10]

We proceed to investigate how much of the underperformance in high-dispersion stocks can be captured by fluctuations in aggregate liquidity. If high-dispersion stocks earn lower returns when liquidity increases, they will have a negative correlation with the aggregate liquidity measure. To the extent that the market on average earns higher returns when liquidity increases, low-dispersion stocks will have a positive correlation with the liquidity factor. 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 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. It is clear from the graph that the regression coefficients become reliably more negative as dispersion increases. This implies that, unlike the market, high-dispersion stocks earn significantly lower returns when liquidity improves.

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[10]Naturally, an increase in liquidity as measured by a reduction in the price impact of trade might mean that either the information asymmetry about the stock value has declined or the relative number of noise traders has increased. One could test correlation of portfolio returns with changes in aggregate dispersion.

Since high- and low-dispersion stocks have an opposite relationship with aggregate liquidity, 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 might be 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. 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

In this paper we present evidence that liquidity affects mispricing because it is directly related to the costs of arbitrage. In particular, we show that high-dispersion stocks are negatively correlated with changes in aggregate liquidity. These results can, however, be consistent with an alternative explanation as follows. Recent literature argues that liquidity risk is a priced factor (see, for example, Pástor and Stambaugh (2003), Acharya and Pedersen (2003), and Sadka (2004)) and is related to other asset-pricing anomalies. For example, Sadka (2004) documents that momentum-based portfolio returns are correlated with changes in aggregate liquidity (as measured here). Similarly, Sadka and Sadka (2004) find that the post-earnings announcement drift is more pronounced in the months following earnings announcement months when liquidity has increased relative to the months of the earnings announcement.

These studies argue that drift anomalies, such as price momentum and earnings momentum, can be viewed, in part, as compensation for liquidity risk. Thus, in this context, one can view

the low returns of high-dispersion stocks as a result of their negative sensitivity to liquidity risk. In this case, the correlations of portfolio returns with aggregate liquidity changes in Table 7 can be interpreted as portfolio loadings on a liquidity risk factor in the framework of an asset-pricing model. The results of Table 8 can then be seen as evidence that liquidity risk prices dispersion-sorted portfolios. Notice that for the risk interpretation of our results, the marginal investor who prices the high-dispersion stocks is no longer likely to be the optimistic investor. In fact, under this explanation, there is no mispricing to begin with, and the high-dispersion stocks earn low returns since they can be viewed as a useful hedge against negative market-wide liquidity shocks. We would like to point out that it is difficult to distinguish between the liquidity risk interpretation and mispricing-costs of arbitrage explanation and we offer both as alternative explanations for our findings.

Finally, the evidence of a relation between liquidity and mispricing is another reason to argue that at least part of the relation between dispersion and future returns might be related to mispricing. In a recent paper, Johnson (2004) argues that high-dispersion stocks are fairly priced if one takes into account the extra value of equity as a call option in the presence of uncertainty. While not disputing the Johnson (2004) interpretation, the evidence presented here indicates that the close link between the future returns of high-dispersion stocks and liquidity can be viewed as evidence that at least part of future underpreformance is related to mispricing due to costly arbitrage.

V. Conclusion

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

We show this effect for stocks with high analyst disagreement about future earnings. Such stocks tend to be overpriced because the unusually high bias in the earnings forecasts carries through to the market prices. We hypothesize that the tendency for these stocks to be overpriced has persisted for the past 20 years in part because these stocks also have unusually high costs of trade. We conjecture that the reason for this is that the market maker is informationally disadvantaged regarding how to aggregate analysts' opinions and protect himself against adverse selection by raising the costs of trade.

We interpret liquidity to capture both information asymmetry and the amount of noise trading in a stock. As the relative number of uninformed traders increases the informational disadvantage of the market maker falls and trade becomes cheaper. The "no-arbitrage" bounds narrow and prices converge down to the fundamentals. Thus, returns on high-dispersion stocks tend to be negatively correlated with changes in aggregate market liquidity. Lower returns during months of increased liquidity indicate that prices converge down to fundamentals more quickly. We also document the cross-sectional relation between mispricing and liquidity. We show that less liquid stocks are initially the most overpriced and substantially underperform more liquid stocks as all information becomes public.

Overall, the results presented in this paper document a close relation between mispricing and liquidity. These findings suggest that market microstructure considerations have an important impact on asset prices.

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 (small)	1 (low)	0.94	2.40	0.24	0.93	0.16	0.76
		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 (large)	1	0.93	3.13	0.29	2.32	0.12	1.10
		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						
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 (small)	1 (low)	0.92	-0.05	-0.29	0.55	0.91	-0.07	-0.39	0.49	0.40	.	.
		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 (large)	1	1.02	0.13	1.04	0.17	1.04	0.20	1.62	0.15	0.07	0.13	1.08
		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

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).

Dispersion	Price impact	Three months				Six months				Nine months				Twelve months			
		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				Panel B: Controlling for Size					
	All Months	Months of Liquidity Change				All Months	Months of Liquidity Change		
Disp.		Positive	Negative	Size	Disp.			Positive	Negative
1 (low)	0.0029	0.0030	0.0032	1	1 (low)	0.0016		0.0007	0.0032
	2.04	1.52	1.55	(small)		0.75		0.29	0.91
5	0.0010	0.0002	0.0015		5 (high)	-0.0114		-0.0155	-0.0064
	0.87	0.10	0.97			-3.47		-4.53	-1.14
21	-0.0039	-0.0040	-0.0025	5	1	0.0012		0.0027	-0.0003
	-2.60	-2.28	-1.05	(large)		1.09		1.73	-0.20
25 (high)	-0.0105	-0.0124	-0.0074		5	-0.0011		-0.0024	0.0013
	-4.61	-4.41	-2.03			-0.73		-1.27	0.57
25-1	-0.0134	-0.0154	-0.0106	1	5-1	-0.0131		-0.0162	-0.0095
	-6.07	-5.24	-3.05			-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
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			Panel B: Controlling for Size			
Disp.	Liquidity Loading	T of Loading	Size	Disp.	Liquidity Loading	T of Loading
1 (low)	0.25	1.18	1	1 (low)	0.14	0.44
	0.62	2.96	(small)		-0.08	-0.21
	0.36	1.79			-0.05	-0.14
	0.37	1.96			-0.10	-0.23
5	0.11	0.63		5 (high)	-0.76	-1.56
	0.06	0.33	2	1	0.25	0.93
	-0.12	-0.71			-0.05	-0.20
	-0.01	-0.07			0.21	0.90
	0.02	0.13			-0.37	-1.49
10	0.09	0.53		5	-0.47	-1.62
	0.04	0.20	3	1	0.42	1.96
	0.01	0.08			0.01	0.08
	0.08	0.44			0.21	1.17
	0.23	1.38			-0.07	-0.40
15	0.01	0.07		5	-0.19	-0.90
	0.13	0.67	4	1	0.23	1.15
	-0.19	-0.97			0.19	1.04
	-0.23	-1.30			0.03	0.15
	-0.13	-0.58			-0.05	-0.33
20	-0.09	-0.40		5	-0.20	-0.90
	-0.04	-0.20	5	1	0.42	2.60
	-0.32	-1.20	(large)		-0.01	-0.11
	-0.42	-1.48			0.02	0.16
	-0.53	-1.60			0.16	1.12
25 (high)	-0.63	-1.89		5	-0.33	-1.54
25 - 1	-0.88	-2.74	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				
0.0404	-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	
0.0305	-0.0228			0.0041	0.79
3.47	-2.50			3.06	
-0.0044				0.0069	0.04
-0.89				4.40	

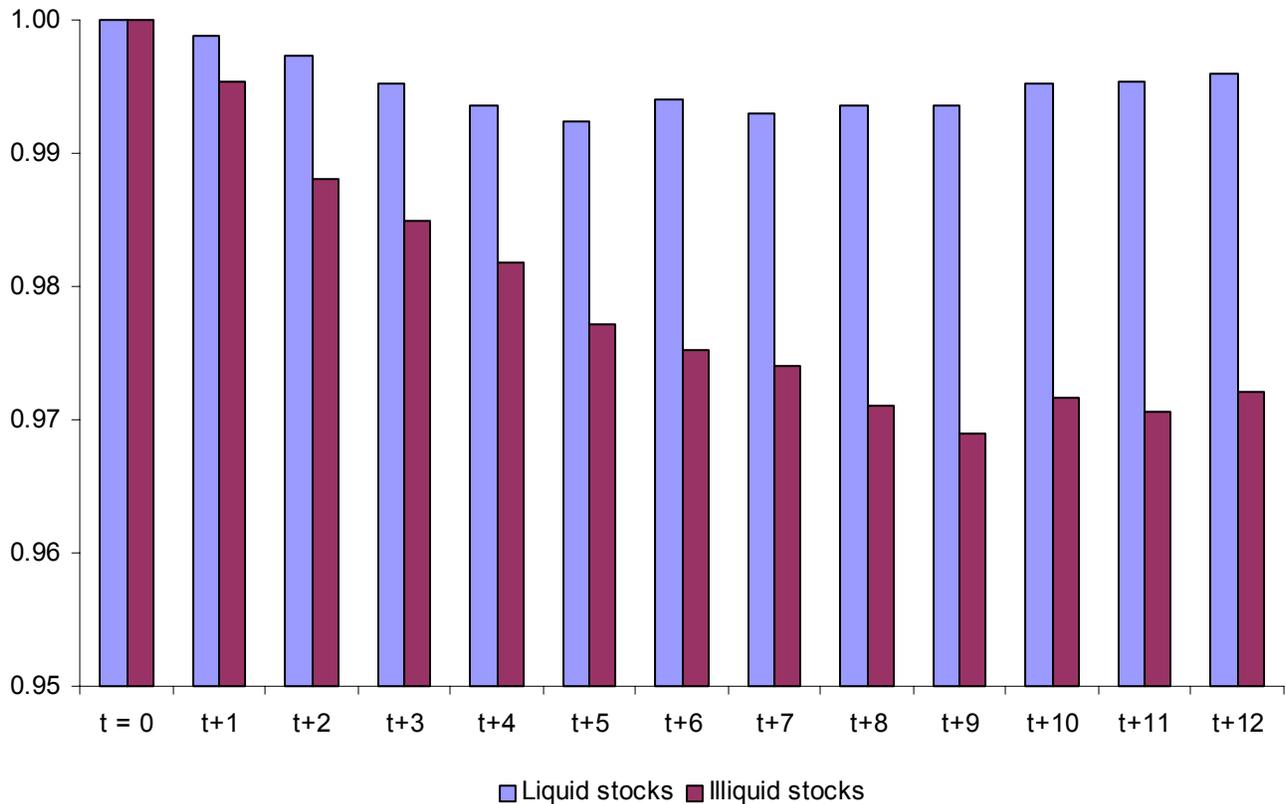| Panel B: 5 x 5 Size and Analysts' Dispersion Portoflios					
Intercept	MKT	SMB	HML	LIQ	Adjusted R^2
0.0256	-0.0172				0.27
3.88	-2.36				
0.0074	0.0008	-0.006	0.0123		0.33
0.68	0.07	-1.67	2.11		
0.0055	0.002	-0.0016	-0.0006	0.0101	0.63
0.49	0.19	-0.51	-0.12	4.55	
0.0175	-0.0118			0.0072	0.44
2.72	-1.63			3.73	
-0.0009				0.0047	0.03
-0.27				2.33	

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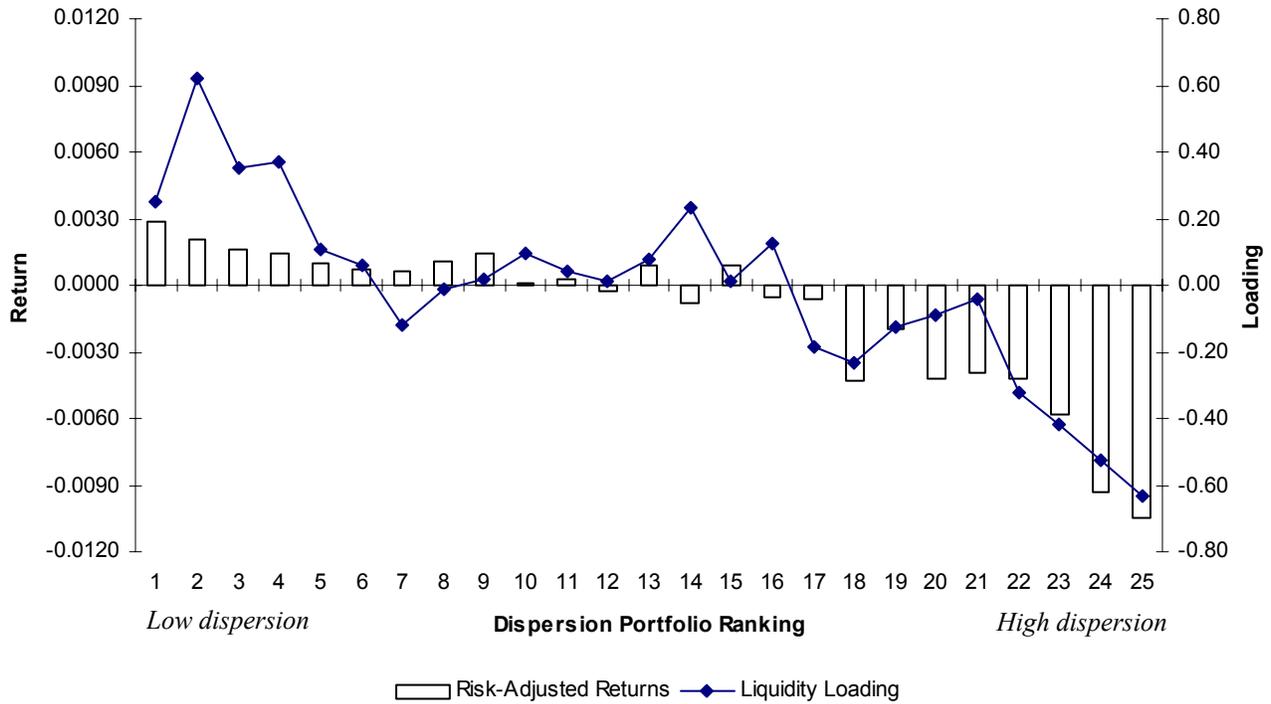
Figure 2. Risk-adjusted returns and liquidity loadings of dispersion portfolios. At the beginning of each month stocks are sorted into 25 groups according to the dispersion in their analysts' earnings forecasts available up to that month. The liquidity loadings are calculated using time-series regressions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