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Analyst Disagreement, Mispricing, and Liquidity*

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ABSTRACT

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

THE FINANCE LITERATURE HAS LONG QUESTIONED whether mispricing can persist in a well-functioning economy. Friedman (1953) argues that prices must reflect fundamental values because even if irrational investors misvalue a security, rational profit-seeking investors will trade against the mispricing, thereby pushing prices back to fundamentals. Others, however, show that prices may persistently diverge from their fundamental values when the trading costs exceed potential profits (see, for example, Shiller (1984), De Long et al. (1990), and Shleifer (2000)). The purpose of this paper is to show that mispricing is related to liquidity, particularly when the mistaken beliefs that cause the mispricing are expected to be corrected in the near future. This is because if the mispricing is expected to be short-lived, transaction costs, or the stock's liquidity, are

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a predominantly important determinant of the arbitrage costs. Furthermore, if the mispriced securities also tend to be illiquid, mispricing could persist.

Although our conjecture about the relation between mispricing and liquidity can be applied to various asset-pricing anomalies, we focus on high-analyst-disagreement stocks, as the mispricing of these stocks tends to be short-lived. Stocks with high analyst disagreement with respect to future earnings tend to underperform otherwise similar stocks (Diether et al. (2002)). This apparent overvaluation might be explained by the finding that although analysts disagree more about unfavorable earnings-related news (Ciccone (2003)), the full extent of unfavorable news is withheld from the market (McNichols and O'Brien (1997) and Hong et al. (2000)). Consequently, the prices of such stocks end up being excessively optimistic but correct downwards as information about the current year's earnings gradually becomes available. Diether et al. (2002) show that the underperformance of high-analyst-disagreement stocks (high-disagreement stocks, hereafter, for ease of exposition) continues for 6 months on average.

The relation between mispricing and liquidity is readily observable in the short-lived mispricing of high-disagreement stocks. We show that for such stocks, mistaken beliefs tend to coincide with high transaction costs. Selling high-disagreement stocks is therefore considerably less profitable after accounting for transaction costs. We conjecture that this could be a reason mispricing has persisted through the years.[1]

The empirically observed positive relation between analyst disagreement and trading costs is consistent with the theoretical models in Kyle (1985) and Glosten and Milgrom (1985). These models predict that trading costs increase with the degree of information asymmetry between the market maker and informed investors. Here, letting analyst disagreement proxy for the earnings uncertainty, the higher the analyst disagreement, the higher the informational advantage of potentially better-informed investors. The market maker therefore protects himself against potential adverse selection by raising the cost of trade.

High trading costs might prevent informed investors from trading on their knowledge. Because informed investors trade only if potential profits exceed costs, prices must lie within the "no-arbitrage" bounds around the fair value (Shleifer (2000)). To take advantage of mispricing, initially overpriced high-disagreement stocks need to be sold short until prices converge to their fundamentals. The costs of such a trade include (1) interest forgone on the margin account, (2) short-selling risks (e.g., the borrowed shares may be recalled early, a further price increase may trigger margin calls forcing the short-seller to close the position, and prices may fail to converge at all), and (3) transaction costs associated with any type of trade, long or short. The first two cost components are associated specifically with the short position and increase with

[1] If, as suggested by Johnson (2004), the underperformance of high-analyst-disagreement stocks could be explained by a rational valuation model but without transactions costs, it would be unlikely that the relation between the costs of arbitrage and future returns established in this paper would be observed.

the short position's time horizon.[2] The rationale is as follows. When convergence to fundamentals is certain and instantaneous, the risks associated with the short position disappear and the interest forgone on the margin account is zero, but transaction costs do not decline. As the time commitment of an arbitrage strategy shortens, transaction costs therefore become the more prominent component of the total cost of arbitrage. Since the mispricing we consider here is fairly short-lived, the no-arbitrage bounds should be determined to a large extent by the assets' liquidity.[3]

We confirm our conjecture that mispricing is closely related to liquidity both in the cross-section and in the time series. We document that in the cross-section of high-disagreement stocks, less liquid stocks are more likely to be mispriced as evidenced by their low future returns relative to more liquid stocks. In the time series, changes in aggregate liquidity are negatively related to the magnitude of mispricing,[4] that is, increases in liquidity reduce the costs of arbitrage and accelerate the convergence of prices to fundamentals. Finally, we show that the returns of high-disagreement stocks are contemporaneously negatively related to changes in aggregate liquidity, and as a result, the differential sensitivity to changes in aggregate liquidity can explain a significant portion of the cross-sectional variation in the returns of portfolios sorted by analyst disagreement.

The evidence of a relation between mispricing and liquidity provided in this paper augments a growing body of empirical literature on costly arbitrage. Lesmond et al. (2004), Korajczyk and Sadka (2004), and Chen et al. (2002) find that the profitability of the standard price-momentum strategy is largely eliminated after considering transaction costs; Sadka (2001) reaches a similar conclusion about the January effect. Mitchell et al. (2002) and Baker and Savasoglu (2002) find that accounting for arbitrage costs greatly reduces potential profits in merger arbitrage. Gabaix et al. (2005) document a relation 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. Wurgler and Zhuravskaya (2002) and

[2] These costs and their consequences are described in the recent literature on the limits of arbitrage. For example, Xiong (2001) and Gromb and Vayanos (2002) show that in imperfect capital markets, a further increase in price can trigger additional demand for capital and thus force informed investors to abandon potentially profitable positions. Abreu and Brunnermeier (2002) and Abreu and Brunnermeier (2003) establish that if prices can diverge from fundamentals indefinitely, informed investors 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 which they considered to be overpriced.

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

[4] See Chordia et al. (2000), Acharya and Pedersen (2005), Amihud (2002), and Pástor and Stambaugh (2003) for evidence of fluctuations in aggregate liquidity. Vayanos (2004) presents a model of how exogenous shocks to market-wide volatility can occasion fluctuations in liquidity.

Kumar and Lee (2006) document that hard-to-arbitrage stocks are more likely to deviate from fundamentals, and Gatev et al. (2006) indicate that accounting for market-microstructure effects and transaction costs can substantially reduce the profits of pairs-trading strategies. This paper shows that in a setting in which arbitrage costs are closely approximated by the costs of trade, liquidity is a significant determinant of mispricing. This suggests that market-microstructure considerations have important implications for asset pricing.

Our cross-sectional results are consistent with those of a set of papers that document that asset-pricing anomalies are more pronounced among firms with high information uncertainty. For example, using various proxies for valuation uncertainty, Zhang (2006) and Jiang et al. (2005) conjecture that the marginal investor underreacts to new information more in uncertain environments. Jiang et al. (2005) argue further that arbitrage is more costly in uncertain environments due to costlier information acquisition, higher information risk, and higher noise-trader risk. Francis et al. (2004) obtain similar results using measures designed to capture cash flow uncertainty. This paper assesses the information environment of a firm from the price impact of trading its stock, and links potential information asymmetries to costly trade and less informative prices. Finally, our time-series results contribute to the literature that documents the sensitivity of returns to aggregate liquidity (Pástor and Stambaugh (2003) and Acharya and Pedersen (2005)).[5]

The rest of the paper is organized as follows. In Section I, we discuss the relation between mispricing and liquidity when analysts disagree about future earnings, and we propose three testable hypotheses. We test these hypotheses in Section II. In Section III, we discuss our results, alternative explanations, and related findings. Section IV concludes.

I. Hypothesis Development

We hypothesize that analyst disagreement about future earnings creates a situation in which mistaken beliefs coincide with unusually high transaction costs. Mistaken beliefs are corrected quickly, ensuring that the mispricing is fairly short-lived. Because of the resulting short horizon of the potential arbitrage strategy, trading costs constitute a large fraction of arbitrage costs. This situation provides an excellent opportunity to detect the nature of the relation between mispricing and liquidity. In this section, we explain our theoretical motivation and develop several testable hypotheses.

A. Analyst Disagreement and Optimistic Beliefs

While analysts disagree more about future earnings following bad news (Ciccone (2003)), the full extent of bad news is not reflected in analysts'

[5] Also related is the work of Anderson et al. (2005) who argue that heterogeneity of beliefs is a priced risk factor. They construct a factor-mimicking portfolio as a return differential between the low- and high-analyst-disagreement portfolios and show that this portfolio can explain the time-series variation in the market index returns.

forecasts, perhaps due to analysts' incentives. Lim (2001) hypothesizes that when a firm's earnings are highly uncertain, analysts are willing to add an optimistic bias to their estimates in exchange for inside information from management about future earnings. Jackson (2005) conjectures that analysts, who derive monetary benefits from issuing optimistic forecasts, tend to add a higher bias to their estimates because they know they will be penalized less for being wrong when earnings are uncertain. The bias may also arise in part due to the fact that analysts with highly negative views choose to keep quiet. The missing left tail of the forecast distribution raises the mean of the observed distribution. The difference between the observed and the true mean is higher the more spread out the distribution, because the missing opinions are those that are the most pessimistic. Scherbina (2007) shows that the imputed bias due to missing forecasts can predict both the forecast error and price reaction around earnings announcements, confirming that the marginal investor does not adjust for missing analysts' opinions. Yet another source of the optimistic bias might be firms' attempts to suppress negative news (Hong et al. (2000)). Because the marginal investor does not realize the full extent of bad news, high-disagreement stocks consequently underperform otherwise similar stocks, and the underperformance continues for 6 months on average (Diether et al. (2002)).

B. Costs of Arbitrage

Because stocks with high analyst disagreement tend to be overpriced, arbitrageurs should sell them short until prices converge down to fundamentals. A short position is generally costly because of the requirement that sufficient cash be set aside in a margin account to ensure against default on the stock loan. A margin account usually pays an interest rate that is below the risk-free rate (see D'Avolio (2002) for a description of the market for borrowing equity). Additionally, an arbitrageur faces the risk that prices will not converge. For example, Mitchell et al. (2002) find that 30% of their sample of 82 potential arbitrage opportunities in which a company is trading at a price that is different from its parts terminates without converging. If prices diverge further before converging to fundamentals, a position might have to be closed prematurely because the additional price divergence will reduce an arbitrageur's current wealth and, if wealth has been used as collateral, more fund would be required to maintain the position. A further price divergence may also generate margin calls. When the capital constraint binds, arbitrageurs might be forced to close their positions before any profits are realized.[6]

Mistaken beliefs associated with analyst disagreement are corrected fairly quickly. The initially optimistic investors revise their beliefs downwards as they learn more about the state of earnings for the current year through press releases, quarterly earnings announcements, sales information, and news about

[6] See Xiong (2001) and Gromb and Vayanos (2002) for the theoretical arguments.

suppliers, customers, and competitors. In fact, most information about annual earnings comes out before the final earnings numbers are announced. Using a time-series model to predict earnings, Ball and Brown (1968) show that only 10% to 15% of an earnings surprise is not anticipated at the time the annual report is released. Francis and Schipper (1999) suggest that the importance of annual earnings announcements has declined even further in recent years. Mispricing is therefore corrected continuously over the entire year, not only at the time of earnings announcements. Indeed, Diether et al. (2002) find that mispricing is corrected over 6 months, on average. The short arbitrage horizon reduces the anticipated cost of the short position, but does not reduce the trading costs. Hence, arbitrage costs will be closely related to the costs of trade, and the equilibrium magnitude of mispricing will be strongly related to the stock's liquidity.

Market-microstructure models predict that trading costs increase with the degree of information asymmetry in the market (e.g., Kyle (1985) and Glosten and Milgrom (1985)). Analyst disagreement generally increases with earnings uncertainty. Hence, it is reasonable to expect that information asymmetry between the market maker and a set of investors who are potentially better informed about future earnings should increase with analyst disagreement. The market maker protects himself against adverse selection by raising trading costs, which in turn makes it costly to trade against mispricing. We conjecture that the market maker knows little about analyst-specific incentives, and thus does not know that on average analyst disagreement gives rise to optimistic forecasts and valuations.

Whereas a broader spread of equity values aggravates the information disadvantage of the market maker, noise trading alleviates this disadvantage. The trading cost that a risk-neutral and competitive market maker charges to protect himself against adverse selection increases with the degree of information asymmetry and decreases with the amount of noise trading. Glosten and Milgrom (1985) model this cost as a bid-ask spread. Kyle (1985) models this cost as a price impact of trade: $\Delta P = \lambda V$, where V is the number of shares traded and λ, commonly referred to as Kyle's Lambda, is the price impact per unit of trade. Kyle (1985) shows that λ is proportional to the standard deviation of the distribution of possible fair values of the security, σ, and inversely proportional to the standard deviation of the distribution of trades by noise traders, σ_u, that is, $\lambda = \frac{2\sigma}{\sigma_u}$. Under the assumption that the stock's value is proportional to earnings, Kyle's Lambda will also be proportional to the standard deviation of the distribution of possible earnings outcomes, as captured by the standard deviation of analysts' earnings forecasts, that is, $\lambda \sim \frac{2\sigma_{EPS}}{\sigma_u}$.[7]

[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 investors' differences of opinion about the value of a security, it implies that the demand schedule for the security will be steep and price impact of trade might be measuring simply the local steepness of the demand curve rather than the informational cost of trade.

Suppose that for a high-disagreement stock the current price, P, is higher than the fair value, P^{Fair}. According to Kyle (1985), the maximized profit of a monopolistic arbitrageur in a simplified setup in which everyone trades just once is $(P - P^{Fair})^2/4\lambda$ (twice as high in a world with continuous trading). Suppose that C captures other costs of selling a stock short beyond the price impact. The informed investor will sell short as long as the profit exceeds the costs, $(P - P^{Fair})^2/4\lambda \geq C$. This condition provides an upper bound to the amount of mispricing that could persist in equilibrium: $P - P^{Fair} = 2\sqrt{\lambda C}$. The equilibrium mispricing therefore increases with the stock's liquidity and with other costs of establishing a short position. Consistent with this analysis, Boehme et al. (2005) show that future returns of high-disagreement stocks decrease with short-sale costs, as proxied by the amount of short interest. Given that in the cross-section the current equilibrium level of mispricing is increasing in λ, future returns will be decreasing in λ, that is, $\frac{\partial Ret}{\partial \lambda} \equiv \frac{\partial[(P^{Fair}-P)/P]}{\partial \lambda} < 0$. Additionally, the time-series increases in liquidity will contemporaneously accelerate the convergence of prices to fundamentals, that is, $\frac{\partial}{\partial t}(P - P^{Fair}) = \dot{P} = \dot{\lambda}\sqrt{\frac{C}{\lambda}} < 0$ if $\dot{\lambda} < 0$ (where $\dot{P}$ and $\dot{\lambda}$ are derivatives with respect to time).

Because the resolution of uncertainty would lead to the convergence of prices to fundamentals independently of any change in arbitrage costs, we wish to test the time-series prediction using a component of liquidity that is unrelated to the resolution of firm-specific uncertainty. Chordia et al. (2000), among others, show that liquidity has a common component. We conjecture that fluctuations in this common component are related to fluctuations in the relative number of liquidity traders in the stock market. An increase in the number of liquidity traders reduces the severity of adverse selection and lowers the price impact of trade. The fluctuations in the common component of liquidity are likely to be exogenous to the resolution of the firm-specific uncertainty and can therefore be used to test our time-series prediction. We obtain changes in the common component of liquidity by averaging the price impact across stocks and calculating the unexpected changes in the resulting time series of aggregate liquidity (as in Sadka (2006)).

C. Testable Hypotheses

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

HYPOTHESIS 1: *Trading costs increase with analyst disagreement.*

HYPOTHESIS 2: *Within the subsample of stocks with a high level of analyst disagreement, the stocks with the highest price impact of trade are the most overpriced and earn the lowest future returns.*

HYPOTHESIS 3: *Initially overpriced high-disagreement stocks exhibit the highest downward price adjustment during months of increasing aggregate market liquidity. The returns of a portfolio of high-disagreement stocks are therefore negatively correlated with changes in market-wide liquidity.*

II. Empirical Results

This section describes the tests of the hypotheses above. Following Diether et al. (2002) and Johnson (2004), we define analyst disagreement, or forecast dispersion, as the standard deviation of all outstanding earnings-per-share forecasts for the current fiscal year scaled by the absolute value of the mean outstanding earnings forecast (with zero-mean-forecast observations excluded). Our sample includes firms covered by at least two analysts. To render observations of disagreement comparable in the cross-section of stocks, we only consider December fiscal-year-end firms (unless otherwise noted). To minimize the bid-ask bounce in stock returns, we follow Jegadeesh and Titman (1993) in eliminating stocks priced lower than \$5 per share. We provide a detailed description of the data in Appendix A.

Table I provides descriptive sample statistics for five portfolios sorted by analyst disagreement. For this table, the statistics of interest are computed as of June of each year and averaged over the sample years (1983 to 2001). As can be seen from the table, although high-disagreement firms have slightly lower analyst coverage and tend on average to be smaller, they are not typically small firms. This reflects the fact that analysts usually do not cover small firms, and our requirement that firms in our sample be covered by at least two analysts. The median high-disagreement firm has a market capitalization of half a billion dollars, and our sample is heavily weighted towards firms in the top four NYSE size deciles. In addition to being smaller than the overall sample, high-analyst disagreement firms tend to have higher book-to-market ratios, higher leverage, and lower returns over the previous 12 months, which together indicate that these firms have been recently struggling. High-analyst-disagreement firms have higher loadings on market, size, and book-to-market factors than other firms in the sample. Moreover, they tend to be more volatile and have higher turnover, which is not surprising given that these variables are often used to measure analyst disagreement. Finally, high-disagreement firms have a relatively high net-fixed-assets-to-assets ratio, although their sales-to-assets ratio does not differ significantly from that of the other firms in the sample.

A. Estimating Price Impact

Our use of price impact as a measure of liquidity is inspired by the Kyle (1985) model. The price impact is designed to capture the cost of trade as a function of information asymmetry and is closely related to Kyle's Lambda. However, the market-microstructure literature documents that price impact contains both informational and noninformational components.[8] The informational price

[8] 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). 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.

Table I

Summary Statistics

This table reports average statistics for five groups of stocks sorted by analyst disagreement. The stocks in the sample have December fiscal year-ends and are sorted into groups in June of each year; their characteristics are averaged first over all stocks in the group each June and then over the sample years (1983 to 2001). Analyst disagreement is measured as the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the mean forecast (with zero-mean-forecast observations excluded from the sample). A firm's adjusted turnover is calculated as turnover (volume scaled by shares outstanding) divided by the cross-sectional average turnover in the market. The loadings on the Fama and French (1993) three factors (MKT, SMB, and HML) are estimated using the prior 60 months of returns. Stocks priced at less than $5 a share are omitted from the sample.

Characteristic	Dispersion	Mean	Std	25%	Median	75%
Number of analysts	Low	15.7	9.8	7.6	15.0	22.8
		14.3	8.4	7.4	12.9	20.4
		12.3	7.9	6.2	10.6	17.3
		11.0	7.5	4.9	9.1	15.6
	High	10.0	7.4	3.9	7.8	14.1
	All	12.7	8.5	5.6	10.9	18.1
Analyst disagreement (multiplied by 100)	Low	0.42	0.19	0.29	0.45	0.58
		1.03	0.20	0.85	1.02	1.20
		2.01	0.40	1.66	1.97	2.33
		4.93	1.64	3.51	4.58	6.08
	High	17.78	11.68	10.70	13.79	20.39
	All	3.20	5.43	0.75	1.56	3.43
Market capitalization (billions of dollars)	Low	9.25	17.90	0.92	2.97	8.69
		5.64	13.22	0.74	1.84	4.82
		4.53	12.86	0.52	1.22	3.38
		2.40	5.55	0.33	0.81	2.21
	High	1.69	4.02	0.21	0.50	1.35
	All	4.70	12.60	0.43	1.19	3.58
Book-to-market ratio	Low	0.54	0.32	0.30	0.49	0.71
		0.62	0.35	0.36	0.56	0.84
		0.64	0.43	0.36	0.57	0.85
		0.68	0.44	0.40	0.62	0.89
	High	0.78	0.63	0.42	0.67	1.02
	All	0.65	0.46	0.36	0.58	0.86
Dividend yield (%)	Low	2.67	2.02	1.36	2.39	3.55
		2.97	2.43	1.20	2.54	4.33
		2.77	2.60	0.80	2.23	4.12
		2.83	5.73	0.36	1.84	3.50
	High	3.24	12.66	0.00	0.81	3.05
	All	2.90	7.47	0.56	2.09	3.71
Leverage	Low	0.21	0.19	0.06	0.16	0.33
		0.24	0.18	0.09	0.21	0.36
		0.25	0.20	0.09	0.23	0.39
		0.27	0.20	0.10	0.25	0.41
	High	0.33	0.22	0.15	0.31	0.48
	All	0.26	0.20	0.09	0.23	0.40

(*continued*)

Table I—*Continued*

Characteristic	Dispersion	Mean	Std	25%	Median	75%
Net-fixed-assets-to-assets ratio	Low	0.28	0.27	0.02	0.22	0.47
		0.36	0.28	0.08	0.32	0.62
		0.37	0.27	0.14	0.33	0.61
		0.38	0.27	0.15	0.35	0.61
	High	0.44	0.28	0.20	0.45	0.69
	All	0.37	0.28	0.11	0.32	0.62
Sales-to-asset ratio	Low	0.76	0.68	0.22	0.61	1.15
		0.81	0.68	0.31	0.65	1.18
		0.87	0.69	0.35	0.75	1.20
		0.95	0.79	0.43	0.82	1.24
	High	0.84	0.67	0.37	0.69	1.09
	All	0.85	0.71	0.33	0.72	1.18
Past 12-month cumulative return (excluding past month)	Low	0.24	0.26	0.09	0.20	0.35
		0.23	0.31	0.06	0.18	0.34
		0.24	0.40	0.02	0.16	0.35
		0.25	0.51	−0.03	0.14	0.38
	High	0.20	0.72	−0.12	0.08	0.32
	All	0.23	0.50	0.01	0.16	0.35
Standard deviation of daily returns over the past year (%, excluding past month)	Low	1.77	0.56	1.42	1.69	1.99
		1.85	0.61	1.43	1.78	2.15
		2.06	0.70	1.56	1.98	2.45
		2.36	0.79	1.80	2.24	2.77
	High	2.78	0.97	2.14	2.63	3.29
	All	2.16	0.83	1.60	2.01	2.58
Average adjusted daily turnover over past year (excluding past month)	Low	0.65	0.42	0.39	0.56	0.79
		0.72	0.55	0.41	0.59	0.86
		0.80	0.64	0.42	0.63	0.99
		0.90	0.73	0.45	0.72	1.12
	High	0.97	0.79	0.49	0.80	1.23
	All	0.81	0.66	0.42	0.64	0.99
Mkt Beta	Low	1.03	0.38	0.76	1.02	1.28
		1.00	0.42	0.69	0.97	1.28
		1.04	0.45	0.70	1.00	1.32
		1.10	0.46	0.78	1.07	1.38
	High	1.14	0.50	0.81	1.13	1.45
	All	1.06	0.45	0.74	1.03	1.34
SMB loading	Low	0.01	0.56	−0.40	−0.03	0.37
		0.10	0.58	−0.32	0.04	0.48
		0.22	0.61	−0.21	0.18	0.60
		0.44	0.66	−0.03	0.39	0.84
	High	0.64	0.74	0.13	0.60	1.09
	All	0.26	0.67	−0.22	0.20	0.67
HML loading	Low	0.27	0.61	−0.06	0.30	0.63
		0.32	0.64	−0.03	0.37	0.70
		0.31	0.68	−0.02	0.35	0.70
		0.39	0.77	−0.07	0.41	0.86
	High	0.48	0.89	−0.02	0.51	1.00
	All	0.35	0.72	−0.05	0.37	0.76

impact is associated with information asymmetry and the amount of noise trading, while the noninformational price impact is often thought to capture market-making costs such as those associated with inventory and search costs. Each component can be further divided into fixed and variable costs. The variable component captures the cost per unit of trade; for example, the Lambda in Kyle (1985) can be represented by the informational variable component of price impact.

Using the empirical model of Glosten and Harris (1988), Sadka (2006) estimates the four price-impact components for a large cross-section of stocks at the monthly frequency. (For summary statistics see Table I in Sadka (2006).) Our empirical analysis employs the variable informational component of price impact (henceforth, "price impact") as a proxy for Kyle's Lambda. Further discussion and details of our estimation are provided in Appendix B. Note, as one of four components, our price-impact measure captures only part of the total cost of trade and should thus be viewed as an ordinal measure of the cost of trade.

B. Analyst Disagreement and Liquidity

We begin by documenting the finding that stocks with high analyst disagreement underperform otherwise similar stocks. Table II shows average monthly portfolio returns for the period February 1983 to August 2001 for different asset-pricing models. The first two columns of each panel present the average excess returns and corresponding *t*-statistics; the next two columns show the CAPM alphas and their *t*-statistics; the fifth and sixth columns report alphas and *t*-statistics for the Fama-French three-factor model; and the last two columns give alphas and *t*-statistics for the three-factor model plus momentum. Panel A presents results for 25 disagreement-sorted portfolios. Panel B sorts stocks first into five size groups, and then into five analyst-disagreement groups within each size quintile. The stocks are sorted monthly into portfolios based on their characteristics as of the previous month and are held in the portfolio for 1 month. Their returns are then equal-weighted. Both panels show that average portfolio returns decline with analyst disagreement, and that risk-adjusted returns of high-disagreement portfolios are negative and statistically significant.

Hypothesis 1 states that trading costs increase with analyst disagreement. Consistent with this hypothesis, Table III shows that both the price impact and the effective spread increase with analyst disagreement. The table reports average trading costs for 25 portfolios sorted by analyst disagreement.[9] Portfolios are formed monthly based on analyst disagreement as of that month. The average informational component of the price impact and the average effective spread are calculated as of the same month. The effective spread is defined as the absolute value of the difference between the trade price and the midpoint

[9] The positive relation between trading costs and analyst disagreement also holds after controlling for size. (Results are available upon request.)

of the quoted bid and ask prices, scaled by the midpoint of these quotes. We estimate the monthly effective spread by averaging the effective spreads of all transactions for a given firm during the month. Both the price impact and the effective spread are reported in percent of price (and thus are returns) and the price impact is calculated for a trade of 10,000 shares.

Table II

Risk-Adjusted Returns of Portfolios Based on Analyst Disagreement

This table reports average returns for portfolios sorted by analyst disagreement. Analyst disagreement is measured as the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the mean forecast (with zero-mean-forecast observations excluded from the sample). Portfolio returns are reported in excess of the risk-free rate or as intercepts (alphas) of several asset-pricing models (the CAPM, the Fama-French (1993) three factors (FF3), and the Fama-French factors plus a momentum factor (FF4)). Two sets of portfolios are analyzed: 25 portfolios sorted by analyst disagreement, and 5x5 dependent sorts of size (market capitalization) and analyst disagreement. The results are reported for the period February 1983 to August 2001. The sample consists of only December fiscal-year-end firms that are available at the intersection of the CRSP and I/B/E/S databases and that are priced at no less than $5/share. Portfolios are equal-weighted and rebalanced monthly.

Panel A: 25 Analyst-Disagreement Portfolios

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

(*continued*)

Table II—*Continued*

Panel B: 5x5 Size and Analyst-Disagreement Portfolios

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

Since our explanation for the persistent underperformance of high-disagreement stocks is the high cost of trade, we could theoretically use either the price impact or the effective spread as a proxy. We are reluctant to base our analysis on the effective spread, however, because the effective spread is an appropriate measure of cost only for relatively small trades. The relevant cost measure for large trades, and the one typically considered by arbitrageurs, is the price impact. As we mention earlier, the price-impact measure we use can be viewed as an ordinal measure of the costs of trade for the purposes of the tests described below.

Note that stocks in the lowest analyst-disagreement portfolio also appear to be relatively illiquid. This might be explained by the fact that analysts tend to herd in highly uncertain environments. Relative to the second-highest disagreement portfolio, high-disagreement firms have nearly twice the price impact and

Table III

Analyst Disagreement and Liquidity

Each month stocks are sorted into 25 portfolios according to level of analyst disagreement. Analyst disagreement is measured as the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the mean forecast (with zero-mean-forecast observations excluded from the sample). The price-impact measure reported below is the permanent variable components of the total price impact of trade, estimated using the Glosten and Harris (1988) model with a dummy variable for trades above 10,000 shares. In addition, the estimation is corrected for unanticipated trade sign and signed volume (see Sadka (2006)). The price impact for every stock is estimated monthly. The effective percentage spread is measured for each transaction as the absolute value of the transaction price and the midpoint of the quoted bid and ask, divided by the bid-ask midpoint. Monthly estimates of effective spread are obtained as simple averages using the trades and quotes throughout each month. Time-series means of the monthly cross-sectional statistics are reported for the period of February 1983 to December 2000 for all NYSE-listed stocks with December fiscal year-end, with available intraday data, and priced at no less than $5/share, at the intersection of the CRSP and I/B/E/S databases. Portfolios are equal-weighted and rebalanced monthly.

Analyst Disagreement	Price Impact (%, per trade of 10,000 shares)					Effective Spread (%)				
	Mean	Std	25%	Median	75%	Mean	Std	25%	Median	75%
1 (low)	0.32	0.50	0.08	0.17	0.41	0.28	0.18	0.14	0.23	0.35
	0.22	0.30	0.08	0.14	0.27	0.23	0.17	0.14	0.19	0.27
	0.24	0.36	0.08	0.16	0.30	0.24	0.14	0.15	0.21	0.29
	0.23	0.32	0.08	0.16	0.29	0.24	0.13	0.16	0.21	0.29
5	0.24	0.29	0.09	0.17	0.31	0.25	0.14	0.16	0.22	0.30
	0.23	0.29	0.08	0.17	0.31	0.25	0.13	0.17	0.23	0.30
	0.26	0.47	0.08	0.17	0.32	0.25	0.13	0.17	0.23	0.30
	0.25	0.32	0.09	0.18	0.33	0.26	0.13	0.17	0.23	0.31
	0.25	0.31	0.09	0.17	0.33	0.26	0.13	0.17	0.23	0.32
10	0.26	0.38	0.08	0.17	0.33	0.27	0.16	0.17	0.24	0.32
	0.25	0.41	0.09	0.18	0.34	0.29	0.20	0.18	0.24	0.33
	0.26	0.38	0.08	0.17	0.33	0.27	0.15	0.17	0.24	0.33
	0.26	0.39	0.09	0.18	0.34	0.28	0.16	0.18	0.25	0.34
	0.27	0.38	0.09	0.18	0.35	0.28	0.16	0.17	0.24	0.34
15	0.28	0.40	0.09	0.18	0.35	0.30	0.19	0.18	0.25	0.36
	0.28	0.40	0.09	0.18	0.36	0.30	0.19	0.18	0.25	0.36
	0.29	0.40	0.09	0.19	0.38	0.33	0.28	0.19	0.27	0.38
	0.28	0.66	0.09	0.20	0.40	0.33	0.22	0.19	0.28	0.40
	0.31	0.43	0.09	0.20	0.41	0.34	0.21	0.19	0.29	0.42
20	0.31	0.48	0.09	0.21	0.43	0.36	0.26	0.20	0.30	0.45
	0.32	0.52	0.10	0.22	0.43	0.37	0.23	0.21	0.31	0.46
	0.33	0.47	0.10	0.23	0.45	0.39	0.24	0.22	0.33	0.50
	0.35	0.51	0.11	0.24	0.49	0.42	0.27	0.23	0.36	0.53
	0.39	0.55	0.12	0.27	0.53	0.58	1.01	0.26	0.40	0.59
25 (high)	0.40	0.65	0.13	0.28	0.57	0.53	0.28	0.32	0.47	0.70
25 – 1[a]	0.08	0.15	0.05	0.11	0.16	0.25	0.10	0.18	0.24	0.34

[a]All the differences are statistically significant at the 1% level.

more than twice the effective spread. The average effective spread for high-disagreement stocks is 0.53%, which is 0.30% higher than the average effective spread for the second disagreement-based portfolio. Short-sale costs of a median stock are small in comparison. Geczy et al. (2002) estimate that the average monthly cost of a short position for 90% to 95% of stocks at any given time is only about 0.017%.

A corollary of Hypothesis 1 is that potential arbitrage profits from selling short high-disagreement stocks will fall dramatically when trading costs are taken into account. The rough estimate of the post-transaction-cost profitability of trading strategies based on analyst disagreement presented in Appendix C shows this to be the case.

C. Mispricing and Price Impact in the Cross-Section

In this section we test Hypothesis 2, which posits that the cross-sectional variation in price impact determines the magnitude of mispricing. In the previous section the costs of trade are shown to increase with analyst disagreement. Liquidity is not perfectly related to analyst disagreement, however, because, perhaps due to different levels of investor awareness (Frieder and Subrahmanyam (2005)), two stocks can systematically attract different amounts of noise trading. Thus, the stock with more noise trading will be more liquid even if both stocks are identical in terms of level of analyst disagreement.[10] Indeed, Table III indicates that there is enough heterogeneity in the costs of trade among high-disagreement stocks to test the cross-sectional implications of liquidity; the 25^{th} and 75^{th} percentiles of price impact are 0.129% and 0.571%, respectively.

Some might argue that one should expect to find the opposite of Hypothesis 2, that when the price impact is high a stock's price should be closer to its fundamentals because the market is "learning." This is not necessarily the case, however, because in anticipation of informed trading following a news event the market maker might preemptively set high trading costs. Moreover, were prices already close to fundamentals, it is unlikely that the information costs of trading would be high.

To test Hypothesis 2, we perform calendar-time analysis, event-time analysis, and cross-sectional regressions. For calendar-time analysis we sort stocks based on both analyst disagreement and price impact. We find that illiquid high-disagreement stocks are more prone to being mispriced and thus to earning lower subsequent returns. In order to illustrate that a stock is currently mispriced, it is important to follow the stock's performance for some time into the future to allow for the resolution of uncertainty and the concurrent downward price adjustment. The sample includes all firms irrespective of fiscal

[10] Another explanation might be that analyst disagreement is not always an indicator of information asymmetry. If analyst disagreement is driven purely by a single analyst who issues an overly optimistic forecast in an attempt to secure investment banking business, analyst disagreement will not coincide with high price impact. Thus, using price impact affords an additional level of screen with respect to whether analyst disagreement is indicative of asymmetric information or simply driven by an irrelevant outlier.

year-end. We consider all firms for this test (1) because uncertainty about earnings is resolved continuously throughout the year (see, for example, Ball and Brown (1968) and Francis and Schipper (1999)) and high-disagreement firms can start converging down in price immediately, and (2) because the statistical power of our tests is higher than if we focus only on December fiscal-year-end firms (focusing on December fiscal-year-end firms reduces our sample of firms and firm-years by 31% and 34%, respectively). To adjust for the different lengths of time until earnings become known for firms of different fiscal year-ends, we scale our measure of analyst disagreement by the square root of the number of quarters left until the fiscal year-end.[11]

Table IV presents the first set of results. In Panel A, the stocks are sorted first by analyst disagreement and then by price impact. In Panel B, the stocks are sorted first by price impact and then by analyst disagreement. The stocks are sorted into portfolios every month based on their characteristics as of the previous month (or 6 months earlier, if the column header indicates that the portfolio was formed with a 6-month lag). We hold stocks in the portfolios for 3 and 6 months, and calculate monthly portfolio returns according to the Jegadeesh and Titman (1993) methodology. We report excess returns and the alphas of the CAPM and Fama-French plus momentum models. Standard errors are adjusted for autocorrelation and heteroskedasticity.

Consistent with Hypothesis 2, the relatively liquid stocks do not become mispriced; rather, it is the illiquid stocks that are likely to deviate from their fundamental values and earn significantly negative returns in the future. The insignificant return differential between the low- and high-disagreement portfolios for the portfolios formed with a 6-month lag indicates that convergence to fundamentals occurs within 6 months of high analyst disagreement having been detected in the data.

A visual illustration of our findings in event time is provided in Figure 1, Panels A and B. The figure plots cumulative abnormal returns of the top and bottom liquidity quintiles for the highest quintile of analyst-disagreement stocks. The top figure shows portfolios formed based on the analyst disagreement/liquidity sort, and the bottom figure depicts portfolios formed based on the liquidity/analyst disagreement sort. To align the time of price convergence across stocks, we use only December fiscal-year-end stocks. Stocks are sorted into portfolios at the end of June of each year and held in the portfolios for 15 months, until September of the following year. To limit the influence of outliers on cumulative abnormal returns, we trim the highest and the lowest return observation from each portfolio each month.[12]

[11] This scaling assumes that the same amount of information about annual earnings comes out every quarter. We also try scaling analyst disagreement by the square root of the number of months left until the fiscal year end, which similarly assumes that the same amount of information comes out every month. Neither scaling, however, significantly affects the result.

[12] The pattern of cumulative abnormal returns documented in Figure 1 is also preserved in the nontrimmed sample, with both equal-weighted and value-weighted portfolios. The main difference is that the standard-error bounds grow wider than in the current figure 12 months after portfolio formation (these results are available upon request).

Table IV

Performance of Portfolios Sorted by Analyst Disagreement and Price Impact

This table reports average monthly returns of two sets of analyst disagreement and liquidity-sorted portfolios. Analyst disagreement is measured as the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the mean forecast (with zero-mean-forecast observations excluded from the sample); liquidity is measured as the price impact of trade. In Panel A portfolios are sorted first by analyst disagreement and then by price impact, while in Panel B the portfolios are sorted first by price impact and then by analyst disagreement. Portfolios are formed monthly (with a 6-month lag if indicated) and stocks are held in the portfolio for 3 or 6 months (as indicated). Portfolio returns are calculated according to the Jegadeesh and Titman (1993) methodology and are equal-weighted. For each portfolio specification, the table reports average returns in excess of the risk-free rate and alphas measured relative to the Fama-French (1993) three-factor model plus the momentum factor (FF4). Returns are reported in percentages. The results are reported for the period February 1983 to August 2002 for all fiscal year-end NYSE-listed firms at the intersection of the CRSP and I/B/E/S databases (with available intraday data). Stocks with share price below $5/share are omitted from the sample. The t-statistics are corrected for autocorrelation and heteroskedasticity.

Panel A: 5x5 Analyst Disagreement/Price Impact Portfolios

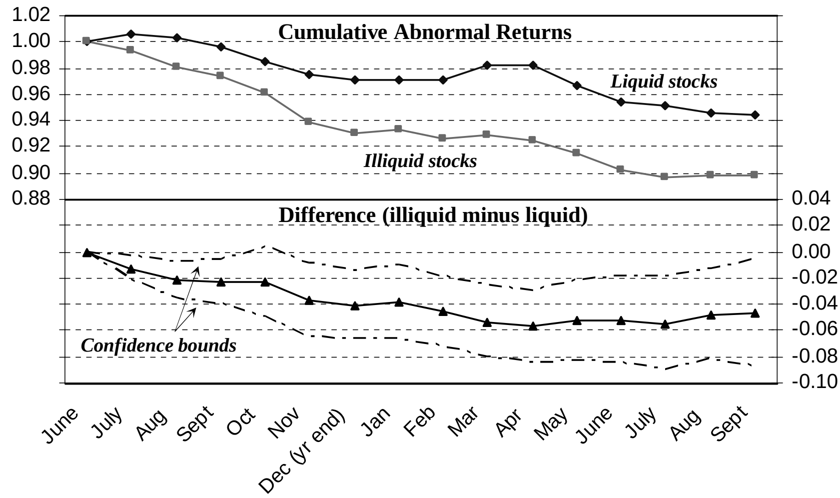
		3 Months				6 Months				6 Months with a 6-Month Lag			
Analyst Disagreement	Price Impact	Excess Return	t of Return	FF4 Alpha	t of Alpha	Excess Return	t of Return	FF4 Alpha	t of Alpha	Excess Return	t of Return	FF4 Alpha	t of Alpha
1	1 (low)	0.99	3.80	0.22	1.45	0.94	3.72	0.19	1.35	0.83	3.18	0.20	1.47
(low)		0.96	3.71	0.17	1.15	0.99	3.94	0.20	1.48	0.86	3.28	0.20	1.52
		1.01	3.80	0.20	1.32	1.01	3.87	0.20	1.39	0.85	3.20	0.13	0.96
		0.92	3.36	0.12	0.73	0.98	3.60	0.16	1.02	0.81	2.80	0.11	0.76
	5 (high)	0.94	3.18	0.19	1.17	0.96	3.34	0.21	1.40	0.69	2.51	0.11	0.81
	5 −1	−0.06	−0.35	−0.03	−0.23	0.03	0.17	0.02	0.15	−0.14	−0.85	−0.09	−0.69
5	1	0.53	1.44	−0.17	−0.92	0.57	1.60	−0.11	−0.67	0.38	1.03	−0.18	−1.14
(high)		0.67	1.91	−0.10	−0.63	0.66	1.93	−0.12	−0.82	0.52	1.45	−0.13	−0.90
		0.61	1.65	−0.23	−1.28	0.64	1.77	−0.20	−1.13	0.44	1.25	−0.21	−1.22
		0.49	1.30	−0.29	−1.73	0.52	1.41	−0.27	−1.61	0.46	1.21	−0.15	−0.99
	5	0.21	0.52	−0.49	−2.48	0.27	0.72	−0.40	−2.12	0.32	0.83	−0.17	−0.89
	5 – 1	−0.32	−2.18	−0.32	−2.30	−0.30	−2.25	−0.29	−2.49	−0.06	−0.32	0.00	0.02

(continued)

Table IV—*Continued*

Panel B: 5x5 Price Impact/Analyst Disagreement Portfolios

		3 Months				6 Months				6 Months with a 6-Month Lag			
Price Impact	Analyst Disagreement	Excess Return	t of Return	FF4 Alpha	t of Alpha	Excess Return	t of Return	FF4 Alpha	t of Alpha	Excess Return	t of Return	FF4 Alpha	t of Alpha
1	1 (low)	0.99	3.81	0.22	1.50	0.94	3.72	0.19	1.42	0.80	3.06	0.18	1.32
(low)		0.73	2.83	0.02	0.17	0.78	3.07	0.09	0.89	0.71	2.71	0.18	1.69
		0.90	3.26	0.13	1.39	0.86	3.15	0.15	1.73	0.59	2.13	0.03	0.29
		0.66	2.11	−0.12	−1.17	0.74	2.47	0.05	0.57	0.64	2.03	0.12	1.36
	5 (high)	0.57	1.57	−0.16	−0.99	0.58	1.61	−0.12	−0.76	0.39	1.07	−0.13	−0.83
	5 −1	−0.42	−1.44	−0.38	−1.49	−0.36	−1.27	−0.31	−1.29	−0.41	−1.45	−0.31	−1.27
5	1	0.90	3.05	0.19	1.21	0.93	3.26	0.20	1.33	0.64	2.30	0.09	0.73
(high)		0.77	2.46	0.03	0.23	0.84	2.89	0.11	0.85	0.65	2.23	0.06	0.51
		0.81	2.49	0.07	0.50	0.81	2.55	0.07	0.55	0.67	2.14	0.02	0.14
		0.66	1.95	−0.07	−0.56	0.68	2.03	−0.08	−0.62	0.56	1.64	−0.04	−0.34
	5	0.20	0.48	−0.49	−2.50	0.25	0.61	−0.46	−2.31	0.28	0.68	−0.27	−1.21
	5 – 1	−0.70	−2.42	−0.68	−2.59	−0.68	−2.57	−0.65	−2.62	−0.37	−1.49	−0.36	−1.51

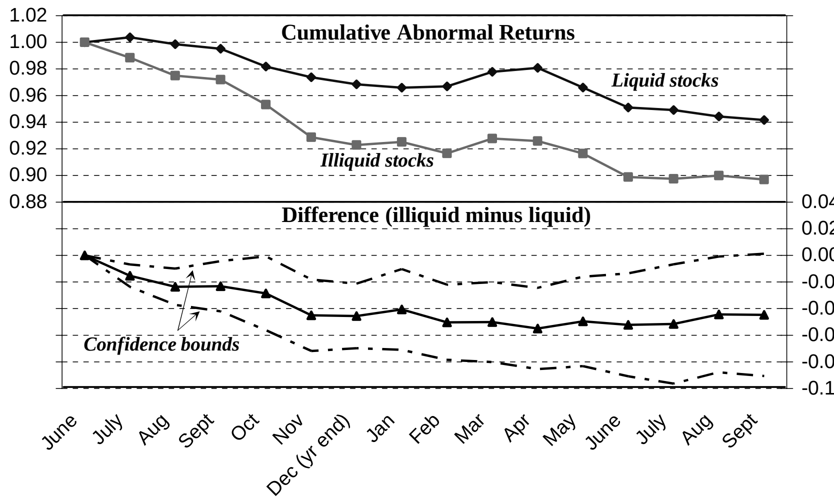


Panel A: High-analyst-disagreement stocks of analyst disagreement/liquidity-sorted portfolios

Figure 1. Cumulative abnormal returns (in event time) of high-analyst-disagreement stocks. The figure plots average cumulative abnormal returns of portfolios sorted by analyst disagreement and liquidity. Analyst disagreement is measured as the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the mean forecast (with zero-mean-forecast observations excluded from the sample); liquidity is measured as the price impact of trade. Only December fiscal-year-end stocks are considered. For Panel A, stocks are sorted every June into five groups according to the level of analyst disagreement and then into five liquidity groups. For Panel B stocks are sorted first into five liquidity groups and then five analyst-disagreement groups. For each sorting, the figures plot cumulative abnormal returns for two portfolios, the highest analyst disagreement, lowest liquidity portfolio (denoted "Illiquid stocks") and the highest analyst disagreement, highest liquidity portfolio (denoted "Liquid stocks"). Portfolios are equal-weighted, with the lowest and highest return observation trimmed, and are held for the following 15 months. Portfolio returns in excess of the risk-free rate are regressed on the Fama and French (1993) three factors plus momentum, and returns net of the model prediction are cumulated monthly over the holding period. Nine months of pre-portfolio-formation returns and 15 months of post-formation returns are used to estimate the time-series model for each portfolio. The cumulative abnormal returns are calculated for each month in a given year and then averaged over the sample years. The bottom panel of each figure plots the mean difference in cumulative returns between illiquid and liquid portfolios. The dashed lines represent 95% confidence intervals, estimated from the empirical distribution. The results are reported for the period June 1983 through Sept 2002 for NYSE-listed stocks (with available intraday data) at the intersection of the CRSP and I/B/E/S databases. Stocks with share price below $5 are omitted from the sample.

The monthly portfolio excess returns are regressed on the Fama-French plus momentum factors, and returns net of the model prediction (i.e., abnormal returns) are cumulated monthly over the portfolio holding period. To increase the precision of our estimates, we compute portfolio factor loadings each year using the 9 months prior to and the 15 months past the portfolio formation date.[13] The cumulative abnormal returns are calculated for each month in a given year, and cumulative returns in each month are then averaged over the

[13] Using 21 rather than 9 months of prior returns (for the total of 3 years of data) to estimate portfolio factor loadings does not significantly affect the results.



Panel B: High-analyst-disagreement stocks of liquidity/analyst disagreement-sorted portfolios

Figure 1—*Continued*

years of portfolio formation (1983 to 2001). The top figures of Panels A and B present the average cumulative returns for the liquid and illiquid portfolios. To estimate whether the differences in cumulative portfolio returns between liquid and illiquid portfolios are statistically significant, we calculate the mean differential cumulative return between the two portfolios up to a given month, and then average the return differential across the sample years and calculate the standard error of the mean from the empirical distribution. The bottom figures of Panels A and B represent the average cumulative return differential (solid line) and 95% confidence bounds (dotted lines).

If a portfolio were to earn no abnormal returns, a dollar invested in a portfolio should stay flat (because abnormal returns are computed net of the risk-free rate and adjusted for the exposure to risk factors). It can be seen in both sorts, however, that the value of a dollar invested in an illiquid high-disagreement portfolio falls by more than five cents by the end of the fiscal year. The figure illustrates that illiquid high-disagreement stocks are initially overpriced but decline in value as the end of the fiscal year is approached, with the price of these stocks dropping fairly quickly in the first 6 months and remaining relatively flat thereafter. These results provide additional support for Hypothesis 2.

We further quantify these liquidity-related differences in the performance of stocks in the top analyst-disagreement quintile by running a set of cross-sectional regressions. Table V presents the results of Fama and MacBeth (1973) regressions of 3-month cumulative stock returns on various predictors. Again, to ensure a fair cross-sectional comparison of the magnitude of disagreement, we limit our sample to December fiscal year-end stocks and use nonoverlapping returns formed in June and September of each year. All right-hand-side variables are known before the returns are calculated. The variable *AD* is analyst disagreement, as defined earlier. The variable *PI* is a dummy variable that takes

Table V

Fama-MacBeth Regressions

This table reports the results of Fama-MacBeth (1973) cross-sectional regressions on individual firms. The independent variable is the natural logarithm of the 3-month cumulative returns (multiplied by 100) for the July–September and the October–December periods of each year, with independent variables measured at the end of the preceding month. The independent variables are analyst disagreement (AD), measured as the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the mean forecast (with zero-mean-forecast observations excluded from the sample), and a dummy for the top 20% of price impact (PI). Control variables are size (measured as the natural logarithm of total market capitalization), book-to-market (BM, also measured in logs), momentum (MOM, measured as the past 12-month cumulative return excluding the previous month), and leverage (Lev). Only December fiscal-year-end firms in the top quintile of analyst disagreement are utilized. The results are reported for the period February 1983 to December 2000 for NYSE-listed firms at the intersection of the CRSP and I/B/E/S databases (with available intraday data). Stocks with share price lower than $5 are omitted from the sample. The *t*-statistics (in parentheses) are corrected for autocorrelation.

AD	PI	AD x PI	Size	BM	MOM	Lev	AD x Lev
−0.06							
[−2.48]							
−0.04			0.79	0.98	1.86	−1.81	
[−2.45]			[4.76]	[2.94]	[2.51]	[−1.48]	
0.09			0.80	0.99	1.85	−1.73	−0.45
[0.88]			[4.79]	[2.99]	[2.51]	[−1.46]	[−1.29]
−0.06	−1.86						
[−2.41]	[−5.58]						
−0.04	−0.48		0.74	0.96	1.84	−1.84	
[−2.39]	[−1.82]		[4.25]	[2.86]	[2.49]	[−1.51]	
0.08	−0.49		0.74	0.98	1.83	−1.77	−0.43
[0.84]	[−1.89]		[4.29]	[2.91]	[2.49]	[−1.49]	[−1.26]
−0.04	−1.63	−0.79					
[−1.20]	[−5.30]	[−2.02]					
−0.02	−0.29	−0.66	0.74	0.96	1.78	−1.74	
[−0.92]	[−1.19]	[−1.90]	[4.25]	[2.85]	[2.43]	[−1.46]	
0.08	−0.30	−0.68	0.74	0.97	1.75	−1.64	−0.41
[0.80]	[−1.21]	[−2.04]	[4.26]	[2.91]	[2.39]	[−1.42]	[−1.17]

the value of one for the highest price-impact-based quintile of stocks. Various control variables are also included in the regressions. The variable *MOM* is the cumulative return over the past 12 months, and *Lev* the firm's leverage, which, together with the leverage and analyst disagreement interaction term, Johnson (2004) shows to be significant.

As can be seen from the table, analyst disagreement tends to be a negative and significant predictor of returns. Including controls reduces the significance of analyst disagreement. The variable *PI* is a negative and significant predictor of returns when the price impact and analyst disagreement interaction term is not included, indicating that illiquid stocks in the top quintile of analyst disagreement tend to be overpriced initially. The variable *MOM* is highly statistically significant, indicating that the underperformance of high-disagreement stocks is strongly related to the momentum phenomenon. The Johnson (2004) leverage variables are negative but not statistically significant predictors of returns. (The discrepancy between our results and Johnson (2004) could be explained by our use of only high-disagreement firms that are also NYSE-traded and have a December fiscal year-end.) The $AD \times PI$ interaction variable is negative and statistically significant in all specifications, indicating that illiquid, high-disagreement firms underperform otherwise similar firms.

The results in this section imply that at least part of the future underperformance of high-disagreement stocks is related to the initial mispricing and the difficulty of arbitraging this mispricing away. The results therefore lend further support for Hypothesis 2, which conjectures that the least liquid high-disagreement stocks tend to be the most mispriced.

D. Portfolio Returns and Aggregate Liquidity Changes

Hypothesis 3 states that unexpected time-series increases in liquidity reduce mispricing. We use the Sadka (2006) time series of unexpected changes in aggregate liquidity rather than changes in liquidity for individual stocks because in using the aggregate measure we are focusing on the common component of liquidity that is not likely to be related to firm-specific information events. Sadka (2006) computes a time series of changes in aggregate liquidity by first averaging price impact across stocks every month, and then estimating the unexpected month-to-month changes in this aggregate measure using Box-Jenkins methods. Since higher price impact implies lower liquidity, the sign of changes in aggregate price impact is reversed in the time series, with negative shocks to the aggregate price impact being reinterpreted as increases in market liquidity.

A decrease in price impact can be caused either by a decrease in information asymmetry or by an increase in noise trading. Because the average level of analyst disagreement about the stocks in the high-disagreement portfolio remains steady over time (albeit decreasing slightly towards the end of the calendar year because most firms have a December fiscal year-end), we interpret an increase in aggregate market liquidity as a signal that more uninformed traders have entered the market.[14] Given a decline in transaction costs, prices of high-disagreement stocks will converge down to fundamentals. This is when high-disagreement stocks will experience the most pronounced price corrections and the lowest returns.

If high-disagreement 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 tends to earn higher returns when liquidity increases (Baker and Stein (2004)), returns on low-disagreement stocks will be positively correlated with changes in aggregate liquidity. Figure 2 plots the alphas of the Fama-French three-factor model for 25 portfolios sorted by analyst disagreement (as bars). This figure also plots

[14] It is possible that some liquidity changes are 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.

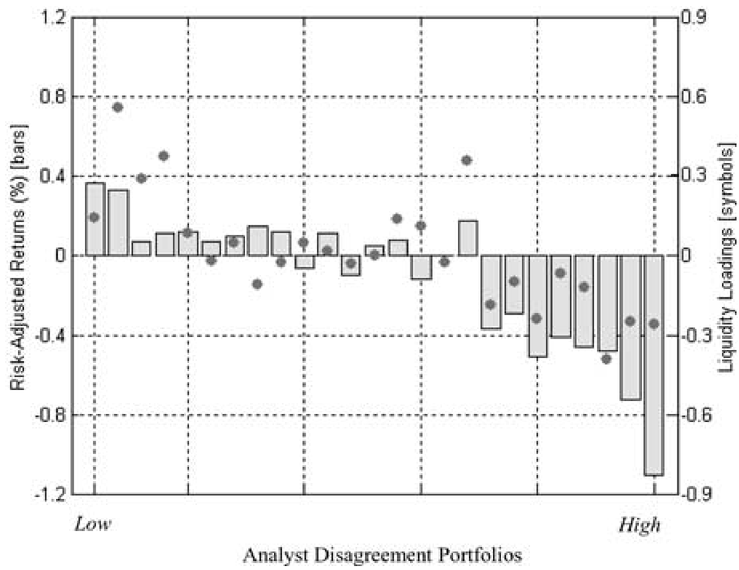


Figure 2. Risk-adjusted returns and liquidity loadings of analyst disagreement-sorted portfolios. Stocks are sorted at the beginning of each month into 25 groups according to the level of analyst disagreement in the previous month. Analyst disagreement is measured as the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the mean forecast (with zero-mean-forecast observations excluded from the sample). Liquidity loadings are calculated using time-series regressions of portfolio returns on the Fama and French (1993) three factors and the Sadka (2006) nontraded liquidity factor. Risk-adjusted returns are calculated using similar time-series regressions, but without the liquidity factor. The results are reported for the period February 1983 through August 2001 for all stocks at the intersection of the CRSP and I/B/E/S databases. Portfolios are equal-weighted and rebalanced monthly. Stocks with share price lower than \$5 are omitted from the sample.

the regression coefficients of excess returns on the time series of changes in aggregate liquidity for these portfolios (as dots). (The three Fama-French factors are also included in the latter regressions.) The results indicate that regression coefficients become more negative as analyst disagreement increases, which implies that returns of high-disagreement portfolios tend to be negatively correlated with changes in aggregate liquidity. This result is consistent with Hypothesis 3.

Since high- and low-disagreement stocks have an opposite relation with respect to aggregate liquidity changes, the performance of an arbitrage strategy that involves selling overpriced, high-disagreement stocks and buying low-disagreement stocks will be positively related to changes in market liquidity, earning the highest returns when liquidity increases. The results reported in Table VI suggest that a large portion of the variation in the mean returns of disagreement-sorted portfolios can be explained by their correlation with the time series of changes in aggregate liquidity. Results for this table are computed in two steps: Portfolio returns are regressed on the times series of factors in each specification, then average portfolio returns are regressed on the

Table VI

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

This table reports the results of cross-sectional regressions of various asset-pricing models using analyst disagreement-sorted portfolios. The models are of the form $E(R_{i,t}) = \gamma_0 + \gamma' b_i$, where $R_{i,t}$ are the returns of portfolio i, b_i is a vector of factor loadings, and γ are the estimated premia. The loadings are computed through a time-series multiple regression of portfolio returns (excess of risk-free rate) on the factors tested. The factors considered are the Fama and French (1993) three factors (MKT, SMB, and HML), the momentum factor (MOM), and the Sadka (2006) nontraded liquidity factor (LIQ). The regression models are estimated using the Fama and MacBeth (1973) procedure. The premium estimates are reported in percent. Two sets of portfolios are analyzed: portfolios sorted into 25 groups based on analyst disagreement, and portfolios sorted into 5x5 dependent sorts of size (market capitalization) and analyst disagreement. Analyst disagreement is measured as the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the mean forecast (with zero-mean-forecast observations excluded from the sample). The results are reported for the period February 1983 to August 2001, and for December fiscal-year-end NYSE-listed firms at the intersection of the CRSP and I/B/E/S databases (with available intraday data). Portfolios are equal-weighted and rebalanced monthly. Stocks with price lower than \$5/share are omitted from the sample. Each adjusted-R^2 is computed from a single cross-sectional regression of average excess returns of the portfolios on their factor loadings. The t-statistics (in parentheses) are corrected for the sampling errors in the estimated b_i (Shanken (1992)).

Intercept	MKT	SMB	HML	MOM	LIQ	Adjusted-R^2
Panel A: 25 Analyst Disagreement Portfolios						
3.16	−1.94	−0.76	0.05			0.72
[4.35]	[−2.58]	[−1.93]	[0.11]			
2.92	−1.61	−0.73	−0.08	0.87		0.72
[4.19]	[−2.18]	[−1.87]	[−0.15]	[1.71]		
2.81	−1.76	−0.49	0.10		0.37	0.75
[3.86]	[−2.36]	[−1.20]	[0.19]		[2.81]	
2.73	−1.62	−0.51	0.03	0.73	0.34	0.74
[3.87]	[−2.19]	[−1.22]	[0.06]	[1.42]	[2.50]	
Panel B: 5 x 5 Size and Analyst Disagreement Portfolios						
4.38	−3.07	−0.19	−1.27			0.33
[4.12]	[−3.15]	[−0.75]	[−2.39]			
4.61	−3.37	0.18	−0.98	1.80		0.34
[4.35]	[−3.45]	[0.81]	[−1.85]	[3.16]		
3.92	−2.58	−0.10	−1.82		0.75	0.49
[3.99]	[−2.91]	[−0.38]	[−3.33]		[4.17]	
4.11	−2.81	0.15	−1.59	2.07	0.73	0.48
[4.25]	[−3.23]	[0.66]	[−2.89]	[3.64]	[3.95]	

factor-regression coefficients in order to determine whether the differences in the coefficients can explain the differences in average returns across portfolios. We employ the Shanken (1992) standard-error correction to account for the two-step nature of the estimation. As can be seen from the table, the coefficient on liquidity is always positive and significant, which implies that high-disagreement stocks that earn low future returns also have substantially lower liquidity betas than other portfolios. For portfolios sorted by size and analyst disagreement, adding the time series of changes in aggregate liquidity as an explanatory factor increases the R^2 of the regressions by as much as 14% relative to the model with the three Fama-French factors and momentum. The additional explanatory power of liquidity is lower for the 25 portfolios sorted by analyst disagreement only, indicating that size and liquidity are closely related.

It is striking that the market, size, and book-to-market factors seem to generate negative risk premia. The reason for the negative risk premia is that high-disagreement stocks have higher loadings on each of these factors, but they end up earning lower returns. Although the time series of liquidity changes alone has little explanatory power with respect to the returns of disagreement-sorted portfolios (not reported here), it works well in conjunction with other factors precisely because it explains the pattern of returns on high-disagreement stocks that is not explained by the Fama-French three-factor model. These stocks have high market betas (because analysts tend to disagree more about stocks with high systematic risk), but tend to earn lower returns than the market portfolio when market-wide liquidity improves. Although the returns of these stocks should be highly correlated with market returns, they move in the opposite direction when market-wide liquidity improves. The regression R^2 increases dramatically with the addition of the changes in the aggregate liquidity variable (rather than going up by less than the R^2 of the regression on this variable alone) 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 of the evidence presented in this section supports Hypothesis 3, which posits that increases in aggregate liquidity coincide with a more rapid convergence of prices to fundamentals.

III. Discussion

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

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

We show that increases in liquidity are related to the returns of initially mispriced stocks because increases in liquidity accelerate the convergence of prices to fundamentals. Distinct in flavor but similar in spirit is the alternative explanation that liquidity is a priced risk factor. If the marginal investor has a preference for liquidity, then high-disagreement stocks, whose returns are negatively correlated with changes in liquidity, will earn lower returns in equilibrium. The view that liquidity is a risk factor is advanced by Pástor and Stambaugh (2003), Acharya and Pedersen (2005), and Sadka (2006). Also related is a recent paper of Anderson et al. (2005) who use the return spread between high- and low-disagreement portfolios to show that heterogeneous beliefs are a priced risk factor.

IV. 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 related to 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 magnitude of mispricing. This is precisely what this paper documents.

One of the principal insights of the market-microstructure literature is that costs of trade are determined endogenously based on the degree of information asymmetry faced by the market maker. Here, the source of information asymmetry is related to uncertainty about future earnings to the extent that this uncertainty translates into uncertainty about a firm's value. In support of this view, we show that high-analyst-disagreement stocks have unusually high costs of trade. These unusually high costs of trade could, in part, be the reason why the mispricing of high-analyst-disagreement stocks has persisted for the past 20 years.

The connection between mispricing and the costs of trade should not be limited only to stocks with high analyst disagreement about future earnings. Any difficult-to-interpret news related to a firm's value could lead to an increase in the information-related trading costs that the market maker would charge in order to protect himself against the adverse selection of potentially better-informed investors. This increase in trading costs could delay the speed with which news is impounded into prices. The relation between mispricing and information-related trading costs should be explored further since it suggests a natural link between asset pricing and market-microstructure considerations. This line of research could shed light on the slow reaction to news and other asset-pricing anomalies that may persist due to endogenously high information-related trading costs.

Appendix A: Data Description

Analysts' earnings forecasts are taken from the Institutional Brokers Estimate System (I/B/E/S) U.S. Detail History and Summary History data sets.

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 ordinarily calculated on the third Thursday of each month. The Detail History file records individual analyst forecasts and dates of issue. Each record also contains the revision date on which the forecast was last confirmed to be accurate.

The standard-issue Summary and Detail files suffer from a data problem that makes them unsuitable for the purposes of this paper. In these data sets, I/B/E/S adjusts the earnings per share for stock splits and stock dividends after the date of the forecast in order 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. However, these firms tend to be the ones that did well ex-post. Observations with a 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 (produced by I/B/E/S at our request) that are not adjusted for stock splits.

Data on stock returns, prices, and shares outstanding are from the monthly stock files of the Center for Research in Security Prices (CRSP). The accounting data are from the merged CRSP/Compustat database. If less than 3 months had elapsed since the latest fiscal-year-end date, accounting data for the preceding year is used. The 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 of preference), as available. The book-to-market ratio is defined as the ratio of the book value of equity to the market value of equity. The latter is calculated as the product of the 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 the 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 not in the top NYSE market-capitalization decile. 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 not in the top NYSE market-capitalization decile. At the end of 1999, the respective numbers were 3,466 and 2,525. The pattern is similar for the intersection of the I/B/E/S, CRSP, and Compustat data sets, although the total number of available observations is lower because Compustat contains only a subset of the stocks in CRSP. The number of stocks in 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.

We obtain intraday data to calculate trading costs from two databases, namely, The Institute for the Study of Securities Markets (ISSM) database, which 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), and The New York Stock Exchange Trades and Automated Quotes (TAQ) database, which includes data for NYSE, AMEX, and NASDAQ for the period January 1993 through August 2001.

Appendix B: Estimating Permanent Price Impact

This appendix summarizes the estimation procedure developed in Sadka (2006). 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):

$$m_t = E_t[\tilde{m}_{t+1} \mid D_t, V_t, y_t], \tag{B1}$$

where V_t is the order flow, D_t is an indicator variable that receives a value of one for a buyer-initiated and negative one for a seller-initiated trade, and y_t is 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 the midpoint are excluded from the estimation.)

The literature distinguishes between the permanent and transitory effects that trades exert on prices. Permanent effects are attributed to the possibility of insiders trading on private information; transitory effects are associated with costs of making market, such as inventory and order processing. Sadka (2006) 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 price-impact components, denoted as follows: Fixed effects are given by Ψ and $\bar{\Psi}$ (permanent and transitory, respectively), and variable costs are given by λ and $\bar{\lambda}$ (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

$$m_t = m_{t-1} + D_t[\Psi + \lambda V_t] + y_t, \tag{B2}$$

where Ψ and λ are the fixed and variable permanent price-impact costs, respectively. Equation (B2) describes the innovation in the conditional expectation of the security's value through new information, both private (D_t, V_t) and public (y_t). Notice that new information exerts a permanent impact on expected value.

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

$$p_t = m_t + D_t[\bar{\Psi} + \bar{\lambda} V_t]. \tag{B3}$$

Notice that $\bar{\Psi}$ and $\bar{\lambda}$ are temporary effects, as they affect only p_t and are not carried on to p_{t+1}. Taking first differences of p_t (equation (B3)) and substituting $\Delta\, m_t$ from equation (B2) we have

$$\Delta p_t = \Psi D_t + \lambda D_t V_t + \bar{\Psi}\Delta D_t + \bar{\lambda}\Delta D_t V_t + y_t, \tag{B4}$$

where y_t is the unobservable pricing error.

The formulation in equation (B4) assumes that the market maker revises expectations according to the total order flow observed at time t. However, the literature documents predictability in the order flow (see, for example, Hasbrouck (1991a,b), 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 et al. (1997), and Huang and Stoll (1997), equation (B4) 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's value 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 (2006) for more details.) Equation (B4) thus translates to

$$\Delta p_t = \Psi \varepsilon_{\Psi,t} + \lambda \varepsilon_{\lambda,t} + \bar{\Psi}\Delta D_t + \bar{\lambda}\Delta D_t V_t + y_t. \tag{B5}$$

Lastly, the literature documents the 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)). Accordingly, large, or block, trades (generally taken to be trades in excess of 10,000 shares) are separated from smaller trades in the estimation using dummy variables. The model in equation (B5) is estimated separately for each stock every month using Ordinary Least Squares (including an intercept) with corrections for serial correlation in the error term.

Appendix C: Arbitrage Profits Net of Trading Costs

We estimate the profitability of disagreement-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 et al. (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 et al. (2002), and Korajczyk and Sadka (2004)). We use the percentage effective spread to proxy for transaction costs. As earlier, the effective spread for each transaction is the absolute value of the transaction price and the midpoint of the quoted bid and ask divided by the midpoint of these quotes. Monthly estimates for each stock are then obtained as simple averages over the trades in a given month. The effective spread is a noisy measure of the cost of trade faced by the arbitrageur, and typically increases with the size of the trade. Ideally, we would like to normalize trading costs across stocks, for example, by using the cost per dollar of trade.

To get a rough idea of how much trading costs will reduce the profits of the convergence strategy of selling high-disagreement stocks, we calculate transaction costs incurred while trading a stock, ignoring the additional costs of a short position. We start by value-weighting stocks in the portfolio in order to avoid the cost of rebalancing. Trading costs are incurred only when a stock enters or exits the portfolio. Because portfolios are reformed at the end of each month, we use a stock's average effective spread over a given month to proxy for the stock's trading costs that month. This methodology no doubt overestimates the trading costs faced by a savvy arbitrageur. A sophisticated arbitrageur could achieve a lower trading cost than the average monthly effective spread by, for example, trading at the times of the month when the stock's liquidity is at its highest or trading illiquid stocks less often.

To address the second concern, we reestimate total trading costs by liquidity-weighting stocks in the portfolios, that is, we set portfolio weights to be inversely proportional to the effective spread. Though liquidity-weighting is not optimal for minimizing overall transaction costs because of the need to rebalance, portfolios will nonetheless thereby contain fewer shares of illiquid stocks, reducing the overall cost of trade. In any case, our estimation of the total cost of the strategy does not take into account portfolio rebalancing costs, and thus provides a lower bound on transaction costs. Illiquidity-weighted portfolios provide the upper bound of the transaction costs by setting portfolio weights proportional to the effective spread.

Table CI reports average returns in excess of the risk-free rate, Fama-French alphas (measured as the risk-adjusted return relative to the Fama and French (1993) three-factor model), and effective spreads for 25 disagreement-sorted portfolios. Table CII reports the results for the 25 size/disagreement-sorted portfolios. As can be seen from the tables, value-weighting reduces the average effective spread relative to equal-weighting because it underweights smaller stocks, which tend to be less liquid. Consistent with our cross-sectional findings, illiquidity-weighting produces the highest alphas, but also the highest transaction costs, while liquidity-weighting produces the lowest alphas, but also the lowest trading costs.

Actual Cost is the average monthly trading cost for a portfolio. For example, the small high-disagreement portfolio has average value-weighted effective spread of 0.62%. That the actual monthly cost of trade is only 0.34% indicates

Table CI

Post-Transaction-Cost Performance of Portfolios Sorted by Analyst Disagreement

This table reports the post-transaction-cost performance of 25 portfolios sorted by analyst disagreement. Analyst disagreement is measured as of the previous month as the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the mean forecast (with zero-mean-forecast observations excluded from the sample). Four different portfolio weighting schemes are implemented: equal-weighted, value-weighted, illiquidity-weighted, and liquidity-weighted. Portfolios are rebalanced each month. The trading cost of a stock is computed as the average percentage effective spread during the month prior to the time when the stock has entered or exited the portfolio. The effective percentage spread is measured for each transaction as the absolute value of the transaction price and midpoint of the 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. Illiquidity weights are the proportions using the effective spread of each stock (measured the previous month), while liquidity weights are the inverse of effective spread. 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 the three Fama-French (1993) factors), the *t*-statistic of alpha, and the average effective spread of the stocks in each portfolio. In addition, the table reports the actual average monthly trading costs, which take into account only the 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. The numbers in the table are reported in percentages. The results are reported for the period February 1983 to December 2000 and for all NYSE-listed firms at the intersection of the CRSP and I/B/E/S databases (with available intraday data). Stocks with share price below $5 are omitted from the sample.

	Equal-Weighted							Value-Weighted						
Analyst Disagreement	Excess Return	FF Alpha	t of Alpha	Effective Spread	Actual Cost	Net Alpha	t of Alpha	Excess Return	FF Alpha	t of Alpha	Effective Spread	Actual Cost	Net Alpha	t of Alpha
1 (low)	1.39	0.49	3.52	0.23	0.18	0.31	2.22	1.22	0.37	1.97	0.10	0.05	0.32	1.69
	0.97	−0.05	−0.31	0.17	0.17	.	.	0.95	0.03	0.18	0.13	0.11	.	.
	1.16	0.20	1.38	0.19	0.21	.	.	1.26	0.38	1.97	0.15	0.15	0.22	1.18
	0.88	−0.09	−0.67	0.20	0.25	.	.	0.90	0.07	0.46	0.16	0.19	.	.
5	0.96	0.04	0.30	0.22	0.29	.	.	1.01	0.13	0.71	0.16	0.21	.	.
	0.95	0.07	0.53	0.22	0.30	.	.	0.84	−0.03	−0.21	0.18	0.23	.	.
	0.82	−0.17	−1.13	0.23	0.32	.	.	0.80	−0.18	−0.96	0.18	0.23	.	.
	0.94	−0.03	−0.17	0.23	0.32	.	.	0.72	−0.16	−0.94	0.18	0.25	.	.
	0.79	−0.15	−1.09	0.24	0.34	.	.	0.57	−0.43	−2.38	0.19	0.27	−0.16	−0.86
10	0.91	−0.06	−0.43	0.26	0.35	.	.	0.78	−0.20	−1.07	0.22	0.28	.	.
	0.80	−0.13	−0.82	0.26	0.37	.	.	0.86	−0.04	−0.19	0.20	0.30	.	.
	0.76	−0.19	−1.36	0.27	0.40	.	.	0.71	−0.19	−0.95	0.20	0.28	.	.
	0.78	−0.21	−1.43	0.30	0.40	.	.	0.81	0.02	0.08	0.22	0.28	.	.
	0.84	−0.13	−0.80	0.29	0.42	.	.	1.06	0.11	0.53	0.23	0.33	.	.
15	0.73	−0.16	−0.97	0.31	0.43	.	.	0.75	−0.13	−0.60	0.24	0.33	.	.
	0.97	−0.09	−0.52	0.31	0.43	.	.	0.63	−0.47	−2.41	0.25	0.32	−0.15	−0.78
	0.86	−0.12	−0.80	0.33	0.43	.	.	0.81	−0.03	−0.12	0.24	0.31	.	.
	0.89	−0.19	−1.12	0.34	0.42	.	.	0.58	−0.36	−1.71	0.24	0.30	−0.07	−0.33
	0.81	−0.29	−1.63	0.37	0.44	.	.	0.93	−0.11	−0.46	0.25	0.30	.	.
20	0.78	−0.23	−1.17	0.38	0.45	.	.	0.88	−0.01	−0.04	0.25	0.28	.	.

(continued)

Table CI—*Continued*

	Equal-Weighted							Value-Weighted						
Analyst Disagreement	Excess Return	FF Alpha	t of Alpha	Effective Spread	Actual Cost	Net Alpha	t of Alpha	Excess Return	FF Alpha	t of Alpha	Effective Spread	Actual Cost	Net Alpha	t of Alpha
	0.58	−0.53	−2.78	0.40	0.45	−0.08	−0.42	0.99	0.00	−0.02	0.26	0.28	.	.
	0.76	−0.29	−1.38	0.44	0.46	.	.	0.96	−0.01	−0.04	0.30	0.33	.	.
	0.65	−0.44	−1.90	0.46	0.45	.	.	0.70	−0.44	−1.56	0.35	0.30	−0.14	−0.48
	0.52	−0.64	−2.37	0.51	0.42	−0.23	−0.84	0.64	−0.42	−1.47	0.34	0.26	−0.16	−0.55
25 (high)	0.22	−0.76	−2.53	0.55	0.30	−0.46	−1.52	0.49	−0.45	−1.33	0.36	0.18	−0.27	−0.81
	Illiquidity-Weighted							Liquidity-Weighted						
Analyst Disagreement	Excess Return	FF Alpha	t of Alpha	Effective Spread	Actual Cost	Net Alpha	t of Alpha	Excess Return	FF Alpha	t of Alpha	Effective Spread	Actual Cost	Net Alpha	t of Alpha
1 (low)	1.57	0.69	3.67	0.37	0.33	0.37	1.93	1.25	0.34	2.56	0.15	0.10	0.24	1.81
	0.88	−0.13	−0.78	0.22	0.22	.	.	1.01	0.01	0.04	0.15	0.13	.	.
	1.24	0.27	1.59	0.24	0.27	0.00	0.02	1.10	0.14	0.99	0.16	0.17	.	.
	0.93	−0.05	−0.30	0.25	0.31	.	.	0.86	−0.09	−0.69	0.17	0.21	.	.
5	0.99	0.05	0.30	0.36	0.55	.	.	0.95	0.05	0.34	0.18	0.23	.	.
	0.98	0.13	0.80	0.29	0.39	.	.	0.88	0.00	0.03	0.19	0.25	.	.
	0.92	−0.08	−0.44	0.28	0.43	.	.	0.78	−0.21	−1.37	0.19	0.26	.	.
	1.00	0.05	0.28	0.28	0.39	.	.	0.88	−0.09	−0.60	0.20	0.28	.	.
	0.93	0.03	0.15	0.29	0.42	.	.	0.70	−0.28	−2.08	0.21	0.29	.	.
10	0.99	0.03	0.17	0.32	0.46	.	.	0.86	−0.12	−0.86	0.22	0.30	.	.
	0.80	−0.09	−0.50	0.30	0.45	.	.	0.83	−0.10	−0.63	0.22	0.31	.	.
	0.74	−0.21	−1.27	0.42	0.68	.	.	0.74	−0.21	−1.49	0.23	0.32	.	.
	0.85	−0.20	−1.03	0.60	0.71	.	.	0.75	−0.20	−1.34	0.24	0.32	.	.
	0.87	−0.06	−0.33	0.46	0.77	.	.	0.82	−0.15	−0.97	0.24	0.34	.	.
15	0.79	−0.10	−0.44	0.54	0.76	.	.	0.75	−0.15	−0.90	0.25	0.34	.	.
	1.13	0.10	0.46	0.47	0.68	.	.	0.86	−0.21	−1.38	0.25	0.34	.	.
	0.75	−0.20	−1.09	0.45	0.61	.	.	0.88	−0.09	−0.61	0.26	0.35	.	.
	0.91	−0.19	−0.91	0.43	0.57	.	.	0.78	−0.29	−1.69	0.27	0.34	.	.
	0.83	−0.29	−1.34	0.61	0.65	.	.	0.79	−0.32	−1.78	0.29	0.35	.	.
20	0.81	−0.19	−0.83	0.47	0.57	.	.	0.73	−0.24	−1.20	0.30	0.35	.	.
	0.40	−0.73	−3.36	0.49	0.57	−0.15	−0.71	0.65	−0.42	−2.06	0.32	0.35	−0.07	−0.34
	0.70	−0.32	−1.37	0.58	0.67	.	.	0.74	−0.30	−1.40	0.34	0.35	.	.
	0.68	−0.31	−1.20	0.69	0.69	.	.	0.64	−0.52	−2.22	0.35	0.33	−0.20	−0.84
	0.48	−0.67	−2.14	0.64	0.57	−0.11	−0.37	0.45	−0.68	−2.52	0.38	0.31	−0.38	−1.39
25 (high)	−0.03	−0.98	−2.86	0.68	0.41	−0.58	−1.68	0.47	−0.54	−1.90	0.41	0.22	−0.33	−1.15

Table CII

Post-Transaction Cost Performance of Portfolios Sorted by Size and Analyst Disagreement

This table reports the post-transaction-cost performance of 5x5 size (market capitalization) and analyst-disagreement sorted portfolios. Analyst disagreement is measured as the standard deviation of all outstanding current fiscal year earnings forecasts scaled by the absolute value of the mean forecast (with zero-mean-forecast observations excluded from the sample). Both size and analyst disagreement are measured as of the previous month, and stocks are sorted first on size and then on analyst disagreement. Four different portfolio weighting schemes are implemented: equal-weighted, value-weighted, illiquidity-weighted, and liquidity-weighted. Portfolios are rebalanced each month. The trading cost of a stock is computed as the average percentage effective spread during the month prior to the time when the stock has entered or exited the portfolio. The effective percentage spread is measured for each transaction as the absolute value of the transaction price and midpoint of the 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. Illiquidity weights are the proportions using the effective spread of each stock (measured the previous month), while liquidity weights are the inverse of effective spread. 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 the three Fama-French (1993) factors), the t-statistic of alpha, and the average effective spread of the stocks in each portfolio. In addition, the table reports the actual average monthly trading costs, which take into account only the 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. The numbers in the table are reported in percentages. The results are reported for the period February 1983 to December 2000 and for all NYSE-listed firms at the intersection of the CRSP and I/B/E/S databases (with available intraday data). Stocks with share price below $5 are omitted from the sample.

		Equal-Weighted							Value-Weighted						
Size	Analyst Disagreement	Excess Return	FF Alpha	t of Alpha	Effective Spread	Actual Cost	Net Alpha	t of Alpha	Excess Return	FF Alpha	T of Alpha	Effective Spread	Actual Cost	Net Alpha	t of Alpha
1	1 (low)	1.13	0.23	1.42	0.42	0.32	.	.	1.08	0.19	1.12	0.39	0.28	.	.
(small)		0.91	0.00	−0.01	0.47	0.41	.	.	0.87	−0.07	−0.35	0.43	0.38	.	.
		0.67	−0.40	−1.86	0.51	0.44	.	.	0.75	−0.35	−1.62	0.47	0.42	.	.
		0.62	−0.40	−2.04	0.58	0.43	.	.	0.66	−0.38	−1.84	0.54	0.41	.	.
	5 (high)	0.38	−0.61	−2.24	0.68	0.37	−0.24	−0.87	0.44	−0.64	−2.26	0.62	0.34	−0.30	−1.05
2	1	1.08	0.21	1.28	0.28	0.18	0.03	0.19	1.06	0.17	1.04	0.28	0.18	.	.
		0.84	−0.02	−0.15	0.30	0.27	.	.	0.86	0.00	0.00	0.30	0.27	.	.
		0.91	0.03	0.19	0.33	0.28	.	.	0.91	0.04	0.23	0.33	0.28	.	.
		1.04	0.03	0.17	0.37	0.28	.	.	1.07	0.08	0.40	0.36	0.27	.	.
	5	0.30	−0.82	−3.32	0.47	0.25	−0.57	−2.29	0.34	−0.78	−3.15	0.46	0.24	−0.54	−2.16
3	1	1.04	−0.01	−0.07	0.23	0.14	.	.	1.03	−0.01	−0.08	0.23	0.14	.	.
		1.06	0.12	0.74	0.24	0.21	.	.	1.05	0.12	0.69	0.24	0.21	.	.
		0.56	−0.46	−2.97	0.28	0.25	−0.22	−1.39	0.58	−0.45	−2.78	0.28	0.24	−0.20	−1.27
		0.84	−0.32	−1.69	0.31	0.23	−0.07	−0.39	0.83	−0.36	−1.88	0.30	0.23	−0.11	−0.60
	5	0.69	−0.50	−1.90	0.33	0.16	−0.34	−1.29	0.66	−0.50	−1.88	0.33	0.16	−0.34	−1.30
4	1	0.99	−0.09	−0.62	0.18	0.09	.	.	1.01	−0.09	−0.60	0.17	0.09	.	.
		0.93	−0.07	−0.47	0.20	0.16	.	.	0.93	−0.07	−0.45	0.20	0.15	.	.
		0.84	−0.17	−1.14	0.21	0.18	.	.	0.87	−0.14	−0.97	0.21	0.17	.	.
		0.72	−0.37	−2.71	0.23	0.16	−0.21	−1.52	0.66	−0.43	−3.15	0.22	0.16	−0.27	−1.98
	5	0.71	−0.37	−1.76	0.25	0.12	−0.26	−1.21	0.76	−0.32	−1.54	0.24	0.11	−0.21	−1.02

(continued)

Table CII—*Continued*

		Equal-Weighted							Value-Weighted						
Size	Analyst Disagreement	Excess Return	FF Alpha	t of Alpha	Effective Spread	Actual Cost	Net Alpha	t of Alpha	Excess Return	FF Alpha	T of Alpha	Effective Spread	Actual Cost	Net Alpha	t of Alpha
5	1	1.10	0.19	1.44	0.12	0.05	0.14	1.05	1.03	0.19	1.23	0.11	0.04	0.15	0.99
(large)		0.99	0.08	0.64	0.15	0.10	.	.	1.10	0.27	2.07	0.14	0.10	0.18	1.35
		0.84	−0.05	−0.43	0.16	0.12	.	.	0.74	−0.14	−1.05	0.16	0.11	−0.02	−0.18
		0.66	−0.29	−2.69	0.18	0.12	−0.18	−1.64	0.70	−0.19	−1.39	0.19	0.10	−0.09	−0.65
	5	0.79	−0.13	−0.85	0.22	0.08	−0.05	−0.35	0.83	0.01	0.06	0.22	0.07	.	.
		Illiquidity-Weighted							Liquidity-Weighted						
Size	Analyst Disagreement	Excess Return	FF Alpha	t of Alpha	Effective Spread	Actual Cost	Net Alpha	t of Alpha	Excess Return	FF Alpha	t of Alpha	Effective Spread	Actual Cost	Net Alpha	t of Alpha
1	1 (low)	1.25	0.32	1.67	0.64	0.74	.	.	1.08	0.21	1.24	0.37	0.25	.	.
(small)		0.96	0.06	0.26	0.93	0.87	.	.	0.90	−0.01	−0.04	0.39	0.33	.	.
		0.49	−0.60	−2.49	0.64	0.62	.	.	0.79	−0.28	−1.32	0.45	0.39	.	.
		0.54	−0.42	−1.90	0.65	0.50	.	.	0.67	−0.40	−2.04	0.52	0.39	−0.01	−0.05
	5 (high)	0.31	−0.65	−2.16	0.76	0.43	−0.21	−0.71	0.43	−0.61	−2.30	0.59	0.31	−0.30	−1.12
2	1	1.18	0.30	1.72	0.30	0.21	0.10	0.55	0.99	0.12	0.76	0.27	0.16	.	.
		0.86	0.02	0.10	0.32	0.30	.	.	0.82	−0.06	−0.36	0.29	0.25	.	.
		0.97	0.08	0.43	0.39	0.35	.	.	0.86	0.00	0.02	0.30	0.26	.	.
		1.14	0.10	0.45	0.40	0.31	.	.	0.95	−0.01	−0.05	0.34	0.25	.	.
	5	0.22	−0.92	−3.56	0.56	0.31	−0.61	−2.31	0.35	−0.77	−2.98	0.40	0.21	−0.56	−2.16
3	1	1.15	0.07	0.40	0.26	0.18	.	.	0.98	−0.06	−0.34	0.21	0.12	.	.
		1.17	0.21	1.19	0.28	0.27	.	.	0.96	0.03	0.18	0.23	0.19	.	.
		0.65	−0.39	−1.74	0.43	0.39	−0.01	−0.02	0.57	−0.45	−2.91	0.25	0.21	−0.23	−1.51
		0.78	−0.40	−1.86	0.50	0.40	.	.	0.79	−0.36	−1.84	0.26	0.19	−0.16	−0.84
	5	0.82	−0.37	−1.34	0.39	0.22	−0.17	−0.61	0.54	−0.64	−2.45	0.29	0.14	−0.51	−1.93
4	1	0.98	−0.11	−0.73	0.20	0.11	0.00	−0.02	1.02	−0.07	−0.45	0.17	0.08	.	.
		0.94	−0.04	−0.27	0.22	0.18	.	.	0.89	−0.12	−0.83	0.19	0.15	.	.
		0.89	−0.12	−0.80	0.25	0.20	.	.	0.84	−0.17	−1.09	0.20	0.16	−0.01	−0.03
		0.75	−0.34	−2.23	0.25	0.19	−0.15	−1.00	0.66	−0.42	−3.08	0.21	0.15	−0.28	−2.02
	5	0.72	−0.33	−1.43	0.30	0.15	−0.18	−0.79	0.68	−0.42	−1.91	0.22	0.10	−0.32	−1.46
5	1	1.08	0.15	1.08	0.14	0.07	0.08	0.59	1.10	0.21	1.55	0.11	0.04	0.16	1.22
(large)		1.04	0.12	0.93	0.19	0.13	.	.	0.96	0.05	0.41	0.13	0.09	.	.
		0.82	−0.08	−0.62	0.22	0.16	.	.	0.85	−0.04	−0.31	0.14	0.10	.	.
		0.69	−0.27	−2.27	0.23	0.15	−0.12	−0.97	0.66	−0.29	−2.53	0.15	0.10	−0.19	−1.68
	5	0.70	−0.24	−1.54	0.52	0.10	−0.14	−0.89	0.83	−0.06	−0.37	0.17	0.07	.	.

that a stock stays in the portfolio for an average of 3.6 months ($\frac{2}{3.6}0.62 \approx 0.34$). Net alpha is the post-transaction-cost performance of the value-weighted portfolios. It is computed by differencing the monthly portfolio returns 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-disagreement portfolios because arbitrage strategies would involve selling these portfolios short. The tables indicate that the post-transaction alphas are rarely statistically significant.

Because transaction costs in these calculations may be overstated (in part because an arbitrageur can find a better rule for forming portfolios), we cannot make the claim that there are no profits to be made by an experienced arbitrageur. It is clear, however, that making a profit is not easy, and that the profits are likely to be much smaller after accounting for transaction costs.

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