Momentum, Liquidity Risk, and Limits to Arbitrage*

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Abstract

This paper demonstrates the importance of liquidity for asset pricing, especially for understanding the momentum anomaly. First, systematic liquidity *risk*, rather than the absolute level of liquidity, is shown to be important in explaining the cross-sectional variation of expected returns. Moreover, momentum returns can be partially attributed to compensation for liquidity risk. Second, seemingly profitable momentum strategies that earn superior risk-adjusted returns (in absolute value) are, in fact, associated with low levels of liquidity. Therefore, the liquidity *level* of momentum portfolios suggests possible limits to arbitrage.

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1 Introduction

This paper demonstrate the importance of liquidity to asset pricing. It shows that liquidity is strongly related to the persistence of the momentum anomaly, which has not been explained by standard asset-pricing models to date. Most of these models take the stand that expected returns vary across assets because of variations in risk (see, e.g., Ferson and Jagannathan (1996)). Typically, the effects of market frictions, such as transaction costs, are ignored.

From a theoretical standpoint, one might argue that transaction costs can be ignored in the pricing of financial assets because investors can choose to trade only in liquid assets with low transaction costs and hold higher transaction-costs assets for longer periods (see, e.g., Constantinides (1986). See also Heaton and Lucas (1996), and Vayanos (1998)). Hence, when transaction costs are amortized over the expected holding period they become rather small and of second order. This argument assumes that transaction costs are constant and that investor are free to choose when to trade. However, these two assumptions may not hold in practice. First, this paper shows empirically that liquidity varies over time, which raises the possibility of a premium associated with liquidity risk. For example, when considering whether to undertake a large investment, an arbitrageur may demand a premium for bearing the risk of incurring large costs when closing out the position in the future. Second, investors may be impatient to execute their trades or they might be subject to liquidity shocks, forcing them to liquidate their positions. This paper finds that transaction costs can impose a first order effect on prices.

This study focuses on the relationship between liquidity and momentum. The momentum anomaly (see, Jegadeesh and Titman (1993)) is recognized as one of the biggest challenges to asset pricing (see, e.g., Fama and French (1996), and Fama (1998)).[1] Momentum strategies exhibit high abnormal returns that cannot be explained by measures of risk to date (see, e.g., Grundy and Martin (2001), and Jegadeesh and Titman (2001)). Hence, behavioral explanations, based on some type of bounded rationality of investors, such as overconfidence or underreaction of investors to information, have been developed to explain momentum continuation (see, e.g., Barberis, Shleifer, and Vishny

[1] The momentum anomaly is part of a growing literature on the predictability of stock returns based on the information contained in past returns. At very short horizons, such as a week or a month, returns are shown to have negative serial correlation (reversal), while at three to twelve month horizons, they exhibit positive serial correlation (momentum). During longer horizons, such as three to five years, stock returns again exhibit reversals. For evidence on short horizon reversal, see Poterba and Summers (1988), and Jegadeesh (1990); for momentum and long run reversal, see DeBondt and Thaler (1985), Jegadeesh and Titman (1993, 2001), and Grinblatt and Moskowitz (2002).

(1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999)). However, exploiting momentum-based strategies involves high turnover (see, e.g., Moskowitz and Grinblatt (1999), and Grundy and Martin (2001)). Therefore, one should take transaction costs explicitly into account while evaluating whether such strategies provide post-transaction-cost returns, to adequately compensate for the risk inherent in them (see, e.g., Korajczyk and Sadka (2002)).

Liquidity and transaction costs have received much attention in recent studies. However, a careful look reveals that liquidity can be defined in many different ways (see O'Hara (1995)). Even while limiting the discussion to execution costs of trades in equity markets, one would naturally distinguish between direct costs, such as brokerage fees, and indirect or invisible costs, such as price impacts of trades (see, e.g., Treynor (1994)). In this paper, the derivation of invisible liquidity costs relies on concepts from the market microstructure literature.

Starting with the work of Demsetz (1968) and Garman (1976), the market microstructure literature has evolved both theoretically and empirically, contingent on the availability of intraday data. Intraday data, such as provided by the Institute for the Study of Securities Markets (ISSM), became available only in the late 1980s. Until then, microstructure research has focused mainly on developing models to explain the role of the bid-ask spread as part of the trading activity (see, e.g., Amihud and Mendelson (1986), Copeland and Galai (1983), Kyle (1985), Glosten and Milgrom (1985), Easley and O'Hara (1987), and Admati and Pfleiderer (1988)). Another front focused on inferring spreads from interday data, such as daily and monthly security returns (see, e.g., Roll (1984)). Currently, tick-by-tick data for a period of almost two decades and for a large cross section of firms is available to researchers of financial markets. We therefore no longer need to use daily/monthly data to infer the bid-ask spreads—we can observe them directly, and we can now apply the core theoretical models of microstructure theory to a large panel of data.

In light of the above, this paper introduces a market microstructure model that integrates various models in the literature. The characterization of the invisible transaction costs should be of independent interest to researchers. The paper studies a large cross-section of NYSE-listed firms for the period January 1983 to August 2001. Most recently, Jones (2002) constructs a time series of annual bid-ask spreads of the Dow Jones stocks for the past century. In contrast, this paper focuses on a large cross-section of firms for the last two decades. Also, Chordia, Roll, and Subrahmanyam (2001), study a similar time period as in this paper, however, their study focuses on spreads and volume, rather than on price impacts of trades.

The evidence in this paper clearly illustrates that liquidity varies across assets and over time. It also documents significant patterns in liquidity associated with several important institutional changes during the sample period. Moreover, since the asset-pricing literature often utilizes various measures to proxy liquidity, such as trading volume or turnover, this paper compares different existing measures with the price impacts measured here. I conclude that the existing measures do not necessarily proxy for invisible transaction costs. This justifies the use of intraday transactions data to measure the costs of trading. However, intraday data limits the time period studied here to only about 20 years, which may impose difficulty in estimating expected returns.

It is important to distinguish between liquidity *level* and liquidity *risk* of assets. Most of the studies that investigate liquidity and asset prices, often make the argument that stocks with low liquidity level, measured by bid-ask spreads, dollar volume, etc., earn higher expected returns (see, e.g., Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Chordia, Subrahmanyam, and Anshuman (2001), and Easley, Hvidkjaer, and O'Hara (2002)). Only a few recent studies investigate whether there exists a systematic component of liquidity (see, e.g., Huberman and Halka (2001), Amihud (2002)). From an asset-pricing standpoint, only undiversifiable risk should be priced. Pástor and Stambaugh (2002) develop a measure of aggregate liquidity and show that assets whose returns highly covary with this aggregate liquidity measure earn higher expected returns than assets whose returns exhibit low covariation with aggregate liquidity.

This paper studies both liquidity risk and liquidity level, and their relation to momentum. I find that liquidity risk is priced, and that the liquidity risk premium explains half of the momentum anomaly. Moreover, the unexplained momentum profits are due to firms whose level of liquidity is low.

Using the estimated price impacts, a liquidity factor, based on shocks to aggregate liquidity, is introduced. This non-traded factor is then tested in several different ways. First, the non-traded liquidity factor is used to form a traded liquidity factor (such as used in Pástor and Stambaugh (2002)). However, due to the relatively short sample period, it is difficult to efficiently construct the traded portfolio, and thus these teste only provide some preliminary diagnostics. Second, cross-sectional regressions (see, e.g., Black, Jensen and Scholes (1972), Fama and French (1992), Shanken (1992), and Jagannathan and Wang (1996)) are used to test different pricing models, such as the CAPM, the Fama and French (1993) three-factor model, and a four-factor model, based on the Fama-French three factors and the non-traded liquidity factor. The results indicate that the four-factor model best explains the cross-sectional variation of expected returns to portfolios based on momentum and liquidity level. Moreover, similar results are found while testing the models using a stochastic discount factor approach (see, Jagannathan and Wang (1996)).

The economic interpretation of the liquidity factor is of special importance. In the microstructure literature it is argued that price impact depends on both the level of information trading and the level of noise trading (see Kyle (1985)). The liquidity factor, therefore, captures shocks to information and/or changes in the amount of activity of noise traders. This is closely related to the literature that studies the implications of the risk of noise traders on asset prices, such as Black (1986), De Long, Shleifer, Summers, and Waldmann (1990), and Campbell and Kyle (1993). The results in this paper indicate that a significant part (but certainly not all) of the returns to momentum strategies can be explained by a liquidity-risk premium. In other words, momentum strategies earn higher returns during periods that experience positive liquidity shocks, and lower returns over negative-shock periods. As a consequence, in the attempt to exploit momentum strategies, an arbitrageur faces the risk of not being able to trade against noise traders or having to trade with many informed traders in the future (which increases the cost of trading). This paper contributes to the current literature, in that it further examines the liquidity risk associated with momentum strategies, which was previously noted by Pastor and Stambaugh (2002).

In addition, this paper investigates the level of liquidity of momentum portfolios and argues that seemingly profitable momentum strategies are, in fact, associated with high levels of transaction costs. In this context, the low liquidity level suggests there may exist limits to arbitrage to momentum strategies.[2] This may explain why the momentum anomaly has not yet been fully arbitraged away since its discovery. Last, this paper relates to previous studies documenting the relation between momentum and each of the following: volume (see Lee and Swaminathan (2000)), book-to-market ratio (see Asness (1997)), and analyst coverage (see Hong, Lim, and Stein (2000)). It demonstrates how liquidity can contribute to explaining these findings.

The rest of this paper is organized as follows. Section 2 describes the methodology for estimating liquidity and discusses empirical results. Section 3 investigates the pricing of liquidity risk.

[2]This paper does not explicitly calculate the amount that can be invested in momentum strategies. In contrast, Sadka (2001), Korajczyk and Sadka (2002), and Chen, Stanzl, and Watanabe (2002) estimate the maximum dollar amount that could be invested in momentum strategies, before profits are subsumed by the costs of trading. Studies of similar interest are Ball, Kothari, and Shanken (1995), Knez and Ready (1996), Grundy and Martin (2001), and Mitchell and Pulvino (2001).

Momentum and liquidity portoflios are then used to test different asset-pricing models in Section 4. Section 5 discusses limits to arbitrage of momentum strategies, and finally Section 6 concludes.

2 Estimation of Liquidity

The market microstructure literature documents that actual trading induces both permanent and transitory effects on prices. Theoretical studies include Glosten and Milgrom (1985), Kyle (1985), Glosten (1987, 1989), and Easley and O'Hara (1987, 1992), while empirical evidence is provided in Glosten and Harris (1988), Hasbrouck (1991a,b), Keim and Madhavan (1996), Kraus and Stoll (1972), Madhavan and Smidt (1991), and Stoll (1989). In the theoretical literature, the permanent price impact is due to new information being reflected in market prices. In these models, the market maker observes the order flow. Given her assessment of the amount of informed trading relative to the amount of noise trading, the market maker adjusts the price. For example, theory predicts that if there are many informed traders and relatively few noise traders, much of the information held by informed traders will be revealed by the order flow and the price impact will be large.

The temporary price impact is driven by inventory and market making costs. Similar to the methodology in Brennan and Subrahmanyam (1996), both parts of price impacts are estimated for stocks traded on the NYSE over the period from January 1983 to August 2001, using trades recorded on ISSM and TAQ databases (see description of data in Section 2.2). In contrast to Brennan and Subrahmanyam (1996), who estimate price impacts once a year, in this study price impacts are estimated on a monthly frequency, so that conclusions on the time variation of price impacts, can be drawn.[3]

A few comments about the chosen methodological approach are in order. First, it is not clear from a theoretical standpoint what the true functional form of price impacts is. For example, Kyle (1985) assumes price is a linear function of the order flow, and proves that under this assumption there exists (a unique) equilibrium (see also Admati and Pfleiderer (1988)). On the other hand, Keim and Madhavan (1996) develop a model that induces non-linearity of price impacts (they focus on block trades). Recent empirical research documents concave price-impact costs (see, e.g.,

[3]Recent studies document the time variation of liquidity. The methodology introduced here can also be implemented on a daily frequency. On the one hand this could enhance the precision of the volatility of liquidity. On the other hand, the results are subject to daily effects (see, e.g., Chordia, Roll, and Subrahmanyam (2001)). I have decided to estimate price impacts on a monthly basis, for 224 months.

Hausman, Lo, and MacKinlay (1992), and Chen, Stanzl, and Watanabe (2002)). Hence, it is difficult to choose a specification of price-impact function. My own experiments along with other recent studies (such as Madhavan and Smidt (1991) and Huang and Stoll (1997)) lead me to believe that the non-linearity of price impacts is mainly due to large trades (see discussion of results). Therefore, the methodology used here is based on the linear specification introduced in Glosten and Harris (1988), along with adjustments for large trades.

Second, to estimate price impacts I choose to work with transaction prices rather than midpoint of bid-ask quotes.[4] Other studies, such as the VAR model of Hasbrouck (1991a,b) and the Box-Cox transformation of Chen, Stanzl, and Watanabe (2002), use quoted midpoints. The use of mid-quotes rather than transaction prices understates the true price impact costs induced by actual trades.

2.1 Methodology

2.1.1 General Framework

Let m_t denote the market maker's expected value of the security, conditional on the information set available at time t (t represents event time of a trade)

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

where V_t is the order flow, D_t is an indicator variable which receives a value of (+1) for a buyer-initiated trade and (-1) for seller-initiated, and y_t is a public information signal. To determine the sign of a trade, I follow the classification scheme proposed by Lee and Ready (1991), which classifies trade whose price is above the midpoint of the quoted bid and ask as buyer-initiated, and below the midpoint—seller-initiated (trades whose price equals the midpoint are discarded from the estimation).[5]

[4] This is similar to Glosten and Harris (1988), but the difference is that the database used for their empirical analysis contained information about prices alone, without quotes. In this study, despite the availability of quotes, I choose to work with prices in order to assess costs induced by actual trading (i.e., from trade to trade rather than from quoted midpoint to quoted midpoint).

[5] As mentioned below in Section 2.2., due to a delay in the time bid and offer are quoted, the algorithm suggests to use the midpoint of the quotes as of five second prior to the trade. There are other classification schemes discussed in the literature. For example, Ellis, Michaely, and O'Hara (2000) discuss on trades on NASDAQ. See also Peterson and Sirri (2002), and Odders-White (2000) for comparisons of different classification schemes. All studies predict more than 90% success rate for the Lee and Ready (1991) scheme.

To ease the derivation of the model below, here is a short description of the different price impact components that are estimated. As mentioned earlier, the literature distinguishes between two main effects, permanent and transitory, that trades may have on prices. The permanent effects are attributed to the possibility of insiders trading on private information, and transitory effects are associated with the costs of making a market, such as inventory and order processing. This paper assumes 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. Hence, there are four components of price impacts, which are denoted as follows. The fixed effects are Ψ and $\overline{\Psi}$ (permanent and transitory, respectively), and the variable costs are λ and $\overline{\lambda}$ (permanent and transitory, respectively).

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

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

where Ψ and λ are the fixed and variable permanent price-impact costs, respectively. Equation (2) describes the innovation in the conditional expectation of the security value through new information, both private (D_t, V_t) and public (y_t). Notice information induces a permanent impact on expected value.

The formulation in (2) assumes that the market maker revises expectations according to the total order flow observed at time t. However, the literature has documented predictability in the order flow (see, e.g., Hasbrouck (1991a,b), Foster and Viswanathan (1993)). For example, to reduce price impact costs, traders may decide to break up large trades into smaller trades, which would create an autocorrelation in the order flow. Thus, I follow Brennan and Subrahmanyam (1996), Madhavan, Richardson, and Roomans (1997), and Huang and Stoll (1997), and adjust the formulation to account for the predictability in the order flow. In particular, the market maker is assumed to revise the conditional expectation of the security value only according to the *unanticipated* order flow rather than the entire order flow at time t. For simplicity, the signed trade size $D_t V_t$ shall henceforth be denoted DV_t. This adjustment induces the following formulation

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

where the operator $E_{t-1}[\cdot]$ denotes conditional expectation. Notice, there are two conditional means to be estimated—that of the sign of the order flow and that of the order flow itself.

It is not clear which statistical model best captures the predictability in the order flow. For example, a general approach is introduced in Hasbrouck (1991a,b), where innovations in midquotes and order flows are jointly estimated through a VAR model. Based on that model, Brennan and Subrahmanyam (1996) use five lags of prices and order flows to estimate the unexpected order flow. Huang and Stoll (1997) assume a first order autoregressive process on the sign of the order flow (captured by D_t in our model). This paper estimates the two conditional means using a two-step procedure. As explained below, first I use a standard autoregressive process with five lags to describe innovations in the (signed) order flow, and then estimate the conditional expected sign of the order flow assuming a Markov chain model.

The order flow is assumed to follow the process

$$DV_t = \eta_0 + \sum_{j=1}^{5} \eta_j DV_{t-j} + \varepsilon_{\lambda,t} \tag{4}$$

This model is estimated using GMM (using a Bartlett kernel to corret for autocorrelation). After computing the estimates $\widehat{\eta}_j$ $(j = 0,...,5)$ the conditional expectation of the order flow, $E_{t-1}[DV_t]$, is calculated as the fitted value. Once $E_{t-1}[DV_t]$ is obtained, $E_{t-1}[D_t]$ can be estimated as follows.

Notice D_t is a binary variable. Therefore, define the probability that the next trade would be a "buy" given the expected order flow as $p\left(D_t = +1 | E_{t-1}[DV_t]\right)$. This probability is equal to $p\left(E_{t-1}[DV_t] > -\varepsilon_t\right)$. Assuming normality of the shocks to the order flow, ε_t, and denoting its variance σ_ε^2, it is easily shown that the probability is further simplified to $1 - \Phi\left(E_{t-1}[DV_t]/\sigma_\varepsilon\right)$, where $\Phi(\cdot)$ denotes the cumulative density function of the normal distribution. Therefore, the expected sign of the order flow is calculated as

$$E_{t-1}[D_t] = 1 - 2\Phi\left(E_{t-1}[DV_t]/\sigma_\varepsilon\right) \tag{5}$$

Denote the unexpected sign of a trade as $\varepsilon_{\Psi,t}$, where $\varepsilon_{\Psi,t} = D_t - E_{t-1}[D_t]$. Using the above formulations for $\varepsilon_{\Psi,t}$ and $\varepsilon_{\lambda,t}$, Equation (3) translates to

$$\Delta m_t = \Psi \varepsilon_{\Psi,t} + \lambda \varepsilon_{\lambda,t} + y_t \tag{6}$$

Notice that the process m_t is unobservable and cannot be directly estimated from the data.

Transitory price effects are added to the model similar to the derivation in Glosten and Harris (1988). They assume linear transaction costs, denoting fixed costs by $\overline{\Psi}$, and variable costs by $\overline{\lambda}$. These costs represent both inventory costs and order processing costs. Glosten and Harris (1988) mention that preliminary diagnostics show that Ψ and $\overline{\lambda}$ are unimportant components, and thus they assume $\Psi = \overline{\lambda} = 0$ for the estimation procedure.[6] However, Glosten and Harris (1988) use a universe of 20 firms for specification tests. Since the sample used in this study contains a large cross-section of stocks, all four price-impact components are estimated.

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

$$p_t = m_t + D_t \left[\overline{\Psi} + \overline{\lambda} V_t\right] + \xi_t \tag{7}$$

where ξ_t is an error term. Notice that $\overline{\Psi}$ and $\overline{\lambda}$ are temporary effects by the of construction Equation (7), as they only affect p_t, and are not carried on to p_{t+1}. Also, in contrast to the information-based components of price impact, while considering the market making costs, the entire order flow is included, rather than its unanticipated part (see also Huang and Stoll (1997) and Madhavan, Richardson, and Roomans (1997)). Taking first differences of p_t (Equation (7)) and substituting Δm_t from Equation (6) we have

$$\Delta p_t = \Psi \varepsilon_{\Psi,t} + \lambda \varepsilon_{\lambda,t} + \overline{\Psi} \Delta D_t + \overline{\lambda} \Delta D V_t + \Delta \xi_t + y_t \tag{8}$$

where $\Delta \xi_t + y_t$ is the unobservable pricing error. The model is estimated using OLS (including an intercept) with corrections for serial correlation in the error term.

2.1.2 Separating Out Large Trades

The model above does not distinguish between small/ordinary trades and block trades. The literature documents different price effects induced by block trades, which points to a possible story of market segmentation according to trade size. For example, Madhavan and Smidt (1991) create four classes according to trade size[7], and show different market making costs for the largest trade size group. Keim and Madhavan (1996) study the price effects of block trades using data on institutional trades, and conclude that the permanent effects of such trades are larger than previously estimated, once the decision date of executing the trade is taken into account. The effects of "shopping the block" are also discussed in Nelling (1996). Huang and Stoll (1997) measure different components

[6] Brennan and Subrahmanyam (1996) use this formulation as well. Other studies that focus on investigating the relative magnitude of the adverse selection versus the order processing components of the bid-ask spread essentially assume these components are invariant to trade size, for example, Huang and Stoll (1997), Madhavan, Richardson, and Roomans (1997), and George, Kaul and Nimalendron (1991).

[7] They include a different classification for every stock, according to the support of the distribution of trade size.

of the bid-ask spread and conclude that their magnitudes vary with trade size.[8]

In light of the above, large/block trades, generally considered as trades above 10,000 shares, are separated from smaller trades in the estimation.[9] Formally, large trades are separated from the regular trades as follows. Define the dummy variable K_t, valued (+1) for trades equal or greater than 10,000 shares, and zero otherwise. The process of m_t described by (3) is rewritten as follows

$$m_t = m_{t-1} + \Psi\varepsilon_{\Psi,t} + \lambda\varepsilon_{\lambda,t} + K_t\Psi^k\varepsilon_{\Psi,t} + K_t\lambda^k\varepsilon_{\lambda,t} + y_t \tag{9}$$

where Ψ^k and λ^k are the differences between regular trades and large trades, with respect to the fixed and variable permenent costs, respectively. Similarly, the transaction price in (7) is re-defined

$$p_t = m_t + D_t\left[\overline{\Psi} + \overline{\lambda}V_t\right] + K_tD_t\left[\overline{\Psi}^k + \overline{\lambda}^kV_t\right] + \xi_t \tag{10}$$

Thus

$$\begin{aligned}\Delta p_t &= \Psi\varepsilon_{\Psi,t} + \lambda\varepsilon_{\lambda,t} + K_t\Psi^k\varepsilon_{\Psi,t} + K_t\lambda^k\varepsilon_{\lambda,t} \\ &\quad + \overline{\Psi}\Delta D_t + \overline{\lambda}\Delta DV_t + \overline{\Psi}^k\Delta KD_t + \overline{\lambda}^k\Delta KDV_t + \Delta\xi_t + y_t.\end{aligned} \tag{11}$$

2.2 Data

The empirical analysis in this paper utilizes several different data bases, starting with intraday data for the estimation of execution costs, and daily/monthly/annual data for the asset pricing analysis. The intraday data is obtained from two databases. The Institute for the Study of Securities Markets (ISSM) database includes tick-by-tick data for trades and quotes of NYSE, AMEX, and NASDAQ listed firms for the period January 1983 until December 1992. Similarly, the New York Stock Exchange Trades and Automated Quotes (TAQ) database includes data for NYSE, AMEX, and NASDAQ, for the period January 1993 to August 2001. The CRSP daily/monthly stock return database is also used, as well as COMPUSTAT annual files.

I choose to focus only on NYSE-listed stocks, since NASDAQ uses a different trading mechanism (also see discussion in Chordia, Roll, and Subrahmanyam (2001)). The sample is sufficiently large

[8] They consider three trade size groups: below 1,000 shares, between 1,000 and 10,000 shares, and above 10,000 shares), and assume price effects are constant within each group.

[9] Besides its attractiveness as a simple cutoff rule, further justification is found in the data. Although the total number of trades in the sample increased from over a million trades during January 1983 up to over 13 million trades during August 2001, during that period the number of trades above 10,000 shares increased from about 22,000 trades to roughly 400,000 trades. Hence, the ratio between the number of trades above 10,000 shares and the total number of trades, in any given month, is quite stable over time—it averages 3.9%, varying between 1.9% and 6.3%.

to reach conclusions on market-wide effects, since it contains most of the market-capitalization in the cross section during the investigated period. More importantly, momentum, the focus of this study from an asset-pricing standpoint, is statistically and economically significant for NYSE-listed stocks alone (see, Conrad and Kaul (1998), Grundy and Martin (2001), and Korajczyk and Sadka (2002)).

It is important to note that prior to using the raw data stored on the intraday databases, one must "clean up" the data; for example, there may be implausibly large spreads, or often not all trades or quotes are appropriate for this study. In what follows I explain the filters used to obtain trades and quotes, and also describe the firms included in my final dataset after merging intraday and interday data.

Following Chordia, Roll, and Subrahmanyam (2001, 2002), I use only BBO (best bid or offer)-eligible primary market (NYSE) quotes. Also, trades out of sequence, trades recorded before the open or after the closing time, and trades with special settlement conditions are discarded. Negative bid-ask spreads and transaction prices are also eliminated from the dataset. Following Lee and Ready (1991), any quote posted less than five seconds prior to a trade is ignored, and the first quote posted at least five seconds prior to the trade is retained. To avoid after hours liquidity effects (see, Barclay and Hendershott (2001)), the first trade after the opening time is ignored.

In addition, only quotes that satisfy the following filter conditions are retained: the bid-ask spread is positive and below five dollars, the bid-ask spread divided by the midpoint of the quoted bid and ask (henceforth defined as quoted spread) is less than 10% if the midpoint is greater or equal $50, and quoted spread is less than 25% for midpoints less than $50. These conditions assure the use of reasonable quotes in our analysis.

Independent of the estimation of transaction costs using the intraday data, the CRSP data files are used to retrieve monthly/daily returns, market capitalization (defined as share price multiplied by the number of shares outstanding), volume, and turnover (defined as volume scaled by the number of shares outstanding). The measure of Book-to-Market equity (BE/ME) is constructed using the COMPUSTAT annual files (for a detailed description of the construction of this measure see Cohen, Polk, and Vuolteenaho (2002)). Since the trading characteristics of ordinary equities might differ from those of other assets, I retain only tradable assets whose last two CUSIP digits are 10 or 11, i.e., I discard certificates, ADRs, shares of beneficial interest, units, companies incorporated outside the U.S., Americus Trust components, closed-end funds, preferred stocks and REITs.

After preparing both high and low frequency datasets, they are merged by matching the firms on ISSM with CRSP by their ticker symbols, and firms on TAQ with CRSP by their CUSIPs (this approach induces the highest matching rate, as discussed in Hvidkjaer (2001)). Our universe includes a cross-section of 1,159 firms beginning in January 1983 gradually increasing to 2,226 in the August 2001 (in all 4,082 different firms are used for this study).[10] The total number of trades used for the analysis is 645 million (of which 26 million trades are above 10,000 shares) which averages 1,700 per month per firm (large firms with very high trading volume often reach over 1,000 trades a day).

2.3 Empirical Results

2.3.1 The Cross Section of Asset Liquidity

This section summarizes the estimated price impact components in the cross-section. First, I describe the components estimated through the model in Equation (**??**) and their statistical properties. The distribution of the order flow is also discussed. Then, to use the price-impact estimates in an asset-pricing framework in subsequent sections, the estimates are scaled by beginning-of-month price. Last, the magnitude of price-impact components and their relation to the bid-ask spread are discussed.

The Unscaled Measures. The methodology described above is implemented to the universe of stocks, each month. Only firms with at least 30 trades that month are included. For identification purposes, the system is estimated without the dummy variables that separate large trades, if there are no more than 3 trades of more than 10,000 shares. The time-series averages of monthly diagnostics are reported in Table 1 and Figure 1.[11] The average information/permanent variable cost and average non-information/temporary fixed cost for trades below 10,000 shares provides additional validation for the methodology in Glosten and Harris (1988)—these seem to be larger than the average non-information variable cost and the average information fixed cost, respectively. The negative average marginal non-information variable cost seems odd at first glance. However,

[10] An exception is July 1987, in which we only observe 506 firms.

[11] A look at the distribution of the estimates reveals several outliers, especially for trades below 10,000 shares. Therefore, the estimates are trancated at 1 and 99 percentiles (i.e., values below the 1% cutoff are re-valued at the 1% cutoff, and similarly, values above the 99% cutoff are re-valued at the 99% cutoff value). The values in Table 1 and Figure 1 are computed after making these adjustments.

four comments are noteworthy. First, this indicates that as the total costs increase with the size of the trade, the fraction of costs attributed to information asymmetry also increases. Indeed, heavy information-based trading induces higher permanent effects. Second, there exists a positive non-information fixed cost along with the negative variable cost, which keeps the total non-information marginal cost positive, even up to trades of 10,000 shares. Third, this finding corresponds to Huang and Stoll (1997) that find decreasing fixed costs. Last, it is likely that the temporary fixed costs are restricted by the size of the tick. Indeed, as discussed below, when the tick size is reduced on June 1997, the temporary fixed costs decreased and the variable costs increased.

For large trades, both the permanent and temporary variable costs are significantly different than those of small trades. The permanent variable cost is significantly reduced, though remains positive, and the transitory variable cost is increased. The fixed costs do not change significantly. As discussed above, several empirical studies find that price-impacts follow a concave function. These studies, however, do not separate large trades in their estimation. The results here indicate that part of the concavity of the price-impact function may be attributed to large trades. The slope of price impact for large trades remains positive, however, is much smaller than that of small trades.[12] It seems that the large trades are executed under favorable conditions (for example, due to credible signalling that the trader is uninformed). Otherwise, they might have been broken up to smaller trades. This hypothesis of market segmentation is also exhibited when looking at the distribution of trade size (discussed below).

Statistical Properties. The statistical properties of the estimates are shown in Figure 2. This figure plots the distribution of the t-statistics of some estimates across the pooled-cross-section sample of firms. The t-statistic of the non-information fixed costs ($\overline{\Psi}$) is significant (i.e., above 1.96) for over 90% of the sample. The t-statistics of the information variable costs (λ) exhibit a distribution that resembles a normal distribution, centered above 1. As expected of a normal distribution, the left tail of the distribution have negative values as low as -4.4 and the right tail reaches 8. Although this may question the precision of which the the information variable costs are estimated, the market-wide information effects are likely estimated with much greater precision. This is one of the reasons that the liquidity factor that is constructed later is based on shocks to

[12] Notice that adding the dummy to the intercept is crucial for the positivity of price impact slope for large trades. A piecewise linear model (that does not allow discontinuity at 10,000) shares would often result with a downward sloping curve for the large trades (see example in Chen, Stanzl, and Watanabe (2002)).

market-wide effect. Last, the significance of the dummy variable on information effects of large trades (λ^k) is examined. Figure 2 shows that over 85% of the estimates are negative, most of which are statistically significant. This supports the inclusion of a dummy variable for the large trades. In fact, it seems that there exist two distinct distributions for this variable, which suggests that maybe another dummy variable is needed for extremely large trades. This point is again related to the market segmentation argument which has been discussed earlier.

The Distribution of Trade Size. Figure 3 shows the distribution of trade size over the sample period for trades below 20,000 shares (as noted above, only about 3% of the trades are above 10,000 shares). The histogram reveals that roughly 80% of the trades are below 3,000 shares. This suggests the existence of a separating equilibrium in the market, in that trades that are executed are either small or very large (this finding is consistent with the theoretical prediction of DeMarzo, Fishman, and Hagerty (1998)). A possible explanation is that insiders break up their trades in order to avoid early revelation of their private information. Liquidity traders, who do not wish to be mistaken for insiders, also break up their trades in order to avoid high costs. On the other hand, if one is interested in executing a very large trade, it is less costly to execute the trade as a block rather than paying the sum of price impacts induced by breaking up the trade to many smaller trades (see, e.g., Nelling (1996)). This is an interesting topic for future research.

The Scaled Measures. To use the cost estimates in an asset-pricing framework in subsequent sections, some adjustments are in order. Each component of price impact is scaled by its stock price in the beginning of the month. This scaling is theoretically motivated by the work of Brennan and Subrahmanyam (1996) and Sadka (2002).[13] Scaling converts the intercepts from dollars to returns, and the slopes from dollars per share to returns per share. Also, the scaling is more plausible when constructing an aggregate measure of liquidity. The relative relation between the different scaled variable measures is similar to that of the unscaled measures discussed above. In contrast, the scaled transitory fixed costs appear to be much higher than the permanent fixed costs (for both regular trades and block trades). This is because low priced stocks tend to have relatively high fixed costs of trading.

[13] Brennan and Subrahmanyam (1996) scale their measures by price as well. The motivation appears in their unpublished working paper version (1995). They introduce a simple equilibrium model, whose first order conditions justify the price scaling. Independently, Sadka (2002) develops a portfolio choice model, accounting for price-impact costs, and finds similar first order conditions.

The Magnitude of Price-Impact Costs. Another important implication is providing evidence on the relative importance of different price-impact components, i.e., information asymmetry costs versus order processing or inventory costs. This is related to the early work of Amihud and Mendelson (1986) and Copeland and Galai (1983) about the role of the bid-ask spread. Some studies estimate that 90% or more of the bid-ask spread is transitory. However, these findings are often obtained from relatively small sets of stocks. Also, George, Kaul, and Nimalendran (1991) do not directly measure the spread but rather estimate it (and its components) using interday data. Table 1 shows that for the regular trades most of the costs are transitory—on average 74% of the total fixed costs and 91% of the total variable costs are transitory. In contrast, when large trades are considered, the permanent costs dominate (34% of the total fixed costs and 44% of the total variable costs). This is in line with the evidence provided in Keim and Madhavan (1996), who argue that the permanent impact of block trades is higher than previously estimated.[14]

To demonstrate the magnitude of transaction costs, I calculate for each stocks the percentage cost of it's average regular trade and the average large trade (per month) using the scaled measures of transaction costs. Costs are also separated into permanent and transitory effects. The costs are calculated as the sum of the intercept and the multiple of the slope and the average trade size. The results are provided in Table 2. On average, the average trade has a total cost of 47 basis points, of which 66% are temporary, while large trades induce costs of 61 basis points, of which 44% are temporary.[15] This complements the result in Table 1, which shows that the fraction of information costs is higher for block trades. Also, notice that although the price impact function of large trades appears to have a lower slope than that of regular trades (see Table 1 and Figure 1), the average total cost per share is higher for large trades. This is because the total cost per share depends both on the slope of the price-impact function and on the trade size (the average trade size for large trades is about 30 times larger than the average trade size of regular trades, while the average slope of regular trades is only four times larger than the average slope of large trades).

[14] To support their argument they use a dataset in which the decision dates of the block trades are recorded. They show that if one compares the prices at which blocks are traded to previous month prices, blocks appear to induce much more permanent impact than if block prices are compared to previous day prices. Here it is possible to deduce similar conclusions using the price difference between consecutive trades.

[15] The magnitude of the total trading costs reported here are somewhat larger than the "implicit costs" reported in Keim and Madhavan (1997). Note that the sample used there includes trades of the Plexus Group during 1991 to 1993. Also, implicit costs are calculated using previous day closing prices, and not using previous trade prices, as used here. See also, Breen, Hodrick, and Korajczyk (2002).

Price Impacts and Bid-Ask Spreads. To relate the results to existing measures of liquidity, additional measures are computed and reported in Table 1, Panel D. Turnover is calculated as the monthly share volume of a stock scaled by its number of shares outstanding. The relative bid-ask spread is the bid-ask spread divided by the midpoint of quotes. Since many trades occur within the spread, the literature includes a measure of effective spread, which is defined as the absolute value of a trade price divided by the midpoint of quotes (as five seconds prior to the trade—see Lee and Ready (1991)). The depth (number of shares offered) on the bid and the ask are also reported. Half the average bid ask spread is 11 cents. This is roughly comparable to the sum of the unscaled intercepts, 7 cents. Also notice that half the quoted spread is 0.69% on average, which is comparable to the sum of scaled fixed costs—0.45%. As expected, effective spreads are lower than half the relative bid-ask spreads, 0.52%, and much closer to the sum of the scaled fixed costs.

2.3.2 The Time Series of Aggregate Liquidity

The time period examined in this paper covers several important institutional changes and other events that are important for examining invisible transactions costs. The time series of the average monthly liquidity measures are plotted in Figure 4. The main message of this figure is that market-wide liquidity is indeed time varying.[16] This is one step further than analyzed by Brennan and Subrahmanyam (1996), who consider the liquidity of each stock constant throughout the time period investigated. This finding justifies the estimation of liquidity month by month (and the cross-sectional results above justifies the estimation for each firm individually). More importantly, it lays ground for considering a liquidity *risk factor* in subsequent sections.

Second, the crash of the stock market in October 1987 is clearly reflected in the data. Both permanent/transitory fixed/variable costs exhibit high levels during that month. Significant patterns are also found around June 24, 1997—when the NYSE reduced the tick size from an eighth to a sixteenth. The tick size is directly related to bid-ask spreads as well as effective spreads, therefore, we should expect this event to have an effect on these measures. Indeed, Jones and Lipson (1999), Goldstein and Kavajecz (1999), and Chordia, Roll, and Subrahmanyam (2001) find that both spreads and depths decline after June 1997. However, since this institutional change should not affect the way information is processed in the market, one would not expect any change to the permanent components of price impact. The results affirm these hypotheses. Both fixed and

[16] See also evidence in Chordia, Roll, and Subrahmanyam (2001, 2002).

variable permanent costs do not exhibit unusual change. In contrast, the temporary costs show a significant change. The temporary fixed costs are cut by half, while the variable costs become less negative (in absolute value, they decrease by almost three times). This finding is important for answering questions about the implications of such institutional changes. While bid-ask spreads (as well as the fixed temporary costs) would indicate the markets have become more liquid after the reduction of the tick size, price impacts (temporary variable costs) would argue otherwise.[17] One possible explanation is that once the tick size constraint is relaxed, market makers retain their profit level by increasing the variable costs, which they can control. This observation stresses the importance of considering price impacts, and not only bid-ask spreads, when discussing the liquidity of markets (see Harris (1994)).

Similarly, the decimalization process that began in January 2001 has mostly affected transitory costs (although the fixed permanent costs appear to have dropped as well). Last, the crash of LTCM during September 1998 is also associated with liquidity effects. In this case, however, only the permanent variable costs appear to have increased during that period, which indicates relatively high information-based trading activity or low noise trading activity.[18,19]

2.3.3 Comparison with Alternative Measures of Liquidity

This paper uses measures of price impacts as proxies for liquidity. The financial literature includes other proxies, such as market capitalization, volume, turnover (defined as volume scaled by the number of shares outstanding), and more recently, measures based on daily data such as introduced in Amihud (2002).[20,21] Related to momentum, Lee and Swaminathan (2000) show that high volume

[17] While bid-ask spreads decreased after June 1997 (i.e., liquidity has improved), the depth (both on the bid and the ask) has decreased as well (i.e., liquidity has worsened). This also indicates the difficulty of assessing the liquidity implications of this event, as there are several conflicting effects.

[18] The time series of large trades, which is not reported here for brevity, shows a slightly different picture. It seems that the historical events discussed above have mostly affected price impacts of the regular trades—price impacts of large trades seem pretty stable throughout the entire sample period. Interestingly, the ratio of number of large trades over the total dropped from 5.5% in April 1997 to 3.9% in August 1997, and from 5.1% in January 2001 to 3.3% in February 2001 (and continuing to drop to 2.8% in August 2001). Also, Fixed costs of large trades seem more volatile than those of regular trades.

[19] The time series of the transaction costs in form of return (as explained in Table 2) exhibits similar patterns as those in Figure 4.

[20] Examples of studies that focus on volume, are Karpoff (1987), Campbell, Grossman, and Wang (1993), Jones, Kaul, and Lipson (1994), Wang (1994), Lo and Wang (2000), Gervais, Kaniel, and Mingelgrin (2001), and Llorente, Michaely, Saar, and Wang (2002).

[21] The measure introduced by Amihud (2002) is defined as the monthly average of absolute value of return divided by dollar volume every day.

stocks exhibit more momentum than low volume stocks.

A comparison of the alternative measures discussed above and the price-impact measures is offered in Table 3. Although there exists some correlation between the different measures, they are far from being perfectly correlated with price impacts. Maybe the most counter-intuitive result is that turnover has low correlation with price impacts. This finding that volume may not always proxy for liquidity in also discussed in Chordia, Roll, and Subrahmanyam (2002). High market capitalization firms generally have lower price impacts than low market capitalization firms. Nevertheless, there are some small firms that are as liquid as large firms. Last, the measure of Amihud (2002) seems the most correlated with price impacts, among the alternative measures examined here. This point is further addressed in subsequent sections.

3 On the Pricing of Liquidity Risk

Early studies have argued that the level of liquidity is incorporated in prices. Amihud and Mendelson (1986) argue that investors demand a premium for relatively low liquidity stocks. They show that stocks with higher bid-ask spreads are associated with higher expected returns. Similarly, Brennan and Subrahmanyam (1996) find that stocks with higher price impacts earn higher future returns. Also, Easley, Hvidjaker, and O'Hara (2002) find that the level of liquidity, measured as the probability of information-based trade (PIN) shows up in asset prices.

Recent studies focus on the systematic component of liquidity rather than its actual idiosyncratic level (see, e.g., Huberman and Halka (2001) and Amihud (2002)). Most recently, Pástor and Stambaugh (2002) construct a liquidity factor and estimate that liquidity earns a premium of 7.5% annually. Similar to the methodology used in Pástor and Stambaugh (2002), I construct tracking portfolios of a liquidity factor, which is based on the estimated price impacts.

The liquidity factor studied in this paper is the economy-wide level of liquidity. I focus on the information component of price impact (this is λ from Equation (2), scaled by beginning-of-month price), whose market average, λ_t^M, time series is plotted in Figure 4. Three minor adjustments are implemented. First, the process of aggregate illiquidity is close to unit root, and therefore first differences are used to attain stationarity of the process (see also discussion in Pástor and Stambaugh (2002)). Second, since λ_t^M measures illiquidity rather than liquidity, a minus sign is added so that negative shocks to λ_t^M could be interpreted as the market becoming more liquid.

Third, for pure expositional purposes the measure is scaled by an order of 7. Specifically, I define the non-traded liquidity factor $\mathcal{L}_t$ as

$$\mathcal{L}_t = \left(-\Delta\overline{\lambda}_t\right) \times 10^7 \tag{12}$$

The average innovation is 0.02, with a standard deviation of 0.66. The minimum is -3.14 and the maximum is 2.36. The correlations of this factor with Fama-French (1993) factors are: MKT_t 0.17, SMB_t 0.11, and HML_t -0.07.[22] The low correlation of the non-traded liquidity factor with other known factors is important to justify its possible inclusion as an orthogonal factor to the return space spanned by the existing factors used by asset-pricing models to date.

3.1 Tracking Portfolios

The factor $\mathcal{L}_t$ is non-traded since it is not constructed by asset returns. In this section portfolios are created to mimic the fluctuations of $\mathcal{L}_t$, and they are used to evaluated momentum strategies. These tracking portfolios provide preliminary diagnostics on whether or not liquidity risk matters for momentum. The relation between momentum and liquidity risk is further explored in Section 4 using the non-traded factor directly.

The construction of a tracking portfolio follows two steps. First, the sensitivity of each stock with the liquidity factor, i.e., the liquidity beta $\beta_i^{\mathcal{L}}$, is estimated. Then, the stocks with the highest and lowest liquidity betas are identified and combined to a long-short portfolio that mimics the behavior of the liquidity factor. Liquidity betas are estimated through the following regression model

$$R_{i,t} = \beta_i^0 + \beta_i^m MKT_t + \beta_i^s SMB_t + \beta_i^h HML_t + \beta_i^{\mathcal{L}} \mathcal{L}_t + \iota_{i,t} \tag{13}$$

where $R_{i,t}$ is the return of stock i at time t (excess of the risk-free rate), MKT_t, SMB_t, and HML_t are Fama-French (1993) three factors, $\mathcal{L}_t$ is the liquidity factor, and $\iota_{i,t}$ is the error term. Notice, this formulation does not allow for the time variation liquidity-betas, in that $\beta_i^{\mathcal{L}}$ is an unconditional estimate of the full sample. However, to construct a liquidity-tracking portfolio one must use only the information given until that time, i.e., stocks must be sorted according to *predicted* liquidity-betas in any given month. To allow for time variation in $\beta_i^{\mathcal{L}}$ we use conditioning variables (see, Shanken (1990)) and model the conditional liquidity-betas through

[22] I also find asymmetries between the correlations in up and down markets. Explicitly, conditioning on the event $[MKT_t \geq 0]$ the correlations are: MKT_t -0.12, SMB_t 0.04, and HML_t -0.02; and for $[MKT_t < 0]$: MKT_t 0.35, SMB_t 0.18, and HML_t -0.02.

$$\beta^{\mathcal{L}}_{i,t-1} = \kappa_1 + \kappa_2' X_{i,t-1} \tag{14}$$

where $X_{i,t-1}$ is a vector of pre-determined conditioning variables. The conditioning variables include past one month return, level of illiquidity during the past month ($\lambda_{i,t-1}$, scaled by beginning-of-month price), standard deviation of past six-month returns, the natural logarithm of the level of illiquidity during the previous month, the natural logarithm of the average dollar volume during the past six months, the natural logarithm of stock price at the end of the previous month, and the natural logarithm of number of shares outstanding[23]. To preserve stationarity of the variables, all conditioning variables are de-meaned by the cross-sectional average every period. An intercept term κ_1 is also included.

The estimation of κ_1 and κ_2' follows two steps. First, the time series of risk-adjusted returns is calculated for each stock

$$\varepsilon_{i,t} = R_{i,t} - \widehat{\beta}_i^m MKT_t - \widehat{\beta}_i^s SMB_t - \widehat{\beta}_i^h HML_t \tag{15}$$

where the loadings $\widehat{\beta}_i^m$, $\widehat{\beta}_i^s$, and $\widehat{\beta}_i^h$ are estimates of a time-series regression of the return of stock i (excess of the risk-free rate) on the three Fama-French factors. In the second step, all $\varepsilon_{i,t}$ are regressed on $\mathcal{L}_t$ (with the conditioning variables) via a pooled-time-series regression

$$\varepsilon_{i,t} = \kappa_0 + \kappa_1 \mathcal{L}_t + \kappa_2' X_{i,t-1} \mathcal{L}_t + e_{i,t}. \tag{16}$$

Due to the relatively short time period of the sample, the regressions are estimated using the full sample. However, to avoid contemporaneous correlations between returns and predicted liquidity-betas, every month the entire procedure (both steps) is repeated, excluding a three month window, from the beginning of the previous month until the end of the next month. As a result, fitted betas are calculated every month using κ_1 and κ_2' estimated that month.

The estimation results of Equation (16) are presented in Table 4 (for the middle of the time series, December 1994). The coefficients of standard deviation of past returns, price and shares outstanding, appear significant. Notice that the level of illiquidity does not appear to have significant effects on sensitivity of returns to aggregate liquidity shocks (this result is consistent with

[23] As mentioned in Pástor and Stambaugh (2002), the vector of characteristics is necessarily arbitrary. Return volatility as a characteristic is motivated by Shleifer and Vishny (1997). They argue that in extreme cases of past idiosyncratic volatilities, investors would not allocate as much funds to arbitrageurs, which may cause persistence of apparent financial anomalies.

the results in Pástor and Stambaugh (2002)). The estimated liquidity-betas are calculated as the fitted values $\widehat{\beta}^{\mathcal{L}}_{i,t} = \widehat{\kappa}_1 + \widehat{\kappa}'_2 X_{i,t-1}$. The $\widehat{\beta}^{\mathcal{L}}_{i,t}$ vary over the sample period between -0.04 and 0.06, with an average of 2.9×10^{-4} (notice $\widehat{\beta}^{\mathcal{L}}_{i,t}$ are directly affected by the scale of the liquidity factor, see Equation (12)).

3.2 Momentum and Liquidity: Risk or Characteristics?

Momentum has long been considered anomalous since it cannot be explained by risk models to date. For example, in a Fama and French (1993) time-series regression, a long-short strategy of winners minus losers, earns a significant Alpha (both statistically and economically) and the adjusted R^2 of the regression is low.[24] In practice, however, implementing momentum strategies requires heavy trading, and therefore, liquidity may have an effect on the actual profitability of such strategies.

The literature considers various momentum-based strategies. Jegadeesh and Titman (1993) consider a matrix of different combinations of holding and ranking periods, such as three, six, nine, and twelve months. They also consider skipping a week after portfolio formation while calculating the returns (because of the evidence of short-run reversals in stock returns). Fama and French (1996), Carhart (1997), and Grinblatt and Moskowitz (2002) skip one month after formation date, and generally analyze the 12/1/1 momentum strategy, i.e., ranking period of twelve months, skip one month, and hold the portfolio for one month (see also detailed description of strategies in Korajczyk and Sadka (2002)). Grundy and Martin (2001) study the 6/1/1 strategy, Korajczyk and Sadka (2002) focus on 11/1/3 and 5/1/6 strategies, and most recently Heston and Sadka (2002) form strategies according to past single month-returns of different lags. This paper focuses on single-holding-month strategies, specifically the 11/1/1 strategy (for robustness, part of the analysis also examines the 5/1/1 strategy). The focus on single month strategies is justified by the fact that the biggest bang-for-the-buck is obtained on the first month of the holding period, and that the results are robust to the chosen ranking period. This is illustrated in Figure 5.

The momentum anomaly is not consistent with a liquidity premium tied to the absolute level of asset liquidity. I find that, on average, winners are more liquid than losers. The momentum anomaly

[24] Notice that factor loadings are assumed constant in this setting. More recent studies relax this assumption and develop methods of time varying factor loadings. For example, Grundy and Martin (2001) estimate a model in which loadings are proportional to factor returns during the momentum ranking period and conclude that the mean returns of momentum remain unexplained. The time variation of momentum returns, however, is better explained as indicated by the increase in the adjusted R^2 (see also Korajcayk and Sadka (2002) and Wu (2002) for similar conclusions).

is due to winners outperforming losers. Thus, in this context, the liquid stocks are expected to outperform the illiquid ones. This is the exact opposite to the conclusions of the body of research arguing that illiquid stocks attain a premium for their investors. Therefore, a liquidity-based explanation for momentum cannot relay on the level of liquidity alone.

To provide empirical evidence, three different liquidity-based factors are constructed: two are based on liquidity levels, and one based on liquidity risk. The first factor is constructed based on the fixed/transitory/non-information component of price impact ($\overline{\Psi}_{i,t}$, scaled by beginning-of-month price). In the beginning of every month stocks are sorted into ten groups of equal number of stocks according to the estimated $\overline{\Psi}_{i,t-1}$ last month. Equally weighted zero-cost portfolios are then constructed by taking long positions in the top decile, i.e., the illiquid stocks, and taking short positions in the bottom decile, i.e., the liquid stocks. The portfolio is held for one month, and the process is repeated every month. This factor is denoted $LIQ^{\overline{\Psi}}$. Similarly, LIQ^{λ} is constructed based on the variable/permanent/information component of price impact. Last, $LIQ^{\mathcal{L}}$ is constructed based on the predicted liquidity betas estimated above.

Having calculated the time-series returns of the three liquidity-based factors, I turn to calculate the returns to momentum portfolios, adjusting for the different type of factors. Explicitly, I run the following time-series regressions

$$R_{p,t} = \alpha_p + \beta_p^m MKT_t + \beta_p^s SMB_t + \beta_p^h HML_t + \beta_p^{\overline{\Psi}} LIQ_t^{\overline{\Psi}} + \beta_p^{\lambda} LIQ_t^{\lambda} + \beta_p^{\mathcal{L}} LIQ_t^{\mathcal{L}} + \iota_{i,t} \qquad (17)$$

where $R_{p,t}$ denotes portfolio return (excess of risk-free rate). The results are given in Table 5. First, the results re-confirm the analysis of previous studies (see, e.g., Jegadeesh and Titman (1993, 2001), Fama and French (1996), and Fama (1998)) for the sample used here: the CAPM and Fama-French factors do not seem to explain momentum. The winners-minus-losers portfolio has an Alpha (risk-adjusted return) of 1.28% per month with a t-statistic of 3.07, and the adjusted R^2 is 1%. Once $LIQ_t^{\overline{\Psi}}$ is added to the Fama-French factors, Alpha is reduced to 0.93% although remains highly statistically significant. The adjusted R^2 increases to 63% which indicates that $LIQ_t^{\overline{\Psi}}$ is important to explain the time-series variation of momentum returns. The loading on $LIQ_t^{\overline{\Psi}}$ is negative and statistically significant (t-statistic of -18.94).[25] The negative loading provides evidence for our hypothesis above, since it suggests that winners are more liquid than losers. Also, it suggests

[25] This t-statistic is extremely negative. This may be explained by several simultaneous effects. First the correlation between momentum (winners-minus-losers) and this liquidity factor is very high (-0.76). Second the time-series varation of returns of the liquidity-based factor is relatively low. Last, the regressions are simple OLS regressions with no adjustment for autocorrelation. Further statistical tests are conduced in the next section.

that in our sample, contrary to the generally accepted hypothesis, liquid stocks outperform illiquid stocks.[26] Similar results are found when LIQ_t^{λ} is added as a fourth factor.

The examination of $LIQ_t^{\mathcal{L}}$ results with an economic sensible conclusion. The Alpha of winners-minus-losers remains statistically significant, however it decreases to 1.01% and 1.02% per month, for equally and value-weighted portfolios, respectively. Similarly, the adjusted R^2 increase to 63% and 26%, respectively. Also notice the loadings on liquidity-risk are positive and statistically significant. The positive signs indicate that winners are associated with higher liquidity-betas, which can possibly explain their high returns. In other words, winners are more sensitive to market-wide liquidity shocks than losers and therefore part of the momentum continuation is explained by a liquidity premium.

Since momentum continuation is only exhibited during non January months (while a strong reversal effect during January (see, e.g., Grinblatt and Moskowitz (2002), Sadka (2001)), the analysis is repeated using these months alone. The results, in Table 6, appear stronger, in that the Alphas of momentum strategies are reduced by half when adding the liquidity factors.

Another interpretation of the findings can be achieved by treating the liquidity factor as a state variable that indicates market trading conditions and affects the investment opportunity set. This suggests that winners-losers strategies are more profitable in times where market liquidity is high. The findings here suggest that liquidity risk is important to explaining momentum returns rather than the liquidity level. This finding is further examined in the next section.

4 Evaluation of Asset-Pricing Models

The previous section formed portfolios to mimic the non-traded liquidity factor and provided intuition about the relation of momentum to liquidity level and liquidity risk. However, as noted above, the short time period of our sample makes it difficult to efficiently construct tracking portfolios, especially when liquidity risk of individual assets is time varying. Therefore, in this section, I use

[26] How can one reconcile these results with previous literature? This paper differs from previous studies on two accounts. First, the difference in samples. For example, Amihud and Mendelson (1986) use a universe of NYSE stocks between 1961 and 1980. More importantly, since this study focuses on the relation of momentum and liquidity, portfolios are rebalanced each month, thereby effectively studying short horizon effects. Amihud and Mendelson (1986) and Brennan and Subrahmanyam (1996) both examine longer horizon returns, in that portfolios are rebalanced once a year. The difference between short- and long-horizon effects of liquidity on future returns is important, yet it is not the focus of this paper.

portfolios, rather than individual stocks, to directly test the non-traded liquidity factor with two approaches: cross-sectional regressions and stochastic discount factors. The portfolios are formed using only information available at time of formation, and their liquidity betas are more stable over time than those of individual assets.

To estimate the risk premium of liquidity, 25 portfolios are formed. Each month stocks are sorted into 5 groups of equal number of firms according to past 12-month cumulative return (excluding last month's return), and within each group stocks are sorted into five groups according to the fixed/transitory/non-information component of price impact ($\overline{\Psi}_{i,t-1}$, scaled by beginning-of-month price) estimated during the previous month. The stocks in each momentum/liquidity group are used to form a portfolio with equal weight assigned to each stock. The portfolios are rebalanced every month. The diagnostics of these portfolios are reported in Table 7. The dependent sorts used to create the portfolios ensure sufficient cross-sectional variation both in momentum and liquidity (and also create sufficient cross-sectional variation in liquidity beta), which is important for the power of the tests below.

4.1 The Cross-Sectional Regressions (CSR) Approach

Assume the following model of expected returns

$$E[R_i] = \gamma_0 + \gamma' \beta_i \tag{18}$$

where $E[R_i]$ denotes the expected return of portfolio i (excess of risk-free rate), β_i are factor loadings and γ is a vector of premiums. Since loadings are unobservable, they are pre-estimated through a multiple time-series regression

$$R_{i,t} = \beta_{0,i} + \beta_i' f_t + \varepsilon_{i,t} \tag{19}$$

where f_t is a vector of factors (either traded or non-traded).

The unconditional model (18) may be consistently estimated using the cross-sectional regression method proposed by Black, Jensen, and Scholes (1972) and Fama and MacBeth (1973). First regression (19) is estimated using the full sample. Then, (18) is estimated every month resulting with a time series $\widehat{\gamma}_t$. The time-series mean and standard error are finally calculated.

Since (18) is estimated using sample estimates of β_i' rather than the true values, (18) is subject to the "errors-in-variables" problem. Thus, I follow Shanken (1992) and Jagannathan and Wang

(1996, 1998) to correct standard errors for this bias. Last, the adjusted R^2 of the cross-sectional regression is calculated as an intuitive measure that expresses the fraction of the cross-sectional variation of average excess returns captured by the model.

The model in Equation (18) is tested for three factor specifications. First, the CAPM is re-examined using MKT as a single factor. Then, the Fama and French (1993) factors, SMB and HML, are added, and finally the non-traded liquidity factor $\mathcal{L}$ is added. To test whether the model in (18) is correctly specified, I follow Shanken (1992), Jagannathan and Wang (1996), Daniel and Titman (1997), and Brennan, Chordia, and Subrahmanyam (1998), and add observed characteristics to the model. If the model is correctly specified, the coefficients of the characteristics should not be statistically different from zero. For this purpose the model is modified to

$$E\left[R_i\right] = \gamma_0 + \gamma' \beta_i + c' Z_i \tag{20}$$

where Z_i is a vector of observed characteristics. The characteristics used in this study are as follows: the natural logarithm of market capitalization and book-to-market (see Fama and French (1992)), the non-information component of price impact ($\overline{\Psi}_{i,t-1}$, scaled by beginning-of-month price), the information component of price impact ($\lambda_{i,t-1}$, scaled by beginning-of-month price), turnover, and momentum.[27] Since portfolios are used to test the asset-pricing models, the average characteristics of the firms in each portfolio are used as the characteristic of the portfolio. Also, following Shanken (1992) and Jagannathan and Wang (1996), characteristic are assumed constant over time, thus, the time-series average of the characteristics of each portfolio is used for Z_i. Due to correlation among the characteristics, the last four characteristics are orthogonalized to the estimated factor loadings (β_i) and all characteristics preceding them.

The results of the estimation are reported in Table 8 and plotted in Figure 6. The CAPM clearly fails to explain the returns of the 25 portfolios sorted on predicted momentum and liquidity. The adjusted R^2 is practically zero and the t-statistic of the market premium is -0.22. When adding characteristics, only the coefficients of turnover and momentum appear positive and statistically significant. The sign on turnover is counter-intuitive since it translates to higher expected returns to more liquid portfolios. However, this result changes when evaluating the Fama-French factors.

The Fama-French three factors improve on the CAPM, nevertheless the resulting adjusted R^2 is only 30%. This is not surprising, since previous studies have already established that momentum is

[27] To preserve stationarity, price impact components and turnover are devided by the cross-sectional market average in any given month.

unexplained by these factors. Interestingly, the estimated premium on HML is negative. This can be explained by the nature of the portfolios chosen here. As shown by Asness (1997), momentum is stronger among growth firms, i.e., low book-to-market ratios. Therefore when testing the model using momentum portfolios, HML receives a negative premium. The characteristics improve the adjusted R^2 to 93%. The premium on turnover is now insignificant. Yet the premium on the λ characteristic is significantly negative, which once again indicates that low liquidity portfolios earn higher expected returns.

Last, the non-traded liquidity factor $\mathcal{L}$ is added as a fourth factor to the existing Fama-French factors. The adjusted R^2 increases to 70%. The premium on liquidity is 0.54% per month with a t-statistic of 2.61. No other factors are statistically significant. Also notice that, contrary to the other factor models, the average pricing error γ_0 is no longer significant. Adding characteristics increases the adjusted R^2 to 93%, and the coefficients of λ, turnover, and momentum are statistically significant. The coefficient of the liquidity factor remains statistically significant. These results suggest that the liquidity factor seems to have power in explaining expected returns to momentum/liquidity portfolios. Nevertheless, it cannot entirely explain the momentum anomaly.

The premium on liquidity risk estimated here is subject to scaling effects (see Equation(12)). Therefore, to get an idea on the magnitude of the premium, one should look at other performance measures, such as appraisal ratio or Sharpe ratio. The annualized Sharpe ratio of the liquidity premium is 0.6. For comparison, the Sharpe ratio of the value-weighted market return is roughly 0.5 and momentum has a ratio of about 1. The Sharpe ratio of the premium reported in Pástor and Stambaugh (2002) is 0.76 (over the period 1983-1999).[28] The conclusion from these tests is that liquidity risk is an important determinant for explaining the cross-sectional variation of expected returns on momentum/liquidity-sorted portfolios.

4.2 The Stochastic Discount Factor (SDF) Approach

The stochastic discount factor appraoch is another method used to evaluate different asset-pricing models. It is well known that as long as the law of one price holds in the economy, there exists some random variable, a stochastic discount factor (SDF) d_t, that prices all assets, i.e., for any

[28]See Pástor and Stambaugh (2002), Table 4, the four factor Alpha of high minus low predicted liquidity-beta portfolio for the period January 1983 until December 1999 (204 months) has a t-statistic of 3.12.

(excess) return $R_{i,t}$ it satisfies

$$E\left[R_{i,t} d_t\right] = 0 \tag{21}$$

If the factor-based asset pricing models explain returns, the stochastic discount factor can be expressed as[29]

$$d_t\left(\delta\right) = 1 + \delta' f_t \tag{22}$$

The universe contains 25 portfolios, which translates to 25 moment conditions over 224 months. The asset-pricing models tested have four factors at most. Therefore we are left with an over-identified system. The moment conditions are constructed as follows. Define R_t as the 25×1 vector of portfolio returns at time t. Define the sample analogs

$$\begin{aligned} R_T &= \frac{1}{T}\sum_{t=1}^{T} R_t \qquad (23) \\ D_T &= \frac{1}{T}\sum_{t=1}^{T} R_t f_t' \end{aligned}$$

The sample analog of the moment conditions is given by

$$w_T = D_T \delta + R_T \tag{24}$$

For a given weighting matrix Ω the estimates of δ are those that minimize $J\left(\delta\right)$ such that

$$J\left(\delta\right) = w_T' \Omega^{-1} w_T \tag{25}$$

Since the system is linear the solution is analytically solved as

$$\delta_T = -\left(D_T' \Omega^{-1} D_T\right)^{-1} D_T' \Omega^{-1} R_T \tag{26}$$

For the empirical analysis, two empirical tests are conducted. First, following Hansen (1982) the optimal weighting matrix is used (this is achieved by first using the identity matrix and conducting several iterations until no improvement is achieved). In this case, δ_T is a consistent estimator of δ, and has an asymptotically normal distributions. Hansen (1982) shows that when Ω^{-1} is optimal, then $T \times J\left(\delta_T\right)$ is asymptotically distributed χ^2 with N-K degrees of freedom (N is the number of moment conditions, i.e., the number of portfolios, and K is the dimension of δ). This is the basis for the over-identifying restriction tests, which is used to test the different asset-pricing models here.

[29] Since excess returns of the portfolios are used, the constant term is normalized to a value of 1.

Second, notice that the optimal weighting matrix depends on the asset-pricing model tested. Hansen and Jagannathan (1997) develop a method that helps to evaluate the different asset-pricing models on a common scale. They propose a common weighting matrix for all model

$$\Omega = E\left[R_t R_t'\right] \tag{27}$$

They show that the resulting $J(\delta)$ has the interpretation of the least-square distance between the given estimated stochastic discount factor and the nearest point to it in the set of all discount factors that price assets correctly. However, since Ω^{-1} may not be optimal, $T \times J(\delta_T)$ will not generally converge to a χ^2 distribution. Therefore, to calculate the p-values I follow the correction presented in Jagannathan and Wang (1996). To adjust for serial correlation of moment conditions, a Bartlett kernel with three lags[30] is applied, both when using the Hansen (1982) optimal matrix and the Hansen and Jagannathan (1997) sample moment matrix (henceforth referred as the HJ matrix).

The empirical results are presented in Table 9. This analysis focuses on testing the over-identifying restrictions of the different asset-pricing models rather than on the significance of the estimates of δ. The reason is that the translation between δ and the premiums γ is not direct (see, e.g., Jagannathan and Wang (1996)). Both Hansen and HJ methods reject the CAPM with p-values of 1.05% and 3.04%, respectively. Fama-French factors are rejected using the optimal matrix (p-value of 3.31%), but cannot be rejected at the 5% significance level with the HJ matrix (p-value of 6.99%). When liquidity is added as a fourth factor, the model cannot be rejected by either method. The p-values are 8.13% and 17.01%, respectively. These results re-affirm the conclusions of the CSR tests regarding the significance of the liquidity factor in explaining the cross-sectional variation of returns.

5 Momentum and the Limits to Arbitrage

The analysis so far suggests that liquidity risk rather than liquidity level is important to understanding asset prices. Specifically, when considering momentum strategies, liquidity risk is shown to explain part, but not all, of the relatively high returns. However, the fact that momentum

[30] There is no consensus in the literature regarding the optimal number of lags. The results presented here are robust up to 5 lags. Andrews (1991) and Andrews and Monahan (1992) discuss various kernels and provide guidelines for each. See also Hansen, Heaton, and Amir (1996) for small sample properties of GMM.

remains profitable in the last two decades remains a puzzle. A natural question is whether or not the apparent momentum profits are exploitable, i.e., are there limits to arbitrage.

Many theoretical studies focus on the forces of an efficient market, which naturally arise in the presence of arbitrage opportunities to limit their economic scale. It is important to distinguish between the different reasons that create these forces. Glosten and Milgrom (1985) and Kyle (1985) develop information asymmetry models that induce trading costs (bid-ask spreads and price impact, respectively) as a result of the market makers protecting themselves from the informed traders. Shleifer and Vishny (1997) argue that limits to arbitrage may be induced by agency costs, as a result of the arbitrageurs managing the funds of other investors. Grossman and Miller (1988) discuss liquidity as the price of immediacy to information traders. The price of immediacy is also discussed by Perold (1988) calling it implementation shortfall, and Treynor (1994) who refers to it as the hidden costs of trading.

In this section I examine the limits to arbitrage of momentum induced by the latter context—a price for immediacy. There is a small difference, however. Momentum has long been known to financial researchers and therefore is less likely to be considered as private information. The price of immediacy is incurred because momentum strategies require trading on a monthly basis. As illustrated in Figure 5, returns gradually drop every month after portfolio formation, which does not allow for patient arbitrage trading.

This work is part of a recently growing empirical literature on the limits to apparent arbitrage opportunities. Knez and Ready (1996) study the opportunity to exploit the size effect (see Banz (1981) and Keim (1983)) and find that size-based strategies are too costly to trade. Ali, Hwang, and Trombley (2002) study the profitability of BE/ME strategies. Mitchell and Pulvino (2001) analyze the profits to risk arbitrage of mergers and acquisitions. Korajczyk and Sadka (2002) focus on momentum strategies. Chen, Stanzl, and Watanabe (2002) examine a variety of strategies based on size, BE/ME, and momentum. In this section I do not explicitly calculate the amount that can be invested in momentum strategies, but rather point to the monotonic relation between the absolute value of risk-adjusted returns and transaction costs. In other words, it turns out that the most attractive stocks a-priori, are those that exhibit the highest transaction costs.

5.1 When Does Liquidity Level Matter?

As a first step, an event-time analysis of trading costs of momentum strategies is conducted. Every month momentum strategies are formed, and the lag and lead averages of trading costs for these portfolios are computed (these averages are computed relative to the average market trading costs every period). The formation time is the end of month 0. The event-time window analyzed is -11 to +12 (a year before and a year after the formation date). The stocks in each portfolio are held constant throughout the event-time period. The patterns for different momentum deciles for 11/1/1 and 5/1/1 strategies are plotted in Figure 7. First, once again, there is clear evidence of time variation in liquidity, as demonstrated by the increasing costs of losers and the decreasing costs of winners during the formation period. Second, both winners and losers remain at their initial level of illiquidity, at the time of formation, even twelve months after formation. This means that momentum strategies are as costly to trade even for holding periods longer than one month. One might argue that even so, rebalancing momentum portfolios, say every two months, would induce half the costs per month, than would monthly rebalancing. However, as shown above, monthly returns decrease with the holding period, and therefore, it is not clear whether a longer holding period would if fact award higher average monthly profits.

Interestingly, winners do not exhibit the lowest trading costs. To investigate this point further, the average trading cost of 50 momentum portfolios at time 0 is plotted in Figure 8. A clear U- or J-shape relation is unraveled in Panel A: both winners and losers, which earn the highest risk-adjusted expected returns in absolute value, are associated with high illiquidity costs. This result is robust to the different measures of transaction costs estimated in this paper, such as the information and non-information components of price impact. Risk-adjusted returns (relative to Fama-French three factors) are also plotted in Figure 8. Notice that negative risk-adjusted returns are associated with low liquidity. Both liquidity costs and risk-adjusted returns (in absolute value) decrease with past momentum. However, for the momentum portfolios that exhibit positive risk-adjusted returns, liquidity costs are increasing with momentum. Therefore, it seems that the momentum portfolios that earn the lowest risk-adjusted returns (in absolute value) are the most liquid among the momentum portfolios, and that extreme winners and losers are associated with higher liquidity costs. Hence, the liquidity *level* may suggest possible limits to arbitrage of the momentum anomaly.

Panel A also displays the liquidity beta of the momentum portfolios. This beta is the coefficient of $\mathcal{L}_t$ in the time-series regression model in Equation (13), applied to each momentum portfolio. Notice that winners have a high liquidity beta and losers have a low liquidity beta, which is again an indication that liquidity *risk* may be part of an explanation for momentum.

A natural extension of this analysis is to investigate other measures of liquidity, such as turnover, and the Amihund (2002) measure (also used by Acharya and Pedersen (2003)). The results are presented in Figure 8, Panel B. Interestingly, turnover exhibits a clear U-shape. This result is counter intuitive, since if turnover is a proxy for liquidity, then this results suggests that winners and losers are the most liquid. This is another indication that volume is a noisy proxy for liquidity. As seen from the graph, winners appear to have more turnover than losers, however, both have above average turnover. This finding is related to Hvidkjaer (2001) that documents that both winners and losers exhibit high order imbalances. Chordia, Roll, and Subrahmanyam (2002) show that order imbalances reduce liquidity (measured by dollar volume). This suggests that, for momentum portfolios, turnover may proxy for order imbalance, which translates to low liquidity for extreme winners and losers. The measure of Amihud (2002) seems to capture similar, although noisier, effects to those of the price impact measures.

5.2 Relation to Previous Findings on Momentum

Previous studies document a relationship between momentum and each of the following: volume, book-to-market, and analyst coverage. Specifically, Lee and Swaminathan (2000) find that momentum exhibits higher returns among the high volume stocks. Asness (1997) finds that momentum achieves higher returns among the low book-to-market stocks (i.e., growth firms). Last, Hong, Lim, and Stein (2000) find that momentum is more profitable among the low analyst-covered firms. Each study focuses on a different economic view of momentum. This section addresses these studies, and show how they are related to the results of this paper.

First, the fact that momentum "works" better among the high volume stocks further deepens the momentum anomaly. To the extent that volume proxies for liquidity,[31] these findings suggest that momentum can be easily exploited in practice. Therefore, the persistence of this anomaly since

[31] Lee and Swaminathan (2000) discuss whether volume proxies liquidity. They test whether volume is related to other liquidity measures such as market capitalization and bid-ask spreads. They do not find strong evidence of such correlation.

its discovery seems even more puzzling. To relate the price impact measures to this finding, triple independent sorts of momentum, volume, and the non-information component of price impact[32] are conducted. The results are presented in Table 10. When looking at the momentum and volume sorts, the results clearly replicate the results of Lee and Swaminathan (2000). However, once a finer cut is conducted using liquidity, it is apparent that the high volume momentum profits are mostly due to the illiquid stocks. When restricting the analysis to the liquid firms, the results are reversed, and momentum appears more profitable among the low volume stocks than in the high volume stocks.

Second, unreported analyses confirm the findings about book-to-market and momentum in the sample used here. I find that the growth/momentum relationship becomes weaker if one restricts the analysis to high liquidity firms alone, although remains economically significant. The book-to-market ratio remains stable over time. Thus restricting momentum trading strategies to growth firms alone, should not particularly increase the turnover of these strategies (and therefore should not increase concerns about liquidity costs). Therefore, I do not find that liquidity effects can explain the growth/momentum relationship.

One of the purposes of the study of Hong, Lim, and Stein (2000) is to test the information-diffusion explanation of momentum, proposed in Hong and Stein (1999). They use analyst coverage (the part unexplained by market capitalization), to proxy for information diffusion, i.e., information is incorporated into prices faster in high analyst-covered stocks. Indeed, they find that low analyst-covered stocks exhibit significantly more momentum than high analyst-covered stocks. Unreported analyses confirm that firms that have low analyst coverage exhibit high levels of price impact. This is not surprising, if one believes that analysts reduce the information asymmetry in the market. Thus, the permanent component of price impact, which proxies information effects (Kyle (1985)), would naturally decrease for firms with high analyst coverage. This observation can contibute to the information-diffusion hypothesis; firms with low analyst coverage exhibit high momentum, but the effect is not arbitraged away since these are relatively low liquidity stocks.

[32] The information component of price impact produces similar results. The non-information component is chosen here because it may be viewed as a pure cost since it is transitory by construction.

6 Conclusions

Many view financial anomalies as strong rejections of the efficient-market hypothesis. However, if these anomalies are associated with some type of risk or/and are too costly to exploit, then their significance is reduced. This paper demonstrates that a liquidity factor, based on intraday data, can contribute to the understanding of the cross-section of expected returns and the momentum anomaly. It is important to note that the evidence in this paper does not fully explain the momentum anomaly. Rather, it emphasizes the liquidity risk that one must bear while engaging in momentum trading. Also, it suggests that achieving abnormal profits with momentum trading in practice, may be viewed more as superior trading ability (e.g., avoiding high transaction costs) and/or cost of obtaining information, than previously considered in the literature.

This paper makes the distiction between liquidity level per se and liquidity risk. Momentum exhibits significant patterns in both. Similarly, one can test other financial anomalies, such as the well known post-earnings announcement drift, merger arbitrage, the January effect, and other event time as well as calender time anomalies. The liquidity factor introduced here can be used to test whether these anomalies carry a premium for liquidity risk, which may practically explain their persistence. Also, these anomalies may exhibit high levels of illiquidity which may indicate a possibility of limits to arbitrage. The portfolios that are formed to test these anomalies in the literature often require frequent rebalancing, and, therefore, is likely to be subject to liquidity concerns. The liquidity risk factor may also be added in the evaluation of portfolio managers (active versus passive funds).

Another interesting line of research is the commonality of liquidity, recently prompted by Chordia, Roll, and Subrahmanyam (2000) and Hasbrouck and Seppi (2001). If the estimated price impacts are driven by some common factors, one could use them to explain expected returns. This paper uses aggregate illiquidity, however, there may be other important factors.

The ability to decompose the level of liquidity into permanent and transitory effects has a broad range of potential applications. For example, investors reaction to corporate news and events, such as earnings announcements and equity issues, has been the focus of many studies. Volume-based measures, usually on a daily level, are often used in these type of studies to assess how investors process new information. Only a few of such studies use intraday data, such as bid-ask spreads (see, e.g., Lee, Mucklow, and Ready (1993) and Affleck-Graves, Callahan, Chipalkatti (2002)). Price impacts can contribute to understanding the nature of trades (information versus non-information) around these financial events. Using the decomposition described in this paper, one could investigate whether there is evidence of information-based trading before the announcement, which could possibly point to information leakage.

The evidence in this paper emphasizes the need for an equilibrium asset-pricing model that incorporates price-impact costs. Preliminary studies of this are the equilibrium model in the working paper version of Brennan and Subrahmanyam (1996), the portfolio choice model in Sadka (2001), and the work of Acharya and Pedersen (2003). Future work should focus on developing general equilibrium models with price impacts. Such models should provide theoretical guidelines as to the exact formulation in which transaction costs affect expected returns. With a rigorous benchmark model in hand, one is likely to sharpen the empirical tests beyond those implemented here. As a result, empirical research could improve the performance evaluation of different trading strategies, along with testing the efficiency of financial markets.

The fact that momentum has been shown to be empirically related to some characteristics and macroeconomic effects, naturally generates interesting questions regarding liquidity. Specifically, momentum is related to industry (see, e.g., Moskowitz and Grinblatt (1999) and Lewellen (2002)), book-to-market ratio (see, e.g., Asness (1997)), and the business cycle (see, e.g., Chordia and Shivakumar (2002) and Griffin, Ji, and Martin (2002)). For example, market-wide liquidity shocks may be related to business-cycle risk. Also, Heston and Sadka (2002) document periodicity of momentum returns. To the extent that this effect indicates periodicity in release and processing of new information or amount of noise trading in the market, one may find supporting evidence by studying the periodicity of price impacts and of the order flow. In summary, this paper shows that momentum is strongly related to liquidity effects (both risk and level), however, it would take more than one explanation to fully understand the momentum anomaly.

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Table 1
Diagnostics of Liquidity Measures

Price impacts are estimated through the following model

$$\Delta p_t = \alpha + \Psi \varepsilon_{\psi,t} + \lambda \varepsilon_{\lambda,t} + \Psi^k K_t \varepsilon_{\psi,t} + \lambda^k K_t \varepsilon_{\lambda,t} + \bar{\Psi}\Delta D_t + \bar{\lambda}\Delta DV_t + \bar{\Psi}^k \Delta KD_t + \bar{\lambda}^k \Delta KDV_t$$

where Δp_t is the price improvement (in dollars) as a result of trading V_t shares at time *t* (here *t* represents event time), D_t is an indicator for buyer-initiated (+1) or seller-initiated (-1) trade, the variables $\varepsilon_{\psi,t}$ and $\varepsilon_{\lambda,t}$ are the unanticipated trade sign and signed volume, respectively, and K_t is a dummy variable, which is assigned a value of (+1) for all trades above 10,000 shares and zero otherwise. The complete derivation of this model is provided in Section 2. The model identifies both information/permanent and non-information/transitory components of the total price impact, as well as fixed and variable costs. Price impacts are estimated on a monthly basis, separately for every stock. Time-series means of monthly cross-sectional statistics are calculated below. Panel A uses the raw estimates of price impact, while Panel B scales the measures by the stock price at the beginning of the month. Panel C computes ratios of the price impact measures, as the transitory part divided by the sum of transitory and permanent parts. Panel D computes similar statistics for other liquidity measures. Turnover is calculated as the monthly share volume of a stock scaled by its number of shares outstanding. The relative bid-ask spread is the bid-ask spread divided by the midpoint of quotes. The effective spread is defined as the absolute value of a trade price divided by the midpoint of quotes (as five seconds prior to the trade). The number of shares offered on the bid and on the ask are also recorded. The estimation analysis includes NYSE-listed stocks for the period January 1983 to August 2001.

		Mean	Std	Min	1%	Median	99%	Max
Panel A: Price impact components								
Regular trades								
Information/Variable $\times 10^6$	λ	7.90	12.00	-20.00	-20.00	5.57	71.00	71.00
Information/Fixed	Ψ	0.02	0.03	-0.08	-0.08	0.01	0.14	0.14
Non-information/Variable $\times 10^6$	$\bar{\lambda}$	-3.08	7.15	-30.00	-30.00	-2.94	26.00	26.00
Non-information/Fixed	$\bar{\Psi}$	0.05	0.01	0.01	0.01	0.05	0.10	0.10
Large trades								
Information/Variable $\times 10^6$	λ^k	2.08	12.57	-159.64	-18.05	0.85	32.85	176.75
Information/Fixed	Ψ^k	0.03	0.18	-2.18	-0.31	0.02	0.38	2.48
Non-information/Variable $\times 10^6$	$\bar{\lambda}^k$	-0.16	13.64	-152.53	-19.23	-0.07	16.53	259.71
Non-information/Fixed	$\bar{\Psi}^k$	0.04	0.18	-2.71	-0.21	0.04	0.32	2.36
Panel B: Scaled price impact components								
Regular trades								
Information/Variable $\times 10^7$		4.45	7.97	-14.50	-14.50	2.37	45.79	45.80
Information/Fixed (%)		0.08	0.18	-0.59	-0.59	0.05	1.00	1.00
Non-information/Variable $\times 10^7$		-2.02	5.32	-28.74	-28.73	-1.19	16.02	16.03
Non-information/Fixed (%)		0.37	0.43	0.03	0.03	0.25	2.95	2.95
Large trades								
Information/Variable $\times 10^7$		1.08	11.54	-148.66	-11.68	0.33	22.75	183.61
Information/Fixed (%)		0.13	1.31	-16.80	-2.00	0.08	2.57	19.77
Non-information/Variable $\times 10^7$		-0.09	13.69	-169.84	-14.22	-0.02	12.06	258.42
Non-information/Fixed (%)		0.28	1.79	-26.88	-1.33	0.15	3.59	25.15
Panel C: Price impact ratios								
Regular trades								
Variable		0.91	158.37	-2311.92	-39.12	-0.31	40.28	3984.96
Fixed		0.74	1.85	-39.92	-0.58	0.81	1.50	19.52
Large trades								
Variable		0.44	107.97	-1501.41	-27.69	-0.01	27.43	2012.77
Fixed		0.34	28.24	-645.78	-7.68	0.59	9.16	343.29
Panel D: Other measures of transaction costs								
Turnover $\times 10^3$		0.62	0.92	0.01	0.04	0.44	3.18	23.36
Bid-Ask Spread ($)		0.22	0.08	0.03	0.11	0.21	0.44	1.61
Relative Bid-Ask Spread (%)		1.38	1.49	0.14	0.25	1.03	8.66	16.95
Effective Spread (%)		0.52	0.95	0.05	0.09	0.37	3.51	21.84
Bid Size (shares)		67	116	2	5	32	586	1338
Offer Size (shares)		66	103	2	5	34	543	1002

Table 2
Diagnostics of Return Costs for Average Monthly Trades

Price impacts are estimated through the following model

$$\Delta p_t = \alpha + \Psi\varepsilon_{\psi,t} + \lambda\varepsilon_{\lambda,t} + \Psi^k K_t\varepsilon_{\psi,t} + \lambda^k K_t\varepsilon_{\lambda,t} + \bar{\Psi}\Delta D_t + \bar{\lambda}\Delta DV_t + \bar{\Psi}^k\Delta KD_t + \bar{\lambda}^k\Delta KDV_t$$

where Δp_t is the price improvement (in dollars) as a result of trading V_t shares at time t (here t represents event time), D_t is an indicator for buyer-initiated (+1) or seller-initiated (-1) trade, the variables $\varepsilon_{\psi,t}$ and $\varepsilon_{\lambda,t}$ are the unanticipated trade sign and signed volume, respectively, and K_t is a dummy variable, which is assigned a value of (+1) for all trades above 10,000 shares and zero otherwise. The complete derivation of this model is provided in Section 2. The model identifies both information/permanent and non-information/transitory components of the total price impact, as well as fixed and variable costs. Price impacts are estimated on a monthly basis, separately for every stock. Price impacts are scaled by beginning-of-the-month price. Diagnostics of the distribution of trade size are provided below. Return costs are calculated as the sum of the fixed costs and the multiple of the variable costs and the average trade size (every month). Panel B uses the estimates of regular trades and average trade sizes of regular trades. Similarly, Panel C uses estimates of trades above 10,000 shares and the average trade sizes of these trades. All panels report the time-series means of monthly cross-sectional statistics. The analysis includes NYSE-listed stocks for the period January 1983 to August 2001.

	Mean	Std	Min	1 Percetile	Median	99 Percentile	Max
Panel A: Overall statistics							
Number of firms with 10k trades over total	0.87	0.03	0.74	0.78	0.88	0.92	0.94
Number of 10k trades over total (per firm with 10k transaction)	3.30	3.10	0.08	0.21	2.53	13.79	38.39
Number of 10k trades over total (all firms, per month, %)	3.88	1.20	1.92	2.07	3.40	6.18	6.28
Panel B: All trades below 10,000 shares							
Number of trades (per firm)	1,628	2,860	31	51	643	14,465	34,731
Average trade size	947	314	122	350	924	1,807	2,630
Permanent relative price change (%)	0.12	0.20	-0.71	-0.50	0.08	0.97	1.54
Temporary relative price change (%)	0.35	0.41	-0.04	0.04	0.24	2.63	3.16
Total relative price change (%)	0.47	0.49	-0.52	-0.17	0.35	2.93	4.17
Temporary/Total	0.66	3.88	-82.47	-0.31	0.72	1.28	48.81
Panel C: All trades greater than or equal 10,000 shares							
Number of trades (per firm)	74	174	1	1	19	823	2,635
Average trade size	30,647	95,881	10,000	10,000	19,679	259,497	1,976,844
Permanent relative price change (%)	0.31	1.51	-22.16	-0.53	0.20	2.69	21.45
Temporary relative price change (%)	0.29	1.75	-8.04	-0.41	0.14	2.59	39.00
Total relative price change (%)	0.61	2.24	-14.76	-0.15	0.38	4.37	45.63
Temporary/Total	0.44	8.85	-162.91	-0.89	0.40	1.86	123.30

Table 3
Price Impacts and Other Measures of Liquidity

Price impacts are estimated through a model described in Section 2. The model identifies both information/permanent and non-information/transitory components of the total price impact, as well as fixed and variable costs. Price impacts are estimated on a monthly basis, separately for every stock. Price impacts are scaled by beginning-of-the-month price, and then scaled by the cross-sectional average that month. Independently, other characteristics and liquidity measures existing in the literature are computed: size is measure as market capitalization, book-to-market equity (BE/ME) is computed according to the description in Cohen, Polk, and Vuolteenaho (2002), volume is the total number of shares traded of each stocks every month, turnover is volume divided by the number of shares outstanding, and the illiquidity measure used in Amihud (2002). Every month stocks are sorted into five groups according to each one of the existing measures. Then, in each group stocks are sorted according to the estimated price impacts. The average price impacts in each group are calculated and the time-series of mean of these averages are reported below. The analysis includes NYSE-listed stocks for the period January 1983 to August 2001.

Liquidity Measures		Low	Non-information fixed costs (regular transactions)			High	Low	Information variable costs (regular transactions)			High	Low	Information variable costs (large transactions)			High
	Low	0.56	1.02	1.40	2.06	5.24	-1.28	0.55	1.50	2.87	6.82	-112.78	-3.67	7.74	27.12	103.44
		0.39	0.69	0.94	1.23	2.19	-0.45	0.42	0.92	1.56	3.63	-46.74	-1.52	1.86	8.15	45.57
Size		0.30	0.51	0.69	0.95	1.71	-0.25	0.33	0.65	1.03	2.28	-38.69	-1.07	1.28	4.39	20.95
		0.26	0.41	0.53	0.69	1.20	-0.05	0.29	0.48	0.70	1.43	-4.74	-0.22	0.90	2.60	11.11
	High	0.19	0.28	0.36	0.46	0.73	0.02	0.17	0.26	0.37	0.76	-1.50	0.04	0.62	1.45	5.29
		0.21	0.33	0.45	0.65	1.81	-0.27	0.21	0.39	0.71	2.59	-49.58	-0.13	0.80	2.62	16.67
		0.21	0.34	0.47	0.63	1.29	-0.27	0.24	0.43	0.74	2.20	-7.41	0.05	1.09	2.83	13.53
BE/ME		0.23	0.39	0.54	0.74	1.50	-0.33	0.27	0.49	0.85	2.56	-6.99	-0.40	0.78	2.25	18.62
		0.26	0.43	0.58	0.80	1.69	-0.33	0.26	0.50	0.90	2.81	-5.46	-0.25	0.63	1.64	9.73
		0.30	0.53	0.75	1.11	2.59	-0.52	0.26	0.59	1.20	3.96	-22.09	-0.26	0.52	2.15	18.78
		0.28	0.62	0.91	1.27	3.06	-1.41	0.40	1.32	2.77	6.85	-25.06	-4.34	2.02	10.92	40.43
		0.33	0.60	0.88	1.25	2.89	-0.37	0.40	0.87	1.53	3.62	-70.17	-2.88	2.63	11.51	64.81
Volume		0.30	0.52	0.74	1.12	2.70	-0.14	0.41	0.72	1.13	2.49	-43.88	-1.66	1.19	5.08	28.58
		0.26	0.41	0.58	0.86	2.25	-0.03	0.31	0.49	0.72	1.48	-5.37	-0.28	0.94	2.92	17.10
		0.22	0.33	0.45	0.63	1.56	0.00	0.16	0.25	0.36	0.72	-6.96	0.10	0.65	1.44	6.56
		0.28	0.57	0.84	1.21	3.13	-1.09	0.38	1.01	2.11	6.00	-20.02	-1.22	2.56	7.11	39.17
		0.28	0.51	0.77	1.14	2.67	-0.42	0.31	0.63	1.17	3.55	-18.85	-0.64	0.78	3.29	26.75
Turnover		0.26	0.44	0.65	1.01	2.37	-0.23	0.27	0.52	0.93	2.78	-34.95	-0.28	0.75	2.52	17.14
		0.25	0.42	0.60	0.92	2.22	-0.17	0.25	0.45	0.81	2.38	-17.82	-0.23	0.80	2.34	19.35
		0.25	0.42	0.61	0.90	2.30	-0.14	0.22	0.41	0.74	2.16	-16.11	-0.11	0.91	2.98	24.81
		0.19	0.28	0.36	0.46	0.75	0.02	0.17	0.25	0.34	0.60	-1.24	0.06	0.59	1.36	4.32
		0.28	0.43	0.56	0.74	1.30	-0.01	0.31	0.49	0.68	1.17	-4.07	-0.36	0.85	2.67	11.31
Amihud (2002)		0.32	0.54	0.73	1.01	1.68	-0.12	0.39	0.70	1.07	1.97	-36.70	-1.01	1.63	5.52	25.62
		0.36	0.66	0.93	1.24	2.15	-0.40	0.47	1.00	1.67	3.46	-60.23	-2.58	2.36	9.82	51.84
		0.44	0.90	1.33	2.08	5.30	-1.47	0.46	1.55	3.09	7.15	-156.93	-5.37	3.14	27.39	115.63

Table 4

Determinants of Conditional Liquidity-Betas

Conditional liquidity-betas are estimated through the following regression model (pooled cross-section and time-series)

$$\varepsilon_{i,t} = \kappa_0 + \kappa_1 L_t + \kappa_2' X_{i,t-1} L_t + e_{i,t}$$

where $\varepsilon_{i,t}$ is the risk-adjusted return of stock *i* at month *t* (relative to Fama-French three factors), L_t is a liquidity factor (based on innovations in aggregate liquidity), $X_{i,t-1}$ is a vector of pre-determined conditioning variables, and $e_{i,t}$ is the error term. The conditioning variables include past one month return, level of liquidity during the past month, standard deviation of past six-month returns, the natural logarithm of the level of liquidity (measured as the information/variable component of price impact) during the previous month, the natural logarithm of the average dollar volume during the past six months, the natural logarithm of stock price at the end of the previous month, and the natural logarithm of number of shares outstanding. All conditioning variables are de-meaned by the cross-sectional average every period. An intercept term κ_1 is also included. The estimation results are presented below. The analysis includes NYSE-listed stocks for the period January 1983 to August 2001.

κ_1	2.80E-04
	0.94
Previous month return	5.59E-03
	1.74
Illiquidity level	1.00E-05
	0.19
Std	2.40E-02
	3.72
Volume	1.00E-05
	0.03
Price	5.74E-03
	8.77
Shares Outstanding	-1.11E-03
	-2.04

Table 5

Momentum Returns under Alternative Liquidity-based Factor Specifications

Ten momentum portfolios are constructed every month according to past twelve-month cumulative returns (excluding last month's return). Risk-adjusted returns of the momentum portfolios (equal-weighted) are then calculated using different asset-pricing models based on the Fama-French three factors and three liquidity factors. Two liquidity factors are based on the level of liquidity (the fixed non-information and the variable information components of price impact) and one is based on predicted liquidity-beta. The liquidity factors are formed each month as the top decile minus the bottom decile of stocks (for example, stocks with high levels of price impact minus stocks with low levels of price impact measured during the previous month). The liquidity factors returns are equally weighted. Panel A examines equally weighted returns of momentum portfolios while Panel B uses value-weighted returns. The analysis includes NYSE-listed stocks for the period January 1983 to August 2001.

Panel A: Equally weighted

Portfolio	Alpha	Mkt	SMB	HML	LIQ $\overline{\Psi}$	LIQ λ	LIQ Beta	Adj R2
1 (losers)	-0.72	1.10						0.45
	-1.97	13.42						
10 (winners)	0.43	1.10						0.77
	2.41	27.16						
10 - 1	1.15	-0.01						0.00
	2.83	-0.07						
1	-1.00	1.26	0.76	0.61				0.55
	-2.93	14.10	7.01	4.66				
10	0.28	1.18	0.45	0.34				0.83
	1.75	28.45	8.90	5.65				
10 - 1	1.28	-0.08	-0.31	-0.26				0.01
	3.07	-0.70	-2.35	-1.66				
1	-0.71	1.14	0.10	0.29	0.77			0.84
	-3.50	21.45	1.35	3.66	20.22			
10	0.22	1.20	0.58	0.40	-0.15			0.85
	1.47	30.48	10.74	6.90	-5.19			
10 - 1	0.93	0.07	0.48	0.12	-0.91			0.63
	3.61	0.99	5.23	1.16	-18.94			
1	-0.73	1.26	0.41	0.47		1.25		0.68
	-2.54	16.84	4.20	4.27		9.65		
10	0.23	1.18	0.51	0.37		-0.21		0.84
	1.48	28.94	9.50	6.08		-2.95		
10 - 1	0.97	-0.08	0.10	-0.10		-1.46		0.28
	2.70	-0.85	0.79	-0.77		-9.07		
1	-0.79	1.19	0.28	0.25			-0.79	0.82
	-3.69	21.28	3.89	2.98			-18.59	
10	0.23	1.20	0.56	0.43			0.18	0.86
	1.55	31.27	11.30	7.44			6.36	
10 - 1	1.01	0.01	0.28	0.18			0.97	0.63
	3.98	0.18	3.24	1.79			19.22	
1	-0.70	1.14	0.09	0.29	0.75	0.07		0.84
	-3.45	21.37	1.30	3.66	14.86	0.61		
10	0.23	1.21	0.58	0.40	-0.16	0.04		0.85
	1.50	30.32	10.66	6.89	-4.21	0.44		
10 - 1	0.93	0.07	0.48	0.12	-0.91	-0.03		0.62
	3.58	0.96	5.22	1.16	-14.14	-0.22		
1	-0.71	1.15	0.12	0.27	0.59	0.07	-0.18	0.84
	-3.51	21.46	1.66	3.45	4.83	0.60	-1.48	
10	0.25	1.19	0.52	0.43	0.17	0.04	0.36	0.86
	1.72	30.74	9.52	7.60	1.91	0.50	4.08	
10 - 1	0.96	0.04	0.39	0.16	-0.42	-0.03	0.54	0.64
	3.83	0.58	4.19	1.64	-2.78	-0.19	3.56	

Panel B: Value weighted

Portfolio	Alpha	Mkt	SMB	HML	LIQ $\overline{\Psi}$	LIQ λ	LIQ Beta	Adj R2
1 (losers)	-0.75	1.08						0.50
	-2.33	14.93						
10 (winners)	0.27	1.07						0.77
	1.50	26.94						
10 - 1	1.02	-0.01						0.00
	2.38	-0.10						
1	-0.90	1.17	0.09	0.23				0.50
	-2.71	13.45	0.82	1.82				
10	0.30	1.05	0.14	-0.01				0.77
	1.68	22.27	2.50	-0.17				
10 - 1	1.20	-0.12	0.06	-0.24				0.00
	2.73	-1.03	0.41	-1.44				
1	-0.72	1.09	-0.31	0.04	0.46			0.62
	-2.50	14.42	-3.02	0.35	8.47			
10	0.24	1.07	0.29	0.06	-0.17			0.80
	1.40	23.98	4.71	0.87	-5.19			
10 - 1	0.96	-0.02	0.60	0.02	-0.63			0.26
	2.53	-0.20	4.41	0.12	-8.78			
1	-0.72	1.17	-0.15	0.14		0.83		0.57
	-2.32	14.49	-1.39	1.17		5.97		
10	0.27	1.05	0.19	0.01		-0.16		0.78
	1.49	22.41	3.07	0.09		-1.99		
10 - 1	0.99	-0.12	0.34	-0.13		-0.99		0.11
	2.36	-1.10	2.35	-0.83		-5.30		
1	-0.77	1.12	-0.21	0.01			-0.48	0.62
	-2.64	14.80	-2.09	0.10			-8.35	
10	0.25	1.06	0.25	0.07			0.18	0.80
	1.49	23.88	4.34	1.04			5.24	
10 - 1	1.02	-0.06	0.46	0.06			0.66	0.26
	2.68	-0.58	3.54	0.39			8.72	
1	-0.70	1.10	-0.32	0.04	0.41	0.19		0.62
	-2.42	14.47	-3.09	0.36	5.68	1.11		
10	0.26	1.08	0.28	0.06	-0.21	0.18		0.80
	1.51	24.14	4.59	0.88	-5.08	1.74		
10 - 1	0.96	-0.02	0.60	0.02	-0.62	-0.02		0.26
	2.51	-0.20	4.40	0.12	-6.58	-0.07		
1	-0.72	1.11	-0.29	0.02	0.23	0.19	-0.20	0.63
	-2.47	14.51	-2.67	0.21	1.34	1.10	-1.12	
10	0.27	1.08	0.26	0.07	-0.12	0.18	0.11	0.80
	1.56	23.88	4.14	1.01	-1.16	1.75	1.04	
10 - 1	0.98	-0.04	0.55	0.04	-0.35	-0.01	0.30	0.26
	2.57	-0.35	3.88	0.29	-1.53	-0.05	1.32	

Table 6

Momentum Returns under Alternative Liquidity-based Factor Specifications (Non-January months)

Ten momentum portfolios are constructed every month according to past twelve-month cumulative returns (excluding last month's return). Risk-adjusted returns of the momentum portfolios (equal-weighted) are then calculated using different asset-pricing models based on the Fama-French three factors and three liquidity factors. Two liquidity factors are based on the level of liquidity (the fixed non-information and the variable information components of price impact) and one is based on predicted liquidity-beta. The liquidity factors are formed each month as the top decile minus the bottom decile of stocks (for example, stocks with high levels of price impact minus stocks with low levels of price impact measured during the previous month). The liquidity factors returns are equally weighted. Panel A examines equally weighted returns of momentum portfolios while Panel B uses value-weighted returns. The analysis includes NYSE-listed stocks for the period January 1983 to August 2001. January months are excluded from the analysis since momentum exhibits strong reversals during these months.

Panel A: Equally weighted

Portfolio	Alpha	Mkt	SMB	HML	LIQ $\overline{\Psi}$	LIQ λ	LIQ Beta	Adj R2
1 (losers)	-1.21	1.04						0.50
	-3.75	14.26						
10 (winners)	0.50	1.13						0.80
	2.87	28.29						
10 - 1	1.71	0.08						0.00
	4.86	1.04						
1	-1.45	1.21	0.62	0.60				0.58
	-4.76	14.89	6.17	4.93				
10	0.40	1.21	0.46	0.35				0.86
	2.61	29.62	9.19	5.66				
10 - 1	1.84	0.00	-0.16	-0.26				0.01
	5.09	-0.03	-1.31	-1.75				
1	-0.54	1.16	0.12	0.38	0.83			0.82
	-2.61	21.56	1.68	4.64	16.12			
10	0.26	1.22	0.53	0.38	-0.12			0.86
	1.71	30.42	9.87	6.24	-3.20			
10 - 1	0.81	0.05	0.41	0.00	-0.95			0.52
	3.10	0.80	4.51	-0.01	-14.78			
1	-1.02	1.23	0.43	0.54		0.97		0.66
	-3.61	16.71	4.49	4.88		6.64		
10	0.34	1.20	0.49	0.35		-0.14		0.86
	2.17	29.64	9.31	5.80		-1.69		
10 - 1	1.36	-0.03	0.06	-0.19		-1.11		0.17
	3.99	-0.33	0.53	-1.40		-6.28		
1	-0.69	1.21	0.31	0.33			-0.80	0.79
	-3.10	20.92	4.21	3.74			-14.11	
10	0.24	1.21	0.52	0.40			0.17	0.87
	1.58	30.96	10.46	6.72			4.40	
10 - 1	0.93	0.00	0.21	0.07			0.97	0.51
	3.55	0.02	2.44	0.68			14.53	
1	-0.52	1.17	0.12	0.38	0.80	0.13		0.82
	-2.49	21.58	1.59	4.65	13.34	1.06		
10	0.26	1.22	0.53	0.38	-0.12	-0.01		0.86
	1.68	30.22	9.82	6.22	-2.69	-0.11		
10 - 1	0.78	0.05	0.42	0.00	-0.92	-0.14		0.52
	2.99	0.72	4.57	-0.02	-12.26	-0.91		
1	-0.52	1.18	0.14	0.36	0.64	0.13	-0.18	0.82
	-2.50	21.67	1.89	4.39	5.24	1.09	-1.47	
10	0.26	1.20	0.49	0.41	0.14	-0.01	0.30	0.87
	1.74	30.44	9.03	6.82	1.59	-0.16	3.36	
10 - 1	0.79	0.03	0.35	0.05	-0.50	-0.15	0.48	0.54
	3.07	0.38	3.82	0.46	-3.33	-0.98	3.18	

Panel B: Value weighted

Portfolio	Alpha	Mkt	SMB	HML	LIQ $\overline{\Psi}$	LIQ λ	LIQ Beta	Adj R2
1 (losers)	-0.93	1.04						0.51
	-2.96	14.56						
10 (winners)	0.34	1.08						0.80
	2.06	28.44						
10 - 1	1.27	0.04						0.00
	3.14	0.47						
1	-1.12	1.16	0.03	0.29				0.52
	-3.49	13.48	0.25	2.26				
10	0.40	1.05	0.18	-0.01				0.81
	2.39	23.43	3.29	-0.13				
10 - 1	1.52	-0.11	0.15	-0.30				0.03
	3.70	-0.97	1.14	-1.82				
1	-0.56	1.13	-0.28	0.16	0.51			0.61
	-1.88	14.53	-2.64	1.32	6.87			
10	0.27	1.06	0.25	0.02	-0.12			0.82
	1.58	23.96	4.23	0.34	-2.83			
10 - 1	0.83	-0.07	0.53	-0.13	-0.63			0.20
	2.15	-0.69	3.90	-0.87	-6.56			
1	-0.80	1.17	-0.12	0.25		0.73		0.56
	-2.55	14.30	-1.09	2.00		4.47		
10	0.39	1.05	0.18	-0.01		-0.01		0.81
	2.29	23.34	3.18	-0.12		-0.15		
10 - 1	1.19	-0.12	0.30	-0.26		-0.74		0.08
	2.91	-1.16	2.17	-1.58		-3.48		
1	-0.65	1.15	-0.16	0.12			-0.50	0.60
	-2.16	14.75	-1.61	1.03			-6.45	
10	0.29	1.05	0.23	0.03			0.12	0.82
	1.70	23.80	3.99	0.45			2.70	
10 - 1	0.94	-0.10	0.39	-0.09			0.61	0.18
	2.41	-1.02	2.99	-0.60			6.17	
1	-0.52	1.14	-0.29	0.16	0.44	0.26		0.61
	-1.73	14.64	-2.76	1.34	5.20	1.44		
10	0.30	1.06	0.24	0.02	-0.16	0.15		0.82
	1.73	24.07	4.10	0.36	-3.21	1.51		
10 - 1	0.82	-0.07	0.53	-0.13	-0.60	-0.10		0.19
	2.09	-0.72	3.92	-0.87	-5.40	-0.45		
1	-0.52	1.14	-0.27	0.14	0.32	0.26	-0.14	0.61
	-1.73	14.62	-2.50	1.20	1.83	1.45	-0.80	
10	0.30	1.06	0.24	0.03	-0.13	0.15	0.03	0.82
	1.73	23.84	3.91	0.40	-1.27	1.50	0.33	
10 - 1	0.82	-0.08	0.51	-0.12	-0.45	-0.11	0.17	0.19
	2.09	-0.80	3.64	-0.75	-1.97	-0.46	0.76	

Table 7
Risk and Characteristics of Portfolios sorted on Momentum and Liquidity

Every month firms are sorted into five groups according to past twelve-month cumulative returns (excluding last month's return). The firms in each group are then sorted by the non-information/fixed component of price impact. Equal-weighted returns (excess of risk-free rate) and average characteristics of the 25 portfolios are reported below. The loading on the Fama-French three factors, MKT, SMB, HML, and the non-traded liquidity factor, LIQ, are computed through a time-series multiple regression of each portfolio on these factors (the adjusted R^2 of these regressions are also reported). Log(ME) is the time-series mean of the average natural logarithm of market capitalization (in millions of dollars) in each portfolio. Similarly, Log(BE/ME) uses the logarithm of the book-to-market ratio. The non-information/fixed ($\overline{\Psi}$) and the information/variable (λ) components of price impact are also reported. For each firm in the portfolio, price impacts are scaled by beginning-of-the-month price, and then scaled by the cross-sectional average that month. The price impact of the portfolio is the average of these scaled measures across the firms in the portfolio. Turnover is the monthly volume scaled by the number of shares outstanding. This measure is then re-scaled by the cross-sectional average each month. Momentum is the average past cumulative return on which the portfolios are sorted. The analysis includes NYSE-listed stocks for the period January 1983 to August 2001.

	Momentum	Low (Liquidity)		Liquidity		High (Liquidity)		Momentum	Low (Liquidity)		Liquidity		High (Liquidity)
Panel A: Risk													
	Low	0.45	0.56	0.46	0.16	0.03		Low	0.65	0.66	0.63	0.58	0.41
Excess		0.69	0.73	0.68	0.62	0.81	Adjusted		0.75	0.74	0.74	0.73	0.61
returns		0.58	0.75	0.69	0.66	0.70	R^2		0.83	0.80	0.78	0.67	0.62
		0.78	0.81	0.84	0.77	0.79			0.86	0.83	0.80	0.77	0.70
	High	0.89	1.10	1.02	1.11	1.33		High	0.80	0.81	0.82	0.78	0.78
		1.10	1.18	1.10	1.14	1.35			19.01	19.49	17.47	15.01	9.88
MKT		0.99	1.00	0.93	0.94	0.90	T-stat		24.43	24.42	23.86	22.89	16.70
beta		0.98	0.94	0.86	0.76	0.72	MKT		31.07	28.37	26.48	19.76	16.97
		1.01	1.01	0.91	0.89	0.86	beta		33.97	30.46	27.49	24.19	20.18
		1.03	1.06	1.08	1.10	1.12			25.98	26.44	27.75	24.46	23.28
		0.17	0.25	0.52	0.68	1.25			2.42	3.47	6.76	7.41	7.60
SMB		0.05	0.13	0.32	0.39	0.62	T-stat		0.96	2.65	6.84	7.81	9.52
beta		0.02	0.11	0.25	0.29	0.44	SMB		0.50	2.63	6.28	6.14	8.54
		-0.01	0.03	0.19	0.34	0.43	beta		-0.19	0.79	4.62	7.68	8.38
		0.13	0.19	0.37	0.48	0.64			2.61	3.92	7.89	8.75	11.08
		0.45	0.53	0.55	0.55	0.92			5.38	6.11	6.03	5.07	4.68
HML		0.43	0.54	0.54	0.60	0.68	T-stat		7.29	9.15	9.54	10.17	8.76
beta		0.45	0.51	0.50	0.46	0.46	HML		9.88	10.55	10.56	8.36	7.63
		0.41	0.41	0.45	0.50	0.49	beta		9.68	8.46	9.46	9.42	8.01
		0.26	0.29	0.41	0.47	0.53			4.56	5.01	7.28	7.23	7.72
		-0.16	-0.41	-0.33	-0.66	-1.16			-0.48	-1.21	-0.93	-1.54	-1.52
LIQ		0.08	-0.04	-0.09	-0.08	-0.37	T-stat		0.35	-0.16	-0.42	-0.34	-1.21
beta		0.58	0.18	0.18	0.15	0.05	LIQ		3.27	0.97	0.98	0.69	0.19
		0.62	0.29	0.39	0.68	0.34	beta		3.70	1.56	2.10	3.30	1.44
		0.76	1.00	0.90	0.47	0.64			3.37	4.43	4.11	1.86	2.38
Panel B: Characteristics													
		6.90	6.24	5.53	4.92	3.79			0.40	0.72	1.09	1.76	4.79
Log(ME)		7.48	6.86	6.12	5.49	4.90	$\overline{\Psi}$		0.29	0.51	0.74	1.08	2.16
		7.64	7.00	6.18	5.58	5.05			0.26	0.47	0.70	1.00	1.85
		7.86	7.31	6.67	5.93	5.11			0.23	0.39	0.55	0.81	1.67
		7.74	7.29	6.71	6.03	5.01			0.21	0.35	0.49	0.72	1.74
		-0.60	-0.47	-0.33	-0.20	-0.17			0.59	0.85	1.27	1.76	2.61
Log(BE/ME)		-0.63	-0.51	-0.40	-0.27	-0.21	λ		0.45	0.67	0.95	1.23	1.58
		-0.68	-0.49	-0.37	-0.29	-0.23			0.44	0.65	0.94	1.17	1.38
		-0.75	-0.58	-0.43	-0.32	-0.23			0.40	0.53	0.75	1.07	1.47
		-0.76	-0.71	-0.56	-0.40	-0.23			0.39	0.49	0.69	0.99	1.67
		-0.19	-0.22	-0.24	-0.28	-0.40			1.24	1.20	1.13	1.05	0.96
Momentum		-0.01	-0.01	-0.01	-0.01	-0.01	Turnover		1.01	0.96	0.86	0.78	0.73
		0.12	0.12	0.12	0.11	0.11			0.94	0.91	0.79	0.69	0.68
		0.25	0.25	0.25	0.25	0.24			0.95	0.96	0.87	0.81	0.79
		0.63	0.63	0.64	0.65	0.68			1.35	1.32	1.28	1.27	1.14

Table 8
Evaluation of Asset-Pricing Models using Cross-Sctional Regressions

Every month firms are sorted into five groups according to past twelve-month cumulative returns (excluding last month's return). The firms in each group are then sorted by the non-information/fixed component of price impact. Equal-weighted returns (excess of risk-free rate) of the 25 portfolios are used to estimate the cross-sectional regression models of the form

$$E[R_{i,t}] = \gamma_0 + \gamma'\beta_i + c'Z_i$$

where $R_{i,t}$ are the returns of portfolio i, β_i is a vector of factor loadings, and Z_i is a vector of portfolio characteristics. The loadings are computed through a time-series multiple regression of portfolio excess returns on the factors tested (over the entire sample period). The factors considered here are the Fama-French three factors, MKT, SMB, HML, and the non-traded liquidity factor, LIQ. The characteristics are computed as follows. Log(ME) is the time-series mean of the average natural logarithm of market capitalization (in millions of dollars) in each portfolio. Similarly, Log(BE/ME) uses the logarithm of the book-to-market ratio. The non-information/fixed ($\overline{\Psi}$) and the information/variable (λ) components of price impact are also used. For each firm in the portfolio, price impacts are scaled by beginning-of-the-month price, and then scaled by the cross-sectional average that month. The price impact of the portfolio is the average of these scaled measures across the firms in the portfolio. Turnover is the monthly volume scaled by the number of shares outstanding. This measure is then re-scaled by the cross-sectional average each month. When the last four characteristics in the table are added to the regressions, they are orthogonalized to all previous risk/characteristics measures, according to the order they appear in the table. The regression models are estimated using the Fama-MacBeth procedure. Standard errors are also corrected for the sampling errors in the estimated β_i. The analysis includes NYSE-listed stocks for the period January 1983 to August 2001.

	Intercept	MKT	SMB	HML	LIQ	Log(ME)	Log(BE/ME)	$\overline{\Psi}$	λ	Turnover	Momentum	Adjusted R^2
Estimate (%)	0.81	-0.11										0.00
T-value	2.54	-0.22										
P-value (%)	1.19	82.41										
Corrected T-value	2.54	-0.22										
Corrected P-value (%)	1.19	82.41										
Estimate (%)	-0.76	0.22				0.30	1.30	-0.21	-0.58	1.89	0.81	0.88
T-value	-0.66	0.46				1.27	1.27	-1.56	-1.44	2.42	2.56	
P-value (%)	50.79	64.68				20.42	20.49	11.92	15.01	1.64	1.11	
Corrected T-value	-0.66	0.46				1.27	1.27	-1.56	-1.44	2.41	2.56	
Corrected P-value (%)	50.89	64.73				20.52	20.59	12.01	15.10	1.67	1.13	
Estimate (%)	1.68	-0.20	0.27	-1.70								0.30
T-value	2.87	-0.41	0.76	-2.06								
P-value (%)	0.45	67.91	44.54	4.04								
Corrected T-value	2.55	-0.38	0.71	-1.84								
Corrected P-value (%)	1.16	70.23	47.78	6.65								
Estimate (%)	-0.90	-0.26	1.13	-1.77		0.52	1.99	-0.18	-1.03	0.37	1.02	0.93
T-value	-0.81	-0.40	1.40	-2.09		1.82	1.87	-1.36	-2.41	0.63	3.12	
P-value (%)	42.07	69.31	16.37	3.79		7.05	6.24	17.55	1.70	52.67	0.21	
Corrected T-value	-0.68	-0.34	1.19	-1.78		1.53	1.58	-1.14	-2.03	0.53	2.63	
Corrected P-value (%)	49.78	73.23	23.51	7.70		12.75	11.63	25.39	4.41	59.41	0.93	
Estimate (%)	0.53	-0.09	0.14	0.30	0.54							0.70
T-value	1.31	-0.19	0.40	0.57	2.61							
P-value (%)	19.28	84.90	68.72	57.26	0.96							
Corrected T-value	1.01	-0.16	0.34	0.45	2.04							
Corrected P-value (%)	31.40	87.28	73.11	65.09	4.30							
Estimate (%)	0.93	0.47	-0.42	0.23	0.59	-0.09	0.40	-0.06	-1.15	1.47	1.10	0.93
T-value	1.09	0.79	-0.71	0.39	2.91	-0.53	0.49	-0.46	-2.57	2.47	2.96	
P-value (%)	27.84	42.84	47.88	69.78	0.40	59.33	62.35	64.48	1.10	1.41	0.34	
Corrected T-value	0.54	0.44	-0.37	0.20	1.47	-0.27	0.24	-0.23	-1.27	1.23	1.47	
Corrected P-value (%)	58.99	66.20	70.87	83.78	14.31	79.07	80.73	81.88	20.39	22.03	14.31	

Table 9

Evaluation of Asset-Pricing Models with a Stochastic Discount Factor Approach

Every month firms are sorted into five groups according to past twelve-month cumulative returns (excluding last month's return). The firms in each group are then sorted by the non-information/fixed component of price impact. Equal-weighted returns (excess of risk-free rate) of the 25 portfolios are used to estimate the following model for the moments

$$E[R_{i,t}(1+\delta' f_t)] = 0$$

where $R_{i,t}$ are the returns of portfolio i, and f_i is a vector of factors. The factors considered here are the Fama-French three factors, MKT, SMB, HML, and the non-traded liquidity factor, LIQ. The models are estimated with the Generalized Method of Moments. Panel A uses the Hansen (1982) optimal weighted matrix, and Panel B uses the weighting matrix proposed by Hansen and Jagannathan (1997). The *J*-value is the minimized value of the GMM criterion, multiplied by the number of periods (224 months). *P*-values are also reported. The analysis includes NYSE-listed stocks for the period January 1983 to August 2001.

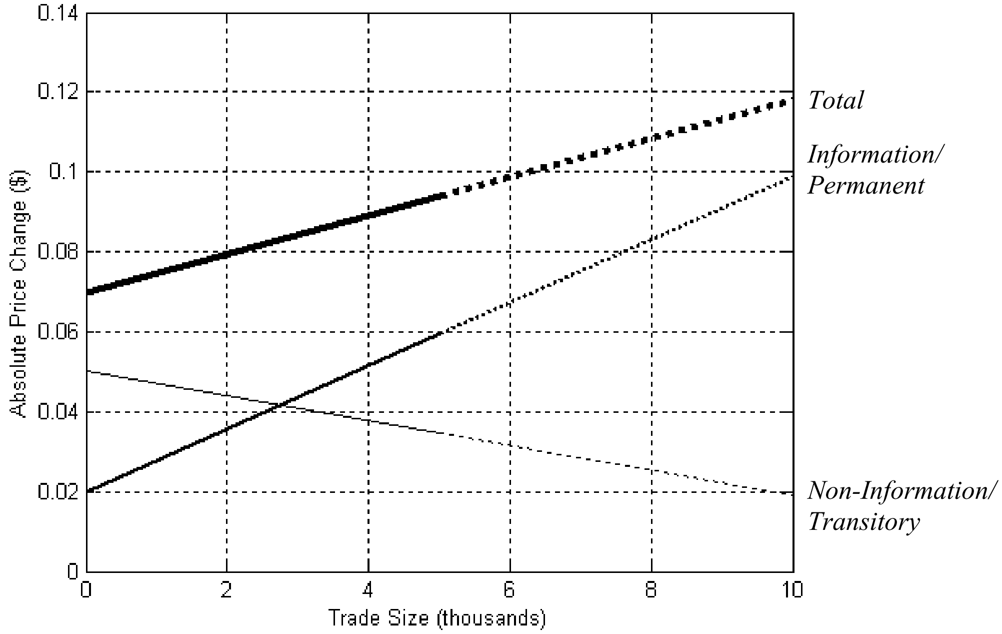
	Panel A: Hansen (1982)					
	MKt	SMB	HML	LIQ	J-value	P-value (%)
Estimate	-5.82				38.75	1.05
T-value	-3.79					
P-value (%)	0.02					
Estimate	-10.48	-6.78	-20.15		34.37	3.31
T-value	-5.30	-2.33	-5.19			
P-value (%)	0.00	2.07	0.00			
Estimate	-10.51	-6.86	-21.39	-35.24	30.56	8.13
T-value	-5.13	-2.22	-5.53	-1.24		
P-value (%)	0.00	2.77	0.00	21.48		
	Panel B: Hansen-Jagannathan (1997)					
	MKt	SMB	HML	LIQ	J-value	P-value (%)
Estimate	-4.21				0.05	3.04
T-value	-1.80					
P-value (%)	7.39					
Estimate	-6.19	2.55	-5.83		0.04	6.99
T-value	-1.65	0.56	-0.66			
P-value (%)	9.96	57.85	50.81			
Estimate	-2.08	-2.38	-13.08	-137.15	0.01	17.01
T-value	-0.48	-0.42	-1.15	-1.54		
P-value (%)	63.51	67.69	25.26	12.62		

Table 10
Sorts of Momentum, Volume, and Transaction costs

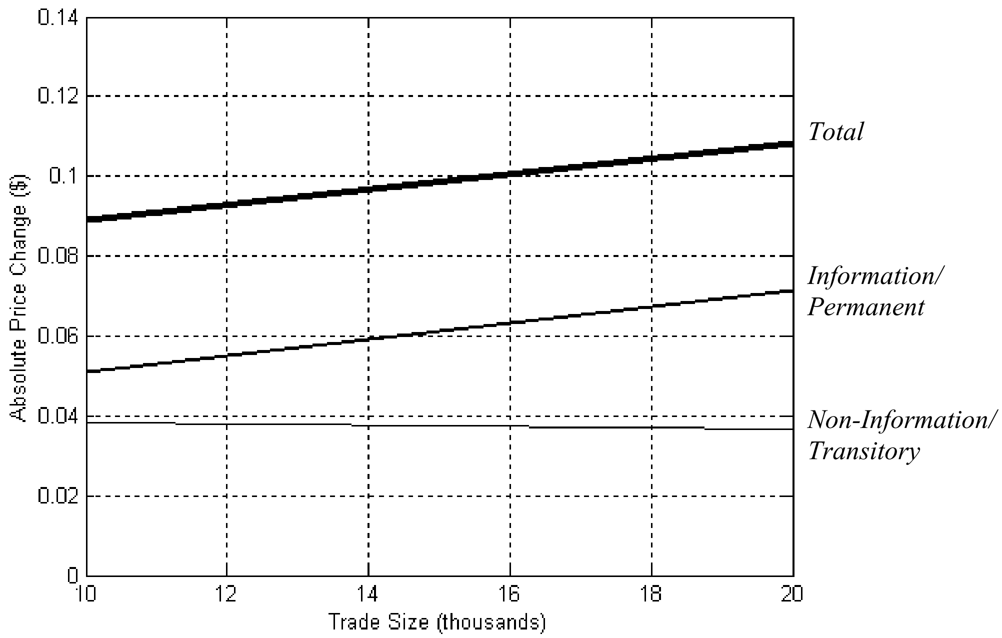
Every month stocks are sorted into five groups according to their past twelve-month cumulative returns (excluding last month's return). P1 is the bottom quintile and P5 is the top quintile. Independently, stocks are sorted each month into three groups according to their volume during the momentum period, where volume is defined as the average daily turnover throughout the period. Low volume group is V1 and high volume group is V3. Also, independent of momentum and volume, every month stocks are sorted into three groups of transaction costs, where transaction costs are measured as the fixed-transitory component of price impact for regular trades (see text). X1 is low transaction costs and X3 is high transaction costs. Stocks in the intersection of different groups of momentum, volume, and transaction costs are combined to form portfolios. Both equal-weighted and value-weighted portfolios are considered. The time-series averages of portfolio returns as well as the associated *t*-statistics (two-digit numbers) are reported below. The analysis includes NYSE-listed stocks for the period January 1983 to August 2001.

		Equal-Weighted				
Mom	Vol	Transaction costs				
		X1	X2	X3	X3-X1	X1,X2,X3
P1	V1	0.0063	0.0102	0.0091	0.0033	0.0094
		1.59	3.26	2.03	0.77	2.46
	V2	0.0084	0.0137	0.0050	-0.0031	0.0081
		2.23	3.59	1.13	-0.82	2.11
	V3	0.0078	0.0073	-0.0005	-0.0083	0.0039
		1.83	1.67	-0.09	-2.25	0.84
	V3-V1	0.0017	-0.0029	-0.0096		-0.0055
		0.44	-1.02	-3.03		-2.23
	V1,V2,V3	0.0075	0.0095	0.0048	-0.0027	
		2.07	2.54	1.06	-0.90	
P3	V1	0.0121	0.0126	0.0112	-0.0009	0.0120
		4.87	5.32	5.23	-0.51	5.63
	V2	0.0108	0.0127	0.0130	0.0022	0.0119
		3.92	4.63	4.21	0.96	4.57
	V3	0.0096	0.0098	0.0061	-0.0036	0.0093
		2.84	2.96	1.53	-1.22	2.91
	V3-V1	-0.0024	-0.0028	-0.0051		-0.0026
		-1.16	-1.44	-1.66		-1.43
	V1,V2,V3	0.0108	0.0119	0.0111	0.0003	
		3.95	4.58	4.57	0.17	
P5	V1	0.0153	0.0166	0.0186	0.0033	0.0167
		5.09	5.35	4.94	1.05	5.89
	V2	0.0159	0.0167	0.0182	0.0023	0.0163
		4.82	5.04	4.51	0.82	5.09
	V3	0.0139	0.0160	0.0180	0.0041	0.0147
		3.89	3.80	3.92	1.55	3.90
	V3-V1	-0.0014	-0.0006	-0.0006		-0.0020
		-0.74	-0.25	-0.16		-1.13
	V1,V2,V3	0.0146	0.0164	0.0173	0.0027	
		4.51	4.70	4.69	1.35	
P5-P1	V1	0.0092	0.0064	0.0095	-0.0001	0.0073
		2.66	2.10	2.08	-0.02	2.23
	V2	0.0076	0.0031	0.0132	0.0056	0.0082
		2.49	0.96	3.68	1.52	2.75
	V3	0.0060	0.0087	0.0185	0.0124	0.0108
		1.88	2.69	4.45	3.12	3.39
	V3-V1	-0.0030	0.0022	0.0090		0.0035
		-0.76	0.72	1.94		1.38
	V1,V2,V3	0.0071	0.0069	0.0125	0.0054	
		2.75	2.41	3.58	1.90	

		Value-Weighted				
Mom	Vol	Transaction costs				
		X1	X2	X3	X3-X1	X1,X2,X3
P1	V1	0.0084	0.0117	0.0060	-0.0022	0.0122
		1.72	3.20	1.58	-0.42	3.39
	V2	0.0093	0.0151	0.0102	0.0012	0.0119
		2.34	3.59	2.43	0.35	3.24
	V3	0.0090	0.0034	0.0054	-0.0036	0.0059
		2.03	0.73	1.07	-1.01	1.37
	V3-V1	0.0005	-0.0083	-0.0006		-0.0063
		0.10	-2.35	-0.18		-2.36
	V1,V2,V3	0.0110	0.0079	0.0075	-0.0036	
		2.92	1.90	1.78	-1.27	
P3	V1	0.0101	0.0114	0.0087	-0.0014	0.0101
		3.38	4.00	3.81	-0.53	3.67
	V2	0.0081	0.0120	0.0132	0.0051	0.0090
		2.74	3.88	4.04	1.85	3.13
	V3	0.0102	0.0101	0.0100	-0.0002	0.0104
		2.86	2.73	2.24	-0.06	3.02
	V3-V1	0.0001	-0.0013	0.0014		0.0003
		0.04	-0.45	0.33		0.11
	V1,V2,V3	0.0089	0.0113	0.0110	0.0021	
		3.09	3.89	4.43	0.96	
P5	V1	0.0146	0.0165	0.0167	0.0021	0.0150
		4.12	4.55	4.06	0.49	4.41
	V2	0.0151	0.0128	0.0165	0.0014	0.0145
		4.49	3.68	4.04	0.42	4.41
	V3	0.0140	0.0133	0.0185	0.0045	0.0133
		3.87	3.44	3.72	1.25	3.70
	V3-V1	-0.0006	-0.0031	0.0018		-0.0017
		-0.22	-1.00	0.39		-0.67
	V1,V2,V3	0.0141	0.0135	0.0173	0.0032	
		4.36	4.03	4.58	1.23	
P5-P1	V1	0.0062	0.0047	0.0107	0.0042	0.0028
		1.28	1.21	2.27	0.70	0.75
	V2	0.0059	-0.0024	0.0063	0.0006	0.0026
		1.50	-0.58	1.50	0.14	0.71
	V3	0.0050	0.0099	0.0131	0.0081	0.0074
		1.29	2.41	2.68	1.68	2.12
	V3-V1	-0.0008	0.0052	0.0024		0.0046
		-0.15	1.21	0.46		1.40
	V1,V2,V3	0.0030	0.0056	0.0098	0.0068	
		0.95	1.48	2.41	1.92	



Panel A: Regular size trades

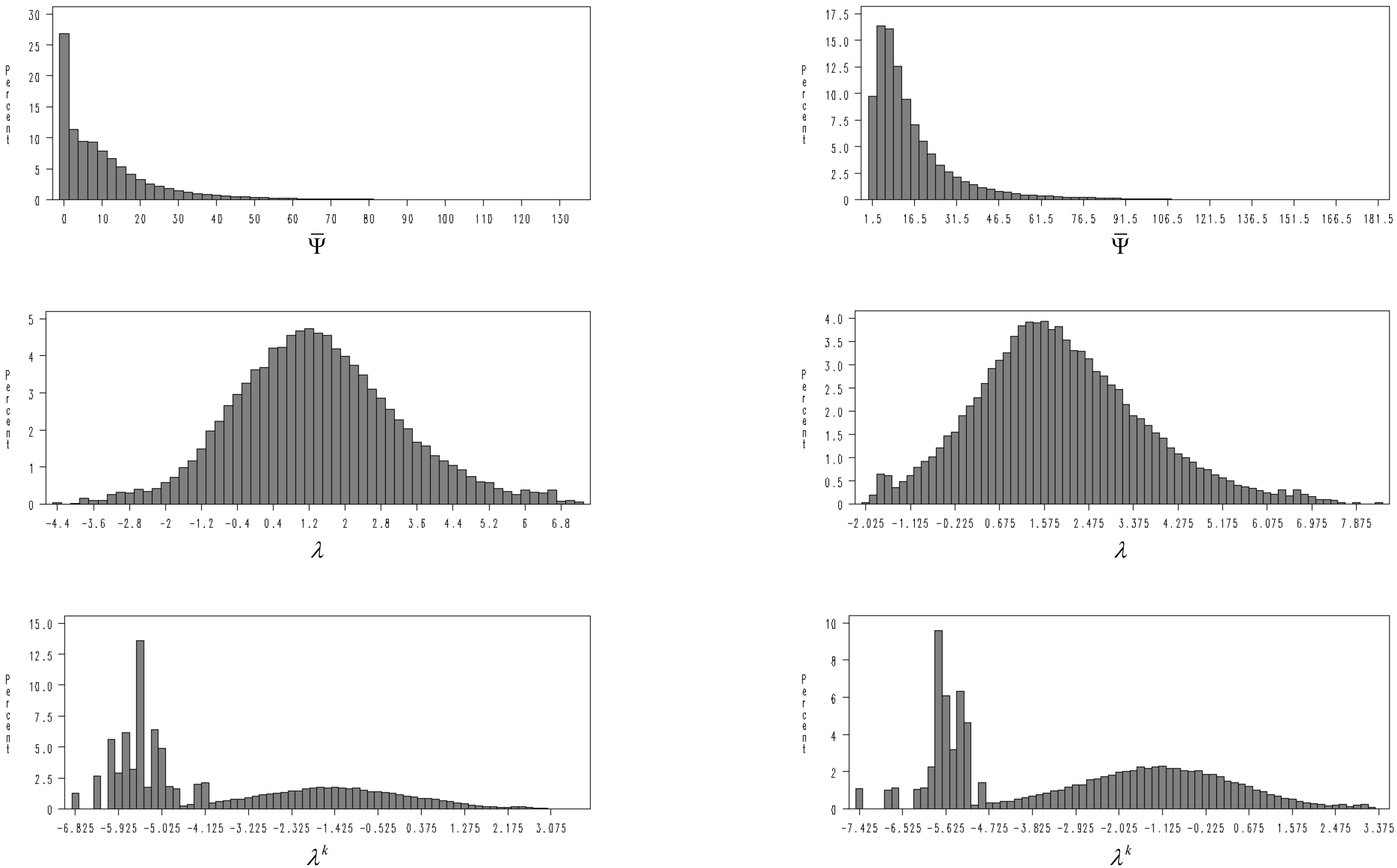


Panel B: Large size trades

Figure 1, Estimated price impact functions. Time-series means of cross-sectional averages of estimated price impact functions are plotted above. The function coefficients are estimates of the model

$$\Delta p_t = \alpha + \Psi \varepsilon_{\psi,t} + \lambda \varepsilon_{\lambda,t} + \Psi^k K_t \varepsilon_{\psi,t} + \lambda^k K_t \varepsilon_{\lambda,t} + \bar{\Psi} \Delta D_t + \bar{\lambda} \Delta D V_t + \bar{\Psi}^k \Delta K D_t + \bar{\lambda}^k \Delta K D V_t$$

where Δp_t is the price improvement (in dollars) as a result of trading V_t shares at time *t* (here *t* represents event time), D_t is an indicator for buyer-initiated (+1) or seller-initiated (-1) trade, the variables $\varepsilon_{\psi,t}$ and $\varepsilon_{\lambda,t}$ are the unanticipated trade sign and signed volume, respectively, and K_t is a dummy variable, which is assigned a value of (+1) for all trades above 10,000 shares and zero otherwise. The complete derivation of this model is provided in Section 2. The model identifies both information/permanent and non-information/transitory components of the total price impact, as well as fixed and variable costs. All functions are estimated on a monthly basis, separately for every stock. The graphs above assume expected trade size of zero. The analysis includes NYSE-listed stocks for the period January 1983 to August 2001.



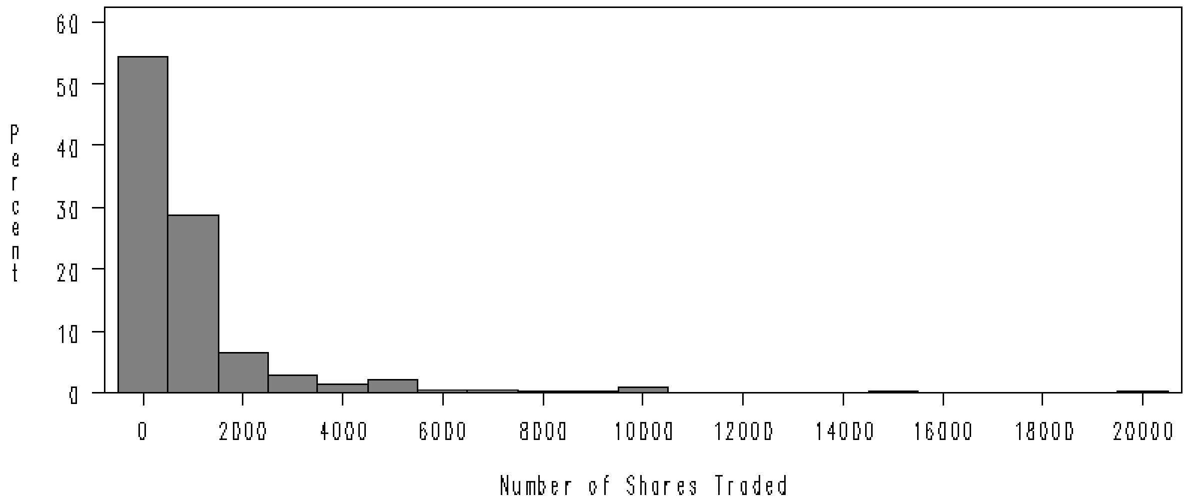
Panel A: January 1983 until December 1985

Panel B: January 1993 until December 1995

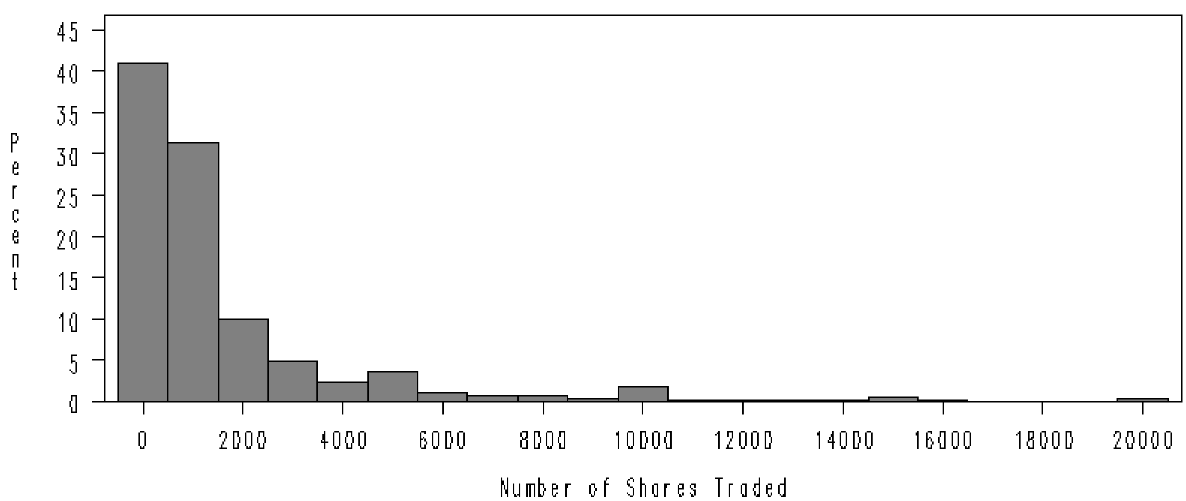
Figure 2, T-statistics of estimated measures of price impact. Price impacts are the estimates of the model

$$\Delta p_t = \alpha + \Psi \varepsilon_{\psi,t} + \lambda \varepsilon_{\lambda,t} + \Psi^k K_t \varepsilon_{\psi,t} + \lambda^k K_t \varepsilon_{\lambda,t} + \overline{\Psi}\Delta D_t + \overline{\lambda}\Delta DV_t + \overline{\Psi}^k \Delta KD_t + \overline{\lambda}^k \Delta KDV_t$$

where Δp_t is the price improvement (in dollars) as a result of trading V_t shares at time *t* (here *t* represents event time), D_t is an indicator for buyer-initiated (+1) or seller-initiated (-1) trade, the variables $\varepsilon_{\psi,t}$ and $\varepsilon_{\lambda,t}$ are the unanticipated trade sign and signed volume, respectively, and K_t is a dummy variable, which is assigned a value of (+1) for all trades above 10,000 shares and zero otherwise. The complete derivation of this model is provided in Section 2. The model identifies both permanent and transitory components of the total price impact, as well as fixed and variable costs. All functions are estimated on a monthly basis, separately for every each NYSE-listed stock. Panel A plots the distribution of the *t*-statistics of the pooled cross-section and time series sample for NYSE-listed stocks for the period 1983-1985. Similarly, Panel B uses the sample for the period 1993-1995.

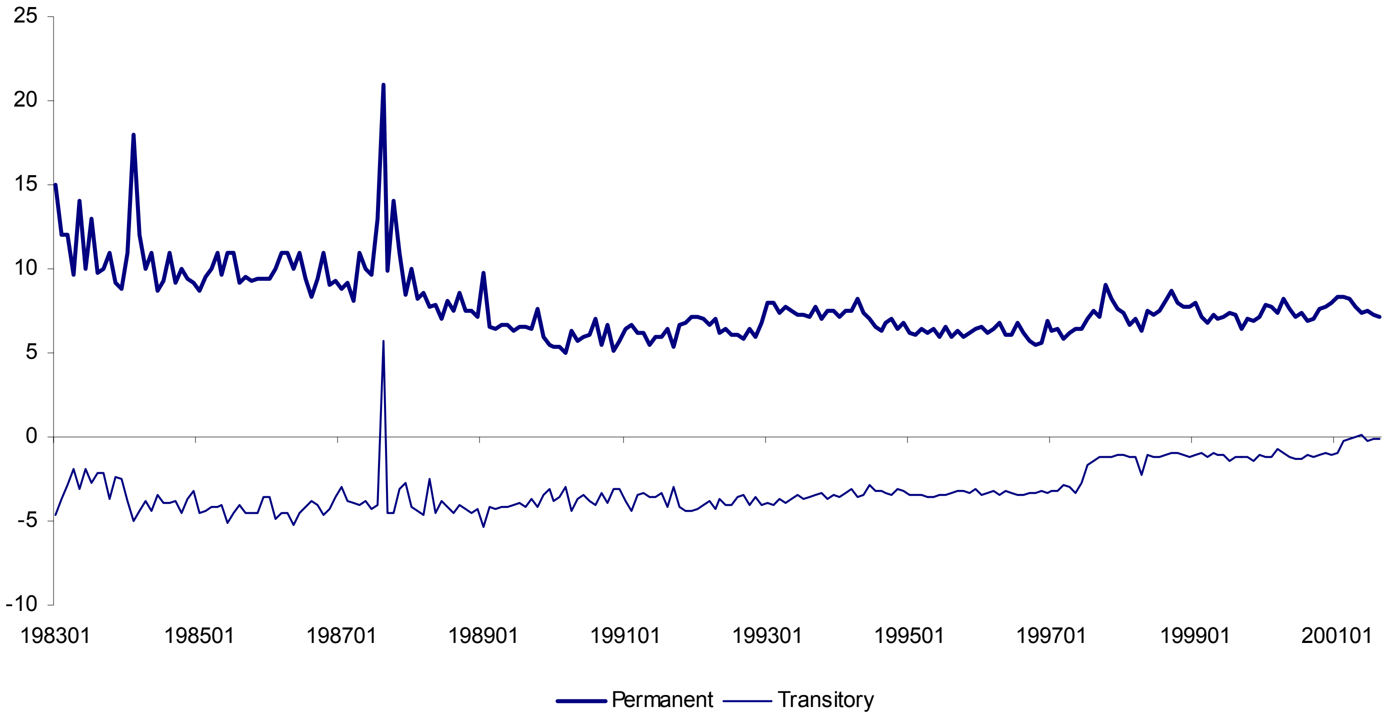


Panel A: January 1983 until December 1985

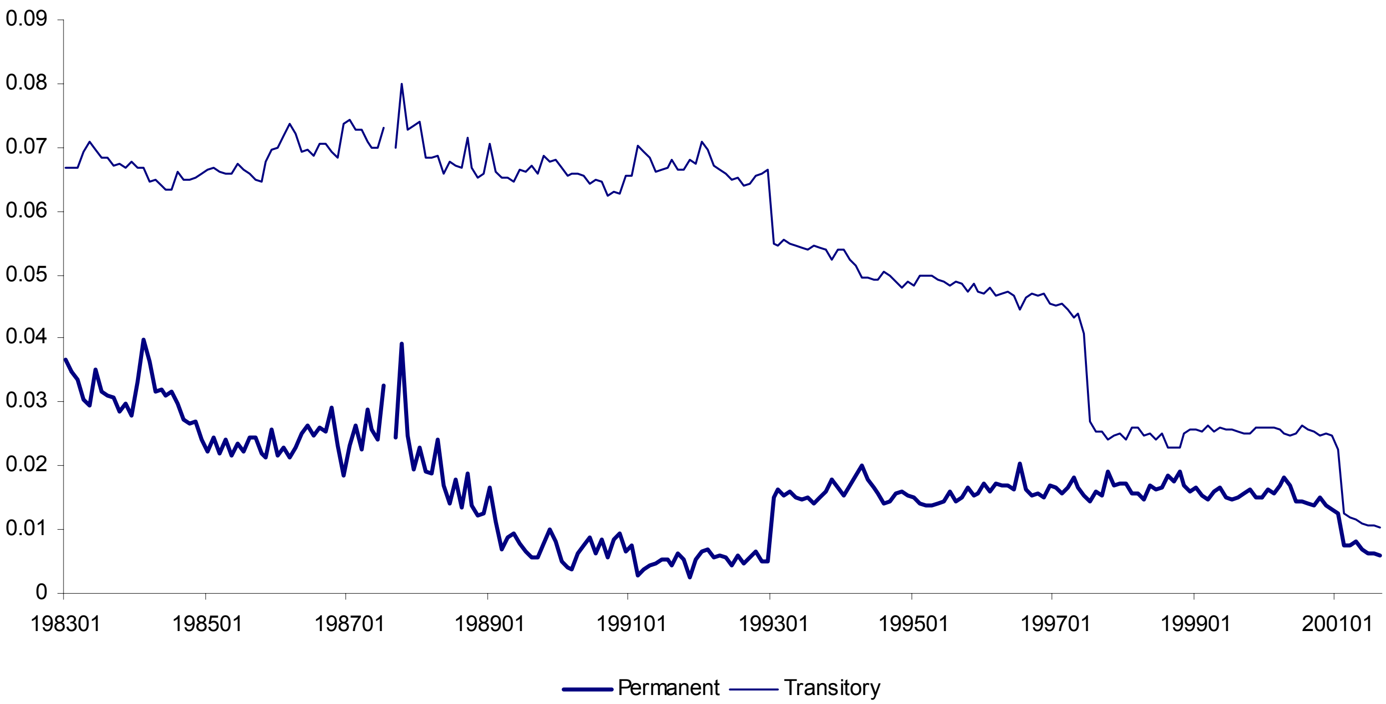


Panel B: January 1993 until December 1995

Figure 3, Distribution of trade size. The distribution of the number of shares traded per transaction of NYSE-listed stocks is plotted above. Panel A includes trades for the period 1983-1985 (using intraday data from ISSM database), while Panel B includes trades for the period 1993-1995 (using intraday data from TAQ database).



Panel A: Variable transaction costs



Panel B: Fixed transaction costs

Figure 4, Time series of liquidity measures (regular size transactions). The time series of cross-sectional averages of estimated price impact functions are plotted above. The function coefficients are estimates of the model

$$\Delta p_t = \alpha + \Psi\varepsilon_{\psi,t} + \lambda\varepsilon_{\lambda,t} + \Psi^k K_t\varepsilon_{\psi,t} + \lambda^k K_t\varepsilon_{\lambda,t} + \overline{\Psi}\Delta D_t + \overline{\lambda}\Delta DV_t + \overline{\Psi}^k\Delta KD_t + \overline{\lambda}^k\Delta KDV_t$$

where Δp_t is the price improvement (in dollars) as a result of trading V_t shares at time t (here t represents event time), D_t is an indicator for buyer-initiated (+1) or seller-initiated (-1) trade, the variables $\varepsilon_{D,t}$ and $\varepsilon_{DV,t}$ are the unanticipated trade sign and signed volume, respectively, and K_t is a dummy variable, which is assigned a value of (+1) for all trades above 10,000 shares and zero otherwise. The complete derivation of this model is provided in Section 2. The model identifies both permanent and transitory components of the total price impact, as well as fixed and variable costs. Panel A plots the cross-sectional average of the variable costs (units are dollars per share multiplied by 10^6), λ (permanent) and $\overline{\lambda}$ (transitory). Panel B plots the cross-sectional average of the fixed costs (units are dollars), Ψ (permanent) and $\overline{\Psi}$ (transitory). All functions are estimated on a monthly basis, separately for every stock. The analysis includes NYSE-listed stocks for the period January 1983 to August 2001 (July 1987 is missing from Panel B due to small sample of firms—see text).

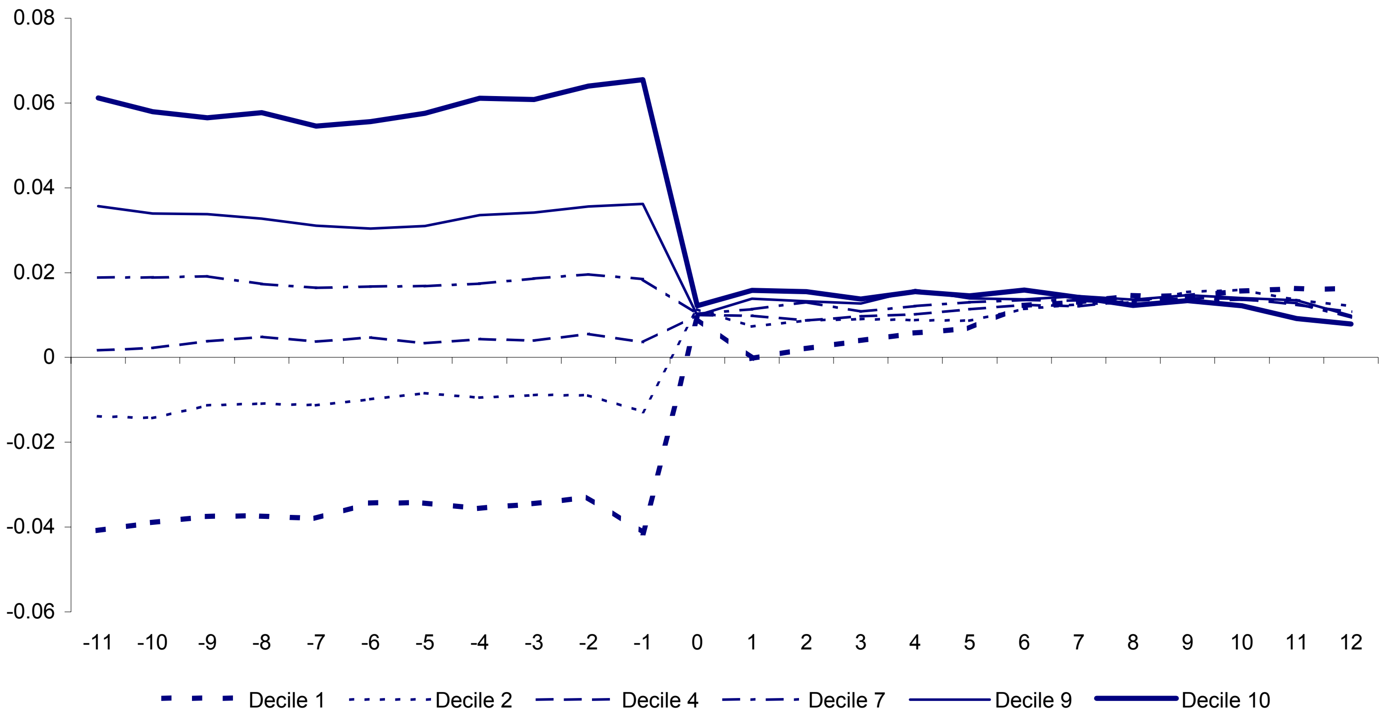
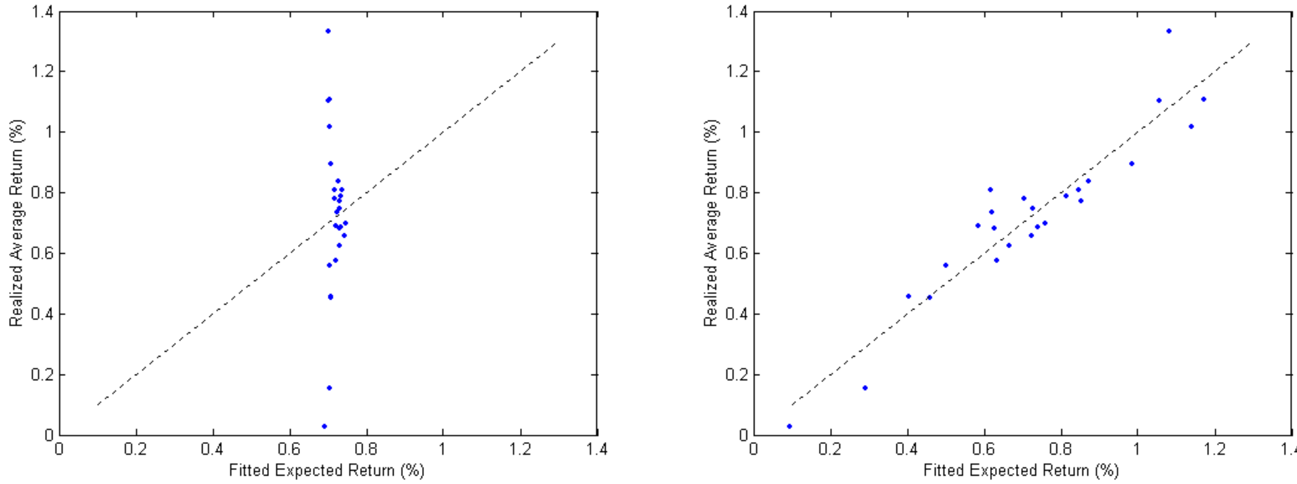
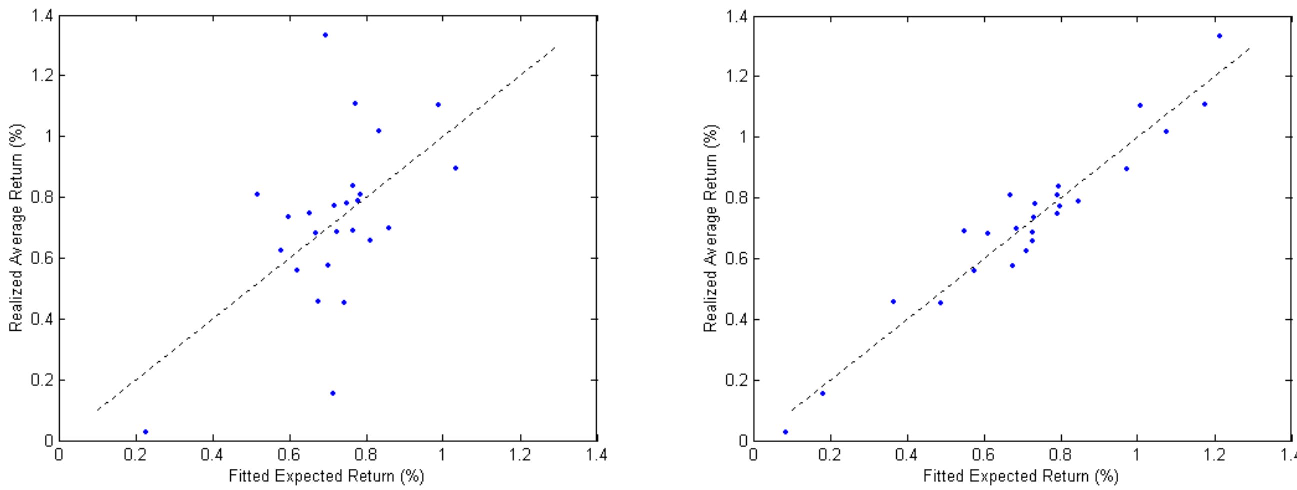


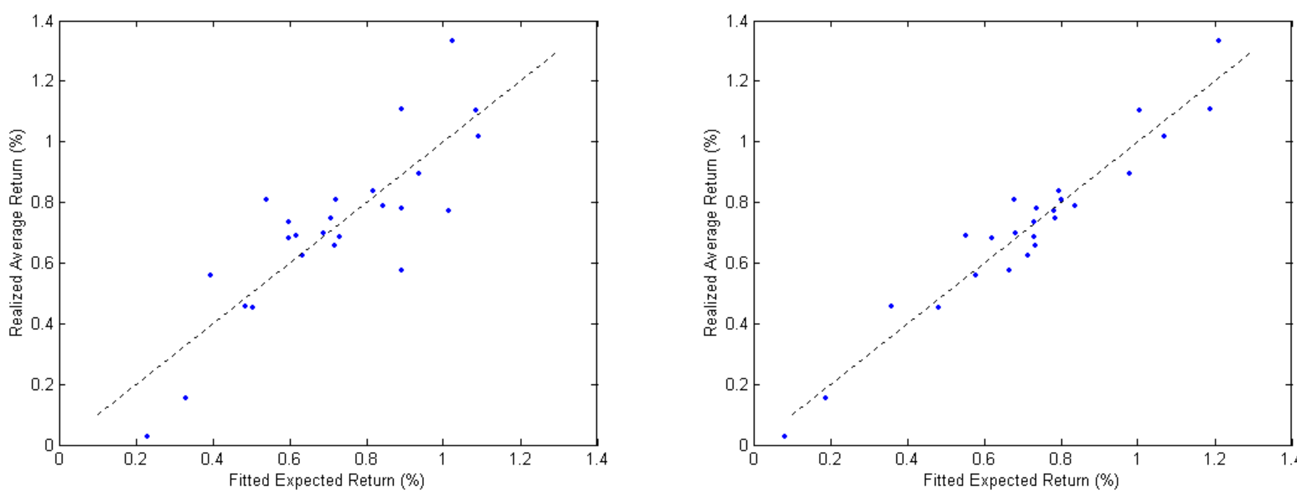
Figure 5, Returns of momentum portfolios in event time. In the beginning of every month stocks are sorted into deciles according to their cumulative returns during the previous twelve months (excluding last month's return). Holding the stocks in the portfolios fixed, lag and lead equal-weighted averages of returns for these portfolios are computed. The time-series averages of these portfolio returns are plotted above. The end of month 0 is denoted formation time. The event-time window analyzed is -11 to +12 (a year before and a year after the formation date). The analysis includes NYSE-listed stocks for the period February 1984 to August 2000.



Panel A: CAPM



Panel B: Fama-French three factors

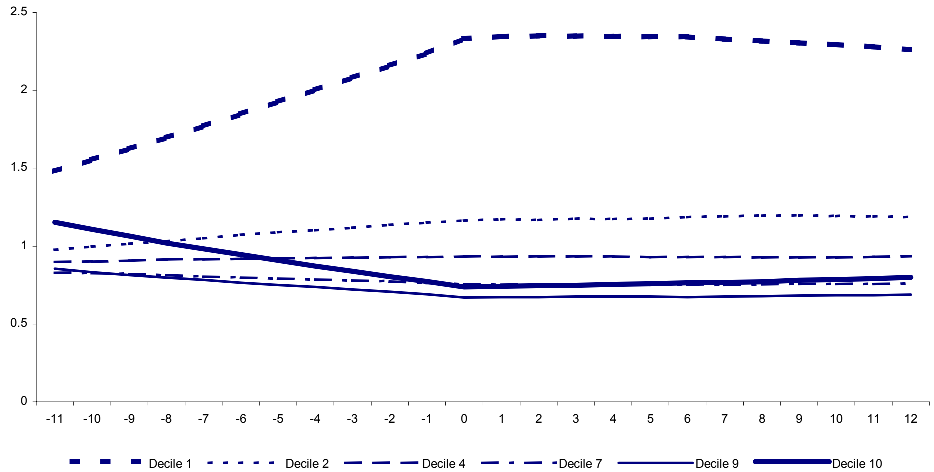


Panel C: Fama-French three factors + LIQ

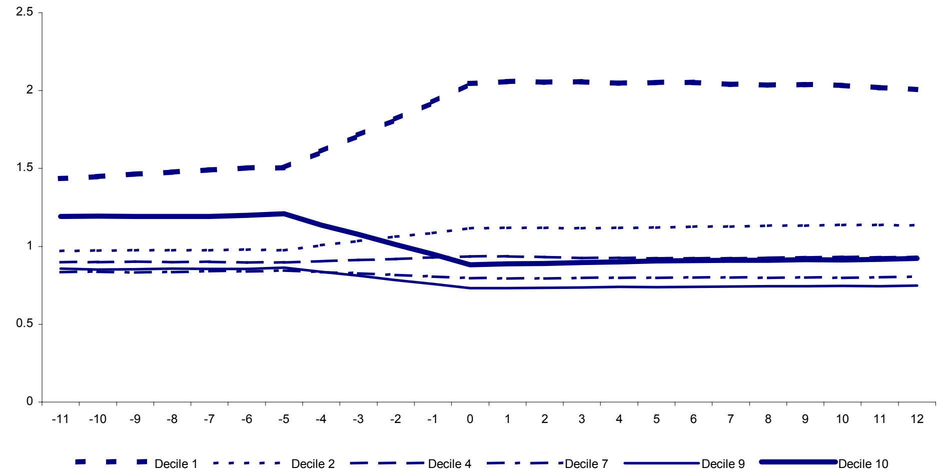
Figure 6, Evaluation of Different Asset-Pricing Models. Every month firms are sorted into five groups according to past twelve-month cumulative returns (excluding last month's return). The firms in each group are then sorted by the non-information/fixed component of price impact. Each scatter point in each of the graphs represents one of the 25 portfolios, with the realized average return (excess of risk-free rate) on the horizontal axes, and the fitted expected return on the vertical axes. The realized average return is the time-series average return, and the fitted expected return is calculated as the fitted value from

$$E[R_{i,t}] = \gamma_0 + \gamma'\beta_i + c'Z_i$$

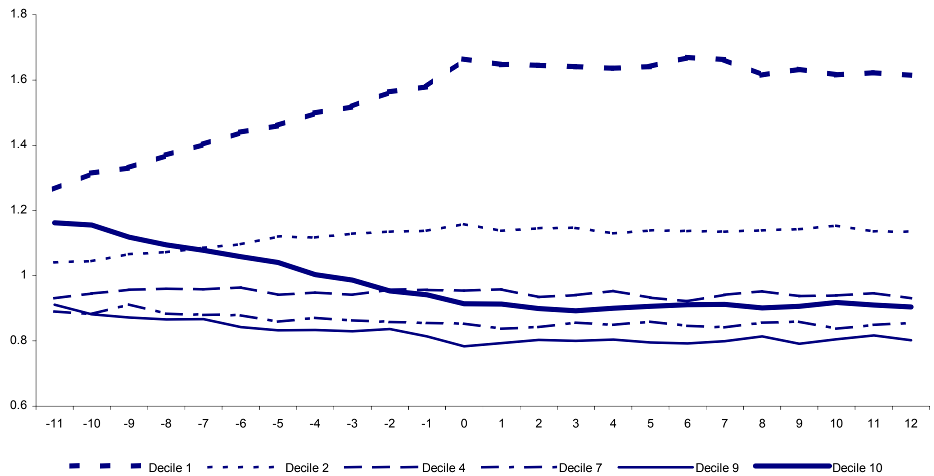
where $R_{i,t}$ are the returns of portfolio i, β_i is a vector of factor loadings, and Z_i is a vector of portfolio characteristics. The loadings are computed through a time-series multiple regression of portfolio excess returns on the factors tested (over the entire sample period). The factors considered here are the Fama-French three factors, MKT, SMB, HML, and the non-traded liquidity factor, LIQ. Characteristics include market capitalization, book-to-market ratio, the non-information/fixed and the information/variable components of price impact, turnover, and momentum. The graphs on the left hand side use only risk factors in the cross-sectional regressions. Characteristics are added to the regressions that form the graphs on the right hand side. The straight line in each graph is the 45° line from the origin. The analysis includes NYSE-listed stocks for the period January 1983 to August 2001.



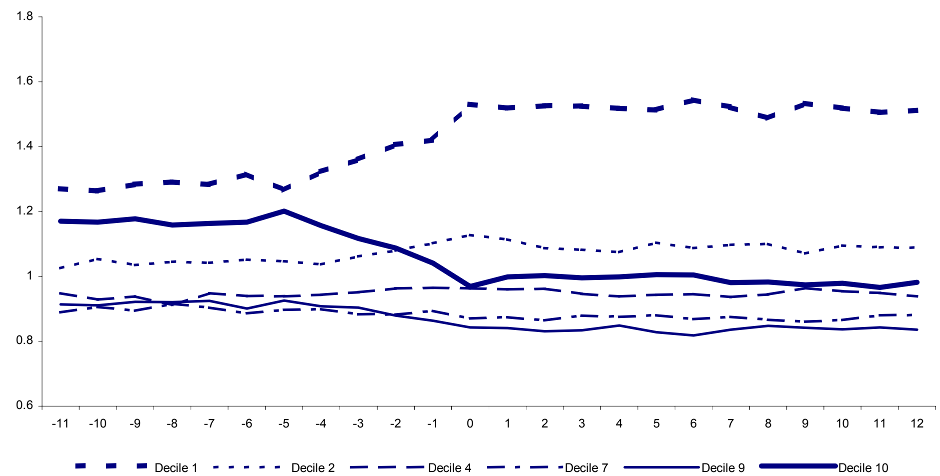
Panel A: Fixed/transitory costs of 11/1/1 strategy



Panel B: Fixed/transitory costs of 5/1/1 strategy

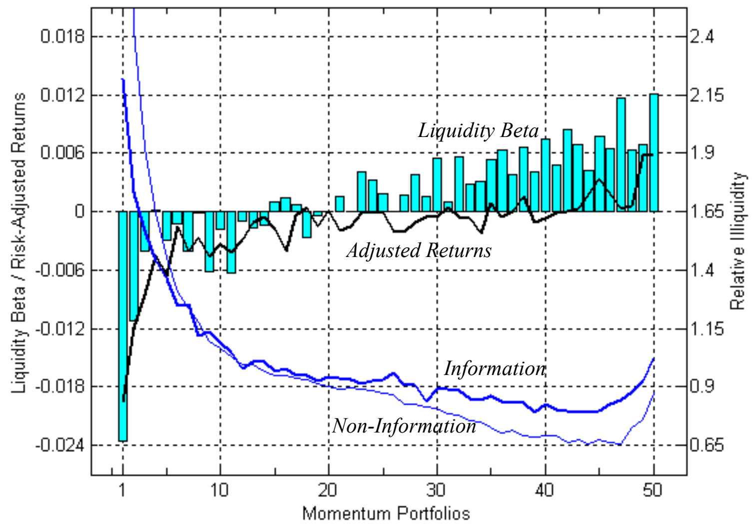


Panel C: Variable/permanent costs of 11/1/1 strategy

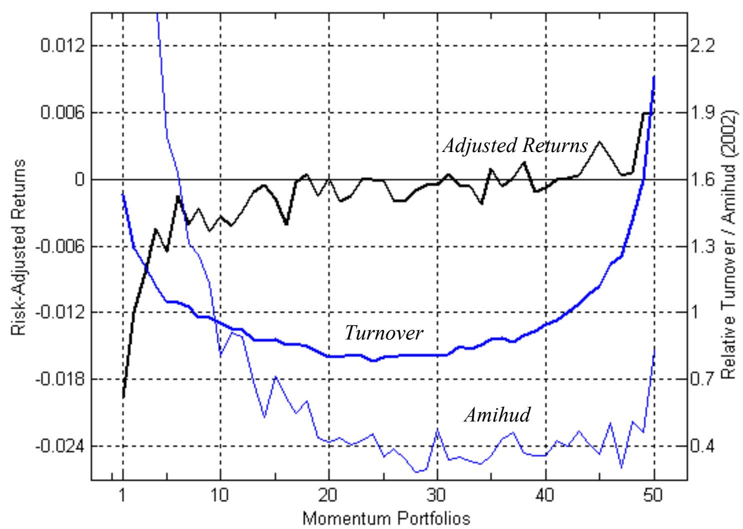


Panel D: Variable/permanent costs of 5/1/1 strategy

Figure 7, Price impacts of momentum portfolios in event time. Price impacts are estimated through the model described in Section 2. All functions are estimated on a monthly basis, separately for every stock. Price impacts are scaled by beginning-of-the-month price, and then scaled again by the cross-sectional average every month. Independently, momentum portfolios are formed as follows. In the beginning of every month stocks are sorted into deciles according to past cumulative returns (twelve months or six months; excluding last month's return). Holding the stocks in the portfolios fixed, lag and lead equal-weighted averages of the trading costs for these portfolios are computed. The time-series averages of these portfolio returns are plotted above. The end of month 0 is denoted formation time. The event-time window analyzed is -11 to +12 (a year before and a year after the formation date). The analysis includes NYSE-listed stocks for the period February 1984 to August 2000.



Panel A: Price impacts



Panel B: Turnover and Amihud (2002)

Figure 8, Momentum returns and measures of liquidity. In the beginning of every month stocks are sorted into 50 groups according to their cumulative returns during the previous twelve months (excluding last month's return). The figures above plot the liquidity beta (using the Fama-French three factors and the non-traded liquidity factor) and risk-adjusted returns (using only Fama-French three factors) of these portfolios, as well as averages of various measures of liquidity, including information and non-information components of price impact (Panel A), and turnover and the measure introduced in Amihud (2002) (Panel B). All liquidity measures are scaled by the cross-sectional average every month. The analysis includes NYSE-listed stocks for the period January 1983 to August 2001.