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Sell-Order Liquidity and the Cross-Section of Expected Stock Returns

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Abstract

We estimate buy- and sell-order illiquidity measures (lambdas) for a comprehensive sample of NYSE stocks. We show that sell-order liquidity is priced more strongly than buy-order liquidity in the cross-section of equity returns. Indeed, our analysis indicates that the liquidity premium in equities emanates predominantly from the sell-order side. We also find that the average difference between sell and buy lambdas is generally positive throughout our sample period. Both buy and sell lambdas are significantly positively correlated with measures of funding liquidity such as the TED spread as well option implied volatility.

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1. Introduction

The liquidity of an asset market refers to the ability of investors to buy and sell significant quantities of the asset, quickly, at low cost, and without a major price concession. A series of market crises that were associated with major decreases in liquidity, including the crash of 1987, the Asian crisis of 1998, and the credit crisis of 2008, has focused the attention of market participants, regulators and researchers on liquidity in financial markets. A major question is whether investors demand higher returns from less liquid securities. Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Brennan, Chordia, and Subrahmanyam (1998), Jones (2002), and Amihud (2002) all provide evidence that liquidity is an important determinant of expected returns. More recently, following the finding of commonality in liquidity by Chordia, Roll, and Subrahmanyam (2000), Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) relate systematic liquidity *risk* to expected stock returns.

An important issue that arises in studies relating liquidity to asset prices and returns is the empirical proxy that is used for illiquidity. The simplest proxy is the bid-ask spread, which is the difference between the price effects of a zero size buy and a zero size sell. Other proxies relate the size of the trade to the size of the price movement (i.e., they measure the price impact of trades), while assuming that the price effects of buys and sells are symmetric. This price impact approach finds theoretical support in the classic Kyle (1985) model, which predicts a linear relation between the net order flow and the price change. Amihud (2002) proposes the ratio of absolute return to dollar trading volume as a measure of illiquidity. In an alternative approach, Brennan and Subrahmanyam (1996) suggest measuring illiquidity by the relation between price changes and order flows, based on the analysis of Glosten and Harris (1988). Pastor and Stambaugh (2003) measure illiquidity by the extent to which returns reverse after high trading volume, an approach based on the notion that such a reversal captures the impact of price pressures due to demand for immediacy. Hasbrouck (2009) provides a comprehensive set of estimates of these and other measures of illiquidity, including the Roll (1984) measure.

All these measures presume a symmetric relation between order flow and price change. In contrast, we allow for an asymmetric relation and estimate separate buy and sell measures of illiquidity ("lambdas") for a large cross-section of stocks over a 26-year period, using a modified version of the Brennan and Subrahmanyam (1996) approach, which assumes that price responses are linear, and is an adaptation of the Glosten and Harris (1988) method. Any differences in buy- and sell-order illiquidity measures and their associated return premia may cast light on the mixed results in studies of the relation between liquidity and the cross-section of expected stock returns. For example, Brennan and Subrahmanyam (1996) find a negative relation between the bid-ask spread and expected returns, and Spiegel and Wang (2005) find no significant relation between expected returns and either bid-ask spreads or Amihud's (2002) measure of liquidity, after controlling for trading activity measures such as share volume and turnover. Thus, we look for evidence on the pricing of the buy- and sell-order illiquidity measures in the cross-section of expected stock returns.

We find that sell-order illiquidity is priced more strongly in the cross-section of expected stock returns than is buy-order illiquidity. This result continues to obtain after controlling for other known determinants of expected returns such as firm size, book-to-market ratio, momentum, and share turnover. The finding is robust to the Fama and French (1993) risk factors as well as to the estimation of factor loadings conditional on macroeconomic variables and firm characteristics such as size and book-to-market ratio. Finally, the pricing of sell-order illiquidity is also economically significant. A one-standard-deviation change in the sell lambda results in an annual premium that ranges from 2.9% to 3.7%.

We also study the time-series behavior of buy and sell lambdas and examine their cross-sectional determinants. We find reliable evidence that sell lambdas exceed buy lambdas.[1] Market-wide averages of buy and sell lambdas are significantly positively correlated with the TED spread (the spread between LIBOR (London Interbank Offer Rate) and U.S. Treasury bills) as well as with the implied market volatility measure, VIX, both of which have been used as

[1] Chordia, Roll, and Subrahmanyam (2002) find that the relationship between daily market returns and aggregate market-wide order imbalances is asymmetric, in that a marginal increase in excess sell orders has a bigger impact on returns than a corresponding increase in buy orders. In this paper we examine differential price impacts for buys and sells at the individual trade level, on a stock-by-stock basis.

measures of funding liquidity by Asness, Moskowitz, and Pedersen (2009). Cross-sectional determinants of buy and sell lambdas accord with those established earlier in the literature, and the time-series average of the cross-sectional correlations between the estimated buy and sell lambdas of individual securities is about 0.72.

The remainder of the paper is organized as follows. Section 2 presents the method for estimating the lambdas and describes the data. Section 3 presents some time-series and cross-sectional characteristics of the estimated lambdas. Section 4 presents the average returns on portfolio sorts, while Section 5 describes the methodology and results of asset pricing regressions. Section 6 concludes.

2. Empirical method and data for estimating lambdas

We use intraday transactions data to estimate separate buy- and sell-order measures of illiquidity. Specifically, we use a modification of the Brennan and Subrahmanyam (1996) model [which, in turn, is based on the Glosten and Harris (1988) approach] to estimate separate liquidity parameters for purchases and sales. Let the order flow and price change at time t be denoted by q_t and Δp_t, respectively. Further, denote D_t to be the sign of the incoming order at time t (+1 for a buyer-initiated trade and -1 for a seller-initiated trade). Allowing for different price responses to purchases and sales, we estimate:

$$\Delta p_t = \alpha + \lambda_{\text{buy}}(q_t \mid q_t > 0) + \lambda_{\text{sell}}(q_t \mid q_t < 0) + \psi(D_t - D_{t-1}) + y_t, \tag{1}$$

and we refer to λ_{buy} and λ_{sell} as the buy lambda and the sell lambda, respectively. The parameters of Eq. (1) are estimated each month for each stock using ordinary least squares, treating y_t as an error term (full details appear in the Appendix).

Our formulation assumes that there is a zero quantity bid-ask spread, ψ, as well as a price schedule with different slopes for buying and selling. In general, as Glosten and Harris (1988), Subrahmanyam (1991), Madhavan and Smidt (1991), and, more recently, Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (2010) suggest, this slope can arise from information considerations, inventory issues, or both. There is also an issue as to whether differential buy and sell lambdas permit manipulation by exploiting differential price impacts for buying and selling orders of the same size (Huberman and Stanzl, 2004). Such manipulation, however, is curtailed by the zero quantity spread, which ensures that manipulation yields zero profits for order sizes below a certain threshold. We propose that for large order sizes, presumably from large traders, strategic considerations would allow for an equilibrium degree of manipulation that would preserve the sell-buy lambda differential.

Our sample for estimation includes common stocks listed on the NYSE in the period January 1983 through December 2008. To be included in the asset pricing tests which are described below, a stock has to satisfy the following criteria: (i) its return in the current month and over at least the past 12 months be available from CRSP (Center for Research in Securities Prices), (ii) sufficient data be available to calculate market capitalization and turnover, and (iii) data be available on the Compustat tapes to calculate the book-to-market ratio as of December of the previous year. To avoid extremely illiquid stocks, we eliminate from the sample, stocks with month-end prices less than one dollar. The following securities are also eliminated from the sample since their trading characteristics might differ from ordinary equities: American Depository Receipts, shares of beneficial interest, units, companies incorporated outside the U.S., Americus Trust components, closed-end funds, preferred stocks, and real estate investment trusts. This screening process yields an average of 1,442 stocks per month. Transactions data are obtained from the Institute for the Study of Security Markets (ISSM) (1983--1992) and the Trade and Quote (TAQ) data sets (1993--2008), and are transformed using procedures described in the Appendix. The resulting data are used to estimate Eq. (1).

In the next section, we present summary statistics on the estimated lambdas. We also analyze how these illiquidity measures covary with previously identified determinants of liquidity in the time-series as well as the cross-section.

3. Characteristics of the estimated lambdas

In this section, we examine the summary statistics, and time-series and cross-sectional determinants of the buy and sell lambdas.

3.1. Summary statistics

Table 1 presents descriptive statistics on the buy and sell lambdas.[2] Motivated by the evidence in Chordia, Roll, and Subrahmanyam (2001) that illiquidity is greater in down markets, we present the statistics separately for months in which the current or previous month's value-weighted market return is positive and in which it is negative. We consider the previous month's return because the market stress created by a sell-off during a particular month could persist beyond that month if market makers face delays in unloading excess inventories.[3]

Panel A of Table 1 shows that for the full sample, the mean sell lambda exceeds the mean buy lambda by about 7%. A simple difference-in-means test of equality of the lambdas, assuming independence within the sample, yields a *t*-statistic in excess of 20. The mean value of the sell lambda is about 0.006 (scaled up by 10^3). Thus, a 1,000-share sell order has a price impact of $1000*0.006*10^{-3} \cong \$0.01$ per share, which is reasonable. The median lambda is smaller than the mean indicating some skewness. In our asset pricing analysis, we use lambda-based portfolio sorts as well as linear regression analysis to ensure our results are not affected by the distributional properties of the lambdas. Panel B shows that both buy and sell lambdas are higher in months in which the market return is negative, suggesting that the price impact is higher during periods of market stress. This finding holds for the sell lambda even when the market return is negative in the previous month, as opposed to the current month (Panel C). For

2 For brevity, we focus on the lambdas and not the fixed cost component, ψ, as the latter component has already been analyzed in earlier work such as Brennan and Subrahmanyam (1996), and because our central contribution is to examine the asymmetric effects of buy and sell lambdas on asset prices. Statistics for ψ are available upon request.

3 Hasbrouck and Sofianos (1993) and Madhavan and Smidt (1993) show that inventory autocorrelations of NYSE specialists are positive and persistent over long lags suggesting slow inventory adjustments.

a considerable majority of stocks (about 60%) the lambdas are significant at the 5% level or better.

In Panel D of Table 1, we provide the mean sell and buy lambdas for portfolios sorted by firm size (market capitalization) as of the end of the previous month. Within each size quintile, the sell lambda exceeds the buy lambda. In absolute terms, the difference in lambdas is higher for the smaller firm quintiles suggesting that liquidity problems are larger for the smaller stocks. Overall, the positive sell/buy lambda differential is not restricted to any specific size quintile but appears to be pervasive in the cross-section.

In Fig. 1, Panel A, we plot the time-series of the value-weighted monthly averages of daily buy and sell lambdas (using market capitalizations at the end of the previous month as weights). The lambdas track each other closely over time, though the sell lambda generally remains above the buy lambda and rises considerably above the buy lambda on a few occasions (notably around the crash of 1987 and around 1992). Consistent with the evidence in Chordia, Roll, and Subrahmanyam (2001), lambdas have declined over time so that liquidity has increased. Panel B of Fig. 1 presents time-series plots of the average equally weighted sell and buy lambdas which exhibit the same general pattern seen in Panel A. We note that the equally weighted average lambdas exceed the value-weighted lambdas, reflecting the association between liquidity and firm size.

We present the plot of the difference between value- and equally weighted buy and sell lambdas in Fig. 2, Panel A. The difference generally remains positive throughout the sample, and has increased for the equally weighted version in recent years. To control for the level of the sell and buy lambdas, in Panel B of Fig. 2 we present the difference in the lambdas scaled by the average of the buy and sell lambda. This scaling ensures that the difference in the lambdas does not depend mechanically on the level of lambda. This scaled value-weighted differential has remained fairly stationary over time, ranging from 5% to 10%, peaking at the higher levels around 1992--1993 and towards the end of the sample period that encompasses the recent financial crisis. However, the equally weighted scaled differential has increased markedly in the latter part of the sample period. This implies a recent widening of the sell-buy lambda differential in the smaller companies. Overall, Fig. 2 indicates that there is a meaningful difference between sell and buy illiquidity, and market-wide sell illiquidity is generally greater than buy illiquidity.

Asymmetric price impacts have been considered in many previous studies. With a few exceptions, the early literature on block trades and/or institutional trades finds that buy-side impacts exceed sell-side impacts. Thus, Kraus and Stoll (1972) and Gemmill (1996) find a bigger impact of buy blocks relative to sell blocks, and Chan and Lakonishok (1993, 1995) show that buy trades of a sample of large institutions have a bigger impact than sell trades. More recently, Frino, Bjursell, Wang, and Lepone (2008) demonstrate a similar finding for large trades by outside customers in four Australian financial futures markets. Kalay, Sade, and Wohl (2004) study all orders placed at the opening auction on the Tel Aviv Stock Exchange and find that buy trades have a bigger impact than sell trades. On the other hand, Holthausen, Leftwich, and Mayers (1987) show that blocks executed on a "downtick" have a bigger total price impact than blocks executed on an "uptick"[4] and Keim and Madhavan (1996) find that "upstairs" sell orders (i.e., large orders executed via negotiation off the exchange floor) have a larger total impact than their buy-side counterparts. More recently, using data on trades by a Dutch pension fund, Bikker, Spierdijk, and van der Sluis (2007) also find that the price impact of institutional sells exceeds that of buys.

Michayluk and Neuhauser (2008) use three months of data (January of 1999, 2000, and 2001) for all trades in 100 Internet and technology firms and find that ask depths exceed bid depths, and effective spreads for sell orders exceed those for buy orders for 1999 and 2000, which is consistent with sell orders being more costly than buy orders. However, a measure of the price impact (the absolute price move subsequent to a trade at the bid or ask) shows no significant differences across buy and sell sides. Saar (2001) presents a theoretical model of asymmetric price impact in which the price impact of buys by institutional investors exceeds

[4] Holthausen, Leftwich, and Mayers (1990) use transactions data to measure price impact of block trades (unlike their 1987 paper, which uses closing prices). Their findings show that the asymmetry between price impacts of blocks executed on upticks and downticks narrows considerably when such data are used.

that of sells, except that after a long run-up in the price of the security, the asymmetry will be reduced and may even be reversed. The argument is that institutional buying is more likely to be informative than institutional selling because of short-selling constraints. After a stock price run-up, the stock is held by so many institutions that the costs of short-selling decline, as does the asymmetry. Chiyachantana, Jain, Jiang, and Wood (2004) show that the empirical difference between the price impacts of institutional buys and sells varies across bull and bear markets. They show that in 1997 and 1998, institutional buy orders have greater impacts than sell orders, whereas in 2001, the opposite is true.[5]

The preceding empirical studies generally span either a subset of orders (block trades/institutional trades) and/or a limited sample period [the maximum time span is eight years from 1985 to 1992 in Keim and Madhavan (1996)]. Our study differs from earlier ones by covering a large cross-section of stocks and considering virtually all orders over a time span of more than 25 years. Our empirical results indicate that for this sample, sell-side price impacts exceed buy-side ones.

3.2. Correlations

Panel A of Table 2 reports the time-series averages of the cross-sectional correlations between the lambda estimate and both the Amihud (2002) illiquidity measure and the quoted and effective spreads. The Amihud measure is calculated as the monthly average of the ratio of the daily absolute return to daily dollar volume. Quoted and effective spreads are monthly averages of all observations for each stock, extracted from the transactions data.

The correlation between estimated buy and sell lambdas is about 0.72. The correlations of both the spread measures and the Amihud illiquidity measure with the lambdas are positive.

[5] Commenting on these findings, Hu (2009) argues that sell-side and buy-side institutional costs depend on whether pre-trade, during-trade, and post-trade benchmark prices are used to measure trading costs. For example, in rising markets, execution prices will tend to be above the pre-trade price, leading to an apparent increase (decrease) in buying (selling) costs. For post-trade measures, the opposite will be true. For measures based on during-trade benchmark prices (like the value-weighted average price), such biases will not apply. Note that in our case, the sell-side lambda remains above the buy-side lambda virtually throughout the sample period, which encompasses bear as well as bull markets. This suggests that the considerations of Hu (2009) do not drive the sell-buy lambda asymmetry.

However, while the quoted and effective spreads have a correlation of about 0.5 with the lambdas, the correlation of the Amihud illiquidity measure with the lambdas is only about 0.19. This suggests that the Amihud measure and the lambdas capture different facets of illiquidity.

Brunnermeier and Pedersen (2009) and Brunnermeier, Nagel, and Pedersen (2008) argue that market liquidity is likely to be positively related to funding liquidity, which affects the ability of dealers to finance their inventory. One measure of funding illiquidity is the TED spread, the difference between the three-month LIBOR and the three-month Treasury bill rate. Specifically, the TED spread may proxy for counterparty risk, which, when elevated, can lead to funding illiquidity. To explore whether the measures of market illiquidity vary with the TED spread, we compute time-series correlations between market-wide average illiquidity measures and the TED spread. The market-wide illiquidity measures are calculated as the value-weighted averages of the individual stock measures each month, and the TED spread is the month-end value obtained from public data sources.[6] The correlations are reported in Panel B of Table 2. The time-series correlation between the two market-wide average lambdas is 0.998, which suggests a common time-varying determinant. Their correlations with the quoted spread and the Amihud measure are, respectively, 0.894 and 0.891. All five measures of illiquidity are positively correlated with the TED spread which confirms the theoretical prediction of Brunnermeier and Pedersen (2009). The highest correlations are with the two lambdas (around 0.45), while the lowest is with the average Amihud measure (0.29). It is likely that these correlations are high because of the long-term increase in liquidity over time. In our time-series regressions we will control for the time trend.

3.3. Macro determinants of average buy and sell lambdas

To explore the determinants of overall market liquidity as measured by the lambdas, we regress the value-weighted average lambdas on variables which may be expected to affect liquidity: (i) the TED spread, (ii) the contemporaneous market return, (iii) the ratio of the number of stocks with a positive return to that with a negative return, (iv) a measure of aggregate volatility, namely, the implied option volatility index, VIX, and (iv) a linear time-trend. The

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[6] http://www.federalreserve.gov/releases/h15/data.htm and http://www.bba.org.uk, for the three-month Treasury bill rate and the three-month LIBOR, respectively.

TED spread is simply a measure of funding liquidity, as described in the previous subsection. The second and third variables are used as measures of market stress. Indeed, Chordia, Roll, and Subrahmanyam (2001) show that bid-ask spreads are higher when market returns are low. Brunnermeier and Pedersen (2009) as well as Anshuman and Viswanathan (2005) argue that market drops reduce the value of market makers' collateral and lead to a sharp decrease in the provision of liquidity. This implies that lambdas should be higher in down markets and in markets where stocks with negative returns outnumber those with positive returns. Liquidity measures should depend on ex ante expected volatility because this quantity is positively related to the market makers' inventory risk, which justifies the inclusion of VIX. The trend term accounts for the decline in the aggregate lambdas shown in Fig. 1.

The coefficient estimates from the time-series regressions for buy and sell lambdas as dependent variables appear in Panel A of Table 3. To capture serial correlation and heteroskedasticity, we present *t*-statistics computed using Newey-West corrected standard errors. Both buy and sell lambdas are increasing in the TED spread, which is consistent with the notion that the TED spread is a measure of funding liquidity. The lambdas are also strongly and positively related to VIX, as expected. The up/down variable and market returns, however, are not significant. As expected, the trend variable is negative and highly significant.[7]

Panel B of Table 3 analyzes the time-series determinants of the *difference* between sell and buy lambdas, for both the unscaled and the scaled lambda differential: the latter is the difference between the buy and sell lambdas scaled by the average of the buy and sell lambdas. The TED spread is negatively related to the unscaled lambda differential with a *p*-value of 0.12, indicating that the spread between sell and buy lambdas narrows when the TED spread is high. However, the insignificant coefficient on the scaled difference suggests that the impact of the TED spread on the unscaled difference is dwarfed by its impact on the level of the lambdas. VIX is significant for the unscaled differential, suggesting that the difference between sell and buy lambda widens during periods of high implied volatility. However, once again, the impact

[7] We experiment with other macroeconomic variables as well. The swap spread is not significant, possibly because it is available only from 2000 onwards. The term spread and the T-bill yield are both negatively related to buy and sell lambdas. Since the term spread declines prior to a recession, this suggests that lambdas are elevated as the economy turns down. Also, T-bill yields are higher during expansions suggesting that lambdas decrease during expansionary periods.

of VIX on the difference between the lambdas is overwhelmed by its impact on the level of the lambdas. The result for the market return is similar. The coefficient on the market return is negative and significant only for the unscaled differential. This is consistent with the notion that sell lambdas rise by more than buy lambdas during periods of selling pressure that strain market maker inventories, and also accords with the findings of Bikker, Spierdijk, and van der Sluis (2007), as well as those of Frino, Bjursell, Wang, and Lepone (2008). Finally, note that the coefficient on the time trend for the unscaled (scaled) lambda differential is negative (positive). This suggests that the sell lambda declines more than the buy lambda over time. However, both the lambdas decline significantly over time.

3.4. Cross-sectional determinants of buy and sell lambdas

To analyze firm-specific determinants of the lambdas, we estimate a simultaneous system of equations for the lambdas, analyst following, institutional holdings, and trading volume as measured by turnover. The system is motivated by Brennan and Subrahmanyam (1995), who argue that lambda, and the number of analysts following a stock, and trading activity are endogenous variables and estimate a system of equations for these variables. Moreover, institutions are likely to be more active in the more liquid stocks that are followed by many analysts and are likely to increase turnover and attract analysts to stocks they hold. We therefore estimate the following system:

$$\lambda_{Ki} = a_2 + b_2\sigma(R)_i + c_2\,Log(P_i) + d_2\,Log(Inst_i) + e_2\,Log(1{+}Analyst_i) + f_2\,Log(Insider_i) + g_2\,Log(Size_i) + h_2\,Turn_i + v_i, \quad (2)$$

$$Log(1{+}Analyst_i) = a_3 + b_3\,\sigma(R)_i + c_3\,Log(P_i) + d_3\,Log(Inst_i) + f_3\,\lambda_{Ki} + \textstyle\sum g_{3j} Ind_{ij} + h_3\,Log(Size_i) + k_3\,Turn_i + w_i, \quad (3)$$

$$Turn_i = a_4 + b_4\,\lambda_{Ki} + c_4\,Log(P_i) + d_4\,Log(Size_i) + e_4\,Log(1{+}Analyst_i) + \omega_i, \quad (4)$$

$$Log(Inst_i) = a_5 + b_5\,\lambda_{Ki} + c_5\,Beta_i + d_5\,S\&P_i + e_5\,Log(1{+}Analyst_i) + \zeta_i, \quad (5)$$

where $\lambda_K = \{\lambda_{buy}, \lambda_{sell}$, and $\lambda_{sell} - \lambda_{buy}\}$; $\sigma(R)$ is the standard deviation of daily returns calculated each month; P is the stock price; *Inst* represents the percentage of shares held by institutions; *Analyst* denotes the number of analysts following a stock; *Insider* represents the percentage of shares held by insiders; *Size* is the market capitalization; *Turn* represents the monthly share turnover; *Beta* represents the market beta of the stock with respect to the CRSP value-weighted index, estimated monthly as per the approach of Fama and French (1992), *S&P* represents an indicator variable denoting S&P 500 index membership, and Ind_j (j=1,…,5) represents five industry dummies obtained from Kenneth French's Web site.

The equation system is motivated as follows. First, it is reasonable to assume that our instruments, the price, size, beta, and industry, as well as index membership, are exogenous since they describe inherent properties of companies which are not dependent on liquidity, trading activity, analyst coverage, and institutional holdings. Our first equation, which is motivated by earlier work on the bid-ask spread (Benston and Hagerman, 1974; Branch and Freed, 1977; Stoll, 1978), models the lambda as a function of: volatility measured by the monthly standard deviation of daily returns, the logarithm of the closing price as of the end of the month, the logarithm of the market capitalization as of the end of the month, and monthly share turnover. Volatility affects inventory risk, and share turnover captures the simple notion that active markets tend to be deeper. The price level controls for scale. As Chordia, Roll, and Subrahmanyam (2000) point out, a $10 stock will not have the same bid-ask spread as a $1,000 stock even if they have otherwise similar attributes. All else equal, we expect high-priced stocks to have both high bid-ask spreads and high lambdas. The size variable captures the notion that large, visible firms would attract more dispersed ownership and hence may be more liquid.

In addition to the preceding variables, we use three variables to capture information production: the logarithm of one plus the number of analysts (obtained from I/B/E/S – Institutional Brokers' Estimate System) making one-year earnings forecasts on the stock, the logarithm of the percentage of shares held by institutions, and the logarithm of the percentage of shares held by insiders. Using our transformation of analyst following allows us to include firms that have no I/B/E/S analysts providing forecasts. Brennan and Subrahmanyam (1995) use a similar measure in considering the role of analysts as information producers. Further, Chiang and Venkatesh (1988) consider the role of insiders in determining the bid-ask spread, given the assumption that inside ownership is the channel through which private information gets conveyed to the market. Also, the role of institutions as information producers has been analyzed in Sarin, Shastri, and Shastri (1999).

In Eq. (3), the number of analysts following a stock is modeled as a function of the institutional holding and the trading volume as measured by turnover because it is likely that analysts follow stocks with high trading volume and high institutional holdings. Price and size are also used as explanatory variables because, in general, analysts follow larger stocks. The price impact measures and the monthly return volatility are also included because analysts are less likely to follow illiquid stocks. In Eq. (4), turnover is modeled as a function of firm size, price, analyst following, and the price impact measures because larger, more liquid stocks with high analyst following are likely to have higher turnover. Finally, in Eq. (5) holdings are modeled as a function of beta, S&P 500 membership, and analyst following. Beta is included because Barry and Brown (1985) and Klein and Bawa (1976, 1977) argue that the measured betas of securities with low information flows would be higher, and that this would influence the holdings of such securities. S&P 500 membership is also likely to influence institutional holdings because of the prevalence of indexation to the S&P 500 (Fabozzi and Molay, 2000). Finally, analyst following is included because institutions are likely to be attracted to stocks more widely followed by analysts.

The cross-sectional regression equations in (2)–(5) are estimated jointly each month by three-stage-least-squares. The average sample size is 593. The time-series averages of the coefficients for the lambda equations are presented in Table 4.[8] The reported *t*-statistics are computed from the time-series of the coefficient estimates using Newey-West (1987, 1994) standard errors. The results are mostly consistent with prior conjectures, and the determinants of buy and sell lambdas are quite similar. Thus, Panels A and B of Table 4 show that both the buy and sell lambdas are positively related to volatility, and negatively related to share turnover. Consistent with the role of the price level as a scale factor, its coefficient is positive. The coefficient of insider holdings, another measure of information asymmetry, is not significant.

[8] Estimates for the other equations are not reported for brevity but are available upon request.

Perhaps a better measure of information asymmetry would be insider trading rather than insider holdings, but data on insider trading are not available for an extended cross-sectional and time-series sample. The percentage of shares held by institutions is negatively related to lambda, which appears to be inconsistent with the role of institutions as information producers. However, this result may arise because more institutions may imply greater competition between institutions using correlated information, and hence a lower lambda, as argued by Brennan and Subrahmanyam (1995) for analyst following. These cross-sectional results for the buy and sell lambdas are similar to those obtained for the bid-ask spread (see, for instance, Chordia, Roll, and Subrahmanyam, 2000).

It is also of interest to examine cross-sectional determinants of the sell-buy lambda *differential*. To this end, Panel B of Table 4 presents the results when the unscaled and scaled differences in lambdas (i.e., the variables used in Table 3, Panel B) are, in turn, used in place of the buy and sell lambdas in the estimation. The lambda differential is negatively related to analyst following and institutional holding. The coefficient on the stock price is positive and significant for the unscaled differential suggesting that the sell lambda increases by more than the buy lambda as price increases. However, the scaled difference between the sell and the buy lambda is unrelated to price suggesting that the impact of price on the average lambda is larger than the impact on the differential.

Overall, the determinants of buy and sell lambdas accord with previous findings on the determinants of illiquidity.[9] To this point, however, we have been concerned only with the time-series and cross-sectional properties of buy and sell lambdas. In the following two sections we address how the buy and sell lambdas affect the return premium demanded by investors.

4. Returns on portfolio sorts

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[9] To address the issue that the lambdas and the sell-buy lambda differential may be affected by stock returns (a stock with negative returns may have greater sell-side price impact because of inventory pressures caused by a lack of buyers), we include the current and lagged returns in the equation for lambda. These return variables, however, are not significant, suggesting that cross-sectional variations in the level of lambda and the difference in sell and buy lambdas are not explained by differences in realized returns.

Before reporting the results of regressions relating average returns to the lambdas, we report mean returns for the portfolios formed by sorting the component stocks into quintiles each month according to the estimated buy and sell lambdas, in turn. We present the subsequent months' average excess returns as well as the Capital Asset Pricing Model (CAPM) and Fama and French (1993) intercepts (alphas) for these value-weighted portfolios in Table 5 (the weights are computed using market capitalization as of the end of the previous month). The intercepts are those from the time-series regression of the quintile portfolio returns on the excess market return and the three Fama-French factors.

We find that excess returns and alphas increase monotonically with the lambda quintile except in one case (quintiles 4 and 5 for the buy lambda). The differences in excess returns and alphas between the extreme lambda quintiles are all positive and significant at the 5% level. The Fama-French alpha for the high lambda portfolio exceeds that of the low lambda portfolio by 40 basis points per month for the buy lambda sort and by 56 basis points for the sell lambda sort.[10] The return spread of about 6.7% per year between the extreme sell lambda portfolios (based on the last column) is economically significant.

The results in Table 5, of course, do not shed light on the differential effects of buy and sell lambda on risk-adjusted expected stock returns. To explore this, we sort stocks first into quintiles by buy lambdas and then sort within each quintile into five portfolios by sell lambdas. Panel A of Table 6 reports the average excess returns and the Fama-French alphas for the high sell lambda minus the low lambda quintile portfolios for each buy lambda quintile. Thus, we examine the return differential across the extreme sell lambda quintile portfolios while holding buy lambdas constant. The differences in both excess returns and the Fama-French alphas between the highest and lowest sell lambda portfolios are positive in all cases and significant at the 5% level or better in three out of the five cases. The alpha differential between the extreme sell-lambda quintiles ranges from 20 to 49 basis points per month across the five buy lambda groups. We also perform a reverse sequential sort in which we sort first into quintiles by sell lambdas and then form five portfolios within each quintile by buy lambdas. Panel B of Table 6

[10] Brennan and Subrahmanyam (1996) find about a 55 basis point return differential across their extreme lambda portfolios (see their Table 4), which is comparable to our corresponding magnitudes.

reports the average excess returns and Fama-French alphas for the high buy lambda minus the low buy lambda quintile portfolios for each sell lambda quintile. In contrast to the results reported in Panel A, the spread between the extreme buy lambda portfolios is insignificant in every case and in three out of the five cases, the point estimate is negative. Thus, the results suggest that there is a premium associated with sell-order illiquidity even after controlling for the effect of buy-order illiquidity, but there is no evidence of a premium for buy-order illiquidity after controlling for sell-order illiquidity.

A potential concern is that the compensation for lambda is simply a manifestation of a return effect related to firm size, since smaller firms have higher lambdas (Panel D of Table 1 and Panel A of Table 4) and have been shown to earn higher returns (Banz, 1981). To distinguish between the effects of lambda and firm size, we sort stocks into 25 portfolios first by firm size and then by sell lambda. The results in Panel C of Table 6 show that within each size quintile, the difference in Fama-French alphas between between the high and low sell lambda quintiles are positive. While the (risk-adjusted) return differential between the extreme sell lambda quintiles is larger for smaller firms, it is present in all firm size quintiles. Our evidence therefore points to a role for sell lambda over and above that of firm size in predicting stock returns.

We perform additional sorts by two other characteristics known to influence the cross-section of stock returns, namely, the book/market ratio (Fama and French, 1992) and a momentum variable; namely, the past seven- to 12-month return (Jegdeesh and Titman, 1993). Results from these sorts appear in Panels D and E. In each of these panels, the return differential across extreme sell lambda portfolios is significant in four of five cases. Overall, the results point to a robust return premium for stocks with high values of the sell lambda.

5. Asset pricing regressions

This section presents the results of asset pricing regressions that aim to investigate differential pricing of buy and sell lambdas. We first introduce our method, and then present the main results, followed by some robustness checks.

5.1. Methodology

Our cross-sectional asset pricing tests follow Brennan, Chordia, and Subrahmanyam (1998) and Avramov and Chordia (2006), who test factor models by regressing risk-adjusted returns on firm-level attributes such as size, book-to-market, turnover, and past returns. We first regress the excess return on stock j, (j=1,..,N) on asset pricing factors, F_{kt}, (k=1,..,K), allowing the factor loadings, β_{jkt}, to vary over time as a function of firm size and book-to-market ratio, as well as macroeconomic variables. The conditional factor loadings of security j are modeled as:

$$\beta_{jkt-1} = \beta_{jk1} + \beta_{jk2}\, z_{t-1} + \beta_{jk3}\, Size_{jt-1} + \beta_{jk4}\, BM_{jt-1}\,, \tag{6}$$

where $Size_{jt-1}$ and BM_{jt-1} are the market capitalization and the book-to-market ratio at time $t-1$, and z_{t-1} denotes a vector of macroeconomic variables: the term spread, the default spread, and the T-bill yield. The term spread is the constant maturity yield differential between Treasury bonds with more than ten years to maturity and T-bills that mature in three months. The default spread is the yield differential between bonds rated Baa and Aaa by Moody's.

The dependence of factor loadings on size and book-to-market is motivated by the general equilibrium model of Gomes, Kogan, and Zhang (2003), who justify separate roles for size and book-to-market as determinants of beta. In particular, firm size captures the component of a firm's systematic risk attributable to growth options, and the book-to-market ratio serves as a proxy for the risk of existing projects. The inclusion of business-cycle variables is motivated by the evidence of time-varying risk–-viz. Rosenberg and Marathe (1976) and Ferson and Harvey (1991).

In the empirical analysis, the factor loadings $\beta_{jk}(t)$ are modeled using three different specifications: (i) an unconditional specification in which $\beta_{jk}(t) = \beta_{jk}$, (constant betas), (ii) a conditional specification in which loadings depend only on firm-level characteristics, $\beta_{jk2} = 0$, and (iii) a model in which loadings depend only on macroeconomic variables, i.e., $\beta_{jk3} = \beta_{jk4} = 0$.

We subtract the component of the excess returns that is associated with the factor realizations to obtain the risk-adjusted returns, R_{jt}^{*}:

$$R_{jt}^{*} = R_{jt} - R_{Ft} - \sum_{k=1}^{K} \beta_{jkt-1} F_{jk} \ . \tag{7}$$

The risk-adjusted returns are then regressed on the equity characteristics:

$$R_{jt}^{*} = c_{0t} + \sum_{m=1}^{M} c_{mt} Z_{mjt-2} + e_{jt} , \tag{8}$$

where $\beta_{jkt\text{-}1}$ is the conditional beta estimated by a first-pass time-series regression over the entire sample period.[11] Z_{mjt-2} is the value of characteristic m for security j at time t-2, and M is the total number of characteristics. This procedure ensures unbiased estimates of the coefficients, c_{mt}, without the need to form portfolios, because the errors in estimation of the factor loadings are included in the dependent variable. Ang, Liu, and Schwarz (2008) also argue in favor of using individual stock betas because forming portfolios shrinks the dispersion in betas and leads to higher asymptotic standard errors of risk premia estimates. Note that we lag all characteristics by at least two months. This is because bid-ask effects and thin trading could affect our results if one-period lagged characteristics are correlated with lagged bid-ask spreads (Jegadeesh, 1990; Brennan, Chordia, and Subrahmanyam, 1998).

The standard Fama-MacBeth (1973) estimators are the time-series averages of the regression coefficients, $\hat{c}_t$. The standard errors of the estimators are traditionally obtained from the variation in the monthly coefficient estimates. We correct the Fama-MacBeth (1973) standard errors using the approach in Shanken (1992) to allow for error in the estimation of factor loadings in the first-pass regression.

[11] Fama and French (1992) and Avramov and Chordia (2006) show that using the entire time-series to compute the factor loadings gives results that are qualitatively similar to those obtained from using rolling regressions.

Based on well-known determinants of expected returns in Fama and French (1992), Jegadeesh and Titman (1993), and Brennan, Chordia, and Subrahmanyam (1998), the firm characteristics included in the cross-sectional regressions are the following:

(i) SIZE: measured as the natural logarithm of the market value of the firm's equity as of the second-to-last month,

(ii) BM: the ratio of the book value of the firm's equity to its market value of equity, where the book value is calculated according to the procedure in Fama and French (1992), measured as of the second-to-last month,

(iii) TURN: the logarithm of the firm's share turnover, measured as the trading volume divided by the total number of shares outstanding, both measured at the end of the second-to-last month,

(iv) RET2--3: the cumulative return on the stock over the two months ending at the beginning of the previous month,

(v) RET4--6: the cumulative return over the three months ending three months previously,

(vi) RET7--12: the cumulative return over the six months ending six months previously,

(vii) the buy and sell lambdas, λ_{buy} and λ_{sell}, as of the second-to-last month.

Under the null hypothesis of exact factor pricing, the coefficients of all of these characteristics should be indistinguishable from zero in the cross-sectional regressions represented by Eq. (8). Significant coefficients point to lacunae in the factor-pricing model. Brennan, Chordia, and Subrahmanyam (1998) find that the predictive ability of size, book-to-market, turnover, and past returns is unexplained by typical factor-pricing models. In this paper, we explore whether buy lambdas and sell lambdas capture elements of expected returns that are not captured by the factor-pricing models using both conditional and unconditional versions of factor loadings.[12] Since Datar, Naik, and Radcliffe (1998) interpret turnover as a measure of liquidity, the challenge is to determine whether the lambda measures have a significant influence on expected returns after accounting for the effect of turnover.

5.2. Results

[12] We use unscaled versions of buy and sell lambdas to ensure that the asset pricing results do not pick up the consequences of scaling, as opposed to the effect of lambdas. However, scaling the lambda by the market price leaves the qualitative conclusions unchanged (results available from the authors).

We now present the results of monthly cross-sectional Fama-MacBeth regressions of risk-adjusted returns on firm characteristics, i.e., estimates of Eq. (8). Results are presented when returns are adjusted for risk using both unconditional and conditional factor loadings. For each of our factor model specifications, we report the time-series averages of the monthly cross-sectional regression coefficients and the associated Shanken (1992) corrected *t*-statistics.

Table 7 reports results for the case in which the Fama-French risk factors are used to calculate risk-adjusted returns. The results are qualitatively similar when the excess market return is used as the single risk factor. The coefficients of both buy and sell lambdas are positive and significant when they are separately included in the regression. However, the statistical significance of the buy lambda disappears (and the absolute coefficient reduces by about 85--90%) when the sell lambda is included in the regression.[13] On the other hand, the sell lambda remains highly significant in the presence of the buy lambda and its coefficient is little changed by the inclusion of the buy lambda in the regression. The use of conditional betas in calculating the risk-adjusted returns has no qualitative effect on these results. These findings imply that the effect of lambda in the cross-section of expected stock returns emanates completely from the sell lambda, as opposed to the buy lambda.[14]

We also find that the longest-term momentum variable is significant, confirming the well-known momentum effect of Jegadeesh and Titman (1993). Turnover is negatively associated with risk-adjusted returns, which is consistent with the evidence of Datar, Naik, and Radcliffe (1998) as well as that of Brennan, Chordia, and Subrahmanyam (1998). That the coefficients of the sell lambda are positive and significant in the presence of turnover suggests that turnover and the lambdas pick up complementary aspects of liquidity. For example,

[13] We address the illiquidity-induced bias in asset pricing tests mentioned by Asparouhova, Bessembinder, and Kalcheva (2010) by conducting the two tests recommended by these authors in their paper. First, we perform a version of the Table 7 regression with mid-quote returns, using the last bid-ask quote matched to a transaction during a day. Second, we perform weighted-least-squares regressions, using the prior period's gross return as weights. The results survive the alternative methods, and are available upon request.

[14] To ensure that our results survive potential asymmetries in momentum across positive and negative return states, we split up the three momentum variables into six variables, two each capturing positive and negative return states. The results are qualitatively unaltered in this alternative return specification.

turnover is a measure of the average time to turn around a position, while lambdas measure the price impact of a trade.[15]

In Table 8, we add the Amihud (2002) illiquidity measure and the log of the stock price as explanatory variables in the cross-sectional regressions. Falkenstein (1996) argues that firms with low prices are often in financial distress, and this may be reflected in their earning higher expected returns, as shown by Miller and Scholes (1982). Also, Berk (1995) observes that price will be related to returns under improper risk-adjustment, because riskier firms would tend to have lower price levels and also earn higher expected returns. Further, low-priced, illiquid firms could be associated with high lambdas, so that our lambda measure could be picking up a price level effect. To address the potential relation between prices and lambdas, we include the logarithm of the two months' prior closing price as an explanatory variable. Further, we add the Amihud measure of illiquidity in our regressions to test whether the lambda measures capture facets of illiquidity that are not captured by this existing illiquidity measure.

Table 8 shows that high-priced stocks have lower expected returns and illiquid stocks as measured by the Amihud measure have higher expected returns.[16] These results are robust to the choice of conditioning variables. Further, in the presence of the stock price variable, larger firms have *higher* expected returns over our 1983--2008 sample period. Also, the effect of turnover on risk-adjusted returns is weaker when the price variable and Amihud measure of illiquidity are included in the regression, especially when the factor loadings are conditioned on macroeconomic variables. Most importantly, the coefficient on the sell lambda continues to be positive and significant. Indeed, the coefficient is larger than in Table 7. The coefficient on the buy lambda remains insignificant in the presence of the sell lambda.

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[15] Kyle (1985, p. 1316), inspired by Black (1971), states the following:

> "Market liquidity" is a slippery and elusive concept, in part because it encompasses a number of transactional properties of markets. These include "tightness" (the cost of turning around a position over a short period of time), "depth" (the size of an order flow innovation required to change prices a given amount), and "resiliency" (the speed with which prices recover from a random uninformative shock)."

It is reasonable to propose that that lambda captures the second aspect of liquidity, and turnover the first one. Pastor and Stambaugh (2003) capture the third (resiliency) aspect of liquidity. To allay concerns about omitted risk factors, in alternative robustness checks (available upon request), we augment the factor model by the liquidity factor of Pastor and Stambaugh (2003) as well as the momentum factor (UMD). We find that the coefficients of the sell lambda are not materially affected by this augmentation.

[16] The fixed cost component, ψ, does not play a significant role in asset pricing; results are available upon request.

In sum, the impact of the sell lambda on risk-adjusted returns dominates that of the buy lambda using either conditional or unconditional models for factor loadings, and irrespective of whether loadings are conditioned on macroeconomic variables or size/book-market. Thus, the pricing of sell illiquidity appears to be a robust phenomenon in the cross-section of stock returns. To assess the economic magnitude of the premium for sell lambda, consider the relevant coefficients in the last row of Table 8. The coefficients in this row range from 0.25 to 0.31. Relating these to the summary statistics in Panel A of Table 1, we find that a one-standard-deviation change in sell lambdas implies an annual sell lambda premium that ranges from 2.9% to 3.7%. This is material. The return required as compensation for sell illiquidity is not only statistically significant but also economically significant.

5.3. Additional robustness checks

We perform further tests to ensure robustness of the results. First, from Table 2, the grand time-series, cross-sectional correlation between buy and sell lambdas is 0.72, which is high. To mitigate concerns about multicollinearity, we estimate a specification where we include the average of and the difference between the sell and buy lambdas as independent variables. Results appear in Table 9 for the unconditional model (they are qualitatively similar for other models). As can be seen, there is both a baseline effect of the average lambda, and an incremental effect of the difference between sell and buy lambdas in that both variables are positive and significant. This confirms the additional premium required for the sell lambda.

Eleswarapu and Reinganum (1993) argue that the premium for the bid-ask spread is almost entirely realized in the month of January. To ascertain if there is a similar January seasonal effect in the premium for sell lambda, we regress the time-series of Fama-MacBeth coefficients (i.e., the reward per unit sell lambda as in column 3 of Table 8) on a constant plus a dummy for the month of January. The coefficient on the dummy variable is positive but has a *t*-statistic of 1.25, indicating that the premium for sell lambda does not exhibit a January seasonal.

Next, Bessembinder and Venkataraman (2010) indicate that the accuracy of the Lee and Ready (1991) trade signing algorithms has not been assessed in the post-decimalization (i.e., post-December 2000) period, which is characterized by a dramatic increase in the frequency of trades and quote updates. Since our sell-buy lambda estimation relies on the Lee and Ready algorithm to separate trades into buys and sells, we re-estimate the Table 8 regressions dropping all months from January 2001 onwards. This results in a loss of 108 sample months but even in this regression, the sell lambda remains significant with a *t*-statistic of 2.3 whereas the buy lambda is insignificant (full results are available from the authors on request).

As a final robustness check, we now turn to the issue of whether the differential pricing of sell and buy lambdas extends to the case where the price response is computed with respect to the unexpected order flow, as opposed to the total order flow. The idea here is to capture the market maker response to the unanticipated portion of the order flow, which may more reliably represent the trades of newly informed agents. To address this issue, we use transactions data to compute a variant of the measure developed by Sadka (2006) and also used in Korajczyk and Sadka (2008). Specifically, in Eq. (8) of Sadka (2006),[17] we decompose the unexpected order flow ($\varepsilon_{\lambda,t}$) into buy and sell components in a manner identical to our Eq. (4), and then estimate the buy and sell lambda separately for each stock over our sample period. These lambdas are then used in an asset pricing regression of the type in Table 8. Results appear in Table 10.[18] As can be seen, the results are qualitatively similar. Both the buy and sell lambdas are positive and significant when included separately, but when included together, the significance of the buy lambda disappears. The coefficient magnitudes are very similar to the ones in Table 8. Thus, overall, our results present compelling evidence that the liquidity premium in equity markets is determined predominantly by sell-order illiquidity.

6. Conclusion

[17] Sadka (2006) uses the residuals from an AR(5) model to compute the unexpected order flow. We follow his procedure to compute the order flow innovations.

[18] The difference between the average sell and buy lambdas over the entire sample period is about 15%, the same order of magnitude as in Table 1, Panel A, and is statistically significant. We also follow Sadka (2006, p. 315) in separately dummying out the effects of block trades (proxied by orders that exceed 10,000 shares), so that the lambdas in Table 10 adjust for the effects of large trades. Again, for conciseness, we present results only for the unconditional asset pricing model.

Previous studies of the effect of liquidity on asset pricing have used measures of liquidity that assume that trading costs are symmetric for purchases and sales. We estimate buy and sell order measures of price impact ("lambdas") for a large cross-section of stocks over 26 years. Averages of individual stock sell and buy lambdas co-move with the TED spread which is a measure of funding illiquidity. We also find that the cross-sectional determinants of buy and sell lambdas are similar, and that sell lambdas tend to exceed buy lambdas.

We examine the differential effects of buy and sell lambdas on the cross-section of expected stock returns. We find that sell illiquidity is priced far more strongly in the cross-section of expected stock returns than is buy illiquidity. These findings obtain in two-way portfolio sorts of buy and sell lambdas, and are also apparent in Fama-MacBeth cross-sectional regressions after controlling for risk, and for other well-known determinants of expected returns. The evidence supports the notion that the pricing of liquidity emanates almost entirely from the sell lambdas. Furthermore, the compensation for sell illiquidity in the cross-section of stock returns is not only statistically significant, but also economically material.

Our results suggest topics for additional exploration. For example, it would be interesting to ascertain whether the asymmetry between sell and buy illiquidity extends to other markets, such as those for index options and futures. Whether derivatives markets yield a liquidity premium largely from the sell-side also is an interesting question. Exploration of these issues is left for future research.

Appendix. Estimation of buy and sell lambdas

Let m_t denote the expected value of the security, conditional on the information set, at time *t*, of a market maker who observes only the order flow, q_t, and a public information signal, y_t. Similar to Glosten and Harris (1988), we assume that m_t evolves according to

$$m_t = m_{t-1} + \lambda q_t + y_t, \tag{9}$$

where λ is the (inverse) market depth parameter and y_t is the unobservable innovation in the expected value due to the public information signal.

We let D_t denote the sign of the incoming order at time *t* (+1 for a buyer-initiated trade and -1 for a seller-initiated trade). Given the order sign D_t, denoting the fixed component of transaction costs by ψ, and assuming competitive risk-neutral market makers, the transaction price, p_t can be written as

$$p_t = m_t + \psi D_t. \tag{10}$$

Using Eqs. (9), (10), and $p_{t-1} = m_{t-1} + \psi D_{t-1}$, the price change, Δp_t, is given by

$$\Delta p_t = \lambda q_t + \psi (D_t - D_{t-1}) + y_t. \tag{11}$$

We modify Eq. (11) to allow for different price responses to purchases and sales:

$$\Delta p_t = \alpha + \lambda_{\text{buy}} (q_t | q_t > 0) + \lambda_{\text{sell}} (q_t | q_t < 0) + \psi (D_t - D_{t-1}) + y_t, \tag{12}$$

and we refer to λ_{buy} and λ_{sell} as the buy lambda and the sell lambda, respectively.

The estimation procedure uses intraday transactions data that are filtered as follows. First, data were purged for one of the following reasons: trades out of sequence, trades recorded before the open or after the closing time,[19] and trades with special settlement conditions (because they might be subject to distinct liquidity considerations). Second, we omit the overnight price change to avoid contamination of the price change series by dividends, overnight news arrival, and special features associated with the opening procedure. Third, to correct for reporting errors in the sequence of trades and quotations, we delay all quotations by five seconds during the 1983--1998 period. Given the generally accepted decline in reporting errors in recent times (see, for example, Madhavan et al., 2002; as well as Chordia, Roll, and Subrahmanyam, 2005), after 1998, no delay is imposed in the 1999 to 2008 period.

To avoid obvious keypunching errors in the transactions database, we apply the Chordia, Roll, and Subrahmanyam (2001) filters to the transaction data by deleting quotes and matched transactions that satisfy the following conditions:[20]

1. Quoted spread > $5
2. Effective spread/Quoted spread > 4.0
3. Relative effective spread/Relative quoted spread > 4.0
4. Quoted spread/Transaction price > 0.4.

These filters removed fewer than 0.02% of all transaction records.

Each month, from January 1983 to December 2008, buy lambdas and sell lambdas for each stock are estimated by running the regression in Eq. (12), i.e., Eq. (1) in the main text. All filtered transactions during a relevant month are used for estimation. This procedure yields a panel of buy and sell lambdas over the sample period. The price change is in dollars per share and quantities are in shares so the lambdas are measured in dollars per share, while the fixed cost

[19] The closing time was taken to be 4:05 p.m. and not the regular closure time of 4:00 p.m. since it is common for regular transactions to be reported up to five minutes after closing time.

[20] In the conditions, the effective spread is the absolute distance between the transaction price and the mid-point of the matched quote. The relative spreads are the raw spreads divided by the mid-point of the matched bid and ask quotes.

component, ψ, is measured in dollars. To remove spurious results due to outliers, in each month buy and sell lambdas greater than the cross-sectional 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and the 0.005 fractile values, respectively. These final estimates are used throughout the paper.

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Table 1
Summary statistics
This table shows buy lambda and sell lambda statistics over the 1983--2008 sample period. The lambdas are estimated for each stock each month as price impact measures in a regression of price changes on signed orders, allowing for separate terms for buys and sells, and are scaled up by 10^3. The table reports the number of observations, mean, standard deviation, and the percentage of buy/sell lambda with *t*-statistics (using Newey-West standard errors) greater than 1.96. Panel A shows full sample results. Panel B and Panel C show the results when market monthly excess value-weighted returns are negative and positive. Panel D sorts the buy and sell lambdas by market.

Panel A: All

	Obs.	25%	Median	75%	Mean	Std. dev.	%(*t*>1.96)
Buy lambda	443,788	0.0008	0.00204	0.00527	0.00519	0.00961	59%
Sell lambda	443,788	0.0009	0.00257	0.00571	0.00555	0.00978	62%
H0: Buy=Sell *p*-value	<0.0001						

Panel B: Sorted by market return at time t

	Mkt(*t*)<0			Mkt(*t*)>0		
	Mean	Std. dev.	%(t>1.96)	Mean	Std. dev.	%(*t*>1.96)
Buy lambda	0.00530	0.00981	59%	0.00513	0.00948	59%
Sell lambda	0.00567	0.00994	63%	0.00548	0.00967	62%
H0: Buy=Sell *p*-value	<0.0001			<0.0001		

Panel C: Sorted by market return at time t-1

	Mkt(t-1)<0			Mkt(t-1)>0		
	Mean	Std. Dev.	%(t>1.96)	Mean	Std. Dev.	%(*t*>1.96)
Buy lambda	0.00519	0.0960	59%	0.00520	0.00961	59%
Sell lambda	0.00564	0.0989	62%	0.00549	0.00970	62%
H0: Buy=Sell *p*-value	<0.0001			<0.0001		

Panel D: Sorted by firm size

	Small	Size 2	Size 3	Size 4	Large
Buy lambda	0.00888	0.00744	0.00494	0.00289	0.00197
Sell lambda	0.00937	0.00788	0.00540	0.00310	0.00216
H0: Buy=Sell *p*-value	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

Table 2

Correlations of lambdas with other illiquidity measures

This table presents time-series correlations and averages of the cross-sectional correlations of lambdas with alternative measures of illiquidity. The lambdas are estimated for each stock each month as price impact measures in a regression of price changes on signed orders, allowing for separate terms for buys and sells. Panel A shows the time-series averages of the cross-sectional correlations between buy lambda, sell lambda, the Amihud illiquidity measure, the quoted spread, and the effective spread. Panel B reports time-series correlations between the value-weighted monthly cross-sectional averages of buy lambda, sell lambda, Amihud measure, the quoted spread, the effective spread, and a measure of funding illiquidity, the TED spread. The Amihud illiquidity measure is computed for each stock as the monthly average of the daily absolute return divided by the daily dollar trading volume. The TED spread is computed as the difference between the three-month LIBOR and the three-month Treasury bill rate. The sample period is 1983 to 2008.

Panel A: Time-series averages of cross-sectional correlations

	Buy lambda	Sell lambda	Quoted spread	Effective spread
Sell lambda	0.716			
Quoted spread	0.491	0.498		
Effective spread	0.446	0.442	0.751	
Amihud illiquidity	0.186	0.178	0.032	0.038

Panel B: Time-series correlations between value-weighted monthly cross-sectional averages

	Buy lambda	Sell lambda	Quoted spread	Effective spread	Amihud illiquidity
Sell lambda	0.998				
Quoted spread	0.894	0.860			
Effective spread	0.864	0.893	0.985		
Amihud illiquidity	0.894	0.891	0.818	0.846	
TED spread	0.453	0.450	0.335	0.299	0.292

Table 3

Time-series regressions

This table presents coefficient estimates from time-series regressions using value-weighted monthly cross-sectional averages of buy lambda, sell lambda, the average of the buy and sell lambdas, and the lambda differential as dependent variables. The lambdas are estimated for each stock each month as the price impact measures in a regression of price changes on signed orders, allowing for separate terms for buys and sells, and are scaled up by 10^3. The explanatory variables are a measure of funding illiquidity, the TED spread, computed as the difference between the three-month LIBOR and the three-month Treasury bill rate, the contemporaneous and lagged NYSE Composite index returns, the ratio of the number of stocks with a positive return to that with a negative return during the current month, the implied volatility index VIX, and a time trend. Since VIX is not available for every month in the sample, we use a variable that equals VIX when available and zero when VIX is missing. In Panel B, the last two columns present results when the dependent variable is the difference between sell and buy lambdas scaled by the average of buy and sell lambdas. Coefficients are multiplied by 1,000 (10,000) in Panel A (B), and *t*-statistics are calculated using Newey-West standard errors. The sample period is 1983 to 2008.

Panel A: Buy and sell lambdas as dependent variables

	Buy lambda as the dependent variable		Sell lambda as the dependent variable		Average lambda as the dependent variable	
	Mean coefficient	*t*-Statistic	Mean coefficient	*t*-Statistic	Mean coefficient	*t*-Statistic
Intercept	2.667	19.19	2.920	21.35	2.794	20.71
TED spread (t)	0.316	3.69	0.267	2.86	0.292	3.23
Market Return (t)	-1.852	-1.25	-2.490	-1.57	-2.171	-1.42
Market Return (t-1)	1.023	1.49	0.462	0.56	0.743	1.06
Up/Down Ratio (t)	0.055	1.22	0.068	1.32	0.061	1.25
VIX	0.021	6.10	0.025	6.69	0.023	6.30
Time trend	-0.012	-23.11	-0.013	-22.72	-0.012	-22.92
Adjusted R-square	0.554		0.565		0.569	

Panel B: Sell lambda minus buy lambda as the dependent variable

	Unscaled difference		Scaled difference	
	Mean coefficient	*t*-Statistic	Mean coefficient	*t*-Statistic
Intercept	2.535	5.28	337.366	2.60
TED spread (*t*)	-0.496	-1.68	-83.092	-1.01
Market return (*t*)	-6.387	-2.06	-679.195	-0.90
Market return (*t*-1)	-5.601	-1.59	-995.173	-1.74
Up/Down ratio (*t*)	0.131	1.57	11.769	0.52
VIX	0.037	2.57	3.318	0.80
Time trend	-0.008	-5.04	1.921	3.96
Adjusted *R*-square	0.146		0.136	

Table 4

Cross-sectional determinants of buy and sell lambdas

This table presents the results of monthly regressions for determinants of lambdas. The lambdas are estimated for each stock each month as price impact measures in a regression of price changes on signed orders, allowing for separate terms for buys and sells, and are scaled up by 10^3. Return std is the monthly standard deviation of daily returns. Price is the closing price. Inst holding is the percentage of shares held by institutions. Analyst is the number of I/B/E/S analysts making one-year earnings forecasts. Insider holding is the percentage of shares held by insiders. Size is market capitalization as of the end of the month. Turnover is the monthly share turnover. Three-stage-least-squares estimation is carried out each month for the equation system that allows for the endogeneity of illiquidity, analyst following, turnover, and institutional holdings. Time-series coefficient averages and Newey-West (1987, 1994) corrected *t*-statistics are reported. The sample period is 1983 to 2008.

Panel A: Buy and sell lambdas

	Buy lambda		Sell lambda	
	Mean coefficient	*t*-Statistic	Mean coefficient	*t*-Statistic
Intercept	0.0200	9.18	0.0280	9.66
Return std	0.0580	4.08	0.0762	6.21
Log (price)	0.0052	14.06	0.0059	18.23
Log (inst holding)	-0.0010	-2.43	-0.0023	-4.92
Log (1+analyst)	-0.0005	-1.23	-0.0006	-1.50
Log (insider holding)	-0.0001	-1.21	-0.0000	-0.91
Log (size)	-0.0023	-11.21	-0.0025	-12.01
Turnover	-0.0018	-4.26	-0.0020	-4.84

Panel B: Sell lambda minus buy lambda

	Unscaled difference		Scaled difference	
	Mean coefficient	*t*-Statistic	Mean coefficient	*t*-Statistic
Intercept	0.0040	1.62	0.3210	1.49
Return std	0.0164	1.56	0.8422	1.73
Log (price)	0.0006	6.09	0.0070	1.02
Log (inst holding)	-0.0010	-2.16	-0.0951	-1.99
Log (1+analyst)	-0.0003	-2.03	-0.0588	-2.32
Log (insider holding)	0.0000	1.29	0.0004	0.60
Log (size)	-0.0000	-0.31	-0.0070	-1.02
Turnover	-0.0001	-0.14	-0.0589	-1.80

Table 5

Returns to buy/sell lambda portfolios

The table reports value-weighted excess returns, as well as risk-adjusted returns (alpha) calculated using the CAPM and Fama-French three factors. Quintiles are formed monthly based on buy lambda (Panel A) or sell lambda (Panel B) in the previous month. The lambdas are estimated for each stock each month as price impact measures in a regression of price changes on signed orders, allowing for separate terms for buys and sells. Stocks with low (high) buy/sell lambda are in quintile 1 (5). The difference in returns between the high and the low buy/sell lambda portfolios are also reported, along with *t*-statistics in parentheses. Returns are expressed in percent per month. The sample period is 1983 to 2008.

	%Excess returns	%Alphas (CAPM)	%Alphas (FF)
Panel A: Buy lambda portfolios			
1	0.39	-0.00	-0.12
2	0.48	0.04	-0.04
3	0.78	0.30	0.21
4	0.76	0.30	0.20
5	0.80	0.38	0.28
5--1	0.40 (2.70)	0.38 (2.37)	0.40 (3.00)
Panel B: Sell lambda portfolios			
1	0.32	-0.07	-0.20
2	0.59	0.16	0.07
3	0.75	0.29	0.20
4	0.80	0.34	0.24
5	0.84	0.43	0.36
5--1	0.52 (3.35)	0.51 (3.11)	0.56 (4.13)

Table 6

Returns to double-sort portfolios

The table reports value-weighted excess returns, as well as risk-adjusted returns (alpha) using the Fama-French three-factor model. In Panel A, quintile portfolios are formed monthly based on buy lambda and within each portfolio, quintiles are formed based on sell lambda in the previous month. The sorting order is reversed in Panel B. Panel C presents results for portfolios first sorted by market capitalization, then by sell lambda. Panel D reports results for portfolios sorted first by book-to-market ratio (BM) and then by sell lambda. Panel E reports results for portfolios sorted first by returns over the six-month period ending six months prior to the date of portfolio formation (Ret7--12) and then by sell lambda. The lambdas are estimated for each stock each month as price impact measures in a regression of price changes on signed orders, allowing for separate terms for buys and sells. The difference in returns between the high and the low sell lambda (buy lambda in Panel B) portfolios are reported, along with *t*-statistics in parentheses. The sample period is 1983 to 2008.

Panel A: Sort by buy lambda, then sell lambda

	Sell lambda 5--1	
	%Excess return	%FF alpha
Low buy lambda	0.22 (1.01)	0.20 (1.16)
Buy lambda 2	0.42 (2.42)	0.37 (2.05)
Buy lambda 3	0.44 (2.57)	0.40 (2.46)
Buy lambda 4	0.45 (2.53)	0.49 (2.70)
High buy lambda	0.18 (0.90)	0.29 (1.40)

Panel B: Sort by sell lambda, then buy lambda

	Buy lambda 5--1	
	%Excess return	%FF alpha
Low sell lambda	0.18 (0.70)	0.12 (0.27)
Sell lambda 2	-0.00 (-0.01)	-0.13 (-0.70)
Sell lambda 3	-0.15 (-1.29)	-0.25 (-1.64)
Sell lambda 4	-0.21 (-1.24)	-0.23 (-1.34)
High sell lambda	0.10 (0.49)	0.10 (0.48)

Panel C: Sort by size, then sell lambda

	Sell lambda 5--1	
	%Excess return	%FF alpha
Small	0.85 (2.59)	1.33 (4.30)
Size 2	0.72 (3.06)	1.05 (4.78)
Size 3	0.19 (1.23)	0.42 (2.66)
Size 4	0.38 (2.30)	0.58 (3.55)
Large	0.52 (3.02)	0.55 (3.23)

Panel D: Sort by BM, then sell lambda

	Sell lambda 5--1	
	%Excess return	%FF alpha
Low book/market	0.48 (2.02)	0.45 (2.17)
BM 2	0.27 (1.55)	0.13 (0.82)
BM 3	0.47 (2.52)	0.39 (2.21)
BM 4	0.44 (2.41)	0.56 (3.23)
High book/market	0.60 (2.54)	0.64 (2.83)

Panel E: Sort by Ret7--12, then sell lambda

	Sell lambda 5--1	
	%Excess return	%FF alpha
Low Ret7--12	1.03 (3.40)	1.20 (4.25)
Ret7--12 2	0.51 (2.67)	0.48 (2.63)
Ret7--12 3	0.65 (3.42)	0.60 (3.51)
Ret7--12 4	0.52 (2.85)	0.57 (3.31)
High Ret7-12	0.31 (1.29)	0.32 (1.36)

Table 7

Fama-MacBeth regression estimates with Fama-French risk factors

This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates. "Unscaled" columns indicate that the dependent variable is the excess return risk-adjusted using the Fama-French (1993) factors. "Size+BM" columns indicate that the dependent variable is the excess return risk-adjusted using the Fama-French (1993) factors with loadings scaled by size and book-to-market ratio. "Term+Def+Tbill" columns indicate that the term spread, the default spread, and the T-bill yield are used as scaling variables. Size represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio with the exception that book-to-market ratios greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and the 0.005 fractile values, respectively. TURN represents turnover. RET2--3, RET4--6, and RET7--12 are the cumulative returns over the second through third, fourth through sixth, and seventh through twelfth months prior to the current month, respectively. Buy and sell lambdas are estimated for each stock each month as price impact measures in a regression of price changes on signed orders, allowing for separate terms for buys and sells, and are scaled up by 10^3. In column 1, buy lambda is used as additional independent variable; in 2 sell lambda is used; in 3 both buy and sell lambda are included as independent variables. t-Statistics in parentheses use standard errors as per Shanken (1992). All coefficients are multiplied by 100. The sample period is 1983 to 2008.

	[1]	[2]	[3]	[1]	[2]	[3]	[1]	[2]	[3]
	Unscaled	Unscaled	Unscale d	Size+B M	Size+BM	Size+BM	Term+Def+ Tbill	Term+Def+ Tbill	Term+Def+ Tbill
Intercept	0.029	0.084	0.054	0.076	-0.023	-0.069	0.040	0.025	0.023
	(0.54)	(0.20)	(0.12)	(0.29)	(-0.06)	(-0.18)	(1.17)	(0.73)	(0.65)
SIZE	-0.049	-0.042	-0.039	-0.035	0.028	-0.025	-0.044	-0.035	-0.033
	(-1.82)	(-1.49)	(-1.39)	(-1.49)	(-1.16)	(-1.01)	(-1.91)	(-1.52)	(1.42)
BM	0.049	0.048	0.049	-0.007	-0.008	-0.007	0.041	0.039	0.041
	(1.27)	(1.23)	(1.28)	(-0.21)	(-0.24)	(-0.20)	(1.10)	(1.05)	(1.11)
TURN	-0.279	-0.264	-0.261	-0.241	-0.228	-0.221	-0.215	-0.201	-0.196
	(-5.21)	(-4.97)	(-4.85)	(-4.69)	(-4.46)	(-4.29)	(-4.32)	(-4.05)	(3.93)
RET2--3	0.518	0.505	0.494	0.446	0.431	0.420	0.123	0.102	0.112
	(1.40)	(1.36)	(1.33)	(1.27)	(1.23)	(1.20)	(0.29)	(0.24)	(0.21)
RET4--6	0.538	0.502	0.504	0.578	0.542	0.544	0.302	0.266	0.276
	(1.87)	(1.76)	(1.77)	(2.01)	(1.89)	(1.89)	(1.10)	(0.97)	(0.99)
RET7--12	0.753	0.730	0.731	0.761	0.737	0.732	0.605	0.578	0.567
	(3.64)	(3.53)	(3.54)	(4.09)	(3.96)	(3.93)	(3.53)	(3.38)	(3.37)
Buy lambda	13.729 (2.86)		-1.911 (-0.92)	14.917 (2.78)		-1.939 (-0.41)	13.239 (2.83)		-1.533 (-0.96)
Sell lambda		19.814 (3.75)	20.941 (3.95)		22.135 (4.11)	22.321 (4.27)		20.106 (3.91)	21.283 (4.12)

Table 8

Fama-MacBeth regression estimates with Fama-French risk factors, including the logarithm of the price level and the Amihud (2002) measure of illiquidity as controls

This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates. “Unscaled” columns indicate that the dependent variable is the excess return risk-adjusted using the Fama-French (1993) factors. “Size+BM” columns indicate that the dependent variable is the excess return risk-adjusted using the Fama-French (1993) factors with loadings scaled by size and book-to-market ratio. “Term+Def+Tbill” columns indicate that the term spread, the default spread, and the T-bill yield are used as scaling variables. Size represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio with the exception that book-to-market ratios greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and the 0.005 fractile values, respectively. TURN represents turnover. RET2--3, RET4--6, and RET7--12 are the cumulative returns over the second through third, fourth through sixth, and seventh through twelfth months prior to the current month, respectively. PRICE is logarithm of stock price. Amihud represents Amihud measure of illiquidity. Buy and sell lambdas are estimated for each stock each month as price impact measures in a regression of price changes on signed orders, allowing for separate terms for buys and sells, and are scaled up by 10^3. In column 1, buy lambda is used as additional independent variable; in 2 sell lambda is used; in 3 both buy and sell lambda are included as independent variables. *t*-Statistics in parentheses use standard errors as per Shanken (1992). All coefficients are multiplied by 100. The sample period is 1983 to 2008.

	[1]	[2]	[3]	[1]	[2]	[3]	[1]	[2]	[3]
	Unscaled	Unscaled	Unscaled	Size+BM	Size+BM	Size+BM	Term+Def+ Tbill	Term+Def+ Tbill	Term+Def+ Tbill
Intercept	-0.132	-0.157	-0.167	-0.115	-0.137	-0.148	-0.133	-0.159	-0.169
	(-3.87)	(-4.44)	(-4.76)	(-3.66)	(-4.27)	(-4.61)	(-4.30)	(-5.00)	(-5.29)
SIZE	0.089	0.115	0.127	0.066	0.088	0.102	0.078	0.105	0.116
	(2.79)	(3.47)	(3.69)	(2.21)	(2.87)	(3.19)	(2.59)	(3.36)	(3.57)
BM	0.065	0.063	0.064	0.012	0.011	0.011	0.061	0.060	0.061
	(1.71)	(1.67)	(1.67)	(0.33)	(0.32)	(0.32)	(1.72)	(1.70)	(1.70)
TURN	-0.159	-0.133	-0.122	-0.138	-0.115	-0.102	-0.152	-0.126	-0.116
	(-2.67)	(-2.23)	(-2.00)	(-2.44)	(-2.04)	(-1.77)	(-2.67)	(-2.21)	(-1.99)
RET2--3	0.624	0.624	0.621	0.512	0.508	0.508	0.289	0.287	0.285
	(1.77)	(1.78)	(1.76)	(1.52)	(1.52)	(1.51)	(0.83)	(0.83)	(0.82)
RET4--6	0.755	0.740	0.743	0.747	0.729	0.734	0.507	0.493	0.495
	(2.51)	(2.46)	(2.47)	(2.67)	(2.60)	(2.62)	(1.77)	(1.74)	(1.73)
RET7--12	0.874	0.859	0.858	0.854	0.841	0.839	0.732	0.717	0.715
	(4.40)	(4.33)	(4.31)	(4.68)	(4.61)	(4.59)	(4.04)	(3.96)	(3.94)
Amihud	0.617	0.637	0.631	0.581	0.597	0.596	0.603	0.618	0.619
	(5.84)	(5.97)	(5.91)	(5.38)	(5.52)	(5.51)	(5.62)	(5.83)	(5.79)
PRICE	-0.171	-0.191	-0.209	-0.113	-0.116	-0.138	-0.126	-0.138	-0.148
	(-1.64)	(-1.79)	(-1.90)	(-1.27)	(-1.22)	(-1.50)	(-1.37)	(-1.19)	(-1.53)
Buy lambda	20.481		4.245	26.503		5.022	25.347		3.333
	(4.86)		(0.81)	(5.47)		(0.96)	(5.25)		(0.64)
Sell lambda		29.169	26.886		30.837	27.405		29.825	25.037
		(5.77)	(5.32)		(5.89)	(5.53)		(5.51)	(5.12)

Table 9

Fama-MacBeth regression estimates with Fama-French risk factors, including the logarithm of the price level and the Amihud (2002) measure of illiquidity as controls, and the the average lambda and the difference between sell and buy lambdas

This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates. The dependent variable is the excess return risk-adjusted using the Fama-French (1993) factors. Size represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio with the exception that book-to-market ratios greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and the 0.005 fractile values, respectively. TURN represents turnover. RET2--3, RET4--6, and RET7--12 are the cumulative returns over the second through third, fourth through sixth, and seventh through twelfth months prior to the current month, respectively. PRICE is logarithm of stock price. Amihud represents Amihud measure of illiquidity. Buy and sell lambdas are estimated for each stock each month as price impact measures in a regression of price changes on unexpected signed orders using the Sadka (2006) method, allowing for separate terms for buys and sells, and are scaled up by 10^3. In column 1, the difference between sell and buy lambda is used as an independent variable; in 2 the above variable is used along with the average of the buy and the sell lambda. *t*-Statistics in parenthesis use standard errors as per Shanken (1992). All coefficients are multiplied by 100. The sample period is 1983 to 2008.

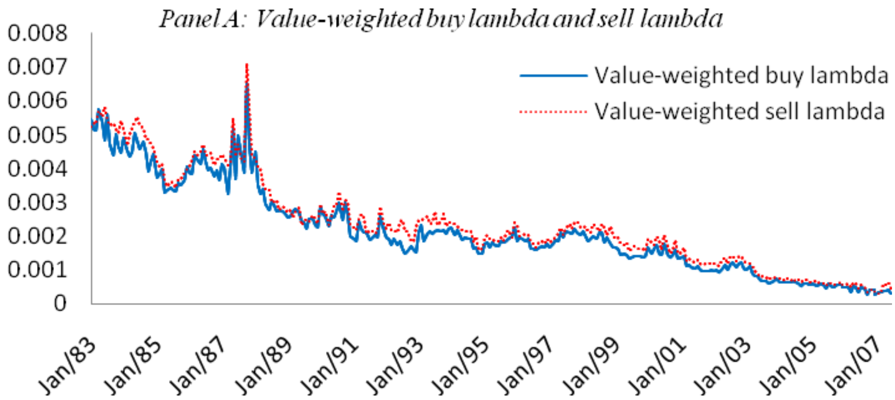
	[1]	[2]
Intercept	-0.741	-0.167
	(-2.22)	(-4.76)
SIZE	0.022	0.127
	(0.84)	(3.69)
BM	0.068	0.064
	(1.78)	(1.67)
TURN	-0.220	-0.122
	(-3.97)	(-2.00)
RET2--3	0.612	0.621
	(1.73)	(1.76)
RET4--6	0.736	0.743
	(2.44)	(2.47)
RET7--12	0.880	0.858
	(4.42)	(4.31)
Amihud	0.621	0.631
	(5.50)	(5.91)
PRICE	-0.015	-0.209
	(-0.16)	(-1.90)
Average		31.131
lambda		(4.66)
Sell-Buy	21.101	11.321
lambda	(4.49)	(3.21)

Table 10
Fama-MacBeth regression estimates with Fama-French risk factors, including the logarithm of the price level and the Amihud (2002) measure of illiquidity as controls, and buy and sell lambdas computed using the Sadka (2006) measure of unexpected order flow

This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates. The dependent variable is the excess return risk-adjusted using the Fama-French (1993) factors. Size represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio with the exception that book-to-market ratios greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and the 0.005 fractile values, respectively. TURN represents turnover. RET2--3, RET4--6, and RET7--12 are the cumulative returns over the second through third, fourth through sixth, and seventh through twelfth months prior to the current month, respectively. PRICE is logarithm of stock price. Amihud represents Amihud measure of illiquidity. Buy and sell lambdas are estimated for each stock each month as price impact measures in a regression of price changes on unexpected signed orders using the Sadka (2006) method, allowing for separate terms for buys and sells, and are scaled up by 10^3. In columns 1, buy lambda is used as additional independent variable; in 2 sell lambda is used; in 3 both buy and sell lambda are included as independent variables. *t*-Statistics in parenthesis use standard errors as per Shanken (1992). All coefficients are multiplied by 100. The sample period is 1983 to 2008.

	[1]	[2]	[3]
Intercept	-0.711	-0.831	-0.887
	(-2.09)	(-2.43)	(-2.54)
SIZE	0.019	0.025	0.026
	(0.54)	(0.90)	(0.91)
BM	0.066	0.067	0.066
	(1.74)	(1.77)	(1.73)
TURN	-0.229	-0.216	-0.213
	(-4.15)	(-3.89)	(-3.83)
RET2--3	0.616	0.633	0.631
	(1.74)	(1.79)	(1.78)
RET4--6	0.744	0.749	0.747
	(2.46)	(2.47)	(2.46)
RET7--12	0.881	0.873	0.829
	(4.43)	(4.39)	(4.36)
Amihud	0.610	0.609	0.605
	(5.42)	(5.38)	(5.36)
PRICE	-0.020	-0.110	-0.125
	(-0.03)	(-1.07)	(-1.19)
Sadka buy	18.177		3.896
lambda	(2.86)		(1.18)
Sadka sell		24.075	21.625
lambda		(3.37)	(2.74)

Fig. 1. Buy lambda and sell lambda. This figure shows the trend in the value-weighted (Panel A) and equally weighted (Panel B) buy lambdas and sell lambdas over the 1983--2008 sample period. The lambdas are estimated for each stock each month as price impact measures in a regression of price changes on signed orders, allowing for separate terms for buys and sells, and are scaled up by 10^3.



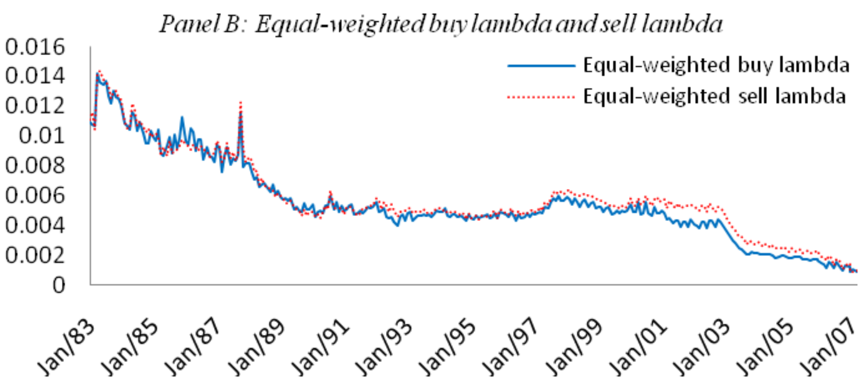
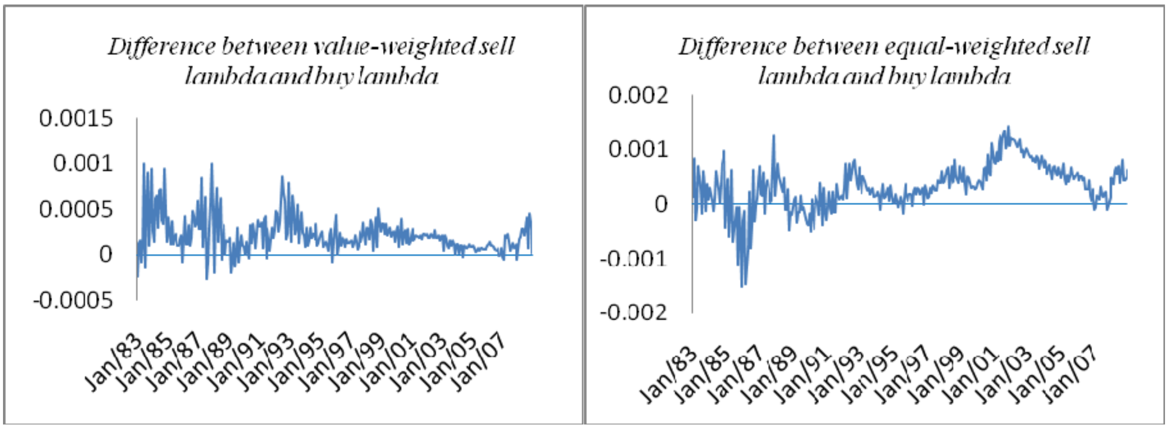


Fig. 2. The difference between buy and sell lambdas. This figure plots the difference between the value-weighted and equally weighted buy lambdas and sell lambdas in Panel A. Panel B presents the difference between the value-weighted and equally weighted buy lambdas and sell lambdas scaled by the average of the buy and sell lambdas. The lambdas are estimated as price impact measures in a regression of price changes on signed orders, allowing for separate terms for buys and sells, and are scaled up by 10^3. The sample period is 1983--2008.

Panel A: Difference level



Panel B: Difference scaled by the average of buy and sell lambdas