Order Flow, Market Risk, and Daily Stock Returns*

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Abstract

This paper explains individual daily stock returns by a fundamental ICAPM component and an idiosyncratic liquidity component. Guided by a theoretical market microstructure model which directly links the liquidity premium to the noise trading risk, the informational trading risk, and the systematic volatility risk, our empirical evidence suggests that: (a) explicitly incorporating the idiosyncratic liquidity component almost doubles the explanatory power of the standard ICAPM, (b) the liquidity premium is almost exclusively compensating for idiosyncratic volatility risk as opposed to market wide volatility risk, and (c) the signed order flow and, to a lessor degree, the signed trades are both informative about the idiosyncratic liquidity risk, while standard raw volume-based measurements are not.

JEL Classification: G12, G14, C22.
Keywords: Information Asymmetry, ICAPM, Liquidity Premium, Market Volatility, Idiosyncratic Volatility.

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Abstract

This paper explains individual daily stock returns by a fundamental ICAPM component and an idiosyncratic liquidity component. Guided by a theoretical market microstructure model which directly links the liquidity premium to the noise trading risk, the informational trading risk, and the systematic volatility risk, our empirical evidence suggests that: (a) explicitly incorporating the idiosyncratic liquidity component almost doubles the explanatory power of the standard ICAPM, (b) the liquidity premium is almost exclusively compensating for idiosyncratic volatility risk as opposed to market wide volatility risk, and (c) the signed order flow and, to a lessor degree, the signed trades are both informative about the idiosyncratic liquidity risk, while standard raw volume-based measurements are not.

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1 Introduction

The explanatory power of traditional asset pricing models for individual stock returns diminishes dramatically as the return horizon decreases from annual to monthly to weekly to daily. Meanwhile, several recent studies report that various market microstructure variables help to explain asset returns at daily, or higher frequencies (see, e.g., Easley et al., 2000; Evans and Lyons, 2001; Froot and Ramadorai, 2001; Chordia et al., 2001). This suggests that the microstructure information may afford a way of explicitly modeling the idiosyncratic return shocks orthogonal to the ex ante fundamental asset pricing component (see, e.g, Malkiel and Xu, 2000). Motivated by these findings, this paper develops and empirically implements a simple market microstructure model in which daily stock returns are determined jointly by a systematic ICAPM market factor in the spirit of Merton (1973) and a firm-specific liquidity factor following the work of Kyle (1985). The inclusion of both factors dramatically increases the explanatory power of the model vis-a-vis traditional asset pricing or market microstructure models.

The representative agent version of the ICAPM model is based on the premise that the systematic market risk factor and the firm-specific, or liquidity, risk factor are orthogonal. Consistent with this framework, the liquidity concept adopted here is based on the trading volume and price changes that are not associated with the market risk factor, but unique to each individual stock.[1] Within a proper microstructure framework, one can define liquidity as the net quantity that may be traded without affecting the market clearing price, or conversely, the price impact of the net trading volume. Since both pricing function and order strategy are endogenously determined within the model by the market maker taking the opposite side of the trades, the net order flow essentially provides a description of this equilibrium relationship. The corresponding liquidity risk premium is directly related to the total market volatility and the volatility of the differentially informed order flow.

Our empirical investigations focus on the thirty individual stocks in the DJIA index over the 1993-2000 time period. We quantify the daily excess order flow using continuously recorded trade and quotation data for each of the stocks along with the well-established

[1] As such, our model and empirical investigations are distinctly different from the recent work on trying to extract a systematic liquidity component from individual stock liquidity; see, e.g., Hasbrouck and Seppi (1999), Huberman and Halka (1999), Chordia et al. (2000), Ľuboš Pástor and Stambaugh (2001).

order classification scheme of Lee and Ready (1991). Following Andersen et al. (2001a) and Andersen et al. (2001b), we also rely on high-frequency data for directly measuring the daily systematic and idiosyncratic volatilities and ICAPM betas by their quadratic variation counterparts. The resulting directly observable liquidity and systematic risk factors allow us to easily assess the importance of each component without having to resort to complicated latent variable procedures.

Anticipating the empirical results, we find that explicitly incorporating the idiosyncratic liquidity component dramatically increases the explanatory power of the standard ICAPM from about twenty to forty percent of the daily return variability. The results also show that the temporal variation in the liquidity risk premium is almost exclusively related to the idiosyncratic volatility risk as opposed to market wide volatility risk. Lastly, the signed order flow and, to a lessor degree, the signed trades are both informative about the idiosyncratic liquidity risk, while simple raw volume-based measurements are not.

The rest of the paper is organized as follows. Section 2 details the theoretical model. Section 3 highlights various practical issues related to the actual implementation of the theoretical model including our high-frequency data based liquidity and risk measurements. In addition to the results for the baseline model, Section 3 also reports the results from several alternative specifications along with various robustness checks. Section 4 concludes.

2 Theoretical Framework

This section incorporates the notion of fundamental stock return, as determined by the systematic market risk, into a microstructure model explicitly allowing firm-specific information, or liquidity risk, to also affect the equilibrium price. The model relates the liquidity premium to the total market volatility and the volatility of the informed and uninformed order flow. This model in turn motivates our empirical investigations.

2.1 Preliminary Discussion

Before proceeding with the formal model developments, it is instructive to briefly review the conceptual model framework. In contrast to the assumption of perfect competition employed in standard asset pricing models, the microstructure framework adopted here consists of a superior informed traders who may materially affect the market price of the stock by their order submissions. To keep the informed traders' monopoly power in check, the monopolistic market maker takes the opposite side of the trades and clears the market. To be more specific, he faces an adverse selection problem and sets the returns so that he earns zero profit on his trades, under the presumed Bertrand price competition. In so doing, he has the incentive to closely match the market clearing return to its expected liquidation value, as both noise shock and information shock are assumed to have ax ante value zero. Consequently, the market clearing return is determined by the fundamental ICAPM return plus the market maker's best guess of the firm-specific return shock, conditional on the aggregate order flow. Since the unconditional expectation of the latter part is zero, the ICAPM return still provides a useful benchmark for all agents with public information. Of course, the standard ICAPM model formally assumes continuous trading, while the microstructure model entails a daily trading cycle. However, the basic intuition from the one-period auction model analyzed below could be generalized to a (more realistic) continuous time setting at the expense of more technical and notational complications.

2.2 Liquidation Value: CAPM plus Information

The ex post liquidation value of the risky stock return is generated by a fundamental ICAPM component and an idiosyncratic information component,[2]

$$r - r_f = \beta(r_m - r_f) + e_i, \tag{1}$$

where β is the covariance between the stock return and the market return divided by the variance of the market return. For simplicity, we assume that $r_m \sim \mathrm{N}(\mu_m, \Sigma_m)$. The expectation of the fundamental return, $E(r) = r_f(1-\beta) + \beta\mu_m$, the distribution of the market return, as well as the factor loading, β, are all assumed to be common knowledge. As such, there is no informational asymmetry regarding this ICAPM component, although the market return is random and the exposure to the systematic volatility demands a risk premium.

On the other hand, the firm-specific private value, e_i, is only revealed to the informed trader, and it has the distribution, $e_i \sim \mathrm{N}(0, \Sigma_i)$. Hence, a priori the liquidation value

[2]For ease of notation, we measure the value of the stock in terms of returns, as it is typically done in the asset pricing literature, rather than by the price as it is common in the market microstructure literature.

is distributed as a normal random variable, $r \sim \mathrm{N}(E(r), \beta^2\Sigma_m + \Sigma_i)$. This is a direct extension of the Kyle (1985) model which does not consider the systematic return risk, i.e., $r = e_i \sim \mathrm{N}(0, \Sigma_i)$ in the present notation.[3]

2.3 Uninformed Trader

The uninformed traders are rational or responsive, and base their trades on the difference between the ex ante ICAPM return, $E(r)$, and the market clearing return, $E_s(r)$, set by the specialist, or market maker. In addition, the uninformed traders receive a noise shock, $e_u \sim \mathrm{N}(0, \Sigma_u)$, which can not be fully insured or internalized. Consequently, the order submission strategy of the uninformed traders, conditional on the information set $\mathcal{F}_u = \sigma\{e_u, E_s(\cdot), E(r)\}$, is characterized by the following linear function,

$$x_u = b_u[E_s(r) - E(r)] + e_u, \tag{2}$$

where the coefficient b_u is exogenously determined by the underlying preference and technology parameters.[4] By convention, the slope of the rational response curve, b_u, is assumed to be positive, i.e., the traders buy more of the asset if the market clearing return (price) is higher than the common expectation of the liquidation return. This is indeed a rational response given the knowledge the market maker's pricing rule and the existence of superiorly informed agent. Also, the noise shock, e_u, is assumed to be independent of the systematic market return. Again, in comparison to Kyle (1985), where the noise trader's demand is purely exogenous, $x_u = e_u \sim \mathrm{N}(0, \Sigma_u)$, there is an additional endogenous component, $b_u[E_s(r) - E(r)]$. This is important, not only because it more realistically allows for the possibility of limit order submission by the noise traders, but also because it internalizes the systematic and idiosyncratic shocks within the model, leaving it an empirical question to distinguish the role of the two risk factors.

[3] In a related extension of the basic market microstructure framework, Kodres and Pritsker (2001) have recently incorporated an APT-type factor return generating process into a strategic trading model.

[4] In Kyle (1989)'s model, the uninformed rational traders submit a price contingent demand schedule, while the demand of the uninformed noise traders is independent of the market clearing price. Here, the uninformed, but rational traders receive a noise shock. Of course, it might be possible to also solve for the optimal b_u within the model. Doing so would not change the basic intuition, but render the closed-form solution impossible.

2.4 Market Specialist

Upon receiving the uninformed trader's order flow, x_u, and the informed trader's order flow x_i (examined next), the market maker, or specialist, sets the market clearing return to its expected value, $E_s(r)$, based upon his information set, $\mathcal{F}_s = \sigma\{x_u + x_i, x_u(\cdot), x_i(\cdot), E(r)\}$. Note that although the specialist observes the total order flow, $x_u + x_i$, he does not observe the two components separately. However, in solving for the liquidity premium, the specialist conditions on the trading strategies of the uninformed and the informed traders, $x_u(\cdot)$ and $x_i(\cdot)$, respectively, along with the relevant underlying distributions.

Following the market microstructure literature, we conjecture that a linear pricing rule by the specialist sustains an equilibrium, which may be formally justified by the following **Proposition 1**. That is,

$$E_s(r) = E(r) + \lambda_s(x_u + x_i), \tag{3}$$

where λ_s denotes the liquidity risk premium for taking the opposite side of the net order flow. If the net total order flow is zero, the specialist will set the market clearing return equal to the expected ICAPM return. If the net order flow is nonzero, the liquidity premium insures him against the potential risk that the non-zero net order flow may be dominated by the informed trading volume, so that the liquidation value of the stock will deviate from the realized ICAPM return. Ex ante, the market clearing return exactly equals the specialist's expectation, and this market efficiency condition plays a central role in solving the equilibrium. Note again, that in the pure liquidity model (Kyle, 1985), the resulting pricing rule reduces to $E_s(r) = \lambda_s(x_u + x_i)$.

Meanwhile, it is clear that in the absence of uninformed traders, or noise trading, the informed trader can not hide his private information in the order flow, so that the price becomes fully revealing. In this situation, the trading process results in zero ex ante profit for either party, although the realized profit or loss due to the uncertain market return will generally not be equal to zero. This corresponds to the notion of strong-form market efficiency — all public and private information are revealed by the market clearing return. Of course, in the presence of information asymmetry, the private information is not fully revealed by the market clearing return, and the market will "only" be semi-strong form efficient.

2.5 Informed Trader

Since the informed trader is risk-neutral, under the normality of return shocks and certain type of utility function, one can concentrate on his linear demand function of the stocks. The trading strategy of the informed investor depends on: (1) his knowledge of the market maker's pricing rule but not the market clearing price itself, (2) his knowledge of the uninformed trader's trading strategy and the distribution of the noise shock but not the actual value and hence not the uninformed order flow, (3) the expected ICAPM return and the distribution of the market return, and (4) the private information shock, e_i. More concisely, his information set may be expressed as, $\mathcal{F}_i = \sigma\{e_i, x_u(\cdot), E_s(\cdot), E(r)\}$. The *realized* liquidation value of the stock in turn equals the realized fundamental return plus the realized firm-specific shock, resulting in the informed trader's ex ante profit of $\pi_i = x_i[E(r) + e_i - E_s(r)]$. Given the linear pricing rule in (3) and the quadratic profit function, the informed trader optimally chooses the following unique linear trading strategy (as a formal result of **Proposition 1**),

$$x_i = -b_i[E_s(r) - E(r)] + b_i e_i, \tag{4}$$

with $b_i > 0$ (as formally justified by **Proposition 2**). Analogous to the trades by the uninformed agent, the strategic order flow is conditioned on the specialist's market clearing return and the common expected liquidation value. However, he takes on an opposite side of the uninformed trade ($-b_i < 0$), but not necessarily in an equal amount ($b_i \neq b_u$), in a *strategic* response to the systematic return difference $[E_s(r) - E(r)]$. In contrast to the uninformed order flow, the informational shock is fully insured, or internalized, by the endogenous trading behavior and the value of b_i. This result hinges critically on the strategic behavioral assumption of the informed trader.

2.6 Equilibrium Solution

Before proceeding to a characterization of the resulting equilibrium, it is instructive to briefly summarize the steps in the trading process. Prior to the start of trading, the (fundamental) expected ICAPM return is revealed to everybody. The uninformed and the informed trader then each submit their demand schedule, x_u and x_i, respectively, as a function of their respective (private) information. Observing the aggregate order flow, $x_u + x_i$, the market maker sets a single market clearing return, $E_s(r)$. Finally, the agents trades, the private information is revealed, and the stock is liquidated.

Proposition 1 (Existence) *Subject to the market efficiency and profit maximization conditions outlined in the text, there exists an equilibrium (or equilibria) characterized by the following two equations,*

$$b_i = \frac{1 - \lambda_s b_u}{\lambda_s}. \tag{5}$$

$$\lambda_s = \frac{(b_u - b_i)\beta^2 \Sigma_m + b_u \Sigma_i}{(b_u - b_i)^2 \beta^2 \Sigma_m + b_u^2 \Sigma_i + \Sigma_u} \tag{6}$$

Proof: The basic outline of the proof follows **Theorem 1** in Kyle (1985), and we omit the details to conserve space. Intuitively, the profit maximization behavior of the informed trader implies that

$$E_i\{x_i[E(r) + e_i - E_s(r)]\} > E_i\{x_i'[E(r) + e_i - E_s(r)]\}, \tag{7}$$

where x_i' denotes any alternative trading strategy. This optimizing behavior results in the solution of b_i in (5) and the linear trading strategy for the informed trader in (4). Second, given the conjectured linear pricing rule and the order submission strategies, the market specialist sets the market clearing return equal to his expected value,

$$E_s(r) - E(r) \equiv E[r - E(r)|x_u + x_i, x_u(\cdot), x_i(\cdot), E(r)], \tag{8}$$

which is a simply calculation of a conditional expectation from a multi-variate normal distribution. Such a zero profit condition leads to the solution for the liquidity premium λ_s in (6) and the endogenous linear pricing function specified in (3).

From **Proposition 1**, the market specialist's liquidity premium and the informed trader's response coefficient are both nonlinearly determined by: (1) the market return volatility, Σ_m, (2) the ICAPM factor loading, β, (3) the slope of the uninformed traders' response curve, b_u, (4) the volatility of the noise shock, Σ_u, and (5) the informational shock volatility, Σ_i. Even though the market return and the two separate shocks are assumed to be independent, the systematic market volatility risk and the idiosyncratic liquidity risk premium are obviously closely linked. Of course, if the informed and uninformed trades are off-setting each other with respect to the systematic return difference (i.e., $b_u = b_i$), but only differ when incorporating the shocks (i.e., e_u versus $b_i e_i$), the above solution reduces to the results in Kyle (1985) where $\lambda_s = (b_i \Sigma_i)/(b_i^2 \Sigma_i + \Sigma_u)$ and $b_i = 1/(2\lambda_s)$.

The result regarding uniqueness also follows by standard arguments, and we have the following simplified characterization of the solutions in **Proposition 1**.[5]

Proposition 2 (Uniqueness) *Under (a) the exogenous assumption $b_u > 0$, (b) the second order condition, $2\lambda_s/(1 - \lambda_s b_u) > 0$, and (c) the regularity condition $b_u^2(2\beta^2\Sigma_m + \Sigma_i)^2 \geq 8\beta^2\Sigma_m\Sigma_u$, the following two equilibria are proper solutions,*

$$b_i = \frac{b_u(2\beta^2\Sigma_m + \Sigma_i) \pm \sqrt{b_u^2(2\beta^2\Sigma_m + \Sigma_i)^2 - 8\beta^2\Sigma_m\Sigma_u}}{4\beta^2\Sigma_m}, \tag{9}$$

$$\lambda_s = \frac{4\beta^2\Sigma_m}{b_u(6\beta^2\Sigma_m + \Sigma_i) \pm \sqrt{b_u^2(2\beta^2\Sigma_m + \Sigma_i)^2 - 8\beta^2\Sigma_m\Sigma_u}}. \tag{10}$$

Given the exogenous parameter values, the informed trader chooses a dominating equilibrium, according to his maximized ax ante (unconditional) profit, which is given by,

$$E(\pi_i) = \frac{\lambda_s^2 b_i(\Sigma_u + b_i^2\Sigma_i)}{[1 - \lambda_s(b_u - b_i)]^2} - \frac{2\lambda_s b_i^2\Sigma_i}{[1 - \lambda_s(b_u - b_i)]} + b_i\Sigma_i. \tag{11}$$

Proof: The proof involves long algebra but is very straightforward hence omitted. Some important observations are worth highlighting:

Observation 1: Verification of Results. The two solutions of b_i and λ_s, characterized by (9) and (10), are both strictly positive given the assumption (a) and (c). This reduces the second order condition (b) to $0 < \lambda_s b_u < 1$, which itself can be easily verified by the above solutions.

Observation 2: Justification of Assumptions. Assumption (a) is a simple convention, nothing qualitatively changes if the convention is in the opposite sign. Assumption (b) follows naturally from the optimization problem and the first order condition in **Proposition 1**. Assumption (c) guarantees that these solutions are real as complex values are hard to interpret. It can be easily met by either a large response of the uninformed trader (high b_u) or a large informational shock (high Σ_i), given other parameter values.

[5] We purposely omit the discussion of any stability condition, i.e., whether the equilibrium is attainable if the economy starts in a disequilibrium. This remains an unresolved issue for most rational expectations models, and its resolution is well beyond the scope of the present paper.

Observation 3: Choice between Multiple Equilibria. Solutions (9) and (10) define two separating equilibria, and we cannot rank them without fixing the exogenous parameter values. However, since that the uninformed trader's response is passive and that the market maker is ambivalent between two zero-profit solutions, the sole responsibility of deciding a unique equilibrium resides on the profit incentive (11) of the informed trader. For example, if the exogenous parameter values are fixed ($\Sigma_m = 0.20$; $\Sigma_u = 0.05$; $\Sigma_i = 0.10$; $\beta = 1.0$; $b_u = 1.0$), then **Proposition 2** implies that the informed trader should rank the two equilibria ex ante as $E(\pi_i|\text{first plus}) = 0.0395 < E(\pi_i|\text{second minus}) = 0.1168$.

Observation 4: Non-Existence or Market Crash. In a standard microstructure model like Kyle (1985)'s, the equilibrium is guaranteed to exist, regardless of how large the noise (or liquidity) shock. This is not the case in our microstructure framework with an ICAPM component incorporated. Indeed, if the liquidity shock is large enough, i.e., $\Sigma_u > [b_u^2(2\beta^2\Sigma_m + \Sigma_i)^2]/(8\beta^2\Sigma_m)$; no real equilibrium solutions exist at all. One can think of the situation as following: an exceptionally large shock hits the financial market, the uninformed traders (mutual funds, e.g.) have to unload their portfolio positions mechanically, market specialists and strategic traders (hedge funds, e.g.) are not willing to take the opposite side of trades, hence trading price crashes triggering the circuit breaker and the financial market is shut down.

Note again, that if the uninformed trader is smart enough to take the exact same amount of trade on the opposite side of the informed trader ($b_i = b_u$), in response to the systematic return difference $[E_s(r) - E(r)]$, the solution in **Proposition 2** reduces to Kyle (1985) with $\lambda_s = 1/2(\Sigma_i/\Sigma_u)^{1/2}$, $b_i = (\Sigma_u/\Sigma_i)^{1/2}$, and $E(\pi_i) = 1/2(\Sigma_i\Sigma_u)^{1/2}$. However, by incorporating this asymmetric systematic response, we are able to combine the market volatility risk and its factor loading into the liquidity premium associated with the information asymmetry. **Proposition 2** thus provides a convenient framework for assessing the influence of both liquidity and systematic market risks in determining asset returns.

3 Empirical Implementation

This section empirically quantifies the importance of the systematic market risk and the liquidity risk in explaining daily individual stock returns. While our empirical investigations will be guided by the theoretical model outlined above, the exact microstructure solution is obviously based on highly restrictive and stylized assumptions that inevitably would find faults with the complex reality of time-varying volatility and other market microstructure frictions. Hence, we will concentrate our empirical investigations on a set of relatively simple reduced form OLS daily return regressions,

$$EXRT_{s,t,t+\Delta} = a_s + b_s ICAPM_{s,t,t+\Delta} + \lambda_s LQDT_{s,t,t+\Delta} + e_{s,t,t+\Delta}, \tag{12}$$

where $\Delta = 1$ corresponds to the one-day horizon, the ex post excess return of stock s is defined as $EXRT_{s,t,t+\Delta} = r_{s,t,t+\Delta} - r_{f,t,t+\Delta}$, and the ex post systematic return component is given by $ICAPM_{s,t,t+\Delta} = \beta_{s,t,t+\Delta}(r_{m,t,t+\Delta} - r_{f,t,t+\Delta})$. Note that in the theoretical model the intercept, a_s, and the slope, b_s, should equal zero and unity, respectively. However, as it is common in the empirical literature on testing the ICAPM, we explicitly allow these coefficients to deviate from their theoretical values to capture the effect of non-trivial measurement errors in the right-hand-side variables. We next turn to a discussion of our actual empirical measurements of the pertinent volatility components and the liquidity risk along with our parameterization of the liquidity risk premium.

3.1 Empirical Expansion of the Liquidity Premium

The equilibrium solution in (10) and (9) dictates that the liquidity premium is a rational function of the market volatility, the market factor loading, the two separate noise and informational volatilities, as well as the exogenous slope of the traders' order response curve. Of course, direct estimation of this relationship is not feasible, as we at best observe the aggregate order flow, $x_u + x_i$, and not its separate components, let alone their (time-varying) volatilities. Meanwhile, by the fundamental ICAPM model, the total stock return volatility may be decomposed into the market wide component, $\beta^2\Sigma_m$, and the firm-specific component, Σ_{iu}. Assuming that $\Sigma_{iu} = \Sigma_i + \Sigma_u$, we can parameterize the liquidity premium as a non-linear function of the two separately identifiable volatility components,

$$\lambda_s = \lambda_0 + \lambda_{1m}(\beta^2\Sigma_m) + \lambda_{2m}(\beta^2\Sigma_m)^2 + \lambda_{1iu}\Sigma_{iu} + \lambda_{2iu}\Sigma_{iu}^2. \tag{13}$$

This expression may be formally justified by a second order Taylor series expansion of the equilibrium solution for λ_s around $\beta^2\Sigma_m$ and Σ_{iu}. Of course, higher order terms could easily be included, but in the empirical estimation no terms beyond the second order were statistically significant. As a simple benchmark, we also report the results assuming the liquidity premium to be constant; i.e., $\lambda_s = \lambda_0$.

3.2 Refined Measurement for Volatility Risk

The market beta entering the fundamental ICAPM return is formally defined as the covariance between the returns on the stock and the market divided by the variance of the market return,

$$\beta_{s,t,t+\Delta} = \frac{\mathrm{Cov}_t(r_{s,t,t+\Delta}, r_{m,t,t+\Delta})}{\mathrm{Var}_t(r_{m,t,t+\Delta})}.$$

Of course, the variances and the covariances are not directly observable. However, by the theory of quadratic variation (Andersen et al., 2001b), the ex post realizations may (in theory) be measured arbitrarily well by the sum of the corresponding high frequency squared returns and the cross products of the returns. Following the descriptive analysis in Andersen et al. (2001a) involving the same thirty DJIA stocks analyzed here, we therefore construct realized daily volatility measurements based on high frequency five-minute returns. This particular sampling frequency strikes a reasonable balance between the desire for finely sampled returns on the one hand and the inherent market microstructure frictions which corrupts the underlying continuous time theory on the other. More precisely, we directly quantify the covariance by $\mathrm{Cov}_t(r_{s,t,t+\Delta}, r_{m,t,t+\Delta}) = \sum_{j=1}^{N} \left(p_{s,\frac{j}{N}\Delta} - p_{s,\frac{j-1}{N}\Delta}\right)\left(p_{m,\frac{j}{N}\Delta} - p_{m,\frac{j-1}{N}\Delta}\right)$, and the variance by $\mathrm{Var}_t(r_{m,t,t+\Delta}) = \sum_{j=1}^{N} \left(p_{m,\frac{j}{N}\Delta} - p_{m,\frac{j-1}{N}\Delta}\right)^2$, where $N = 82$, corresponding to the number of five-minute segments in a typical trading day. We also decompose the individual stock volatility into a systematic and an idiosyncratic component according to the ICAPM framework (assuming constant $\beta_{s,t,t+\Delta}$ from t to $t+\Delta$),

$$\mathrm{Var}_t(r_{s,t,t+\Delta}) = \beta^2_{s,t,t+\Delta}\Sigma_{m,t,t+\Delta} + \Sigma_{s,iu,t,t+\Delta}, \tag{14}$$

where the total volatility for the stock s is similarly measured by its five-minute quadratic variation $\mathrm{Var}_t(r_{s,t,t+\Delta}) = \sum_{j=1}^{N} \left(p_{s,\frac{j}{N}\Delta} - p_{s,\frac{j-1}{N}\Delta}\right)^2$. Recall, that the so constructed firm-specific volatility acts as our combined proxy for the individually unobservable information and noise volatility components; i.e., $\Sigma_{s,iu,t,t+\Delta} = \Sigma_{s,i,t,t+\Delta} + \Sigma_{s,u,t,t+\Delta}$.

3.3 Refined Measurement for Liquidity Risk

The liquidity variable entering the baseline regression model (12) is quantified by,

$$LQDT_{s,t,t+\Delta} = \frac{\text{BuyOrders}_{s,t,t+\Delta} - \text{SellOrders}_{s,t,t+\Delta}}{\text{BuyOrders}_{s,t,t+\Delta} + \text{SellOrders}_{s,t,t+\Delta}}. \tag{15}$$

This scaled net order flow provides a direct measure of the total excess supply, $(x_u + x_i)$. The normalization by the total order flow is imposed to ensure that the $LQDT_{s,t,t+\Delta}$ variable lies between -1 and +1 (consistent with the scale for the returns). Our classification of trades as buys or sells rely on the well established Lee and Ready (1991) algorithm.[6]

Ideally, we would like our net order flow variable to reflect only the liquidity trades unique to the particular stock, and not the trade imbalances associated with the market-wide up and down movements. In theory, (fundamental) ICAPM induced trades should only happen at equilibrium prices, and such all "systematic trades" should appear as "crosses", and not result in any price movements. In practice, all trades happen sequentially and some "systematic trades" may be mistakenly classified as buys or sells, especially in a volatile market environment. Since our analysis focuses on the daily frequency, the aggregation of net order flow through the trading day is likely to cancel some misclassifications on either sides. On the other hand, the trades induced by the firm-specific informational shock may exhibit a persistent imbalance, as the informed traders tries to best exploit their strategic advantage intertemporally. Empirically, the validity of the excess order flow as an idiosyncratic risk measure, may be judged by its orthogonality to the systematic market factor.[7] We return to this issue in the empirical discussion below.

[6]Recent studies by Ellis et al. (2000), Theissen (2001), and Odders-White (2000) report that the Lee and Ready algorithm correctly classifies between 70-85% of all trades. The algorithm is based on a mixture of quote and tick tests. The first step classifies a trade by comparing the transaction price to the "prevailing" quote — a buy order if the trade price is closer to the ask, a sell if it is closer to the bid, and an unclassified trade if the price is equal to the average of bid and ask. The "prevailing" quote is the current quote if it has lasted at least for 5 seconds, otherwise it is the previous quote. If the quote test fails, the tick test is applied by comparing the current trade price with the previous trade price. An up-tick is classified as a buy and a down-tick is a sell. For a "flat" tick, the price is compared with the preceding transaction price using the same rule. Two "flat" ticks result in an unclassified trade. All unclassified orders are excluded from the $LQDT_{s,t,t+\Delta}$ measure. Similarly, we do not include any after-hours trades, nor the first or second opening trade of the day (the tick test requires the two preceding trades).

[7]Chordia et al. (2001) argue that the order imbalance reflects both the private information of the strategic trader and the inventory considerations of the market maker, which in turn may be triggered by either market or individual shocks. Since we explicitly incorporate the influence of the market risk factor (ICAPM), the firm specific, or idiosyncratic risk, is naturally associated with private information.

3.4 Data Description and Summary Statistics

Our empirical analysis is based on the NYSE Trade and Quote (TAQ) database from 1993 to 2000. The TAQ data set provides intraday trading prices, trading volume, and bid ask quotes for the majority of NYSE and NASDAQ listed stocks. We focus on the thirty individual DJIA stocks and use the S&P500 index as a proxy for the aggregate market portfolio. Tick data for the S&P500 cash index is obtained from the Futures Industry Institute. In addition, we use the daily returns for the individual stocks and the S&P500 index as supplied by Bloomberg.

Summary statistics for the excess stock return, $EXRT_{s,t,t+\Delta}$, the systematic return component, $ICAPM_{s,t,t+\Delta}$, and our liquidity measure, $LQDT_{s,t,t+\Delta}$, are reported in Table 1. The daily average excess returns, both ex post and ex ante, are very close to zero. Also, not surprisingly the variation in the ex ante return is much smaller than the ex post return. Importantly, while the stock returns and their ICAPM components are approximately serially uncorrelated, the first order autocorrelations for the signed order flow are all positive and on average equal to 0.212. It is also worth noting that the average liquidity is positive with a mean of 0.073. Thus, on average during the sample period buy orders are roughly 3.5% more likely than sell orders.[8] As discussed further below, this is, of course, directly related to the long (un-precedent) bull market during the 90's and the workings of the classification algorithm with average positive returns. The dynamic dependency in the $LQDT_{s,t,t+\Delta}$ variable is not materially affected by this, however, as the daily returns for the individual stocks and the market index are close to serially uncorrelated. Rather, the strategic intertemporal order submission by informed trades, followed by the rational response of other (uninformed) trades, may explain the small yet positive serial correlation in the daily order imbalances.

3.5 Daily Stock Returns and the CAPM

Table 2 reports on the excess stock returns explained by the fundamental ICAPM component only,

$$EXRT_{s,t,t+\Delta} = a_s + b_s ICAPM_{s,t,t+\Delta} + e_{s,t,t+\Delta}. \tag{16}$$

[8] Chordia et al. (2001) report similar results for the value-weighted market wide order imbalance from 1988-1998.

The intercepts are generally indistinguishable from zero. The average of the slope coefficients equals 0.560, and all of the slopes are highly statistically significant with an average t-ratio of 21.41. Also, the average R-square equals 0.199, ranging from a high of 0.424 for GE to a low of almost zero for MO (a clear outlier). To further illustrate the fit by the model, Figure 1 gives the time series plot of the ICAPM and residual unexplained components for the representative stock, AA.

Theoretically, if the liquidity risk and the fundamental ICAPM return components are orthogonal, the slope coefficients should equal unity. Empirically this requires that the ICAPM returns and the underlying high-frequency betas are measured without error. Even though the market index may be measured (almost) continuously and very accurately (the S&P500 futures prices are captured very smoothly at an average interval of fifteen seconds), individual high-frequency stock returns are inevitably subject to discretization errors and bid-ask bounce effects (see Andersen et al., 2001a, for further discussion along these lines). Hence, the five-minute based daily realized beta measurements, although theoretically consistent, are still subject to measurement error, resulting in a downward bias in the estimated OLS slope coefficients.[9] This is similar to the measurement error problem that plague standard CAPM type tests over longer horizons based on lower frequency, say monthly, data.

3.6 Daily Stock Returns and the Liquidity Augmented ICAPM

Table 3 shows that the inclusion of the daily liquidity measure (LQDT) in the baseline regression model (12), even under the simplifying assumption of a constant liquidity premium ($\lambda_s = \lambda_0$), dramatically increases our ability to explain the realized daily stock returns. In agreement with the results in the previous section, the impact of the market factor does not adhere exactly to the model predictions. The average intercept equals -0.113 with an average t-ratio of -6.98, while the average slope is now 0.453 with a t-ratio of 18.80. As discussed above, these systematic biases vis-a-vis the theoretical predictions may (in part) be explained by the measurement error in the realized betas.[10] More importantly, the results

[9] We also experimented with imposing the restrictions $a_s = 0$ and $b_s = 1$. None of the results reported on below were qualitatively different, although the in-sample R-squares were, of course, slightly lower in all cases.

[10] In addition to the measurement errors in the betas, as discussed in footnote 5, the liquidity variables are also subject to measurement errors. If the LQDT variable is uncorrelated with the ICAPM component, the measurement error in the liquidity variable will only result in a downward bias in the estimate for the

show that the constant liquidity premium has an average impact of 1.607 basis points for every one percentage point order flow imbalance. All of the estimates are highly significant with an average t-ratio of 21.02. Moreover, the average R-square from this regression equals 0.359, much higher than the 0.199 for the ICAPM model alone, or the 0.233 for the liquidity variable in isolation.

It is important to note that the systematic volatility risk and the idiosyncratic liquidity risk are almost orthogonal. The average squared correlation between the two variables equals 0.049. This is, of course, one of the fundamental assumptions behind the ICAPM framework. Nonetheless, as our theoretical model implies and our subsequent empirical results confirm, the liquidity risk premium is closely linked to the market volatility even though the two risk factors are approximately uncorrelated.[11]

3.7 Time-Varying Liquidity Premium

Contrary to the vast empirical evidence documenting time-varying financial market volatility, the constant liquidity premium model in the previous section implicitly assumes that the volatility risks are time invariant. More realistically, we now report the results based on the second order series expansion for the liquidity premium in equation (13) substituted in the baseline regression model (12). That is,

$$\begin{aligned} EXRT_{s,t,t+\Delta} &= a_s + b_s ICAPM_{s,t,t+\Delta} + \lambda_0 LQDT_{s,t,t+\Delta} \\ &\quad + \lambda_{1m}\beta^2_{s,t,t+\Delta}\Sigma_{m,t,t+\Delta}LQDT_{s,t,t+\Delta} + \lambda_{2m}\beta^4_{s,t,t+\Delta}\Sigma^2_{m,t,t+\Delta}LQDT_{s,t,t+\Delta} \\ &\quad + \lambda_{1iu}\Sigma_{s,iu,t,t+\Delta}LQDT_{s,t,t+\Delta} + \lambda_{2iu}\Sigma^2_{s,iu,t,t+\Delta}LQDT_{s,t,t+\Delta} + e_{s,t,t+\Delta}, \end{aligned} \tag{17}$$

where the market and the firm specific volatilities are both allowed to be time-varying. Note that by assumption, the firm-specific, or idiosyncratic component, $\Sigma_{s,iu,t,t+\Delta}$, encompasses both the informational and the noise trading risks in the theoretical market microstructure model.

liquidity premium. However, with a positive, albeit very small, correlation between the two components, the measurement error in either variable will aggravate the downward bias in the OLS parameter estimate associated with the other variable. This explains the lower b_s estimates in Table 3.

[11] Our results also suggest that the strong contemporaneous association between the market index returns and the aggregated order flow, recently documented (independently) by Chordia et al. (2001) and Ľuboš Pástor and Stambaugh (2001), may be explained by a systematic liquidity factor which is (or ought to be) orthogonal to the market volatility factor.

The estimation results for the intercept and the slope of the ICAPM component reported in Table 4 are almost identical to the case of a constant liquidity premium. The average intercept equals -0.111, while the average slope is 0.449, with average t-ratios of -7.03 and 18.53, respectively. The estimates for the different liquidity components are quite revealing, however. First the constant term, reduces to 0.832 basis points with a t-ratio of 4.79 (from 1.607 basis points with a t-ratio of 21.02 in the constant liquidity premium case). Meanwhile, the market induced volatility (average value 0.074 and t-ratio 0.95) and its squared term (average value -0.154 and t-ratio -1.25) have little systematic impact on the liquidity premium. In contrast, the firm specific volatility (average value 0.335 and t-ratio 5.39) and its squared term (average value -0.008 and t-ratio -2.83) are both highly significant. This suggests that the time-varying part of the liquidity premium is almost solely attributable to the firm-specific risk. Note also, that the average R-square increases to 0.388 (compared to 0.359 for the constant liquidity premium model).

To further underscore the above findings, Table 5 reports the average sample values of the decomposition of the total liquidity premium, λ_s, into the market-induced volatility and the firm-specific volatility components based on the series expansion in (13).[12] It follows from the table, that the average total liquidity premium of 1.826 basis points is mostly explained by the constant term (0.936 basis points, or 54.73% on average) and the time-varying firm-specific terms (0.870 basis points, or 45.39% on average), while the average market induced liquidity premium is negligible (-0.020 basis points, or -0.11% on average).[13] The fundamental market risk factor and the idiosyncratic information, or noise risk, factor are orthogonal by construction. The agents order submission strategies internalize both of these risks as manifest in the liquidity risk premium. The constant part of the liquidity premium may therefore be compensating for both risk factors, but the time-varying part is clearly dominated by the firm-specific risk.

[12] We also experimented with a fourth order expansion. However, none of the higher order terms were statistically significant, and all were numerically very small.

[13] The polynomial expansion does not guarantee that the different terms are positive. Consequently, for some of the stocks the average market volatility induced liquidity premium is actually negative. Of course, the corresponding estimates for the λ_m coefficients are generally not significant.

3.8 Robustness Check Including Lagged Returns and Liquidity

In order to check the robustness of the findings in the previous section, we include the lagged stock excess return, $EXRT_{s,t-\Delta,t}$, and the lagged order flow, $LQDT_{s,t-\Delta,t}$, in the general time-varying liquidity premium regression,

$$\begin{aligned} EXRT_{s,t,t+\Delta} \;=\;& a_s + \gamma_s EXRT_{s,t-\Delta,t} + \delta_s LQDT_{s,t-\Delta,t} \\ &+ b_s ICAPM_{s,t,t+\Delta} + \lambda_0 LQDT_{s,t,t+\Delta} \\ &+ \lambda_{1m}\beta^2_{s,t,t+\Delta}\Sigma_{m,t,t+\Delta} LQDT_{s,t,t+\Delta} + \lambda_{2m}\beta^4_{s,t,t+\Delta}\Sigma^2_{m,t,t+\Delta} LQDT_{s,t,t+\Delta} \\ &+ \lambda_{1iu}\Sigma_{s,iu,t,t+\Delta} LQDT_{s,t,t+\Delta} + \lambda_{2iu}\Sigma^2_{s,iu,t,t+\Delta} LQDT_{s,t,t+\Delta} + e_{s,t,t+\Delta}. \end{aligned} \tag{18}$$

As seen from Table 6, the lagged return coefficients are overwhelmingly negative, but the impact is generally small (average value -0.033 and t-ratio -1.49). Meanwhile, the lagged liquidity variables are statistically significant, and enters with a negative coefficient, for almost all of the stocks (average value -0.339 and t-ratio -4.14). The inclusion of the lagged return and liquidity variables also marginally increases the explanatory power of the regression (average R-square 0.401 compared to 0.388). Nonetheless, the estimates for all of the other parameters are very similar to the results reported in Table 4.

Chordia et al. (2001) also report a negative impact of the lagged aggregate liquidity measure, or signed order flow, for explaining current S&P500 index returns. Inventory considerations provides one possible explanation for this negative relationship. Moreover, in the present context, some of the market, or ICAPM, induced trades which should only happen at equilibrium prices and consequently result in unclassified trades, may be misclassified by the Lee and Ready (1991) algorithm as imbalanced order flow. This misclassification of some systematic trades as idiosyncratic trades, may help explain the relatively high degree of intertemporal persistence in the net order flow variable and the small, but positive correlation, with the ICAPM component, which in turn may account for some of the predictability by the lagged LQDT variable.

3.9 Alternative Order Flow Measures

It has long been argued in the literature that trading volume contains information about asset returns (Wang, 1994) and/or the return-volatility relationships (Gallant et al., 1992).[14] Of course, the total trading volume does not distinguish between buyer or seller initiated trades, or between market induced or information induced trades, and as such is likely less informative than the net order flow measure analyzed above.[15] In order to investigate this conjecture, Table 7 reports the results from the daily return regression,

$$EXRT_{s,t,t+\Delta} = a_s + b_s ICAPM_{s,t,t+\Delta} + \lambda_s VLMCH_{s,t,t+\Delta} + e_{s,t,t+\Delta}, \tag{19}$$

where the change in the total daily logarithmic volume variable for stock s (the growth rate) is defined as

$$VLMCH_{s,t,t+\Delta} = \log\left(\frac{\text{Volume}_{s,t+\Delta}}{\text{Volume}_{s,t}}\right) \times 100.$$

Not surprisingly, the estimates for the ICAPM component are close to the benchmark ICAPM case in Table 2, with an average intercept equal to 0.006 (average t-ratio 0.28) and an average slope of 0.562 (average t-ratio 21.53). Interestingly, the total volume variable is significantly positive at the usual five-percent level for nineteen of the thirty stock. However, the 0.204 average R-square for the regressions including the total volume measure is only marginally higher than the 0.199 for the ICAPM alone. It is also noteworthy, that the change in total trading volume alone explains less than half-a-percent of the excess return (average R-square 0.003).[16]

The empirical results in Jones et al. (1994) suggest that the number of trades, as opposed to the total trading volume, is more closely related to the underlying return volatility.

[14] Recent empirical studies confirming that trading volume, or volatility conditional on trading volume, demands a significant return premium include Llorente et al. (2001), Marsh and Wagner (2000) and Gervais et al. (2001).

[15] Related liquidity measures often employed in the literature include the bid-ask spread, the inside depth, and the elasticity between price and volume changes. A small sample of recent empirical applications involving these measures is given by Engle and Lange (1997), Domowitz and El-Gamal (1999), Shen and Starr (2000), Dufour and Engle (2000), Ball and Chordia (2001), and Engle and Patton (2001).

[16] In a related empirical analysis involving the US Treasury market, Fleming (2001) reports that net order flow (and net number of trades) has a significant impact on concurrent price changes whereas the trade size do not. Zhang et al. (2001) also find that order imbalances better explains the temporal variation in the bid-ask spread for an individual stock than do the total trading volume. Similar findings are reported in Werner (2001).

Similarly, the relative number of buys versus sells may afford a superior measure relative to the excess order flow in terms of revealing the true (latent) firm-specific information, or idiosyncratic shocks. To further investigate this, Table 8 reports the results from the regression,

$$EXRT_{s,t,t+\Delta} = a_s + b_s ICAPM_{s,t,t+\Delta} + \lambda_s RNNT_{s,t,t+\Delta} + e_{s,t,t+\Delta}, \qquad (20)$$

where the relative net number of trades of stock s is defined as

$$RNNT_{s,t,t+\Delta} = \frac{\text{NumberofBuyTrades}_{s,t,t+\Delta} - \text{NumberofSellTrades}_{s,t,t+\Delta}}{\text{NumberofBuyTrades}_{s,t,t+\Delta} + \text{NumberofSellTrades}_{s,t,t+\Delta}}.$$

For illustration, Figure 2 plots the RNNT variable, along with the net order flow, LQDT, and the change in total volume, VLMCH, for the representative stock, AA. It is evident that the longer-run dynamic dependencies in the net order flow and the net excess number of trades are fairly similar, but that the day-to-day movements in the two variables are generally very different. Turning to the results in the table, it follows that the excess number of trades is indeed somewhat more informative than the daily change in the total volume, but much less so than the relative net order flow measure. The total explanatory power of the model as measured by the average R-squared equals 0.244, compared to 0.199 and 0.359, respectively, for the ICAPM and ICAPM plus LQDT case. The net number of trades alone explains 0.077 (average R-square), whereas the relative net order flow in isolation explains 0.233. Lastly, we note that the RNNT variable is even less correlated with the ICAPM factor than is the LQDT variable (average R-square of 0.029 compared to 0.049). This lack of correlation between the two different liquidity measures and the systematic risk factor is, of course, consistent with our basic theoretical microstructure model.

4 Conclusion

This paper explains individual daily stock returns by a systematic (market related) risk factor and a (information related) liquidity factor. Our empirical investigations are motivated by a market microstructure model explicitly incorporating the liquidity risk premium within an asset pricing framework. We rely on intraday high-frequency data for measuring daily ICAPM betas and the associated market-related risks along with continuously recorded trade and quote data for quantifying the net daily order flow. Summarizing the empirical results, we find that the (systematic) ICAPM component accounts for roughly twenty percent of the ex post variability in the daily stock returns, while the (idiosyncratic) liquidity component explains another twenty percent. Directly in line with the implications from the underlying theoretical model, we find that the ICAPM and the liquidity components are approximately uncorrelated, in turn explaining close to forty percent of the daily return variability. Allowing the liquidity premium to be a time-varying function of the firm specific and market related volatility risks further enhances the explanatory power of the return regressions. Consistent with the idea that the liquidity premium is mostly compensating for informational asymmetries, we also find that the temporal variation in the liquidity premium is almost exclusively attributable to the temporal variation in the firm specific volatility risk.

Several extensions of our results warrant further investigation. First, it would be interesting to extend the empirical results to other, less frequently, traded stocks. Doing so presents new challenges concerning the measurement of the systematic factor exposures and the net order flow. Second, one may want to re-examine the return-volatility tradeoff, or volatility-feedback, relationship studied extensively in the existing literature (e.g., Gallant et al., 1992), by explicitly incorporating an information, or liquidity, premium. Third, the theoretical model in Easley and O'Hara (1987) suggests that large trades may be more informative than smaller ones, while the empirical results reported in Barclay and Warner (1993) and Hansch et al. (1999) indicate that medium sized trades may actually be the most informative. It would be interesting to further decompose the liquidity factor and the premium according to the size and/or other characteristics of the trades. Fourth, it might be possible to incorporate the effect of directly observable firm specific news, thus disentangling the impacts of pure liquidity and informational shocks. We leave all of these questions for future research.

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Table 1: Summary Statistics for Main Regression Variables

The table presents the summary statistics of excess return $EXRT_{s,t,t+\Delta} = r_{s,t,t+\Delta} - r_{f,t,t+\Delta}$, systematic component $ICAPM_{s,t,t+\Delta} = \beta_{s,t,t+\Delta}(r_{m,t,t+\Delta} - r_{f,t,t+\Delta})$, and liquidity measurement $LQDT_{s,t,t+\Delta} = \frac{\text{BuyOrders}_{s,t,t+\Delta} - \text{SellOrders}_{s,t,t+\Delta}}{\text{BuyOrders}_{s,t,t+\Delta} + \text{SellOrders}_{s,t,t+\Delta}}$, as defined in Sections 3.2-3.3. In all the tables bellow, we first present the result for each of the individual stocks in the DJIA30, and then summarize the results in terms of the mean, standard deviation, 25%, 50%, and 75% quantiles across the thirty stocks.

	Excess Return			Systematic Component			Liquidity Measurement		
Stock	Mean	StdDev	AR(1)	Mean	StdDev	AR(1)	Mean	StdDev	AR(1)
AA	0.0078	0.8552	0.0041	0.0077	0.5501	0.0171	0.0723	0.2305	0.1399
ALD	0.0162	0.7607	-0.0066	0.0265	0.7282	0.0026	0.0674	0.2443	0.1464
AXP	0.0264	0.8948	-0.0130	0.0134	0.8082	0.0063	0.0848	0.2108	0.1823
BA	-0.0016	0.8435	-0.0015	-0.0029	0.5374	0.0219	0.0749	0.2139	0.2178
C	0.0338	0.9971	0.0310	-0.0068	0.7043	0.0258	0.0667	0.2186	0.2926
CAT	0.0023	0.9029	-0.0005	0.0197	0.7082	-0.0266	0.0867	0.2249	0.2154
DD	-0.0050	0.7966	0.0279	0.0105	0.7329	0.0068	0.0719	0.2092	0.1785
DIS	0.0043	0.8343	-0.0294	-0.0013	0.5978	0.0156	0.0807	0.2039	0.2399
EK	-0.0050	0.7802	0.0641	0.0131	0.5519	0.0080	0.0707	0.2190	0.2043
GE	0.0273	0.6664	0.0042	0.0278	0.6930	0.0018	0.0587	0.1777	0.1717
GM	0.0000	0.8251	-0.0248	0.0014	0.6350	0.0056	0.0560	0.2127	0.2537
HD	0.0161	0.8959	0.0129	0.0011	0.6510	0.0192	0.0849	0.1959	0.2616
HWP	0.0327	1.0782	-0.0304	0.0138	0.8476	0.0340	0.1115	0.1800	0.2334
IBM	0.0310	0.9121	-0.0251	-0.0027	0.6842	0.0160	0.1212	0.1639	0.2790
INTC	0.0552	1.0917	-0.0333	0.0074	0.4332	0.0218	0.0181	0.0909	0.1913
IP	-0.0211	0.8409	-0.0288	-0.0126	0.6977	0.0059	0.1168	0.2170	0.1729
JNJ	0.0138	0.7283	0.0380	0.0066	0.6802	-0.0023	0.0620	0.1983	0.2494
JPM	0.0105	0.9054	0.0313	0.0210	0.7604	0.0416	0.0780	0.2083	0.2098
KO	0.0044	0.7333	0.0288	0.0213	0.6507	-0.0042	0.0827	0.2077	0.1835
MCD	0.0040	0.7368	0.0003	0.0122	0.6081	-0.0069	0.0288	0.2159	0.1669
MMM	-0.0063	0.6865	-0.0258	0.0166	0.6276	0.0277	0.0815	0.2128	0.1400
MO	-0.0158	0.9364	-0.0640	0.0112	0.5196	0.0076	0.0659	0.2126	0.2478
MRK	0.0100	0.7904	0.0072	0.0062	0.6257	0.0233	0.0512	0.2139	0.3571
MSFT	0.0517	0.9408	-0.0236	0.0028	0.4297	0.0348	0.0123	0.0918	0.1988
PG	-0.0013	0.8253	-0.0146	0.0206	0.7672	0.0145	0.0830	0.1964	0.2274
SBC	0.0015	0.7791	-0.0408	0.0061	0.6784	-0.0152	0.0884	0.2253	0.2222
T	-0.0114	0.8464	-0.0124	0.0003	0.5846	-0.0092	0.0771	0.2192	0.2786
UTX	0.0174	0.7384	0.0364	0.0030	0.5798	0.0264	0.0741	0.2366	0.1165
WMT	0.0111	0.9093	0.0087	0.0244	0.8224	-0.0266	0.0594	0.2303	0.2516
XON	0.0052	0.5827	-0.0637	0.0131	0.6509	0.0126	0.0885	0.1988	0.1216
Summary Statistics									
Mean	0.0105	0.8372	-0.0048	0.0094	0.6515	0.0102	0.0725	0.2027	0.2117
StdDev	0.0180	0.1132	0.0303	0.0101	0.1027	0.0168	0.0243	0.0347	0.0548
25% Q	-0.0013	0.7607	-0.0258	0.0014	0.5846	0.0018	0.0620	0.1983	0.1729
Median	0.0065	0.8376	-0.0040	0.0091	0.6510	0.0103	0.0745	0.2127	0.2126
75% Q	0.0174	0.9054	0.0129	0.0166	0.7082	0.0219	0.0848	0.2190	0.2494

Table 2: Stock Returns Explained by ICAPM

The table reports the results from the regression,

$$EXRT_{s,t,t+\Delta} = a_s + b_s ICAPM_{s,t,t+\Delta} + e_{s,t,t+\Delta}.$$

Stock	a_s	t-ratio	b_s	t-ratio	R^2
AA	0.0036	0.1979	0.5451	16.2942	0.1229
ALD	0.0027	0.1745	0.5116	24.4423	0.2398
AXP	0.0181	1.0604	0.6151	29.0797	0.3087
BA	0.0000	0.0007	0.5393	15.9230	0.1181
C	0.0391	2.0280	0.7664	28.0203	0.2931
CAT	-0.0080	-0.4234	0.5219	19.5240	0.1675
DD	-0.0099	-0.5975	0.4628	20.4783	0.1813
DIS	0.0050	0.2856	0.5549	18.8582	0.1581
EK	-0.0112	-0.6634	0.4773	15.6113	0.1140
GE	0.0099	0.8514	0.6261	37.3246	0.4238
GM	-0.0007	-0.0419	0.5497	20.3185	0.1790
HD	0.0154	0.8603	0.6845	24.9535	0.2474
HWP	0.0248	1.1198	0.5685	21.7444	0.1998
IBM	0.0327	1.7457	0.5991	21.8922	0.2019
INTC	0.0477	2.0776	1.0110	19.0608	0.1609
IP	-0.0157	-0.8708	0.4239	16.3528	0.1237
JNJ	0.0102	0.7070	0.5363	25.1847	0.2509
JPM	-0.0036	-0.2084	0.6736	29.8590	0.3201
KO	-0.0063	-0.4185	0.5016	21.6313	0.1981
MCD	-0.0020	-0.1303	0.4947	19.4668	0.1667
MMM	-0.0137	-0.9526	0.4468	19.4760	0.1669
MO	-0.0160	-0.7441	0.0187	0.4515	0.0001
MRK	0.0061	0.3870	0.6253	24.7933	0.2450
MSFT	0.0490	2.5234	0.9630	21.3181	0.1935
PG	-0.0110	-0.6436	0.4685	21.0528	0.1896
SBC	-0.0017	-0.1091	0.5292	22.5983	0.2124
T	-0.0116	-0.6481	0.5723	18.7299	0.1563
UTX	0.0156	1.0409	0.5937	22.9322	0.2173
WMT	-0.0011	-0.0607	0.5020	22.1750	0.2061
XON	-0.0002	-0.0209	0.4177	22.9573	0.2177
Summary Statistics					
Mean	0.0056	0.2842	0.5600	21.4168	0.1994
StdDev	0.0180	0.9365	0.1700	6.0713	0.0764
25% Q	-0.0080	-0.4234	0.4947	19.0608	0.1609
Median	-0.0001	-0.0101	0.5422	21.4747	0.1958
75% Q	0.0154	0.8603	0.6151	24.4423	0.2398

Table 3: Stock Returns Explained by ICAPM and Liquidity

This table presents the results from the baseline regression,

$$EXRT_{s,t,t+\Delta} = a_s + b_s ICAPM_{s,t,t+\Delta} + \lambda_s LQDT_{s,t,t+\Delta} + e_{s,t,t+\Delta}.$$

R^2_{01} refers to the correlation squared between $EXRT_{s,t,t+\Delta}$ and $ICAPM_{s,t,t+\Delta}$, R^2_{02} the correlation between $EXRT_{s,t,t+\Delta}$ and $LQDT_{s,t,t+\Delta}$, and R^2_{12} the correlation between $ICAPM_{s,t,t+\Delta}$ and $LQDT_{s,t,t+\Delta}$.

Stock	a_s	t-ratio	b_s	t-ratio	λ_s	t-ratio	R^2	R^2_{01}	R^2_{02}	R^2_{12}
AA	-0.1014	-5.7791	0.4651	15.1615	1.4598	19.9352	0.2751	0.1229	0.1871	0.0171
ALD	-0.0845	-6.0967	0.4403	23.6705	1.3210	23.8250	0.4151	0.2398	0.2421	0.0259
AXP	-0.1009	-5.9387	0.5368	26.9596	1.4149	18.5344	0.4148	0.3087	0.1902	0.0449
BA	-0.1518	-9.2902	0.3754	12.8375	2.0211	27.5091	0.3698	0.1181	0.3150	0.0415
C	-0.0009	-0.0470	0.7227	25.9686	0.5950	6.6376	0.3091	0.2931	0.0631	0.0560
CAT	-0.1665	-9.4600	0.4207	17.8762	1.8511	24.9865	0.3739	0.1675	0.2683	0.0296
DD	-0.1384	-9.1798	0.3532	17.7665	1.8026	25.8855	0.3952	0.1813	0.2944	0.0454
DIS	-0.1620	-10.1075	0.3917	15.3407	2.0682	27.6328	0.4000	0.1581	0.3254	0.0535
EK	-0.1269	-8.1800	0.3474	12.7388	1.6596	24.1449	0.3225	0.1140	0.2645	0.0389
GE	-0.0632	-5.7069	0.5156	32.1280	1.2985	20.7527	0.5306	0.4238	0.2747	0.1100
GM	-0.1032	-6.7509	0.4249	17.8854	1.8327	25.8412	0.3930	0.1790	0.2905	0.0413
HD	-0.1346	-7.6453	0.5620	22.1302	1.7685	20.9514	0.3890	0.2474	0.2310	0.0530
HWP	-0.2769	-12.1206	0.4261	18.1486	2.7237	24.6288	0.3939	0.1998	0.2885	0.0607
IBM	-0.3088	-15.6121	0.4204	17.6742	2.8138	28.3376	0.4396	0.2019	0.3471	0.0703
INTC	0.0121	0.5250	0.9217	17.2577	2.0047	7.8753	0.1876	0.1609	0.0598	0.0450
IP	-0.2290	-12.8052	0.3484	15.3424	1.8175	24.8988	0.3398	0.1237	0.2578	0.0179
JNJ	-0.0927	-7.0769	0.4099	21.5853	1.6731	25.6838	0.4444	0.2509	0.3077	0.0672
JPM	-0.0364	-1.9961	0.6482	28.2403	0.4270	5.0951	0.3293	0.3201	0.0468	0.0471
KO	-0.1512	-11.0316	0.3292	16.0999	1.7952	28.0196	0.4331	0.1981	0.3555	0.0906
MCD	-0.0457	-3.3679	0.3590	15.7279	1.5753	24.4976	0.3672	0.1667	0.2846	0.0589
MMM	-0.1129	-8.0375	0.3793	17.9129	1.2310	19.7100	0.3087	0.1669	0.1915	0.0261
MO	-0.0318	-1.4126	-0.0028	-0.0657	0.2431	2.3492	0.0030	0.0001	0.0030	0.0466
MRK	-0.0801	-5.7494	0.4810	21.5313	1.7026	26.0527	0.4442	0.2450	0.3082	0.0615
MSFT	0.0272	1.4130	0.8726	19.1215	1.7995	8.4204	0.2226	0.1935	0.0725	0.0554
PG	-0.1624	-9.9481	0.3570	17.7388	1.8534	23.5751	0.3735	0.1896	0.2694	0.0551
SBC	-0.1246	-8.1593	0.4489	21.1145	1.3963	21.8166	0.3706	0.2124	0.2224	0.0300
T	-0.1597	-9.8933	0.4013	15.0085	1.9230	26.9638	0.3903	0.1563	0.3178	0.0563
UTX	-0.0643	-4.4277	0.5226	21.6015	1.0805	18.2254	0.3341	0.2173	0.1700	0.0259
WMT	-0.1067	-6.4311	0.3901	19.4932	1.8237	25.5124	0.4092	0.2061	0.2906	0.0480
XON	-0.1075	-9.3146	0.3343	20.1716	1.2243	22.5621	0.3834	0.2177	0.2509	0.0498
Summary Statistics										
Mean	-0.1129	-6.9876	0.4534	18.8056	1.6067	21.0287	0.3588	0.1994	0.2330	0.0490
StdDev	0.0755	3.9895	0.1712	5.7405	0.5535	7.3777	0.0953	0.0764	0.0958	0.0199
25% Q	-0.1518	-9.4600	0.3590	15.7279	1.3210	19.7100	0.3293	0.1609	0.1902	0.0389
Median	-0.1071	-7.3611	0.4205	17.8991	1.7355	23.9849	0.3787	0.1958	0.2664	0.0476
75% Q	-0.0643	-5.7069	0.5156	21.5853	1.8511	25.8412	0.4092	0.2398	0.2944	0.0563

Table 4: Stock Returns Explained by ICAPM and Time-Varying Liquidity Premium

This table presents the OLS regression results based on,

$$
\begin{aligned}
EXRT_{s,t,t+\Delta} &= a_s + b_s ICAPM_{s,t,t+\Delta} + \lambda_0 LQDT_{s,t,t+\Delta} \\
&+\lambda_{1m}\beta^2_{s,t,t+\Delta}\Sigma_{m,t,t+\Delta}LQDT_{s,t,t+\Delta} + \lambda_{2m}\beta^4_{s,t,t+\Delta}\Sigma^2_{m,t,t+\Delta}LQDT_{s,t,t+\Delta} \\
&+\lambda_{1iu}\Sigma_{siu,t,t+\Delta}LQDT_{s,t,t+\Delta} + \lambda_{2iu}\Sigma^2_{siu,t,t+\Delta}LQDT_{s,t,t+\Delta} + e_{s,t,t+\Delta}
\end{aligned}
$$

and the ICAPM volatility decomposition $\text{Var}_t(r_{s,t,t+\Delta}) = \beta^2_{s,t,t+\Delta}\Sigma_{m,t,t+\Delta} + \Sigma_{s,iu,t,t+\Delta}$.

Stock	a_s	t-ratio	b_s	t-ratio	R^2	λ_0	t-ratio
AA	-0.0979	-5.8760	0.4393	15.0005	0.3471	0.0102	0.0786
ALD	-0.0845	-6.3716	0.4186	21.9022	0.4684	0.4873	5.6120
AXP	-0.1066	-6.1889	0.5266	26.1949	0.4194	1.1107	6.3671
BA	-0.1493	-9.3710	0.3663	12.6859	0.4018	0.8019	4.0892
C	0.0013	0.0622	0.7145	24.5370	0.3107	0.3168	1.3725
CAT	-0.1563	-9.2944	0.4498	19.3004	0.4346	0.4272	3.1975
DD	-0.1259	-8.7321	0.3351	17.1867	0.4499	0.0809	0.5397
DIS	-0.1525	-9.6826	0.3966	15.7821	0.4270	1.0543	5.7634
EK	-0.1160	-7.9250	0.3116	11.8924	0.3984	0.0576	0.4586
GE	-0.0626	-5.6437	0.5096	30.8840	0.5333	1.1056	10.1629
GM	-0.0991	-6.5084	0.4397	17.2743	0.4014	1.0756	6.2346
HD	-0.1283	-7.2765	0.5596	21.8718	0.3947	1.1745	6.2086
HWP	-0.2671	-11.9695	0.4268	18.5477	0.4281	1.2091	5.5001
IBM	-0.2969	-15.6979	0.4209	18.6022	0.4966	1.4428	9.2856
INTC	0.0132	0.5640	0.9406	17.4788	0.1909	2.1067	4.4213
IP	-0.2377	-13.8696	0.3532	15.9067	0.3960	0.5978	4.4448
JNJ	-0.0854	-6.4699	0.3983	20.4467	0.4561	1.0951	7.7951
JPM	-0.0450	-2.4024	0.6317	27.3560	0.3402	0.1966	1.2914
KO	-0.1485	-10.7491	0.3253	15.6441	0.4381	1.3196	8.2429
MCD	-0.0429	-3.1621	0.3522	15.1988	0.3741	0.9828	6.0888
MMM	-0.1242	-9.0265	0.3728	18.0740	0.3474	0.2210	1.8188
MO	-0.0245	-1.1200	0.0064	0.1545	0.0768	0.5290	3.1088
MRK	-0.0788	-5.4779	0.4736	21.0340	0.4480	1.3683	8.8691
MSFT	0.0305	1.5713	0.8939	19.4091	0.2267	2.1404	5.9093
PG	-0.1559	-9.9087	0.3561	18.4605	0.4334	0.3053	2.1161
SBC	-0.1226	-8.1342	0.4413	20.7848	0.3965	0.4802	3.3109
T	-0.1577	-9.9970	0.3889	14.7400	0.4198	0.7186	4.7653
UTX	-0.0821	-5.7646	0.5051	21.3263	0.3698	0.3671	3.9454
WMT	-0.1127	-6.7837	0.3941	18.7709	0.4172	1.8045	10.1809
XON	-0.1110	-9.7546	0.3262	19.5916	0.4033	0.3645	2.7650
Summary Statistics							
Mean	-0.1109	-7.0320	0.4492	18.5346	0.3882	0.8317	4.7981
StdDev	0.0736	4.0410	0.1743	5.4284	0.0908	0.5859	2.8733
25% Q	-0.1493	-9.6826	0.3561	15.7821	0.3698	0.3645	2.7650
Median	-0.1119	-7.0301	0.4198	18.5750	0.4025	0.7602	4.6051
75% Q	-0.0788	-5.6437	0.5051	21.0340	0.4346	1.1745	6.2346

Table 4: (continued)

Stock	λ_{1m}	t-ratio	λ_{2m}	t-ratio	λ_{1i}	t-ratio	λ_{2i}	t-ratio	R^2
AA	0.5530	1.3634	-0.6081	-3.7052	0.7649	11.0535	-0.0291	-6.1266	0.3471
ALD	0.0200	0.1297	-0.0179	-1.0596	0.3008	11.8807	-0.0037	-12.8466	0.4684
AXP	0.6183	3.1031	-0.0673	-1.8833	0.0295	0.7284	0.0005	0.3270	0.4194
BA	1.1244	2.6177	-0.6139	-2.4411	0.3756	3.9403	-0.0027	-0.2742	0.4018
C	-0.0748	-0.1660	0.1621	0.8657	0.0961	1.1754	-0.0035	-0.7525	0.3107
CAT	-0.6003	-2.7902	-0.0085	-0.3679	0.6797	11.3985	-0.0210	-6.6481	0.4346
DD	0.5629	2.1443	-0.2861	-3.5054	0.6915	11.1457	-0.0198	-6.4441	0.4499
DIS	-0.3389	-0.8160	-0.2088	-0.8931	0.4086	5.6289	-0.0073	-1.5508	0.4270
EK	1.5738	3.7174	-0.8924	-3.7948	0.6692	14.4048	-0.0167	-13.0145	0.3984
GE	0.4028	1.1456	-0.2262	-1.3162	0.0755	2.0355	-0.0001	-0.8292	0.5333
GM	0.0998	0.2521	-0.2529	-1.7037	0.3105	4.7007	-0.0101	-3.2126	0.4014
HD	-0.2147	-0.5854	0.1159	0.8936	0.2086	3.4931	-0.0042	-1.8110	0.3947
HWP	-0.5908	-1.6002	-0.2589	-2.0225	0.7824	7.5010	-0.0282	-4.4118	0.4281
IBM	0.1325	0.4187	0.0601	0.6728	0.6101	10.0007	-0.0100	-4.9957	0.4966
INTC	-2.1494	-1.0820	-1.1935	-1.0465	0.0607	0.3332	-0.0004	-0.0298	0.1909
IP	-0.1868	-0.7319	-0.0407	-0.6115	0.4218	8.4524	-0.0055	-1.9825	0.3960
JNJ	0.8225	3.4132	-0.1578	-2.3214	0.1711	2.4617	0.0018	0.3179	0.4561
JPM	0.0130	0.0429	-0.0106	-0.1284	0.1014	1.2512	0.0057	1.8074	0.3402
KO	0.4916	1.5468	-0.1050	-0.6205	0.1617	2.2675	-0.0047	-0.8077	0.4381
MCD	0.6039	1.6082	-0.2906	-1.5899	0.1710	3.0915	-0.0044	-1.2868	0.3741
MMM	0.8474	2.5679	-0.3125	-2.0435	0.5223	7.2486	-0.0177	-3.1848	0.3474
MO	-2.2202	-2.7071	1.2754	2.0899	-0.0521	-1.2416	0.0011	3.9438	0.0768
MRK	0.9296	2.3736	-0.2647	-1.1653	0.0677	1.2321	-0.0012	-0.4130	0.4480
MSFT	-4.5093	-2.2179	0.8394	0.4243	0.0550	0.4568	0.0006	0.1135	0.2267
PG	0.4699	1.8301	-0.2134	-2.6065	0.6460	11.5876	-0.0036	-2.9299	0.4334
SBC	0.8326	3.7658	-0.0352	-0.5291	0.2745	5.1964	-0.0071	-2.9140	0.3965
T	1.5662	3.1119	-0.6942	-1.9469	0.5071	6.9782	-0.0136	-4.5274	0.4198
UTX	-0.2464	-0.8267	0.1033	0.9082	0.4736	8.7354	-0.0189	-6.3160	0.3698
WMT	0.8507	4.3321	-0.1612	-4.5447	-0.0394	-1.2891	0.0012	1.3503	0.4172
XON	0.8357	2.6857	-0.2677	-1.5910	0.5105	5.8804	-0.0202	-5.3418	0.4033
Summary Statistics									
Mean	0.0740	0.9549	-0.1544	-1.2528	0.3352	5.3910	-0.0081	-2.8264	0.3882
StdDev	1.2217	2.0261	0.4498	1.5577	0.2584	4.4301	0.0093	3.8200	0.0908
25% Q	-0.2147	-0.7319	-0.2861	-2.0435	0.0961	1.2512	-0.0167	-4.9957	0.3698
Median	0.4364	1.2545	-0.1850	-1.2408	0.3056	4.9486	-0.0046	-1.8967	0.4025
75% Q	0.8326	2.6177	-0.0106	-0.3679	0.5223	8.7354	-0.0004	-0.2742	0.4346

Table 5: Liquidity Premium Decomposition

This table reports the decomposition of the liquidity premium according to the series expansion,

$$\lambda_s = \lambda_0 + \lambda_{1m}(\beta^2\Sigma_m) + \lambda_{2m}(\beta^2\Sigma_m)^2 + \lambda_{1iu}\Sigma_{iu} + \lambda_{2iu}\Sigma_{iu}^2,$$

into the constant term, the market induced term, and the idiosyncratic liquidity term.

		Constant Volatility		Market Volatility		Idiosyncratic Volatility	
Stock	Total	Premium	%	Premium	%	Premium	%
AA	1.9333	0.0417	2.1551	0.0235	1.2150	1.8682	96.6299
ALD	1.4922	0.5451	36.5315	-0.0035	-0.2321	0.9506	63.7005
AXP	1.5836	1.1914	75.2330	0.2572	16.2390	0.1351	8.5280
BA	2.1692	0.9321	42.9705	0.1519	7.0033	1.0852	50.0262
C	0.7087	0.3577	50.4786	0.0390	5.4981	0.3120	44.0233
CAT	2.2612	0.5237	23.1610	-0.2070	-9.1528	1.9445	85.9918
DD	2.1166	0.1233	5.8247	0.0966	4.5638	1.8967	89.6115
DIS	2.2558	1.2207	54.1146	-0.1223	-5.4215	1.1574	51.3069
EK	1.9590	0.1051	5.3648	0.2122	10.8330	1.6417	83.8023
GE	1.3859	1.1421	82.4090	0.0939	6.7769	0.1499	10.8141
GM	2.0303	1.2920	63.6340	-0.0433	-2.1308	0.7816	38.4968
HD	2.0271	1.3711	67.6394	-0.0345	-1.7003	0.6905	34.0608
HWP	3.3493	1.4024	41.8719	-0.4761	-14.2148	2.4229	72.3429
IBM	3.1121	1.6771	53.8891	0.0622	1.9993	1.3728	44.1116
INTC	1.8832	2.0307	107.8322	-0.3675	-19.5146	0.2200	11.6824
IP	2.1223	0.6856	32.3034	-0.0958	-4.5118	1.5325	72.2085
JNJ	1.8505	1.1710	63.2807	0.2280	12.3224	0.4515	24.3969
JPM	0.4165	0.1889	45.3606	-0.0031	-0.7350	0.2307	55.3744
KO	1.9137	1.4297	74.7089	0.1383	7.2243	0.3457	18.0668
MCD	1.6960	1.0573	62.3438	0.1041	6.1362	0.5346	31.5200
MMM	1.4943	0.2431	16.2704	0.1791	11.9854	1.0721	71.7442
MO	0.3743	0.6407	171.1698	-0.2662	-71.1088	-0.0002	-0.0610
MRK	1.9902	1.6492	82.8671	0.1992	10.0112	0.1417	7.1217
MSFT	1.8290	2.2492	122.9714	-0.5400	-29.5244	0.1199	6.5530
PG	2.0636	0.4420	21.4198	0.1108	5.3700	1.5108	73.2102
SBC	1.6429	0.6113	37.2100	0.2432	14.8038	0.7884	47.9862
T	2.2586	0.9267	41.0323	0.2248	9.9532	1.1070	49.0145
UTX	1.4108	0.3718	26.3555	-0.0397	-2.8151	1.0787	76.4595
WMT	1.9719	2.0337	103.1347	0.2508	12.7207	-0.3127	-15.8554
XON	1.4650	0.4135	28.2283	0.1908	13.0228	0.8606	58.7489
Summary Statistics							
Mean	1.8256	0.9357	54.7255	0.0202	-0.1128	0.8697	45.3872
StdDev	0.6221	0.6203	37.3968	0.2131	16.9753	0.6861	30.1224
25% Q	1.4943	0.4135	28.2283	-0.0433	-2.8151	0.2307	18.0668
Median	1.9235	0.9294	47.9196	0.0780	4.9669	0.8245	48.5003
75% Q	2.1166	1.3711	74.7089	0.1908	10.0112	1.3728	72.2085

Table 6: Robustness Check with Lagged Return and Lagged Liquidity

This table reports the OLS regression including the lagged (excess) return and the lagged order flow,

$$\begin{aligned} EXRT_{s,t,t+\Delta} &= a_s + \gamma_s EXRT_{s,t-\Delta,t} + \delta_s LQDT_{s,t-\Delta,t} \\ &+ b_s ICAPM_{s,t,t+\Delta} + \lambda_0 LQDT_{s,t,t+\Delta} \\ &+ \lambda_{1m}\beta^2_{s,t,t+\Delta}\Sigma_{m,t,t+\Delta} LQDT_{s,t,t+\Delta} + \lambda_{2m}\beta^4_{s,t,t+\Delta}\Sigma^2_{m,t,t+\Delta} LQDT_{s,t,t+\Delta} \\ &+ \lambda_{1iu}\Sigma_{siu,t,t+\Delta} LQDT_{s,t,t+\Delta} + \lambda_{2iu}\Sigma^2_{siu,t,t+\Delta} LQDT_{s,t,t+\Delta} + e_{s,t,t+\Delta} \end{aligned}$$

Stock	a_s	t-ratio	γ_s	t-ratio	δ_s	t-ratio	b_s	t-ratio	R^2
AA	-0.0827	-4.7799	-0.0065	-0.3154	-0.2461	-3.2041	0.4369	14.9681	0.3518
ALD	-0.0672	-4.9430	-0.0221	-1.1307	-0.3016	-5.0534	0.4167	22.0376	0.4800
AXP	-0.0811	-4.5026	-0.0456	-2.3540	-0.3914	-4.7409	0.5250	26.4157	0.4331
BA	-0.1237	-7.4286	-0.0295	-1.3887	-0.4691	-5.5511	0.3596	12.6384	0.4198
C	-0.0069	0.3360	-0.0034	-0.1705	-0.1193	-1.2700	0.7135	24.4867	0.3113
CAT	-0.1255	-7.1328	-0.0300	-1.5035	-0.4736	-5.8416	0.4471	19.4856	0.4521
DD	-0.1132	-7.4385	-0.0391	-1.9077	-0.2447	-3.1651	0.3330	17.1932	0.4579
DIS	-0.1304	-7.8608	-0.0583	-2.7922	-0.4252	-4.9112	0.3832	15.4821	0.4469
EK	-0.0991	-6.4819	0.0100	0.4814	-0.2926	-3.9136	0.3093	11.8556	0.4041
GE	-0.0479	-4.1638	-0.0180	-0.9745	-0.3049	-4.4105	0.5072	30.9992	0.5414
GM	-0.0827	-5.3459	-0.0520	-2.4952	-0.4504	-5.4719	0.4261	16.9956	0.4224
HD	-0.0989	-5.3246	-0.0340	-1.6746	-0.5155	-5.4926	0.5518	21.8370	0.4107
HWP	-0.2076	-8.4330	-0.0428	-2.1087	-0.7627	-6.1791	0.4085	18.0320	0.4504
IBM	-0.2568	-11.9341	-0.0496	-2.4874	-0.5313	-4.6616	0.4050	18.1120	0.5123
INTC	0.0119	0.5022	-0.0439	-2.0561	0.2608	1.0010	0.9385	17.4555	0.1928
IP	-0.2065	-10.8705	-0.0479	-2.3294	-0.3598	-4.4847	0.3478	15.8503	0.4109
JNJ	-0.0704	-5.1780	-0.0253	-1.2356	-0.3384	-4.4782	0.3915	20.2553	0.4669
JPM	-0.0478	-2.4796	0.0104	0.5369	0.0465	0.5436	0.6313	27.2893	0.3405
KO	-0.1245	-8.4231	-0.0125	-0.5807	-0.3785	-4.9952	0.3167	15.3762	0.4508
MCD	-0.0367	-2.7027	-0.0364	-1.6997	-0.2848	-3.8924	0.3447	14.9840	0.3852
MMM	-0.1088	-7.5072	-0.0503	-2.4478	-0.2474	-3.7183	0.3743	18.3050	0.3589
MO	-0.0351	-1.5572	-0.1159	-4.2428	-0.0841	-0.8305	0.0382	0.9074	0.0856
MRK	-0.0604	-4.2098	-0.0099	-0.4903	-0.6198	-7.9725	0.4542	20.5733	0.4739
MSFT	0.0340	1.7487	-0.0149	-0.7093	-0.3410	-1.5572	0.8896	19.2901	0.2282
PG	-0.1326	-7.9621	-0.0304	-1.5078	-0.4057	-4.7342	0.3507	18.3641	0.4459
SBC	-0.0957	-6.0952	-0.0357	-1.7869	-0.4164	-5.9203	0.4289	20.4666	0.4152
T	-0.1271	-7.7672	-0.0180	-0.8638	-0.5850	-7.0977	0.3676	14.1640	0.4437
UTX	-0.0692	-4.6879	-0.0004	-0.0219	-0.2032	-3.2430	0.5045	21.3589	0.3740
WMT	-0.0908	-5.3936	-0.0137	-0.6630	-0.5231	-6.3138	0.3811	18.3830	0.4355
XON	-0.1008	-8.2244	-0.0794	-3.9023	-0.1645	-2.7523	0.3186	19.3046	0.4168
Summary Statistics									
Mean	-0.0923	-5.5414	-0.0315	-1.4941	-0.3391	-4.1437	0.4434	18.4289	0.4006
StdDev	0.0620	3.1527	0.0262	1.1411	0.2030	2.0886	0.1726	5.3825	0.0943
25% Q	-0.1245	-7.7672	-0.0456	-2.3294	-0.4691	-5.4926	0.3507	15.4821	0.3740
Median	-0.0932	-5.3697	-0.0302	-1.5057	-0.3504	-4.5732	0.4068	18.3346	0.4211
75% Q	-0.0604	-4.2098	-0.0137	-0.6630	-0.2461	-3.2041	0.5045	20.5733	0.4508

Table 6: (continued)

Stock	λ_0	t-ratio	λ_{1m}	t-ratio	λ_{2m}	t-ratio	λ_{1i}	t-ratio	λ_{2i}	t-ratio	R^2
AA	0.0417	0.3218	0.5576	1.3788	-0.5947	-3.6354	0.7665	11.1160	-0.0291	-6.1506	0.3518
ALD	0.5451	6.3130	0.0118	0.0773	-0.0157	-0.9356	0.2996	11.9509	-0.0036	-12.6143	0.4800
AXP	1.1914	6.8945	0.6784	3.4400	-0.0786	-2.2188	0.0310	0.7751	0.0005	0.2941	0.4331
BA	0.9321	4.8072	1.1857	2.8015	-0.6338	-2.5590	0.3700	3.9397	-0.0025	-0.2593	0.4198
C	0.3577	1.5372	-0.0696	-0.1546	0.1559	0.8328	0.0935	1.1437	-0.0032	-0.6860	0.3113
CAT	0.5237	3.9628	-0.5881	-2.7716	-0.0078	-0.3442	0.6881	11.7046	-0.0212	-6.8054	0.4521
DD	0.1233	0.8249	0.5711	2.1913	-0.2722	-3.3545	0.6989	11.3134	-0.0197	-6.4624	0.4579
DIS	1.2207	6.7484	-0.3111	-0.7623	-0.2122	-0.9234	0.3991	5.5945	-0.0066	-1.4457	0.4469
EK	0.1051	0.8361	1.5813	3.7524	-0.8813	-3.7606	0.6724	14.4530	-0.0168	-13.1300	0.4041
GE	1.1421	10.5660	0.4809	1.3786	-0.2414	-1.4169	0.0823	2.2393	-0.0002	-1.0955	0.5414
GM	1.2920	7.5279	0.0028	0.0072	-0.2009	-1.3763	0.2916	4.4901	-0.0094	-3.0489	0.4224
HD	1.3711	7.2658	-0.2467	-0.6816	0.1193	0.9314	0.2064	3.4988	-0.0048	-2.0921	0.4107
HWP	1.4024	6.4642	-0.6055	-1.6728	-0.2458	-1.9584	0.8112	7.9212	-0.0306	-4.8853	0.4504
IBM	1.6771	10.7072	0.1365	0.4382	0.0519	0.5891	0.6019	10.0086	-0.0101	-5.1300	0.5123
INTC	2.0307	4.2371	-2.1468	-1.0817	-1.1841	-1.0388	0.0786	0.4313	-0.0008	-0.0701	0.1928
IP	0.6856	5.1364	-0.2846	-1.1267	-0.0123	-0.1861	0.4249	8.6122	-0.0052	-1.8948	0.4109
JNJ	1.1710	8.3830	0.8820	3.6934	-0.1762	-2.5983	0.1796	2.6100	0.0020	0.3454	0.4669
JPM	0.1889	1.2384	0.0089	0.0293	-0.0110	-0.1336	0.1007	1.2426	0.0058	1.8339	0.3405
KO	1.4297	8.9810	0.5337	1.6980	-0.1056	-0.6305	0.1420	2.0093	-0.0030	-0.5117	0.4508
MCD	1.0573	6.5882	0.6804	1.8268	-0.3190	-1.7593	0.1641	2.9936	-0.0038	-1.1408	0.3852
MMM	0.2431	2.0176	0.9104	2.7818	-0.3284	-2.1645	0.5318	7.4444	-0.0179	-3.2564	0.3589
MO	0.6407	3.6890	-2.0504	-2.5085	1.1326	1.8618	-0.0008	-0.0187	0.0007	2.6085	0.0856
MRK	1.6492	10.7249	0.9071	2.3712	-0.2465	-1.1114	0.0537	0.9998	-0.0008	-0.2999	0.4739
MSFT	2.2492	6.1409	-4.4960	-2.2135	0.8847	0.4476	0.0431	0.3575	0.0010	0.1854	0.2282
PG	0.4420	3.0656	0.5165	2.0321	-0.2161	-2.6683	0.6315	11.4443	-0.0036	-2.9524	0.4459
SBC	0.6113	4.2447	0.8078	3.7099	-0.0251	-0.3835	0.2675	5.1383	-0.0065	-2.7099	0.4152
T	0.9267	6.1982	1.5131	3.0702	-0.7222	-2.0674	0.5047	7.0841	-0.0138	-4.6874	0.4437
UTX	0.3718	4.0089	-0.2401	-0.8083	0.0854	0.7502	0.4864	8.9699	-0.0193	-6.4777	0.3740
WMT	2.0337	11.4964	0.8248	4.2610	-0.1536	-4.3977	-0.0550	-1.8219	0.0016	1.8530	0.4355
XON	0.4135	3.1660	0.9355	3.0374	-0.3311	-1.9865	0.5033	5.8600	-0.0195	-5.2123	0.4168
Summary Statistics											
Mean	0.9357	5.4698	0.0896	1.0065	-0.1595	-1.2732	0.3356	5.4502	-0.0080	-2.8633	0.4006
StdDev	0.6203	3.1638	1.2176	2.0839	0.4388	1.5458	0.2596	4.4572	0.0096	3.7875	0.0943
25% Q	0.4135	3.1660	-0.2467	-0.7623	-0.3190	-2.2188	0.0935	1.2426	-0.0168	-5.1300	0.3740
Median	0.9294	5.6387	0.4987	1.3787	-0.1885	-1.2439	0.2956	4.8142	-0.0043	-1.9934	0.4211
75% Q	1.3711	7.2658	0.8248	2.8015	-0.0110	-0.1861	0.5318	8.9699	-0.0008	-0.2593	0.4508

Table 7: Robustness Check based on Change in Volume as Liquidity Measure
The regression model is formulated as,

$$EXRT_{s,t,t+\Delta} = a_s + b_s ICAPM_{s,t,t+\Delta} + \lambda_s VLMCH_{s,t,t+\Delta} + e_{s,t,t+\Delta},$$

where the change in volume change is defined as, $VLMCH_{s,t,t+\Delta} = \log\left(\frac{\text{Volume}_{s,t+\Delta}}{\text{Volume}_{s,t}}\right) \times 100$. The R^2_{01} column gives the correlation squared between $EXRT_{s,t,t+\Delta}$ and $ICAPM_{s,t,t+\Delta}$, R^2_{02} the correlation between $EXRT_{s,t,t+\Delta}$ and $VLMCH_{s,t,t+\Delta}$, and R^2_{12} the correlation between $ICAPM_{s,t,t+\Delta}$ and $VLMCH_{s,t,t+\Delta}$.

Stock	a_s	t-ratio	b_s	t-ratio	λ_s	t-ratio	R^2	R^2_{01}	R^2_{02}	R^2_{12}
AA	0.0036	0.1966	0.5478	16.4269	0.0014	3.5649	0.1288	0.1229	0.0047	0.0005
ALD	0.0026	0.1733	0.5114	24.4413	0.0004	1.1533	0.2403	0.2398	0.0007	0.0001
AXP	0.0180	1.0614	0.6187	29.3854	0.0017	4.4932	0.3160	0.3087	0.0041	0.0015
BA	-0.0000	-0.0022	0.5412	16.0198	0.0013	3.1471	0.1226	0.1181	0.0038	0.0003
C	0.0389	2.0337	0.7702	28.3510	0.0022	5.1969	0.3030	0.2931	0.0072	0.0007
CAT	-0.0080	-0.4234	0.5219	19.5236	-0.0000	-0.0359	0.1675	0.1675	0.0000	0.0000
DD	-0.0100	-0.6046	0.4649	20.6107	0.0012	3.0005	0.1852	0.1813	0.0024	0.0010
DIS	0.0050	0.2836	0.5564	19.0488	0.0022	5.2976	0.1704	0.1581	0.0114	0.0001
EK	-0.0112	-0.6639	0.4774	15.6142	0.0002	0.4910	0.1141	0.1140	0.0001	0.0000
GE	0.0098	0.8470	0.6274	37.5040	0.0011	3.3309	0.4272	0.4238	0.0018	0.0006
GM	-0.0008	-0.0477	0.5552	20.7009	0.0023	5.9500	0.1940	0.1790	0.0117	0.0012
HD	0.0152	0.8571	0.6810	24.9272	-0.0016	-4.1154	0.2541	0.2474	0.0094	0.0009
HWP	0.0248	1.1190	0.5689	21.7639	0.0006	1.1524	0.2003	0.1998	0.0003	0.0001
IBM	0.0326	1.7444	0.5987	21.8738	-0.0003	-0.5997	0.2021	0.2019	0.0005	0.0006
INTC	0.0477	2.0816	1.0149	19.1672	-0.0015	-2.8002	0.1644	0.1609	0.0023	0.0007
IP	-0.0159	-0.8844	0.4241	16.4354	0.0017	4.1931	0.1318	0.1237	0.0080	0.0000
JNJ	0.0101	0.7024	0.5387	25.3514	0.0012	3.2320	0.2550	0.2509	0.0022	0.0012
JPM	-0.0037	-0.2178	0.6757	30.0456	0.0014	3.6254	0.3248	0.3201	0.0029	0.0007
KO	-0.0064	-0.4227	0.5015	21.6556	0.0009	2.2390	0.2002	0.1981	0.0022	0.0000
MCD	-0.0021	-0.1349	0.4962	19.5521	0.0009	2.4568	0.1694	0.1667	0.0017	0.0006
MMM	-0.0138	-0.9568	0.4482	19.5372	0.0005	1.6302	0.1680	0.1669	0.0004	0.0014
MO	-0.0160	-0.7446	0.0189	0.4554	-0.0002	-0.4040	0.0002	0.0001	0.0001	0.0001
MRK	0.0061	0.3859	0.6272	24.8940	0.0010	2.4099	0.2473	0.2450	0.0011	0.0010
MSFT	0.0492	2.5391	0.9694	21.4804	0.0013	2.8823	0.1970	0.1935	0.0014	0.0024
PG	-0.0109	-0.6387	0.4679	21.0449	-0.0008	-1.9553	0.1913	0.1896	0.0022	0.0002
SBC	-0.0019	-0.1203	0.5317	22.7634	0.0014	3.4209	0.2172	0.2124	0.0030	0.0010
T	-0.0118	-0.6631	0.5749	18.8885	0.0018	3.9441	0.1631	0.1563	0.0055	0.0005
UTX	0.0156	1.0397	0.5948	22.9858	0.0005	1.6948	0.2185	0.2173	0.0005	0.0007
WMT	-0.0012	-0.0630	0.5030	22.2378	0.0009	1.9725	0.2077	0.2061	0.0009	0.0005
XON	-0.0004	-0.0320	0.4189	23.2005	0.0017	5.4114	0.2296	0.2177	0.0107	0.0002
Summary Statistics										
Mean	0.0055	0.2815	0.5616	21.5296	0.0008	2.1993	0.2037	0.1994	0.0034	0.0006
StdDev	0.0180	0.9402	0.1709	6.1107	0.0010	2.4395	0.0770	0.0764	0.0036	0.0006
25% Q	-0.0080	-0.4234	0.4962	19.1672	0.0004	1.1524	0.1675	0.1609	0.0007	0.0001
Median	-0.0002	-0.0171	0.5445	21.5680	0.0011	2.6696	0.1986	0.1958	0.0022	0.0006
75% Q	0.0152	0.8571	0.6187	24.4413	0.0014	3.6254	0.2403	0.2398	0.0047	0.0010

Table 8: Robustness Check based on the Relative Net Number of Trades as Liquidity Measure
The regression takes the form,

$$EXRT_{s,t,t+\Delta} = a_s + b_s ICAPM_{s,t,t+\Delta} + \lambda_s RNNT_{s,t,t+\Delta} + e_{s,t,t+\Delta},$$

where $RNNT_{s,t,t+\Delta} = \frac{\text{BuyTradeNumber}_{s,t,t+\Delta} - \text{SellTradeNumber}_{s,t,t+\Delta}}{\text{BuyTradeNumber}_{s,t,t+\Delta} + \text{SellTradeNumber}_{s,t,t+\Delta}}$. Further, R^2_{01} denotes the correlation squared between $EXRT_{s,t,t+\Delta}$ and $ICAPM_{s,t,t+\Delta}$, R^2_{02} the correlation between $EXRT_{s,t,t+\Delta}$ and $RNNT_{s,t,t+\Delta}$, and R^2_{12} the correlation between $ICAPM_{s,t,t+\Delta}$ and $RNNT_{s,t,t+\Delta}$.

Stock	a_s	t-ratio	b_s	t-ratio	λ_s	t-ratio	R^2	R^2_{01}	R^2_{02}	R^2_{12}
AA	-0.1410	-6.5402	0.4785	14.6024	1.7805	11.8288	0.1833	0.1229	0.0913	0.0295
ALD	-0.1025	-6.5424	0.4483	22.4306	1.8061	16.2900	0.3332	0.2398	0.1561	0.0379
AXP	-0.0555	-3.0334	0.5763	27.4310	1.3571	9.7952	0.3420	0.3087	0.0806	0.0354
BA	0.0080	0.4500	0.4989	15.0756	1.1516	10.7648	0.1689	0.1181	0.0692	0.0129
C	0.0128	0.6328	0.7450	26.8907	0.5962	4.1729	0.2995	0.2931	0.0321	0.0342
CAT	-0.1295	-6.4274	0.4512	17.3326	1.9464	13.6127	0.2417	0.1675	0.1215	0.0397
DD	-0.1128	-6.5695	0.4000	18.3281	2.0586	14.7547	0.2657	0.1813	0.1354	0.0381
DIS	-0.0787	-4.1027	0.5087	17.4842	1.1533	9.7740	0.1985	0.1581	0.0691	0.0264
EK	-0.0454	-2.7447	0.4085	13.5824	1.5795	11.7993	0.1747	0.1140	0.0943	0.0375
GE	-0.0360	-2.6472	0.6049	35.7344	0.7628	6.3473	0.4358	0.4238	0.0554	0.0387
GM	0.0190	1.1767	0.4726	18.3172	2.4451	16.1703	0.2786	0.1790	0.1508	0.0341
HD	-0.0935	-4.2713	0.6514	23.9170	1.2589	8.3059	0.2739	0.2474	0.0546	0.0214
HWP	-0.1544	-5.1307	0.5258	20.1279	1.6574	8.6144	0.2299	0.1998	0.0652	0.0360
IBM	-0.0174	-0.8958	0.5713	21.0764	1.3499	8.2171	0.2294	0.2019	0.0487	0.0156
INTC	0.0305	1.1542	0.9997	18.6146	0.2335	1.3151	0.1617	0.1609	0.0084	0.0255
IP	-0.1603	-7.7838	0.3715	14.7594	1.5850	12.9932	0.1954	0.1237	0.1029	0.0258
JNJ	-0.0909	-5.3173	0.4945	23.4416	1.2044	10.4255	0.2915	0.2509	0.0860	0.0362
JPM	-0.0021	-0.0880	0.6739	29.5432	-0.0160	-0.0947	0.3201	0.3201	0.0067	0.0220
KO	-0.0627	-4.1594	0.4455	19.7178	1.5626	13.1919	0.2656	0.1981	0.1148	0.0354
MCD	-0.0760	-4.5700	0.4538	18.1313	1.0515	10.3989	0.2117	0.1667	0.0749	0.0247
MMM	-0.0709	-4.6094	0.4173	18.4108	1.1513	9.2698	0.2030	0.1669	0.0604	0.0198
MO	-0.0149	-0.6941	0.0102	0.2436	0.2701	1.6847	0.0016	0.0001	0.0016	0.0148
MRK	-0.0722	-4.5584	0.5533	22.7166	1.9949	14.8601	0.3239	0.2450	0.1396	0.0396
MSFT	-0.0315	-1.3041	0.9120	19.9327	0.9477	5.5328	0.2063	0.1935	0.0399	0.0407
PG	-0.1172	-5.7677	0.4257	19.1196	1.6004	9.1810	0.2242	0.1896	0.0744	0.0438
SBC	-0.0191	-1.2203	0.5061	21.9895	1.0884	9.4390	0.2478	0.2124	0.0557	0.0113
T	-0.1228	-6.6740	0.4918	16.7573	2.0728	15.1295	0.2473	0.1563	0.1356	0.0329
UTX	-0.0435	-2.8499	0.5379	21.2121	1.3566	12.1229	0.2737	0.2173	0.1011	0.0329
WMT	0.0381	2.0239	0.4839	21.7056	0.8789	8.6888	0.2365	0.2061	0.0466	0.0087
XON	0.0137	1.1631	0.3966	21.8795	0.9267	7.6956	0.2414	0.2177	0.0497	0.0229
Summary Statistics										
Mean	-0.0576	-3.0634	0.5172	20.0169	1.2937	9.7427	0.2436	0.1994	0.0774	0.0291
StdDev	0.0573	2.8882	0.1722	6.0046	0.5773	4.2457	0.0754	0.0764	0.0419	0.0099
25% Q	-0.1025	-5.3173	0.4455	17.4842	0.9477	8.2171	0.2030	0.1609	0.0497	0.0220
Median	-0.0591	-3.5680	0.4931	19.8253	1.3044	9.7846	0.2415	0.1958	0.0718	0.0329
75% Q	-0.0149	-0.6941	0.5713	22.4306	1.6574	12.9932	0.2786	0.2398	0.1029	0.0375

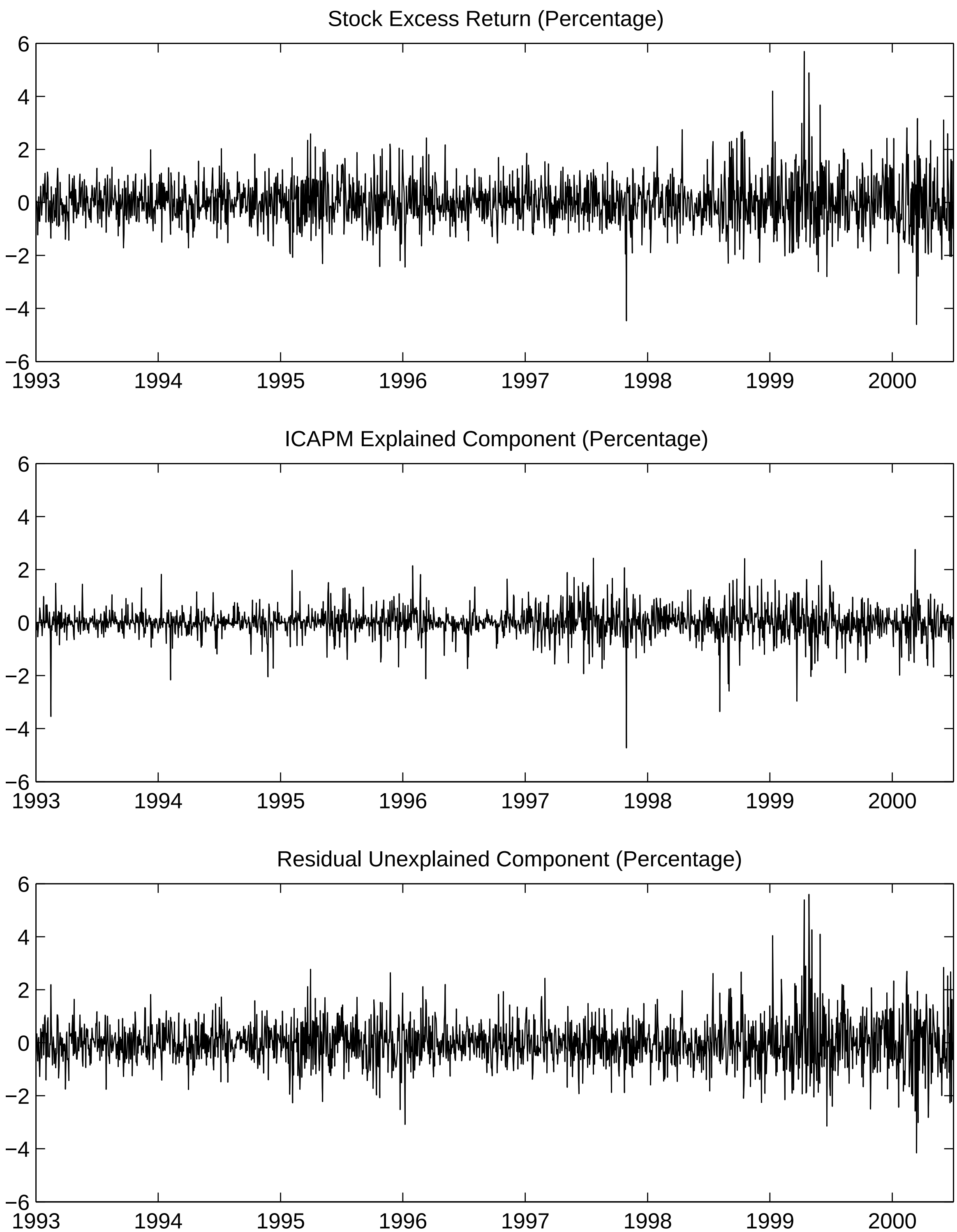

Figure 1: Explained and Unexplained Excess Returns for Stock AA

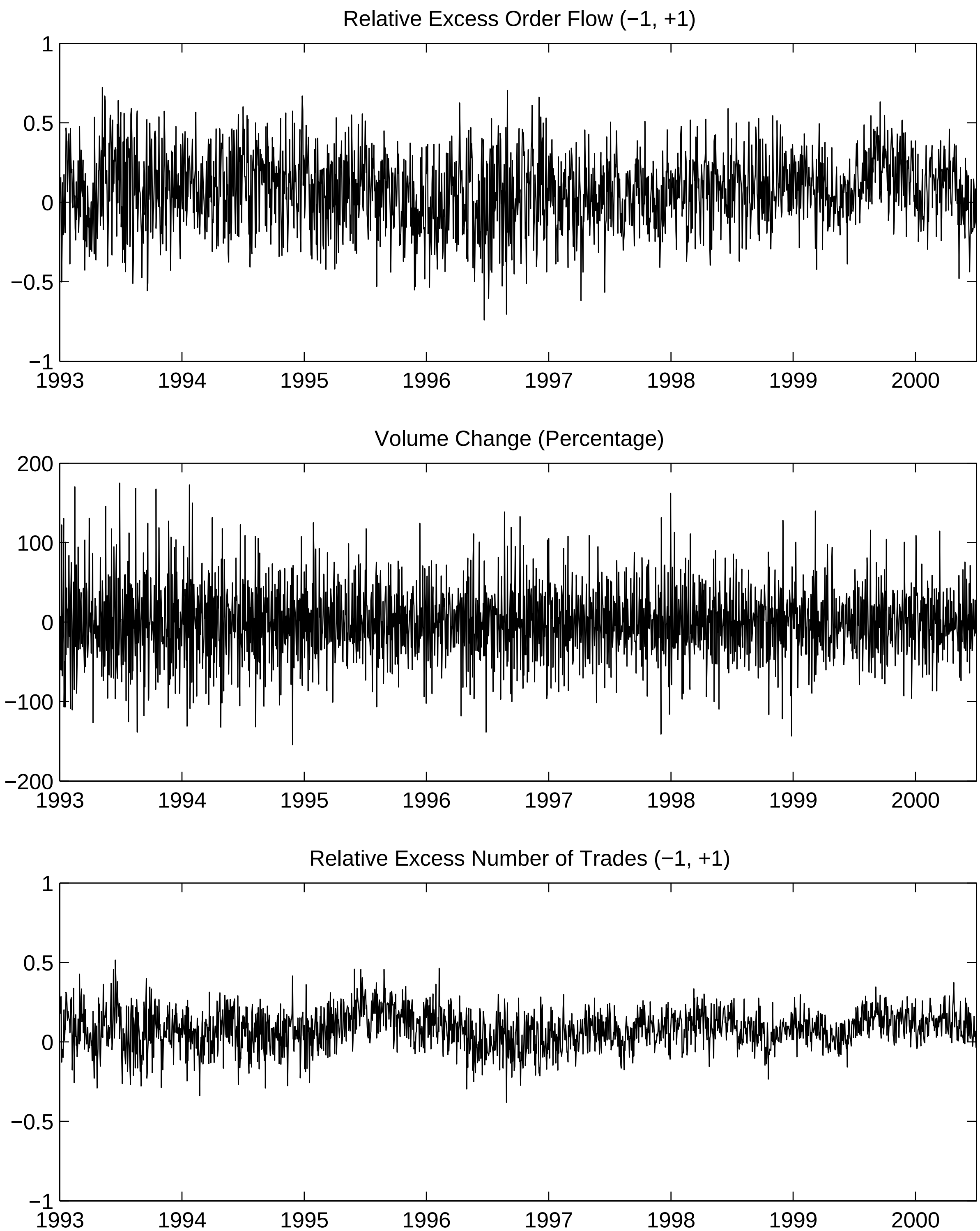

Figure 2: Microstructure Information Measurements for Stock AA