Risk Sharing, Costly Participation, and Monthly Returns

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This Version: 10-Dec-2010*

Abstract

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Keywords: Transitory Volatility, Liquidity, Individual Investors, Market Makers
JEL Number: G12, G14
Internet Appendix: http://dl.dropbox.com/u/5179651/ia.pdf

*We thank Hank Bessembinder, Paolo Pasquariello, and Stefan Ruenzi for comments as well as seminar participants at HEC Paris, KAIST (Korea), RMI Singapore, UC Berkeley, and CERAG University of Grenoble. We also thank attendees at the NY Fed's 6^{th} Annual Workshop on the Microstructure of Financial Markets, the 8^{th} QMBA Conference at GSM Beijing University, the 3^{rd} Liquidity Conference at Erasmus University, Rotterdam, and the 23^{rd} Australasian Finance and Banking Conference, Sydney. Menkveld gratefully acknowledges Robert Engle and Boyan Jovanovic for sponsoring NYU visiting positions 2008-2011, VU University Amsterdam for a VU talent grant, and NWO for a VIDI grant. Contact information: **Terrence Hendershott**, Haas School of Business, University of California at Berkeley, 545 Student Services Bldg 1900, Berkeley CA 94720, Tel: +1.510.643.0619, Email: hender@haas.berkeley.edu; **Sunny X. Li**, VU University Amsterdam, FEWEB, De Boelelaan 1105, 1081 HV, Amsterdam, Netherlands, Email: xysunnyli@gmail.com; **Albert J. Menkveld**, VU University Amsterdam, FEWEB, De Boelelaan 1105, 1081 HV, Amsterdam, Netherlands, Tel: +31.20.598.6130, Email: albertjmenkveld@gmail.com; **Mark S. Seasholes**, HKUST Dept of Finance (Rm 2413), Clear Water Bay, Kowloon Hong Kong, HK Tel: +852.2358.7668, USA Tel: +1.510.931.7531, Email: Mark.Seasholes@gmail.com

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1 Introduction

We examine how two market frictions, nonzero participation costs and limited risk bearing capacity, affect overall stock price efficiency at a monthly horizon. We propose a theoretical model with two groups of long-term investors (institutions and individuals) along with a third group of market makers. Agents differ along two key dimensions. The long-term investors seek to hedge non-traded risky income; the market makers do not. One group (individuals) pays a participation cost enabling them to trade in both the model's periods; the other two groups are free to trade in both periods. Despite its parsimony, our model produces numerous predictions regarding return dynamics, order flow dynamics, and return-flow interactions. It provides a unified framework that integrates recent empirical results on trader types, order imbalances, liquidity, and return predictability.[1]

To test the predictions of our theoretical model, we estimate a state-space (statistical) model. We start with the hypothesis that a stock's observable price can be decomposed into two unobservable components. The first component reflects information about the stock's fundamental value and is thus known as the stock's "efficient price". A stock's efficient price can be thought of as containing a part related to private information and a part related to public information. The part related to private information is assumed to be related to trading variables (order flows) while the part related to public information is not.

The second unobservable component represents transitory deviations from a stock's efficient price and is known as the "transitory component of price" (or just "transitory component".) A stock's transitory component can be thought of as containing a part related to trading variables (known as "price pressure") and a part unrelated to trading. A goal of this paper is to test the relations between market makers' inventories, individuals' order flows, and price pressure at a monthly frequency.[2]

The actual estimation of the state-space model uses maximum likelihood. We follow a

[1] Papers from the last five years show that: i) Market makers' inventories predict future returns at daily and weekly horizons; ii) Both individuals and market makers trade against price movements on the New York Stock Exchange (NYSE); iii) Individuals' order imbalances (net trades) on the NYSE predict returns at weekly and monthly horizons; and iv) Institutions tend to be on one side of a given trade while market makers and individuals are on the other. See, for example, Hendershott and Seasholes (2007); Kaniel, Saar, and Titman (2008); Boehmer and Wu (2008); and Hendershott and Menkveld (2010).

[2] There exists an adding up constraint in our framework. The signed order flows of institutions, individuals, and market makers must sum to zero. Therefore, and when estimating our statistical model, we drop trading measures from one of the three groups (institutions).

standard microstructure identification strategy based on the joint dynamics of order flows and prices so as to separate changes in the efficient price from transitory price movements—see Hasbrouck (1993), George and Hwang (2001), and Section 4 of this paper for further discussions.[3]

Estimation of the state-space model enables estimation of the transitory component of prices and how it relates to trading variables. This is particularly relevant for empirical asset pricing studies—especially those using monthly price series. How "noisy" are these monthly data? More precisely, how large are transitory price deviations? How far do trading imbalances *push* observed prices away from fundamental values at a monthly frequency? How can we use trading measures from market participants to help answer these questions?

The data used in the estimation includes NYSE market makers' (specialists') closing inventories for each stock, at the end of each month, starting January 1999, and ending December 2005. We also obtain monthly order imbalances (buys minus sells) for individuals trading on the NYSE and over the same time period.

Our main empirical result is that the transitory component in price changes is substantial and correlates highly with the trading variables. At a monthly frequency, transitory variance is more than 25% the magnitude of idiosyncratic return variance. The amount is both statistically and economically significant. These transitory price changes themselves correlate negatively with contemporaneous market makers' inventory and individuals' net trades. In fact, these trading variables explain 40% of this transitory variance.

We also find that market maker inventory is stationary and positively autocorrelated. And, it is positively correlated with next month's individuals' net trades which is consistent with market makers being able to unwind their positions (at least in part) by trading with individuals who delay their arrival to the market. The individuals' cumulative net trades series on the other hand is nonstationary and their trading is therefore inconsistent with traditional models of market making.

The state-space model's most attractive feature is that it enables the researcher to specify how explanatory variables operate on the transitory component and on the permanent component of price change in a parsimonious way. The parameter estimates quantify how important market maker inventory and individuals' net trades are for the transitory com-

[3] Our references to a stock's "transitory component of price" is called its "pricing error" in Hasbrouck (2006, p.87).

ponent. A $100,000 deviation in a market makers's inventory is associated with a 0.20% transitory deviation in a stock's monthly price. A one standard deviation in inventory is associated with a 1.52% deviation in the transitory component and accounts for 23.53% of transitory variance. The results are larger for small stocks (0.36%, 2.43% and 37.50% respectively). A $100,000 deviation in individuals' net trades is associated with a 0.06% transitory deviation in a stock's monthly price. Because the standard deviation of individuals' net trades is large, a one standard deviation in individuals' net trades is associated with a 1.52% deviation in the transitory component and accounts for 18.18% of transitory price variance. The first two results are larger for small stocks (0.23% and 1.86% respectively).

Our empirical results are consistent with our theoretical model of imperfect risk sharing and costly participation. Market makers have low participation costs, continuously monitor the market, and trade to provide liquidity. Individuals, on the other hand, have higher participation costs and participate intermittently. Some individuals trade at the time of an initial shock; others delay their trades. When market makers unwind positions, they are able to trade with the second (delayed) group of individuals.

1.1 Related Literature

Due to our paper's goal of providing a unified framework, our results touch on a number of different literatures. First, studies of NYSE market makers (specialists) date back to Hasbrouck and Sofianos (1993) and Madhavan and Smidt (1993). Understanding of these market makers has recently been enhanced by Hendershott and Seasholes (2007) and Hendershott and Menkveld (2010). As with existing studies, we show market makers trade against price movements and later work to mean revert their inventories.

Second, a paper by Kaniel, Saar, and Titman (2008) motivates studying individuals' net trades on the NYSE. The authors study a large cross-section of NYSE stocks from January 2000 to December 2003. Individuals are shown to buy (sell) stocks that have recently fallen (risen) in price. Sorting stocks by the degree of buying and selling allows the authors to form a long-short portfolio that earns over 120 basis points in the 20 days following formation. Kaniel et al. (2010) extend this analysis by examining individual trading and return dynamics around earnings announcements. Finally, Foucault, Sraer, and Thesmar (2010) estimate that "retail trading contributes to about 23% of the volatility of stock returns" using a separate sample of French data.

Third, our paper is tangentially related to a long history of research into institutional trading. Some papers, such as Nofsinger and Sias (1999) and Cohen, Gompers, and Vuolteenaho (2002), use an adding up constraint to set individual imbalances equal to one minus institutional imbalances. More recently, Griffin, Harris, and Topaloglu (2003) and Boehmer and Wu (2008) show individuals and institutions typically have order imbalances with opposite signs, indicating these groups trade against each other (at least in part). The earlier paper studies daily and intradaily data and suggests (on p. 2316) that horizons longer than a week are needed in order to draw clear inferences about reversals (exactly our paper's approach).

Fourth, two recent papers introduce an econometric approach to disentangling permanent and transitory price changes. Menkveld, Koopman, and Lucas (2007) propose a state-space model to study price discovery in partially overlapping markets. Hendershott and Menkveld (2010) use the approach to estimate the time series properties of daily price pressures.

Fifth, our participation cost model is related to recent work by Lo, Mamaysky, and Wang (2004) and Vayanos and Wang (2009). Both papers study trading between two groups of long-term investors, while we add a third group of market makers. Our modeling of participation costs is simplified and we assume the costs only affect one group (individuals).

Finally, our work follows an older literature on transitory and permanent changes to stock prices. Poterba and Summers (1988) identify a transitory component in stock prices. In Cochrane (1994), transitory components of prices originate from time-varying risk premiums and are identified from variations in the price-dividend ratio. Our paper focuses on idiosyncratic, transitory components of prices, and relates them to trading variables. Brennan and Wang (2010) show that noise in stock returns is a priced factor in the cross-section of stock returns. Asparouhova, Bessembinder, and Kalcheva (2009) develop a correction for asset pricing tests to control for noise in observed prices. Asparouhova, Bessembinder, and Kalcheva (2010) show how asset pricing tests that use variables correlated with noise (e.g., size, skewness, and illiquidity) affect these tests.

The remainder of our paper is structured as follows. Section 2 outlines an economic framework with imperfect risk sharing and costly participation. Section 3 describes the paper's data and provides overview statistics. Section 4 estimates a state space model and produces our paper's main empirical results. Section 5 concludes.

2 Theoretical Framework

We model an economy in which two groups of long-term investors hedge their exposure to non-traded risk. We deviate from existing work by adding market makers as a third group and by assuming only one group of long-term investors pays a participation cost. A nonzero participation cost captures the notion that the opportunity cost of participating continuously in the market is higher for non-professionals (individuals) than for professionals (institutions).

The Economy: There are three dates denoted $t \in \{1, 2, 3\}$ and two assets. The first asset is a riskless security, used as the numeraire good, and assumed to have a zero rate of return. The second is a risky asset that pays $\tilde{D}_3$ units of the consumption good at t=3, where $\tilde{D}_3 = \bar{D} + \tilde{\epsilon}_2 + \tilde{\epsilon}_3$. The distribution of $\tilde{\epsilon}_t$ is normal with mean 0 and variance σ_t^2. We denote $\tilde{P}_t$ as the risky asset's price on date t with $\tilde{P}_3 = \tilde{D}_3$.

Agents: There are three types of agents in the market denoted $\{a, b, m\}$. Consider Group a to be comprised of long-term investors called "institutions", Group b to be long-term investors called "individuals", and Group m to be short-term investors called "market makers" or "arbitrageurs". Each group consists of infinitely many agents of mass zero. In aggregate, a given group has a mass of one and holds an initial endowment of θ risky assets and no riskless assets.

The agents differ along two important dimensions. First, Groups a and b have opposite exposure to a non-traded risk (for example, through an endowment process or labor income) which is perfectly correlated with the t=3 payoff of the risky asset. Second, Group b pays a participation cost in order to trade the risky asset at t=1. These differences are discussed below the following chart which helps summarize the model at t=1:

		Risk Sharing Motive to Trade	
		Yes	No
Costly Partic.	Yes	Group b Individuals	
	No	Group a Institutions	Group m Market-Makers

Participation Costs: Group a's participation cost is zero, so they can trade freely at both t=1 and t=2. Group b has a participation cost of "c" at t=1. Due to this cost, some individuals refrain from trading at t=1 leading to a "participation intensity" for the group that is denoted λ. λ is endogenous in our model. At t=2, all individuals participate. Group m's participation costs are zero.[4]

Model Timing: There is a shock to the non-traded risk exposure at $t = 1$ which induces investors to trade to rebalance their portfolios. Group a investors receive a shock $\tilde{z}^a$; Group b receives a shock $\tilde{z}^b$. Without loss of generality, and for ease of exposition, we set $\tilde{z}^a = +1$ and $\tilde{z}^b = -1$ for the remainder of this paper.[5]

At t=1, if any Group b investors do not participate, $\lambda < 1$, then the trading interests of Group a and Group b are not balanced. Market makers offset any temporary imbalances by taking positions. At t=2, all investors are present and market makers are able to unwind their positions. Part of the dividend (ϵ_2) is revealed to all investors at t=2 which is the reason why market makers need compensation as carrying the position from t=1 to t=2 becomes risky. The final dividend uncertainty (ϵ_3) gets revealed at t=3 and generates a standard risk premium in prices at t=2.

Agents' Maximization Problems: Investors maximize the expected utility of wealth at t=3 which is denoted $\mathbb{E}\big[U(W_3^j)\big]$ for Group j. We assume agents have exponential utility functions of the form $U(W_3^j) = -e^{-\delta W_3}$ where δ is the coefficient of risk aversion. Let $\bar{x}_t^j$ be the number of risky assets owned by Group j at date t. The group's excess demand is denoted $x_t^j = \bar{x}_t^j - \theta$. For example, at t=1, institutions own $x_1^a + \theta$ risky assets. We use B_t^j to denote Group j's holdings of the riskfree asset. Wealth at time t is given by $B_t^j + \bar{x}_t^j \tilde{P}_t$.

Equilibrium Prices and Holdings: We solve for equilibrium prices and holdings by backwards induction and define the expectation of $\tilde{D}_3$ at t=2 as $\mathbb{E}_2\left[\tilde{D}_3\right] = \bar{D} + \epsilon_2$. Please see Appendix A for associated proofs and expanded equations. A summary of the model's results are presented in the chart below. The term "Group $b(p)$" indicates individuals who

[4]We can consider that individual investors may not participate at short term horizons due to participation costs but in the long run they will all participate at least once in the market. Our 3-date model is stylized. Back-of-the-envelope calculations based on work by Barber and Odean (2000) and Feng and Seasholes (2008) suggest individuals adjust their stock portfolios approximately once every four months. For evidence of slow household rebalancing in aggregate risky assets see Brunnermeier and Nagel (2008).

[5]The model's results hold under a general formulation with exposures $\tilde{z}^a = \bar{z} + \tilde{z}$ and $\tilde{z}^b = \bar{z} - \tilde{z}$. To avoid inducing an aggregate risk factor into the pricing equation and having the market maker become a long-term investor, we follow Lo, Mamaysky, and Wang (2004) and set $\bar{z}$ to zero. We note that many model formulations with private gains from trade between Groups a and b would generate similar price and trading dynamics. We choose the non-traded risk approach for its elegance, its consistency with the literature, and the ease with which market makers can be incorporated.

choose to participate at both t=1 and t=2. The term "Group $b(np)$" indicates individuals who only participate at t=2.

	t=1	t=2
Price of Risky Asset	$\bar{D} - \theta\delta(\sigma_2^2 + \sigma_3^2) - \frac{1-\lambda}{\lambda+2}\delta\sigma_2^2$	$\bar{D} + \epsilon_2 - \theta\delta\sigma_3^2$
Holdings of Group a	$-\frac{2\lambda+1}{\lambda+2} + \theta$	$-1 + \theta$
Holdings of Group $b(p)$	$\lambda \cdot \left(\frac{3}{\lambda+2} + \theta\right)$	$\lambda \cdot (1 + \theta)$
Holdings of Group $b(np)$	$(1-\lambda) \cdot \theta$	$(1-\lambda) \cdot (1+\theta)$
Holdings of Group m	$\frac{1-\lambda}{\lambda+2} + \theta$	$+\theta$
Aggregate Holdings	$3\ \theta$	$3\ \theta$

The price at time t=1 is the sum of the expected future payoff ($\bar{D}$) and two terms. The first term is a risk premium of $-\theta\delta(\sigma_2^2 + \sigma_3^2)$ and stems from dividend uncertainty. The second term equals $-\frac{1-\lambda}{\lambda+2}\delta\sigma_2^2$. This is the stock price's transitory component and denoted "s_1".

$$
\begin{aligned}
s_1 &\equiv P_1 - P_1^* \\
&= P_1 - \left(\bar{D} - \theta\delta\left(\sigma_2^2 + \sigma_3^2\right)\right) \\
&= -\frac{1-\lambda}{\lambda+2}\delta\sigma_2^2
\end{aligned}
$$

The stock's transitory component represents a deviation from the risk-adjusted price that would have been observed in a frictionless world (P_1^*). Notice that s_1 is monotonically decreasing in magnitude as λ goes from zero to one. The expression above also shows that s_1 is the product of two terms. The first term, $\frac{1-\lambda}{\lambda+2}$, is the mass of trades that need to be cleared divided by the mass of traders in the market at t=1. The second term, $\delta\sigma_2^2$, is the risk premium associated with holding the risky asset until t=2. Therefore, s_1 is naturally interpreted as a liquidity premium.

Finally, we note that at t=2, the risk premium is $\theta\delta\sigma_3^2$ reflecting the remaining dividend uncertainty. The transitory price pressure has dissipated at t=2 (in our model) and does not affect the stock's total risk premium.

Endogenous Intensity Level: Individual investors are indifferent between delaying one period and participating at both t=1 and t=2 when $\mathbb{E}\left[U(W_3^{b(p)})\right] = \mathbb{E}\left[U(W_3^{b(np)})\right]$. Using this condition, we solve for the endogenously determined participation intensity:

$$
\begin{aligned}
\lambda &= \frac{3\sqrt{\delta}}{\sqrt{2c}}\sigma_2 - 2 && \text{if} \quad c \in \left(\tfrac{1}{2}\delta\sigma_2^2, \tfrac{9}{8}\delta\sigma_2^2\right) \\
&= 0 && \qquad\quad c \geq \tfrac{9}{8}\delta\sigma_2^2 \\
&= 1 && \qquad\quad c \leq \tfrac{1}{2}\delta\sigma_2^2
\end{aligned}
$$

We provide some comparative statics for the expression $\frac{3\sqrt{\delta}}{\sqrt{2c}}\sigma_2 - 2$. As participation costs go up ($c \uparrow$), participation intensity falls ($\lambda \downarrow$). As risk aversion rises ($\delta \uparrow$) or uncertainty about future dividends rises ($\sigma_2 \uparrow$), participation intensity also rises ($\lambda \uparrow$). If $c \geq \frac{9}{8}\delta\sigma_2^2$, no individual investor participates at t=1. If $c \leq \frac{1}{2}\delta\sigma_2^2$, all individual investors participate at t=1 and t=2.

2.1 Model's Testable Predictions

To test the model's predictions, please note: 1) Market clearing imposes an adding-up constraint. Therefore, and from this point onward in the paper, we focus on trading variables from two of the three participant groups (market makers and individuals). 2) As explained in Section 3, NYSE data contain individuals' net trades (Δx_t^b) but not their holdings (x_t^b). 3) Individuals' net trades are only observable for the group as a whole and denoted Δx_t^b.

	Transitory Component s_1	Market Maker Inventories $\bar{x}_1^m$	Individuals' Net Trades Δx_1^b
$\bar{x}_1^m$	−		
Δx_1^b	−	+	
Δx_2^b	−	+	+

The chart above summarizes the signs of some of our model's predictions. A list of eight predictions is shown below. Note that items 3, 4, 5, 6, and 8 represent more novel predictions of the model.

1. A stock price's transitory component is negatively related with market makers' inventory positions at t=1. From the model's results, we can show: $s_1 = -x_1^m\delta\sigma_2^2 = -(\bar{x}_1^m - \theta)\delta\sigma_2^2$. Market makers buy (sell) as prices fall (rise).

2. A stock price's transitory component is negatively related with individual investors' t=1 net trading imbalances: $s_1 = -\frac{1-\lambda}{3\lambda}\Delta x_1^b \delta \sigma_2^2$. This prediction is consistent with empirical findings in Kaniel, Saar, and Titman (2008).

3. A stock price's transitory component is negatively related with individual investors' t=2 net trading imbalances: $s_1 = -\frac{1}{2}\Delta x_2^b \delta \sigma_2^2$. Transitory components are larger in magnitude as participation intensity drops. Low participation intensity at t=1 implies "more" individuals are trading at t=2.

4. Market makers' inventories at t=1 are positively related with individual investors' net trading imbalances at t=1. Since $1 - \lambda$ individuals do not participate at t=1, market makers must "lean against the wind" to help clear the market.

5. Market makers' inventories at t=1 are positively related with individual investors' net trading imbalances at t=2. Market-makers' ability to unwind positions comes from trading with the individual investors who enter the market at t=2.

6. Individual investors' net trading imbalances are persistent. The average net trading imbalance at time t=1 is $\Delta x_1^b = \frac{3\lambda}{\lambda+2}$ and the average net trading imbalance at time t=2 is $\Delta x_2^b = \frac{2(1-\lambda)}{\lambda+2}$. In order to hedge the non-tradeable risk, individuals want to buy (or sell). A fraction λ arrives at the market at t=1 and buy (or sell). In fact, they buy more than needed at t=1 and offload the difference $\frac{\lambda(1-\lambda)}{\lambda+2}$ at t=2. They help to clear the market at t=1 and earn the liquidity premium.The remaining individuals arrive at t=2 and also want to buy (or sell).

7. Market makers' inventories are mean-reverting and they fully unwind positions built at t=1. To see this point, notice that market maker's net trading imbalances are $\Delta x_1^m = +\frac{1-\lambda}{\lambda+2}$ and $\Delta x_2^m = -\frac{1-\lambda}{\lambda+2}$. The market makers' ability to unwind positions comes from trading with the individual investors who enter the market at t=2.

8. Individual investors' participation intensity increases with the risk-aversion parameter (δ), uncertainty about future dividends (σ_2), and size of the shock to the non-traded risk (set to ± 1 in this paper). We do not test this prediction in the paper, but leave it for future research.

3 Data and Overview Statistics

We study monthly trading activity and stock prices starting January 1999 and ending December 2005 for a total of 84 months. Four sources provide the data used in this paper.

- An internal New York Stock Exchange ("NYSE") database called the Specialist Summary File (or "SPETS") contains specialists' closing inventory positions for each stock at the end of each month. The NYSE assigns one specialist per stock and a given specialist is responsible for making a market in approximately 10 stocks. Throughout this paper, we refer to market makers and their inventories using the variable "*MM*".
- An internal NYSE database called the Consolidated Equity Audit Trail Data (or "CAUD") contains the number of shares bought and sold by individual investors, for each stock, over each month. In addition, the CAUD database provides trading volume. See Kaniel, Saar, and Titman (2008) for further discussion of the CAUD database.
- The Trades and Quotes ("TAQ") database provides closing midquotes prices. Prices and returns in this paper are measured at the midquote to avoid bid-ask bounce. All prices are adjusted to account for stock splits and dividends.
- The Center for Research in Security Prices ("CRSP") provides the number of shares outstanding (used to calculate market capitalizations) and information necessary to adjust prices for stock splits/distributions.

We start with the 2,357 common stocks that can be matched across the NYSE, TAQ, and CRSP databases. We construct a balanced panel of data to ensure results are comparable throughout time. There are 1,037 stocks that exist for all 84 months in our sample period. Stocks with an average share price of less than US$ 5 or larger than US$ 1,000 are removed from the sample. The final sample consists of 1,019 stocks.

We convert market makers' inventory positions and individual net trades to US dollars (both variables are originally in numbers of shares.) For a given stock, we multiply the number of shares by the stock's sample average price so as not to introduce price changes directly into the trading variables.

Importantly, our statistical group has an unmodeled third group—institutions. We drop this group due to the adding-up constraint in our model. In other words, if we know individuals' net trades and market makers' net trades, then we know institutional net trades as well.

Finally, many results are presented after sorting stocks into size quintiles. To ensure the quintiles have constant compositions throughout the sample period, stocks are ranked based on their average market capitalizations over the entire sample period.

3.1 Summary Statistics

Table 1, Panel A presents summary statistics for seven "raw" variables. For each of the five market capitalization quintiles, we calculate each variable's average value. The smallest quintile's average market capitalization is US$ 0.26 billion while the largest quintile's is US$ 33.90 billion. The last column shows the within standard deviation is US$ 6.57 billion.

[Insert Table 1]

The table also shows overview statistics for trading volume (in millions of shares) and closing mid-quote prices. Trading variables include market makers' inventories (in both thousands of shares and dollars) and individuals' net trades. On average, market makers hold half a million U.S. dollars of inventory for large capitalization stocks. The positive average inventory values may be due to asymmetric costs as shorting may involve more expenses than holding stocks long. The within standard deviation is US$ 1.32 million and substantial relative to the average position. The large standard deviation suggests that NYSE market makers are active intermediaries.

Individuals' average net trades are negative across all size quintiles indicating that individuals' positions have been reduced over our sample period. Individual investors, on average, sell US$ 0.20 million in small-cap stocks and US$ 14.12 million in large-cap stocks each month. The within standard deviation of individual net trades is US$ 18.17 million, which is also large relative to their net trades. The summary statistics suggest individual investors trade actively at a monthly frequency.

3.2 Idiosyncratic Variables

Risks associated with market-wide return shocks can be hedged using highly-liquid index products. Therefore, our empirical analysis focuses on idiosyncratic components of our variables. For each return and trading variable, we construct a common factor equal to the monthly market capitalization weighted average of the underlying variable. We regress each variable on its common factor and save the residual as the corresponding idiosyncratic variable. This procedure is detailed in Appendix C. For notational simplicity, we omit any subsricpts or superscripts referring to "idiosyncratic," and use $MM_{i,t}$ (for example) to denote the idiosyncratic portion of the market makers' dollar inventories.

Table 1, Panel B provides summary statistics for idiosyncratic trading variables used in this paper. Since the idiosyncratic variables are defined as residuals from a market model regression, means are zero. The panel focuses on standard deviations for the five size quintiles and for the sample as a whole. We see the largest stocks have volatile inventories (US$ 2.6 million) and volatile net trades by individuals (US$ 39.5 million).

For completeness, we also report the standard deviation of idiosyncratic returns. As shown in Appendix C, $r^{idio}_{i,t}$ is stock i's residual from a regression on value-weighted market return. Small stocks have a standard deviation of 13.30% while large stocks have a standard deviation of 9.00%.

3.3 Unit Root Tests

Predictions 6 and 7 from the model, and listed in Section 2.1, imply that market makers' inventory positions should mean revert while individuals trading is not mean reverting. We test these predictions with a unit root test, which is also needed to verify stationarity of the trading variables that enter the econometric model. The augmented Dickey-Fuller test is performed on a stock-by-stock basis using the regressions below. Note that while $MM_{i,t}$ and $\Delta Indv_{i,t}$ are variables found throughout this paper, $\Delta MM_{i,t}$ and $Indv_{i,t}$ are used only for the unit root tests. All variables are defined explicitly in Appendix C.

$$\begin{aligned}
\Delta MM_{i,t} &= \alpha + \beta MM_{i,t-1} + \phi_1 \Delta MM_{i,t-1} + \ldots + \phi_4 \Delta MM_{i,t-4} + \varepsilon_{i,t} \\
\Delta Indv_{i,t} &= \alpha + \beta Indv_{i,t-1} + \phi_1 \Delta Indv_{i,t-1} + \ldots + \phi_4 \Delta Indv_{i,t-4} + \varepsilon_{i,t}
\end{aligned}$$

Table 2 presents the results of the augmented Dickey-Fuller tests. The table reports the cross-sectional mean of the β coefficients and the mean of the associated "t-statistics". The table also reports the p-value of a meta test statistic that counts the number of significant $t-$values under (over) the 10% (90%) critical value if the cross-sectional mean is negative (positive).[6] This meta test statistic is binomially distributed under null where the probability of "success" equals the significance level of the augmented Dickey-Fuller test performed for each stock. We use a 10% critical value.

[Insert Table 2]

We reject the existence of unit roots in the market makers' inventory positions at all conventional levels. 862 of the 1,019 stocks reject the null. Our results indicate that NYSE market makers behave in a manner consistent with theoretical models of market making. After building a position, market makers quickly unwind their trades and mean-revert inventories towards target levels.[7]

We fail to reject the existence of unit roots in the individual inventory positions. Cross-sectionally, we fail to reject for 968 of the 1,019 stocks at the 10%-level. Note that using the 10% threshold represents a weaker-than-normal test that still results in the vast majority of stocks failing to reject. Our results indicate that individuals do not seem to mean revert their holdings.

NYSE market makers' inventory levels are stationary, while the levels for individuals are not stationary. These results provide support for using the *level* of NYSE market makers' inventories ($MM_{i,t}$) and the *change in levels*, or net trades, of individuals' holdings ($\Delta Indv_{i,t}$) throughout the paper.

3.4 Correlations of Trading and Price Variables

Table 3 reports average correlation results—averaged across all stocks' correlation matrices. t-statistics are based on standard errors that are adjusted for contemporaneous correlations. Please see the associated Internet Appendix for a full description of the standard errors.

[6] The 10% critical value of an augmented Dickey-Fuller test is -2.57—see Cheung and Lai (1995).

[7] For related examples, see Ho and Stoll (1981), Hasbrouck and Sofianos (1993), Madhavan and Smidt (1993), and Grossman and Miller (1988).

There are five main results we focus on.

First, we note the negative autocorrelation of idiosyncratic returns is consistent with prior evidence on a transitory component in idiosyncratic prices—see Lo and MacKinlay (1990) for an example. The first-order auto-correlation coefficient is -0.07 and supports Prediction 1 from our theoretical model—see Section 2.1.

[Insert Table 3]

Second, individuals' net trades are persistent as shown by the +0.32 first order autocorrelation coefficient. The positive autocorrelation indicates individual investors holdings may not mean-revert. To further support the finding, the (unreported) second-order auto-correlation coefficient is 0.16 for $\Delta Indv$. These correlation results corroborate findings from the more formal unit root tests (Section 3.3) and support Prediction 6 from Section 2.1.

Third, individuals' net trades at t-1 are positively correlated with idiosyncratic returns at time t (+0.04), net trades at time t are negative correlated with idiosyncratic returns at time t (-0.20), and net trades at time t+1 are negatively correlated with idiosyncratic returns at time t (-0.21). We can infer that the individual investors buy stocks when prices are falling and sell later when prices go up. The future price rise appears smaller in magnitude (+0.04) than the contemporaneous price fall (-0.21). The results are consistent with Predictions 2 and 3 from Section 2.1.

Fourth, the correlation between market maker inventories and subsequent idiosyncratic returns is positive (0.06). This result suggests that temporary price deviations compensate market makers for risks associated with deviations from their optimal inventory positions.[8]

Fifth, market makers' inventory positions at t-1 are positively correlated (+0.08) with individual net trades at time t. This finding suggests that market makers (at least partially) unwind their positions by selling to individual investors. The result is consistent with Prediction 5.

We finish this section by emphasizing the general take-away from Table 3: The correlations between trading and price variables provide support for including trading variables in a state

[8] Hendershott and Menkveld (2010) provide a detailed analysis of such compensation by solving the market maker's dynamic program with inventory as a state variable.

space model.

4 State Space Model

We estimate a state space model that includes measures of market makers' inventories and individuals' net trades. The state space model assumes a stock's observed price ($p_{i,t}$) can be decomposed into two unobservable components. The first component is its efficient price ($m_{i,t}$) and the second is the transitory component ($s_{i,t}$).

$$p_{i,t} = m_{i,t} + s_{i,t} \quad (1)$$

$$m_{i,t} = m_{i,t-1} + \delta_{i,t} + \beta_i f_t + w_{i,t} \quad (2)$$

$$w_{i,t} = \kappa_i^{MM} \tilde{MM}_{i,t} + \kappa_i^{indv} \Delta \tilde{I}ndv_{i,t} + u_{i,t} \quad (3)$$

$$s_{i,t} = \alpha_i^{MM} MM_{i,t} + \alpha_i^{indv} \Delta Indv_{i,t} + \alpha_i^{D} D_{i,t} + \epsilon_{i,t} \quad (4)$$

The efficient price ($m_{i,t}$) is modeled as a process of uncorrelated increments with a nonzero drift equal to the stock's required return. This characterization is appropriate for a process that is meant to capture information arrivals. The required return ($\delta_{i,t}$) is assumed to be equal to the monthly risk free rate plus the stock's beta times a market risk premium of 6%. The increments consist of the market factor ($\beta_i f_t$) and an idiosyncratic increment ($w_{i,t}$). We note that β_i is a coefficient to be estimated while f_t represents the demeaned market return. Appendix C provides details related to calculating both $\delta_{i,t}$ and f_t.

The idiosyncratic innovation of stock i's efficient price is denoted $w_{i,t}$ and is one focus of this paper since it represents undiversifiable risk to those who temporarily hold inefficient positions (e.g., the market makers). Equation (3) defines $w_{i,t}$ for stock i over month t. Including the trading variables $\tilde{MM}_{i,t}$ and $\Delta \tilde{I}ndv_{i,t}$ in the equation is important for identification if we believe these variables may be picking up trades based on private information. Note that a tilde over the trading variable's name indicates autocorrelation has been removed using an AR(1) regression. Appendix C provides details related to calculating both $\tilde{MM}_{i,t}$ and $\Delta \tilde{I}ndv_{i,t}$.

The transitory component of price ($s_{i,t}$) is assumed to be stationary. In Equation (4), we allow for market makers' inventories ($MM_{i,t}$) and individuals' net trades ($\Delta Indv_{i,t}$) to affect the transitory component of price. $D_{i,t}$ is a dummy variable which takes a value of plus one (+1) if both $MM_{i,t}$ and $\Delta Indv_{it}$ are positive and $MM_{i,t}$ is in the top quartile of its distribution. $D_{i,t}$ takes a value of negative one (-1) if both variables are negative and $MM_{i,t}$ is in the bottom quartile of its distribution. $D_{i,t}$ is zero (0) otherwise.

While technically outside our thoeretical model, the dummy variable allows us to estimate interaction effects between market makers' and individuals' trades. One could think of a dynamic model that is more complicated than the one presented in Section 2 and that includes repeated shocks to the non-traded risk. Such shocks might lead investors to start a trading period with inefficient positions. Thus, $D_{i,t}$ could indicate times when a market maker is far from his typical inventory levels and individuals do not trade in such a manner so as to enable the market maker to unwind his position. Alternatively, $D_{i,t}$ can be thought of as a proxy for times when funding constraints are likely to be binding.[9]

4.1 Estimation Procedure

The state-space model is estimated on a stock-by-stock basis using maximum likelihood. The procedure exploits a Kalman filter. For estimation purposes, $p_{i,t}$ denotes stock i's log price. The estimation is implemented in `Ox` using standard optimization techniques. The Kalman filter routines are from `ssfpack` which is an add-on package. See Koopman, Shephard, and Doornik (1999) for additional information about related estimation procedures. The optimization procedure follows steps designed to avoid getting stuck in local maxima. Appendix B has additional details. There are at least four advantages associated with using a state space model in our setting.

1. A state space model explicitly separates short-term transitory effects from long-term permanent effects. This separation allows for parsimonious modeling of how an observed variable might affect different horizons.

2. Maximum likelihood estimation is asymptotically unbiased and efficient.

3. The state space statistical model offers a structural analysis that helps identify effects that would otherwise be unobserved. After estimation, the Kalman filter offers an in-

[9] For examples of models with funding constraints, see Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009).

sample decomposition of price time series into the efficient and transitory components. The decomposition is available at any point in the sample period using past and current prices.

4. The Kalman filter deals with missing observations in the most informationally efficient way. The model implies that the differenced price series ($\Delta p_{i,t}$) follows a MA(1) process which can be expressed as an infinite lag autoregressive model or AR(∞). It is cumbersome to estimate such a model if the price series has missing values. The Kalman filter in the state space model considers the likelihood of all level series changes even if they have missing observations over multiple periods. Methods based on differenced series typically do not consider such information.

The t-statistics reported in this section assume residuals are uncorrelated across stocks as the state-space model is estimated on a stock-by-stock basis. Estimating all stocks together is not computationally feasible. Therefore, we test the robustness of our results with an alternative model. An ARIMA model is estimated with OLS and t-statistics are based on standard errors clustered by month. Beyond the previously discussed advantages of the state space model, another drawback of the ARIMA approximation is that it requires one to add, in theory, infinite lagged polynomials in order to disentangle short- and long-term effects. A more detailed discussion of the ARIMA model, along with results that mirror those found in this paper, can be found in the associated Internet Appendix.

We begin by including only one group's trading variables at a time. Section 4.2 uses market makers' trading variables and Section 4.4 uses individuals' trading variables. Section 4.5 ends our analysis by presenting a statistical model that simultaneously considers both groups' trading variables.

4.2 Market Maker Trading Variables

We focus on the role of market makers' inventories by restricting $\kappa_i^{indv} = 0$ in Equation (3) and $\alpha_i^{indv} = 0$ and $\alpha_i^D = 0$ in Equation (4).

[Insert Table 4]

Table 4 reports our estimates. For both the efficient price equation and the transitory equation, we report three facets of results. First, we see that κ_i^{MM} = -1.10 and the negative value indicates that market makers face adverse selection. Their inventories tend to be high as prices are falling and their inventories tend to be low/negative as prices are rising. We can interpret the coefficient as the amount of fundamental price movement (in basis points) associated with every \$1,000 dollars of idiosyncratic inventory.

Second, to quantify the average effect associated with the adverse selection, we multiply the κ_i^{MM} coefficient by the standard deviation of $\tilde{MM}_{i,t}$. We see the total effect is 268 bp on average. In other words, a one standard deviation change in $\tilde{MM}_{i,t}$ is associated with a 2.68% change in the efficient price.

Finally, to assess the economic magnitude of 268 bp, we compare the number to the 972 bp shown in third column. Market makers' trading can roughly explain $\left(\frac{268^2}{972^2}\right)$ or 7.60% of the permanent variance.

The key parameter in Table 4 is α_i^{MM}. The estimated value of -0.20 is negative matching Prediction 1 from Section 2.1. The result signifies that a \$100,000 deviation in a market maker's inventory is associated with a 0.20% transitory deviation in a given stock's monthly price. Market makers' inventories are high during times of temporary negative shocks. In other words, market makers absorb excess selling pressure and are partially compensated for providing liquidity via buying at temporarily low prices (with the proviso noted in Footnote 8).

The average transitory price pressure is 152 bp as shown in the fifth column. When making cross-sectional comparisons, note that the standard deviation of market makers' inventories is higher for large-cap stocks than for small-cap stocks. This leads to a smaller range of values in column 5 than the differences α_i^{MM} might lead one to believe. As the table shows, estimated price pressure varies from 243 bp for small-cap stocks to 111 bp for large-cap stocks.

The magnitude of our price-pressure/market makers'-inventories result is larger than the related return predictability in Hendershott and Seasholes (2007). The earlier paper sorts stocks into quintiles based on market makers' inventories. Stocks in the highest quintile outperform stocks in the lowest quintile by 0.45% over the next 10 trading days. The magnitude of our results are also greater than the comparable (daily) results in Hendershott and Menkveld (2010) who find an average 0.49% price pressure associated with market makers' inventories. Our larger results suggest that there is a low frequency component to market maker inventories which is associated with substantial price distortions.

4.3 Variance Decomposition

Our state space model also allows us to decompose stock price variance. We are particularly interested in two questions asked at the start of this paper: How "noisy" are monthly data? How large are transitory price deviations? Given the state space model defined by Equations (1) to (4), the idiosyncratic return of stock i over month t is defined as: $r_{i,t}^{idio} \equiv w_{i,t} + s_{i,t} - s_{i,t-1} = w_{i,t} + \Delta s_{i,t}$. The variance of our price variables are shown below and one can think of $\sigma(w)$ as the size of permanent price changes while $\sigma(\Delta s)$ is the size of changes to the transitory component.

$$
\begin{aligned}
\sigma^2(w) &= var[\kappa_i^{MM}\tilde{M}M_{i,t} + \kappa_i^{indv}\Delta\tilde{I}ndv_{i,t}] + \sigma^2(u) \\
\sigma^2(s) &= var[\alpha_i^{MM}MM_{i,t} + \alpha_i^{indv}\Delta Indv_{i,t} + \alpha_i^D D_{i,t}] + \sigma^2(\epsilon) \\
\sigma^2(\Delta s) &= var[\alpha_i^{MM}(MM_{i,t} - MM_{i,t-1}) + \alpha_i^{indv}(\Delta Indv_{i,t} - \Delta Indv_{i,t-1}) + \alpha_i^D(D_{i,t} - D_{i,t-1})] + 2\sigma^2(\epsilon) \\
\sigma^2(r^{idio}) &= \sigma^2(w) + \sigma^2(\Delta s) + 2cov(w, \Delta s)
\end{aligned}
$$

where,

$$
\begin{aligned}
cov(w, \Delta s) = \; & cov[\kappa_i^{MM}\tilde{M}M_{i,t} + \kappa_i^{indv}\Delta\tilde{I}ndv_{i,t}, \\
& \alpha_i^{MM}(MM_{i,t} - MM_{i,t-1}) + \alpha_i^{indv}(\Delta Indv_{i,t} - \Delta Indv_{i,t-1}) + \alpha_i^D(D_{i,t} - D_{i,t-1})]
\end{aligned}
$$

The last two columns of Table 4 show the results of the variance decomposition. The ratio $(\frac{\sigma(\Delta s)}{\sigma(r^{idio})})^2$ reflects the size of transitory variance relative to idiosyncratic return variance. Across all stocks, we see a 0.17 ratio.[10] The ratio in the last column is $\frac{\sigma^2(\Delta s) - 2\sigma^2(\epsilon)}{\sigma^2(r^{idio})}$ and has a value of 0.04 across all stocks. This ratio represents the size of transitory variance that is explained by market makers' inventories relative to the idiosyncratic return variance. One can think of the numerator as the size of price pressure variance.

We end by comparing the degree of price pressure explained by market makers' inventories to the total movements of the transitory component. For all stocks, we estimate that market makers' trading accounts for $\frac{0.04}{0.17}$ or 23.53% of transitory variance. This value is 37.50%

[10] The Roll (1988, p.564, Table IV) decomposition of idiosyncratic volatility yields a noise component that is roughly 25% of idiosyncratic variance. See Foucault, Sraer, and Thesmar (2010) for further discussion.

for small stocks. Finally, note that the statistical and economic significance of these results remain qualitatively similar using an ARIMA model.

4.4 Individual Trading Variables

We focus on the role of individuals' net trades by restricting $\kappa_i^{MM} = 0$ in Equation (3) and $\alpha_i^{MM} = 0$, and $\alpha_i^D = 0$ in Equation (4).

[Insert Table 5]

Table 5 reports our estimates. We see κ_i^{indv} is negative indicating that individuals' face adverse selection. While the slope coefficient is smaller in magnitude than the market makers' coefficient (-0.08 vs. -1.10) the average effect is similar in magnitude. The second column multiplies the slope coefficient by the standard deviation of $\Delta \tilde{I}ndv_{i,t}$ to estimate a 273 bp effect. The 273 bp represents 8.4% of total variance calculated as $\frac{273^2}{941^2}$.

We focus again on the α_i^{indv} parameter which is equal to -0.06. The negative value matches Prediction 2 from Section 2.1. We interpret the results as coming from imperfect risk sharing among individual investors who find it costly to continuously participate in the market.

The conditional price pressure relating to individual investors (the α_i^{indv} coefficient) varies from -0.23 for small-cap stocks to -0.01 for large-cap stocks. The average price pressure explained by individual investors' trades is 152 bp at a monthly frequency. The economic magnitude is similar to what is associated with market makers. We find individuals' net trades explain $\frac{0.04}{0.22}$ or about 18.18% of transitory variance.

The magnitude of our price-pressure/individual-net trade results is somewhat larger than the related return predictability in Kaniel, Saar, and Titman (2008). The authors sort stocks into deciles based on individuals' past net trades. The authors find that the stocks in the highest decile outperform stocks in the lowest decile by 1.25% over the next 50 trading days. See Figure 2 of their paper. Differences between their results and ours may be due to a somewhat different sample period and/or our focus on the idiosyncratic component of individuals' net trades.

4.5 Both Market Maker and Individual Variables

Our final analysis includes both market makers' and individuals' trading variables in our state space model. One goal of this section is to test whether one group's trading variables "drive out" the other group's variables. Or, do trading variables from both groups combine to impact stock price volatility?

[Insert Table 6]

Table 6 clearly shows that both groups' trading variables play an important role in our state space model. In the efficient price equation, both κ_i^{MM} and κ_i^{indv} remain negative with values of -0.96 and -0.10.[11] Both groups buy as prices are falling and both groups tend to sell as prices are rising. The permanent volatility explained by market makers is 239 bp while the permanent volatility explained by individuals is 263 bp. These values can be compared to an average total permanent volatility of 951 basis points.

The transitory equation clarifies the value of including both groups. Both α_i^{MM} and α_i^{indv} are negative. Trades/holdings from one group do not "drive out" trades/holdings from the other group. We see α_i^{MM} is -0.21 or 160 bp of price pressure (with 114 bp for large stocks and 264 bp for small stocks). Also, α_i^{indv} is -0.04 or 151 bp of price pressure (with 149 bp for large stocks and 189 bp for small stocks).[12]

While Section 2 presents a single-shock model, a fully dynamic and recursive model may lead to a non-linear relationship between price pressure and inventories. From Table 6, we notice that the interaction coefficient, α_i^D, is negative and statistically significant. The interaction coefficient indicates that price pressure is disproportionately large at times that market makers' inventories are high and individual investors are buying.

We end our analysis with a variance decomposition based on the full state space model. It is in this section that we obtain some of the paper's main results. First, we see a 0.25 ratio in the column labeled $(\frac{\sigma(\Delta s)}{\sigma(r^{idio})})^2$. This result indicates that transitory variance due to noise

[11] The negative values, together with the market clearing constraint, imply that estimating the model with institutional net trades would yield $\kappa_i^{inst} > 0$. The result indicates that institutional traders may have value-relevant information.

[12] Table 3 shows both groups' trading variables are positively autocorrelated (0.17 for market makers and 0.32 for individuals). These autocorrelations lead to positive autocorrelation of price pressures and the total transitory component of prices. The average autocorrelation for the transitory component component of price is 0.15 (0.23 for small stocks and 0.13 for large stocks.)

in monthly returns is more than 25% the magnitude of idiosyncratic return variance. The ratio is relatively constant across our size quintiles

We also calculate how much of the transitory noise can be explained by our trading variables. The last column reports that the conditional price pressure variance explained by our trading variables is 10% the size of idiosyncratic return variance. To calculate the economic magnitude of the explained price pressure, we divide the ratios in the last two columns. Considering all stocks, the explained power of market makers' and individuals' trading variables is $\frac{0.10}{0.25} = 40.00\%$. This finding is somewhat stronger for small stocks: $\frac{0.11}{0.24} = 45.83\%$.

5 Conclusions

This paper provides a unified framework to better understand return dynamics, order flow dynamics, and return-flow interactions. We model holdings and trades of three groups of agents (institutions, individuals, and market makers).

We begin by proposing a theoretical model with agents who differ in their risk sharing motives and participation costs. Despite its relative parsimony, our framework produces numerous predictions. Some predictions support existing empirical results: a) Market makers' inventories are negatively correlated with transitory price movements; b) Individuals' net trades are negatively correlated with transitory price movements; and c) Market makers' inventories are stationary. Some predictions are new: d) Transitory price movements are negatively correlated with individuals' future net trades; e) Individuals's net trades are positively autocorrelated; and f) Market makers' inventories are positively correlated with individuals' future trades.

To test theoretical predictions, we present a state space (statistical) model in which a stock's observable price is composed of two unobservable components. The first component represents the stock's fundamental value while the second represents the transitory component of prices (including both price pressures and components unrelated to trading.) Estimating the model with monthly CRSP prices/returns and proprietary NYSE trading data allows us to ask: How large are transitory price deviations related to trading?

The state space model explicitly makes the trading variables operate both on the efficient price innovation and on the transitory component of prices. Operating on both parts is strictly necessary if one wants to establish the size of pricing errors which is otherwise not identified—see Hasbrouck (1993), George and Hwang (2001), and Menkveld, Koopman, and Lucas (2007). Model estimation produces a plethora of results. For example, we find a one standard deviation change in a market maker's inventories (or individuals' net trades) is associated with transitory volatility of 1.52% (also 1.52%). The results are larger for smaller stocks (2.43% and 1.86%). Together, trading variables from the two groups explain 40.00% of transitory variance (45.83% for small stocks). The large magnitudes of price distortions documented in our paper suggest researchers need to address the biases discussed in Asparouhova, Bessembinder, and Kalcheva (2009, 2010). Finally, we estimate that transitory variance accounts for 25% of idiosyncratic return variance at a monthly frequency.

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A Proofs for Theoretical Framework

We start with the institutional investors (Group a) at t=2. Agents choose holdings of risky ($\bar{x}_t^a$) and riskfree assets (B_t^a) to maximize the expected utility of t=3 wealth ($\mathbb{E}\left[U(W_3^a)\right]$) subject to the following constraints. We use a standard approach when solving for equilibriums in CARA-normal frameworks. Our treatment of the participation costs is motivated by Vayanos and Wang (2009).

$$\begin{aligned} W_3^a &= B_2^a + \bar{x}_2^a \tilde{P}_3 + (\tilde{D}_3 - \bar{D}) \\ W_2^a &= B_2^a + \bar{x}_2^a \tilde{P}_2 = B_1^a + \bar{x}_1^a \tilde{P}_2 \\ W_1^a &= B_1^a + \bar{x}_1^a \tilde{P}_1 = W_0^a + \theta \tilde{P}_1 \end{aligned}$$

where θ represents the initial endowment of the risky asset and W_0^a represents other initial wealth. We eliminate B_1^a and B_2^a from the equations above to obtain

$$W_3^a = W_0^a + (\tilde{P}_2 - \tilde{P}_1)(\bar{x}_1^a - \theta) + (\tilde{P}_3 - \tilde{P}_2)(\bar{x}_2^a - \theta) + \tilde{P}_3\theta + (\tilde{D}_3 - \bar{D})$$

where $\bar{x}_t^a - \theta$ is the trader's excess demand. Let $x_t^a \equiv \bar{x}_t^a - \theta$, we have

$$W_3^a = W_0 + (\tilde{P}_2 - \tilde{P}_1)x_1^a + (\tilde{P}_3 - \tilde{P}_2)x_2^a + \tilde{P}_3\theta + (\tilde{D}_3 - \bar{D}) \tag{5}$$

We assume that the agents have exponential utility function, i.e., $U(W) = -e^{-\delta W}$. By backward induction, we solve for the optimal excess demand at t=2

$$\max_{x_2^a} \mathbb{E}_2 \left[U\big(W_2 - P_2\theta + (\tilde{P}_3 - P_2)x_2^a + \tilde{P}_3\theta + (\tilde{D}_3 - \bar{D})\big)\right]$$

Using the exponential utility function,

$$\mathbb{E}_2\left[U(W_3^a)\right] = \exp\left\{-\delta[W_2 - P_2\theta + (\mathbb{E}_2[\tilde{D}_3] - P_2)x_2^a + \mathbb{E}_2[\tilde{D}_3]\theta - \frac{1}{2}\delta\sigma_3^2(x_2^a + \theta + 1)^2]\right\}$$

The optimal value for x_2^a with all means/variances conditional on the information at t=2:

$$x_2^a = \frac{\mathbb{E}_2[\tilde{D}_3] - P_2}{\delta\sigma_3^2} - (\theta + 1)$$

For the individual investors, only a fraction $\lambda \in [0, 1]$ of the group participate at t=1 while all participate at t=2. Denote the excess demand of those participating at t=1 and t=2 as $x_t^b(p)$ and the excess demand of those only participating at t=2 as $x_t^b(np)$. At t=2, the excess demands for risky assets are:

$$x_2^b = x_2^b(p) = x_2^b(np) = \frac{\mathbb{E}_2[\tilde{D}_3] - P_2}{\delta\sigma_3^2} - (\theta - 1) \tag{6}$$

Market makers have the same utility function and initial endowment as other investor types, but they do not have a non-tradable endowment of wealth at t=3. Their total excess demand at t=2 is

$$x_2^m = \frac{\mathbb{E}_2[\tilde{D}_3] - P_2}{\delta\sigma_3^2} - \theta$$

The market-clearing condition at t=2 requires that the aggregate excess demand is 0

$$x_2^a + \lambda x_2^b(p) + (1-\lambda)x_2^b(np) + x_2^m = 0$$

i.e.,

$$\frac{\mathbb{E}_2[\tilde{D}_3] - P_2}{\delta\sigma_3^2} - (\theta + 1) + \frac{\mathbb{E}_2[\tilde{D}_3] - P_2}{\delta\sigma_3^2} - (\theta - 1) + \frac{\mathbb{E}_2[\tilde{D}_3] - P_2}{\delta\sigma_3^2} - \theta = 0 \tag{7}$$

Equation (7) gives the expression for P_2:

$$\begin{aligned} \frac{\mathbb{E}_2[\tilde{D}_3] - P_2}{\delta\sigma_3^2} &= \theta \\ P_2 &= \bar{D} + \epsilon_2 - \delta\theta\sigma_3^2 \end{aligned} \tag{8}$$

The equilibrium excess demand at t=2 of each group is

$$\begin{aligned} x_2^a &= -1 \\ \lambda \cdot x_2^b(p) &= 1 \cdot \lambda \\ (1-\lambda) \cdot x_2^b(np) &= 1 \cdot (1-\lambda) \\ x_2^m &= 0 \end{aligned} \tag{9}$$

At t=1, substitute equation (8) and (9) into (5) to get

$$W_3^a = W_0 + \left(\mathbb{E}_2[\tilde{D}_3] - \theta\delta\sigma_3^2 - P_1\right) x_1^a + (\tilde{P}_3 - \mathbb{E}_2[\tilde{D}_3] + \theta\delta\sigma_3^2)(-1) + \tilde{P}_3\theta + (\tilde{D}_3 - \bar{D})$$

Solve the maximization problem of Group a and find the excess demand at t=1

$$x_1^a = \frac{\bar{D} - \theta\delta\sigma_3^2 - P_1}{\delta\sigma_2^2} - (\theta + 1)$$

Similarly, we get the excess demands of the other two groups at t=1

$$\begin{aligned} x_1^b(p) &= \frac{\bar{D} - \theta\delta\sigma_3^2 - P_1}{\delta\sigma_2^2} - (\theta - 1) \\ x_1^b(np) &= 0 \\ x_1^m &= \frac{\bar{D} - \theta\delta\sigma_3^2 - P_1}{\delta\sigma_2^2} - \theta \end{aligned}$$

Market clearing at t=1 requires

$$x_1^a + \lambda x_1^b(p) + (1-\lambda)x_1^b(np) + x_1^m = 0$$

which gives the expression below and defines P_1

$$\begin{aligned} \frac{\bar{D} - \theta\delta\sigma_3^2 - P_1}{\delta\sigma_2^2} &= \theta + \frac{1-\lambda}{\lambda+2} \\ P_1 &= \bar{D} - \theta\delta(\sigma_2^2 + \sigma_3^2) - \frac{1-\lambda}{\lambda+2}\delta\sigma_2^2 \end{aligned}$$

and the equilibrium excess demand of the three groups at t=1 is

$$\begin{aligned} x_1^a &= -\frac{2\lambda+1}{\lambda+2} \\ \lambda \cdot x_1^b(p) &= \frac{3\lambda}{\lambda+2} \\ (1-\lambda)\cdot x_1^b(np) &= 0 \\ x_1^m &= \frac{1-\lambda}{\lambda+2} \end{aligned}$$

Now we determine the participation intensity λ of individual investors. Participating at t=1 provides the ability to better hedge the non-traded risk but costs c. In equilibrium, individual investors are indifferent between participating and not participating at t=1: $\mathbb{E}_1\left[U(W_3^b(p))\right]$. Equating the expected utility of these two groups yields:

$$\begin{aligned} & \mathbb{E}_1\left[\exp\left\{-\delta[W_0 + (\tilde{P}_2 - P_1)x_1^b(p) + (\tilde{P}_3 - \tilde{P}_2)x_2^b + \tilde{P}_3\theta - (\tilde{D}_3 - \bar{D}) - c]\right\}\right] \\ = \ & \mathbb{E}_1\left[\exp\left\{-\delta[W_0 + (\tilde{P}_3 - \tilde{P}_2)x_2^b + \tilde{P}_3\theta - (\tilde{D}_3 - \bar{D})]\right\}\right]. \end{aligned}$$

Note that the x_2^b term on both sides of the equation does not carry the additional label (p) or (np) as they are the same, see equation (6).

B Implementing the State Space Model

Estimation of the state space model is described for the model with only market makers' inventories.

$$
\begin{aligned}
p_{i,t} &= m_{i,t} + s_{i,t} \\
m_{i,t} &= m_{i,t-1} + \delta_{i,t} + \beta_i f_t + w_{i,t} \\
w_{i,t} &= \kappa_i \tilde{MM}_{i,t} + u_{i,t} \\
s_{i,t} &= \alpha_i MM_{i,t} + \epsilon_{i,t}
\end{aligned}
$$

The procedure consists of essentially two steps:

1. Estimate β_i using a standard CAPM regression.

2. Maximize the likelihood by the quasi-Newton method developed by Broyden, Fletcher, Goldfarb, and Shanno.

   The likelihood is calculated using the Kalman filter. To speed convergence, the optimization runs only over the parameters $(\sigma_i(u),\ \sigma_i(\epsilon))$. The remaining parameters (κ_i, α_i) are specified as unobserved (constant) states. The 'true' time-varying unobserved state is the efficient price $m_{i,t}$. All remaining variables are known. The likelihood is based on a diffuse initial state for $(\kappa_i, \alpha_i, m_{i,t})$, i.e., a random variable with infinite variance (see Durbin and Koopman (2001)).

   The trick of making (κ_i, α_i) a state along with the diffuse initialization of the states allows us to invoke the envelope theorem as, implicitly, the likelihood has been optimized relative to the parameters (κ_i, α_i). The remaining function is smooth and well-behaved in $(\sigma_i(u),\ \sigma_i(\epsilon))$ so as to avoid finding local maxima.

Kalman filter calculations and the optimization is implemented in `Ox` with the add-on package `ssfpack` for various filter routines. The benefit of this implementation is that the filters are coded in `C` so that calculations are extremely fast. The implementation of a standard state space model is described in Koopman, Shephard, and Doornik (1999). Our model translates into this standard framework as follows:

$$\Phi = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{pmatrix} \qquad J_\Phi = \begin{pmatrix} -1 & 0 & -1 \\ -1 & -1 & -1 \\ -1 & -1 & -1 \\ -1 & -1 & 1 \end{pmatrix}$$

$$\Omega = \begin{pmatrix} \sigma^2(u) & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma^2(\epsilon) \end{pmatrix} \qquad \Sigma = \begin{pmatrix} -1 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 \\ 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

$$\Delta = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \qquad J_\Delta = \begin{pmatrix} 2 \\ -1 \\ -1 \\ -1 \end{pmatrix} \qquad X_t = \begin{pmatrix} \tilde{M}M_{i,t} \\ MM_{i,t} \\ \delta_{i,t} + \beta_i f_t \end{pmatrix}$$

C Variable Definitions

β_i	Stock i's beta coefficient from standard CAPM regression.
$D_{i,t}$	Interaction of market makers' and individuals' trading. $D_{i,t} = +1$ if $MM_{i,t} > 0$, $\Delta Indv_{i,t} > 0$, and $MM_{i,t} \in$ Q1 $D_{i,t} = -1$ if $MM_{i,t} < 0$, $\Delta Indv_{i,t} < 0$, and $MM_{i,t} \in$ Q4 $D_{i,t} = 0$ otherwise Q1 and Q4 represent the high/low quartiles of $MM_{i,t}$'s distribution.
$\delta_{i,t}$	Required return of stock i's over month t. Defined as: $\delta_{i,t} = r_{f,t} + \beta_i \left(1.06^{\frac{1}{12}} - 1\right)$.
f_t	Demeaned series of market-wide returns. Defined as: $f_t = r_{m,t} - \bar{r}_m$.
γ_t^{Indv}	Common (market-wide) cumulative net trading factor at the end of month t. Defined as: $\gamma_t^{Indv} = \sum_i \omega_i \times Indv_{i,t}^{std}$. Where ω_i is the weight of stock i in our "market" of 1,019 stocks.
γ_t^{MM}	Common (market-wide) inventory factor at the end of month t. Defined as: $\gamma_t^{MM} = \sum_i \omega_i \times MM_{i,t}^{std}$.
$\Delta\gamma_t^{Indv}$	Net trading of common factor over month t: $\Delta\gamma_t^{Indv} = \gamma_t^{Indv} - \gamma_{t-1}^{Indv}$.
$Indv_{i,t}^{sh}$	Individuals' cumulative net trading (in shares) of stock i at the end of month t.
$Indv_{i,t}^{\$}$	Individuals' cumulative net trading (in dollars) of stock i at the end of month t. Defined as: $Indv_{i,t}^{\$} = Indv_{i,t}^{sh} \times \overline{P}_i$.
$Indv_{i,t}^{std}$	Standardized value of Individuals' cumulative net trading of stock i at the end of month t. Defined as: $Indv_{i,t}^{std} = \frac{Indv_{i,t}^{\$} - \overline{Indv}_{i,t}^{\$}}{std\left(Indv_{i,t}^{\$}\right)}$.
$Indv_{i,t}$	Idiosyncratic part of individuals' cumulative net trading. Defined as: $Indv_{i,t} = \varepsilon_{i,t}$ from the regression: $Indv_{i,t}^{\$} = \alpha + \beta \cdot \gamma_t^{Indv} + \varepsilon_{i,t}$.
$\Delta Indv_{i,t}^{\$}$	Individuals' net trading (in dollars) of stock i's at the end of month t. Defined as: $\Delta Indv_{i,t}^{\$} = Indv_{i,t}^{\$} - Indv_{i,t-1}^{\$}$.

$\Delta Indv_{i,t}$	Idiosyncratic part of net trading. Defined as: $\Delta Indv_{i,t} = \varepsilon_{i,t}$ from the regression $\Delta Indv^{\$}_{i,t} = \alpha + \beta \cdot \Delta\gamma_t^{Indv} + \varepsilon_{i,t}$.
$\Delta\tilde{I}ndv_{i,t}$	Defined as the residual from an AR(1): $\Delta\tilde{I}ndv_{i,t} = \varepsilon_{i,t}$ from the regression: $\Delta Indv_{i,t} = \phi_0 + \phi_1 \Delta Indv_{i,t-1} + \varepsilon_{i,t}$.
$MktCap_{i,t}$	Market capitalization of stock i, in dollars, at the end of month t.
$\overline{MktCap}_i$	Average market capitalization of stock i, in dollars, over the sample period.
$MM^{sh}_{i,t}$	Market Maker's inventory (in shares) of stock i at the end of month t.
$MM^{\$}_{i,t}$	Market Maker's inventory (in dollars) of stock i at the end of month t. Defined as: $MM^{\$}_{i,t} = MM^{sh}_{i,t} \times \overline{P}_i$.
$MM^{std}_{i,t}$	Standardized value of market maker's inventory of stock i's at the end of month t. Defined as: $MM^{std}_{i,t} = \frac{MM^{\$}_{i,t} - \overline{MM}^{\$}_{i,t}}{std\left(MM^{\$}_{i,t}\right)}$.
$MM_{i,t}$	Idiosyncratic part of market maker's inventory. Defined as: $MM_{i,t} = \varepsilon_{i,t}$ from the regression: $MM^{\$}_{i,t} = \alpha + \beta \cdot \gamma_t^{MM} + \varepsilon_{i,t}$.
$\tilde{M}M_{i,t}$	Defined as the residual from an AR(1): $\tilde{M}M_{i,t} = \varepsilon_{i,t}$ from the regression $MM_{i,t} = \phi_0 + \phi_1 MM_{i,t-1} + \varepsilon_{i,t}$.
$\Delta MM_{i,t}$	Defined as: $MM_{i,t} - MM_{i,t-1}$.
$P_{i,t}$	Price of stock i, in dollars, at the end of month t.
$\overline{P}_i$	Average price of stock i, in dollars, over the sample period.
$p_{i,t}$	Natural log of stock i's price at the end of month t.
$r_{f,t}$	Return of riskfree rate over month t from Ken French's website.
$r_{i,t}$	Return of stock i's over month t: $r_{i,t} = p_{i,t} - p_{i,t-1}$.
$r_{m,t}$	Value-weighted market return from CRSP.
$\bar{r}_m$	Average of the market wide return over the sample period: $\bar{r}_m = \frac{1}{84}\sum_{t=1}^{84} r_{m,t}$.
$r^{idio}_{i,t}$	Idiosyncratic portion of stock i's return. Defined as: $r^{idio}_{i,t} = \xi_{i,t}$. from the regression: $r_{i,t} = \alpha + \beta_i r_{m,t} + \xi_{i,t}$.

Table 1: Summary Statistics

The table presents summary statistics of our monthly data. Four sources provide data used in this paper: SPETS, CAUD, TAQ, and CRSP. We construct a balanced panel that contains monthly observations of 1,019 NYSE common stocks starting January 1999 and ending December 2005. Stocks are sorted into constant-composition quintiles based on market capitalizations. The first quintile (Q1) contains the smallest stocks. Panel A shows quintile means and the within standard deviation. Panel B considers demeaned idiosyncratic variables.

Panel A: Raw Variables

Variable	Description	Units	Source	Small Q1	Q2	Q3	Q4	Large Q5	Within Stdev[a]
MarCap$_{it}$	Market capitalization	\$ billion	CRSP	0.26	0.75	1.63	4.19	33.90	6.57
Volume$_{it}^{sh}$	Average daily share volume	Millions	TAQ	0.05	0.14	0.29	0.69	2.39	0.66
P_{it}	Closing midquote price[b]	\$	NYSE	16.61	25.22	32.94	40.42	58.67	18.74
MM_{it}^{sh}	Market Makers' closing inventory	1,000 shares	NYSE	5.93	2.77	3.12	5.40	13.04	40.55
$MM_{it}^{\$}$		\$ 1,000[b]	NYSE/CRSP	69.48	50.52	63.02	134.94	530.98	1,315
$\Delta Indv_{it}^{sh}$	Individual's net trades	1,000 shares	NYSE	-12.85	-29.66	-44.88	-81.43	-313.32	529.3
$\Delta Indv_{it}^{\$}$		\$ 1,000[b]	NYSE/CRSP	-195	-683	-1,160	-2,589	-14,116	18,170

Notes: The number of observations is equal to N × T = 1,019 × 84 = 85,586.

[a] Based on deviations from time-series means i.e. $x_{i,t}^{*} = x_{i,t} - \overline{x}_i$.

[b] We adjust all price series to account for stock splits and dividends.

Panel B: Stdev of Idiosyncratic Variables

Variable	Description	Units		Small Q1	Q2	Q3	Q4	Large Q5	Within Stdev
$MM_{i,t}$	Market Makers' inventory	$ 1,000	Std-Avg	275.4	347.4	553.8	888.8	2,623.4	1,275.0
$\Delta Indv_{i,t}$	Individual's net trades	$ 1,000	Std-Avg	1,088.0	2,883.8	3,978.5	7,574.8	39,505.0	18,062.0
$r_{i,t}^{idio}$	Idiosyncratic returns	%	Std-Avg	13.30	11.85	10.74	10.17	9.00	11.11

Table 2: Augmented Dickey-Fuller Tests

This table presents results of augmented Dickey-Fuller tests. We report the cross-sectional mean of the β coefficient. Below the coefficients, and in parentheses, we report the cross-sectional means of the associated t-statistics. We consider variables from market makers and individuals:

$$\Delta MM_{i,t} = \alpha + \beta MM_{i,t-1} + \phi_1 \Delta MM_{i,t-1} + \ldots + \phi_4 \Delta MM_{i,t-4} + \varepsilon_{i,t}$$

$$\Delta Indv_{i,t} = \alpha + \beta Indv_{i,t-1} + \phi_1 \Delta Indv_{i,t-1} + \ldots + \phi_4 \Delta Indv_{i,t-4} + \varepsilon_{i,t}$$

The p-values, reported in square brackets, are based on a test statistic that counts the number of significant augmented Dickey-Fuller test statistics across all stock-estimates in the bin. The test statistic is binomial distributed under the null (we use the 0.10 or 0.90 critical values from the DF-test). The data are monthly starting January 1999 and ending December 2005.

		Market Makers	Individuals
All	β-Avg	-0.782	-0.019
	T-Avg	(-3.52)	(-0.82)
	P-value	[0.00]	[1.00]
Q1 (Small)	β-Avg	-0.606	-0.023
	T-Avg	(-3.28)	(-0.95)
	P-value	[0.00]	[0.95]
Q2	β-Avg	-0.815	-0.020
	T-Avg	(-3.64)	(-0.84)
	P-value	[0.00]	[0.99]
Q3	β-Avg	-0.830	-0.018
	T-Avg	(-3.62)	(-0.83)
	P-value	[0.00]	[0.99]
Q4	β-Avg	-0.846	-0.020
	T-Avg	(-3.60)	(-0.86)
	P-value	[0.00]	[0.99]
Q5 (Large)	β-Avg	-0.813	-0.014
	T-Avg	(-3.44)	(-0.62)
	P-value	[0.00]	[0.99]

# of Obs: N $\times$ T = 1,019 $\times$ 84 = 85,586.

Table 3: Correlations of Trading and Price Variables

This table presents correlations of idiosyncratic inventories of NYSE market makers ($MM_{i,t}$), individuals' net trades ($\Delta Indv_{i,t}$), and the idiosyncratic part of monthly returns ($r_{i,t}^{idio}$). A full description of all variables is given in the text and in Appendix C. Correlations are calculated on a stock-by-stock basis using the entire January 1999 to December 2005 sample period. The table shows average correlation matrices (across stocks). t-statistics are reported in parentheses and standard errors are adjusted for contemporaneous correlations across the stocks.

		Lag -1 month			Contemporaneous			Fwd +1 month		
		MM_{-1}	$\Delta Indv_{-1}$	r_{-1}^{idio}	MM	$\Delta Indv$	r^{idio}	MM_{+1}	$\Delta Indv_{+1}$	r_{+1}^{idio}
All	MM_t	0.17			1.00			0.17		
		(10.3)						(10.3)		
	$\Delta Indv_t$	0.08	0.32		0.06	1.00		0.02	0.32	
		(15.5)	(24.7)		(10.9)			(3.3)	(24.7)	
	r_t^{idio}	0.06	0.04	-0.07	-0.25	-0.20	1.00	-0.05	-0.21	-0.07
		(6.5)	(5.1)	(-4.1)	(-35.8)	(-28.6)		(-6.4)	(-30.5)	(-4.1)
Q1 (Small)	MM_t	0.33			1.00			0.33		
		(20.2)						(20.2)		
	$\Delta Indv_t$	0.14	0.33		0.08	1.00		0.04	0.33	
		(13.7)	(21.9)		(7.7)			(3.7)	(21.9)	
	r_t^{idio}	0.04	0.05	-0.07	-0.33	-0.14	1.00	-0.10	-0.23	-0.07
		(2.9)	(4.6)	(-3.3)	(-25.8)	(-12.6)		(-7.4)	(-21.1)	(-3.3)
Q2	MM_t	0.14			1.00			0.14		
		(7.6)						(7.6)		
	$\Delta Indv_t$	0.09	0.29		0.07	1.00		0.03	0.29	
		(9.3)	(19.8)		(7.1)			(2.7)	(19.8)	
	r_t^{idio}	0.08	0.05	-0.08	-0.27	-0.18	1.00	-0.06	-0.20	-0.08
		(6.2)	(4.2)	(-3.7)	(-25.0)	(-17.4)		(-4.5)	(-18.9)	(-3.7)
Q3	MM_t	0.13			1.00			0.13		
		(6.5)						(6.5)		
	$\Delta Indv_t$	0.06	0.29		0.04	1.00		0.01	0.29	
		(6.4)	(19.9)		(4.3)			(1.5)	(19.9)	
	r_t^{idio}	0.07	0.04	-0.08	-0.23	-0.19	1.00	-0.03	-0.20	-0.08
		(5.9)	(3.4)	(-4.0)	(-21.9)	(-19.5)		(-2.9)	(-20.1)	(-4.0)
Q4	MM_t	0.11			1.00			0.11		
		(6.2)						(6.2)		
	$\Delta Indv_t$	0.08	0.33		0.06	1.00		0.02	0.33	
		(8.6)	(22.2)		(6.9)			(1.8)	(22.2)	
	r_t^{idio}	0.04	0.03	-0.06	-0.24	-0.22	1.00	-0.05	-0.21	-0.06
		(3.5)	(2.4)	(-2.8)	(-24.0)	(-21.3)		(-4.1)	(-20.5)	(-2.8)
Q5 (Large)	MM_t	0.12			1.00			0.12		
		(6.6)						(6.6)		
	$\Delta Indv_t$	0.05	0.38		0.04	1.00		-0.00	0.38	
		(5.2)	(24.4)		(4.8)			(-0.6)	(24.4)	
	r_t^{idio}	0.05	0.04	-0.09	-0.20	-0.26	1.00	-0.03	-0.20	-0.09
		(5.0)	(3.0)	(-4.2)	(-21.3)	(-25.1)		(-2.8)	(-17.8)	(-4.2)

# of Obs: N × T = 1,019 × 84 = 85,586.

Table 4: State Space Model with NYSE Market Makers' Inventories

This table presents estimates from a state space model that includes NYSE market makers' inventories and is shown below. $p_{i,t}$ is the observable log price of stock i at the end of month t. $m_{i,t}$ is the unobservable efficient price. $s_{i,t}$ is the unobservable transitory component of prices. $\delta_{i,t}$ is the required rate of return.

$$\begin{aligned} p_{i,t} &= m_{i,t} + s_{i,t} \\ m_{i,t} &= m_{i,t-1} + \delta_{i,t} + \beta_i f_t + w_{i,t} \\ w_{i,t} &= \kappa_i^{MM} \tilde{MM}_{i,t} + u_{i,t} \\ s_{i,t} &= \alpha_i^{MM} MM_{i,t} + \epsilon_{i,t} \end{aligned}$$

Full descriptions and definitions of variables are given in Appendix C. The model is estimated on a stock-by-stock basis using maximum likelihood estimates where the error terms u_{it} and $\epsilon_{i,t}$ are assumed to be normally and independently distributed. The optimization is implemented in Ox with `ssfpack` routines. A Kalman filter is used to evaluate the likelihood function. Δs is the change in the transitory component and $r_{i,t}^{idio} = w_{i,t} + \Delta s_{i,t}$ is the idiosyncratic return implied from the state space model. The ratio $(\frac{\sigma(\Delta s)}{\sigma(r^{idio})})^2$ reflects the size of transitory variance relative to idiosyncratic return variance. $\frac{\sigma^2(\Delta s) - 2\sigma^2(\epsilon)}{\sigma^2(r^{idio})}$ represents the size of price pressure caused by market makers' inventories relative to the idiosyncratic return variance. The table reports t-values in parentheses and we assume zero correlations among stocks.

	Efficient Price Equation			Transitory Equation			Variance Decomposition	
	κ_i^{MM}	$\lvert\kappa_i^{MM}\rvert \times \sigma(\tilde{MM})$	$\sigma(w)$	α_i^{MM}	$\lvert\alpha_i^{MM}\rvert \times \sigma(MM)$	$\sigma(\Delta s)$	$(\frac{\sigma(\Delta s)}{\sigma(r^{idio})})^2$	$\frac{\sigma^2(\Delta s)-2\sigma^2(\epsilon)}{\sigma^2(r^{idio})}$
All	-1.10	268	972	-0.20	152	368	0.17	0.04
	(-30.1)			(-6.7)				
Q1 (Small)	-3.22	446	1192	-0.36	243	443	0.16	0.06
	(-20.2)			(-2.7)				
Q2	-1.09	282	1045	-0.32	164	391	0.16	0.05
	(-16.1)			(-6.2)				
Q3	-0.56	212	931	-0.20	122	329	0.15	0.04
	(-12.9)			(-6.1)				
Q4	-0.45	229	910	-0.08	122	323	0.15	0.04
	(-15.6)			(-3.4)				
Q5 (Large)	-0.15	171	780	-0.05	111	352	0.21	0.04
	(-10.7)			(-4.4)				

# of Obs: N × T = 1,019 × 84 = 85,586.

Table 5: State Space Model with Individuals' Net Trades

This table presents estimates from a state space model that includes individuals' net trades and is shown below. $p_{i,t}$ is the observable log price of stock i at the end of month t. $m_{i,t}$ is the unobservable efficient price. $s_{i,t}$ is the unobservable transitory component of prices. $\delta_{i,t}$ is the required rate of return.

$$\begin{aligned} p_{i,t} &= m_{i,t} + s_{i,t} \\ m_{i,t} &= m_{i,t-1} + \delta_{i,t} + \beta_i f_t + w_{i,t} \\ w_{i,t} &= \kappa_i^{indv} \Delta \tilde{I}ndv_{i,t} + u_{i,t} \\ s_{i,t} &= \alpha_i^{indv} \Delta Indv_{i,t} + \epsilon_{i,t} \end{aligned}$$

Full descriptions and definitions of variables are given in Appendix C. The model is estimated on a stock-by-stock basis using maximum likelihood estimates where the error terms $u_{i,t}$ and $\epsilon_{i,t}$ are assumed to be normally and independently distributed. The optimization is implemented in Ox with `ssfpack` routines. A Kalman filter is used to evaluate the likelihood function. Δs is the change in the transitory component, and $r_{i,t}^{idio} = w_{i,t} + \Delta s_{i,t}$ is the idiosyncratic return implied from the state space model. The ratio $(\frac{\sigma(\Delta s)}{\sigma(r^{idio})})^2$ reflects the size of transitory variance relative to idiosyncratic return variance. $\frac{\sigma^2(\Delta s) - 2\sigma^2(\epsilon)}{\sigma^2(r^{idio})}$ represents the size of price pressure caused by individuals' net trades relative to the idiosyncratic return variance. The table reports t-values in parentheses and we assume zero correlations among stocks.

	Efficient Price Equation			**Transitory Equation**			**Variance Decomposition**	
	κ_i^{indv}	$\lvert\kappa^{indv}\rvert \times \sigma(\Delta\tilde{I}ndv)$	$\sigma(w)$	α_i^{indv}	$\lvert\alpha_i^{indv}\rvert \times \sigma(\Delta Indv)$	$\sigma(\Delta s)$	$(\frac{\sigma(\Delta s)}{\sigma(r^{idio})})^2$	$\frac{\sigma^2(\Delta s)-2\sigma^2(\epsilon)}{\sigma^2(r^{idio})}$
All	-0.08 (-6.5)	273	941	-0.06 (-6.5)	152	450	0.22	0.04
Q1 (Small)	-0.14 (-2.3)	278	1139	-0.23 (-4.8)	186	536	0.22	0.04
Q2	-0.13 (-11.7)	280	1018	-0.05 (-4.7)	155	474	0.21	0.04
Q3	-0.07 (-11.4)	261	893	-0.03 (-4.9)	127	423	0.21	0.03
Q4	-0.04 (-13.8)	280	886	-0.01 (-4.0)	140	403	0.21	0.04
Q5 (Large)	-0.01 (-14.7)	268	763	-0.01 (-6.2)	152	415	0.25	0.05

# of Obs: N × T = 1,019 × 84 = 85,586.

Table 6: State Space Model with Both Market Makers and Individuals

This table presents estimates from a state space model that includes NYSE market makers' inventories and individuals' net trading. $p_{i,t}$ is the observable log price of stock i at the end of month t. $m_{i,t}$ is the unobservable efficient price. $s_{i,t}$ is the unobservable transitory component of prices. $\delta_{i,t}$ is the required rate of return.

$$
\begin{aligned}
p_{i,t} &= m_{i,t} + s_{i,t} \\
m_{i,t} &= m_{i,t-1} + \delta_{i,t} + \beta_i f_t + w_{i,t} \\
w_{i,t} &= \kappa_i^{MM} \tilde{M}M_{i,t} + \kappa_i^{indv} \Delta \tilde{I}ndv_{i,t} + u_{i,t} \\
s_{i,t} &= \alpha_i^{MM} MM_{i,t} + \alpha_i^{indv} \Delta Indv_{i,t} + \alpha_i^D D_{i,t} + \epsilon_{i,t}
\end{aligned}
$$

Full descriptions and definitions of variables (including the interaction dummy $D_{i,t}$) are given in Appendix C. The model is estimated on a stock-by-stock basis using maximum likelihood estimates where the error terms u_{it} and $\epsilon_{i,t}$ are assumed to be normally and independently distributed. The optimization is implemented in Ox with `ssfpack` routines. A Kalman filter is used to evaluate the likelihood function. Δs is the change in the transitory component, and $r_{i,t}^{idio} = w_{i,t} + \Delta s_{i,t}$ is the idiosyncratic return implied from the state space model. The ratio $(\frac{\sigma(\Delta s)}{\sigma(r^{idio})})^2$ reflects the size of transitory variance relative to idiosyncratic return variance. $\frac{\sigma^2(\Delta s) - 2\sigma^2(\epsilon)}{\sigma^2(r^{idio})}$ represents the size of price pressure caused by trading variables relative to the idiosyncratic return variance. The table reports t-values in parentheses and we assume zero correlations among stocks.

	Efficient Price Equation					Transitory Equation						Variance Decomposition	
	κ_i^{MM}	$\lvert\kappa_i^{MM}\rvert \times \sigma(\tilde{M}M)$	κ_i^{indv}	$\lvert\kappa_i^{indv}\rvert \times \sigma(\Delta \tilde{I}ndv)$	$\sigma(w)$	α_i^{MM}	$\lvert\alpha_i^{MM}\rvert \times \sigma(MM)$	α_i^{indv}	$\lvert\alpha_i^{indv}\rvert \times \sigma(\Delta \hat{I}ndv)$	α_i^D	$\sigma(\Delta s)$	$(\frac{\sigma(\Delta s)}{\sigma(r^{idio})})^2$	$\frac{\sigma^2(\Delta s)-2\sigma^2(\epsilon)}{\sigma^2(r^{idio})}$
All	-0.96	239	-0.10	263	951	-0.21	160	-0.04	151	-65.79	519	0.25	0.10
	(-26.3)		(-8.4)			(-6.5)		(-4.8)		(-9.3)			
Q1 (Small)	-2.85	395	-0.24	257	1159	-0.47	264	-0.16	189	-91.67	623	0.24	0.11
	(-17.6)		(-4.2)			(-3.2)		(-3.5)		(-4.9)			
Q2	-0.94	259	-0.13	267	1024	-0.28	161	-0.03	156	-93.81	557	0.24	0.11
	(-14.2)		(-11.6)			(-4.9)		(-3.3)		(-5.4)			
Q3	-0.49	193	-0.08	261	904	-0.17	132	-0.02	121	-63.31	486	0.23	0.09
	(-12.2)		(-12.4)			(-4.7)		(-3.7)		(-4.3)			
Q4	-0.38	202	-0.04	271	895	-0.11	128	-0.01	139	-40.71	466	0.24	0.10
	(-13.7)		(-13.3)			(-4.3)		(-3.0)		(-2.8)			
Q5 (Large)	-0.13	145	-0.01	260	769	-0.05	114	-0.00	149	-39.06	462	0.28	0.10
	(-9.5)		(-13.7)			(-3.9)		(-5.2)		(-3.0)			

# of Obs: N × T = 1,019 × 84 = 85,586.