Risk Sharing, Costly Participation, and Monthly Returns

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Abstract

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Keywords: Transitory Volatility, Liquidity
JEL Number: G12, G14

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1 Introduction

Financial economics has seen a recent surge of empirical research on trader types, order imbalances, liquidity, and return predictability. 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 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.[1]

The goal of our paper is to provide a unified framework that integrates the above results. 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 simplicity, our model produces numerous predictions regarding return dynamics, order flow dynamics, and return-flow dynamics.[2] These predictions are both consistent with results mentioned in the opening paragraph and new.

To test predictions of our model, we estimate a statistical state-space model. We start with the hypothesis that a stock's observable market price reflects both information about the stock's fundamental value (known as its "efficient price") and the effects of transitory liquidity shocks (known as "price pressure"). Neither the efficient, nor the transitory, price is observable. We introduce trading measures (market maker inventories and individuals' order imbalances) into the estimation and then employ a Kalman filter to disentangle changes in a stock's fundamental value from transitory price pressure.[3]

Estimation of the state-space model raises additional, possibly broader, questions that are relevant to empirical asset pricing studies using monthly stock prices and returns. How "noisy" are these data? More precisely, how large are transitory price deviations around

[1] For examples, see Hendershott and Seasholes (2007); Hendershott and Menkveld (2010); Kaniel, Saar, and Titman (2008); and Boehmer and Wu (2008).

[2] Note that any prediction involving order flows can be produced each of the three investor groups.

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

fundamental values? How far do trading imbalances *push* prices away from fundamentals at a monthly frequency? How can we use trading measures from market participants to help answer these questions?

In this paper, we study monthly prices and returns of NYSE stocks. Our dataset includes NYSE specialists' (market makers') 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 first empirical result is that, at a monthly frequency, transitory price pressure is more than 28% the magnitude of efficient price variation. The amount is both statistically and economically significant. The Kalman filter provides time series estimates of a stock's efficient prices and associated price deviations. We are then able to study correlations of changes in efficient prices, price deviations, and trading measures from different market participants. These correlations, along with our theoretical model, provide support for including trading measures directly into the state space estimation.

Including trading measures into the state space model produces a plethora of results. We briefly summarize the findings here, while noting that results 1, 2, 3, 5, and 9 below represent some of this paper's main empirical contributions:

1. Specialists' inventories are negatively correlated with transitory price movements.

   (New) In terms of magnitude, a $100,000 deviation in a specialist's inventory is associated with a 0.25% transitory deviation in a stock's monthly price. A one standard deviation in inventories is associated with a 1.58% deviation in transitory prices and accounts for 12.22% of transitory price variance. The results are larger for small stocks (0.50%, 2.48% and 30.10% respectively).

2. Individuals' net trades are negatively correlated with transitory price movements.

   (New) In terms of magnitude, a $100,000 deviation in individuals' net trades is associated with a 0.06% transitory deviation in a stock's monthly price (but, the standard deviations of individuals' net trades are large.) A one standard deviation in individuals' net trades is associated with a 1.66% deviation in transitory prices and accounts for 13.49% of transitory price variance. The results are larger for small stocks (0.17, 1.97%, and 19.00% respectively).

3. (New) Transitory price movements this month are negatively correlated with individuals' net trades next month.

4. Specialists' inventories and individuals' net trades are contemporaneously and positively correlated. Both groups can be said to trade against price movements.

5. (New) Specialists' inventories are positively correlated with individuals' future net trades. This result is consistent with specialists being able to unwind their positions (at least in part) by trading with individuals who arrive to the market with "delay".

6. Individuals' net trades are positively auto-correlated. There is no evidence that individuals mean revert their positions nor do they appear to manage inventory risk. In brief, individuals do not act in a manner consistent with traditional models of market making.

7. Specialists' inventories are negatively auto-correlated indicating this group manages inventory risk in a manner consistent with traditional models of market making.

8. Specialists are (partially) compensated for providing immediacy via return reversals. Their respective inventories and net trades are positively correlated with future returns.

9. (New) Our two trading variables provide separate and complementary information about transitory price pressure. When both variables are included/interacted in our state-space model, they explain 37.81% of transitory variance (59.73% for small stocks). Put differently, downward (upward) transitory price pressure is particularly severe when specialists are long (short) and individuals are buying (selling).

Our empirical results are consistent with our theoretical model of imperfect risk sharing and costly participation. Market makers have low participation costs and continuously monitor the market. They are able to quickly trade against price movements. 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 specialists date back to Madhavan and Smidt (1993) and have recently been enhanced by Hendershott and Seasholes (2007) and Hendershott and Menkveld (2010). As with these studies, we show specialists trade against price movements and later work to mean revert their inventories.

Second, a paper by Kaniel, Saar, and Titman (2008) is our motivation for 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.

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, 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).

Fourth, two recent papers introduce an econometric approach to disentangling permanent and transitory price changes. Menkveld, Koopman, and Lucas (2007) proposes a state-space model to study price discovery in partially overlapping markets. Hendershott and Menkveld (2010) uses the approach to estimate the time series properties of daily price pressures. These properties are shown to identify the deep parameters from a stylized model of an intermediary who dynamically controls his inventory.

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).

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 base case version of the state space model. The base case version does not use trading variables. Section 5 introduces trading variables into the state space model and produces this paper's main empirical results. Section 6 concludes.

2 Theoretical Framework

We model an economy in which two groups of long-term investors hedge non-traded risky income. 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 $t = \{1, 2, 3\}$ 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 $\{a, b, m\}$. All are assumed to be present with measure zero. For concreteness, 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". For simplicity, each group is assumed to be mass one and have an initial endowment of θ risky asset shares and no riskless assets.

The agents differ along two important dimensions. First, Groups a and b have opposite exposure to a non-traded risk 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 costs are discussed directly below a chart which helps summarize the model:

		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 costs are 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. At t=2, all individuals participate. Importantly, λ is endogenously determined in this model. Group m's participation costs are zero.[4]

Timing of the Model: There is a shock to the non-traded risk at t=1 which induces investors to trade. Group a investors receive a shock equal to $+z(\tilde{D}_3 - \bar{D})$ of the consumption good and Group b receives a shock $-z(\tilde{D}_3 - \bar{D})$. Without loss of generality, we set z=1 for the remainder of this paper.

Part of the dividend (ϵ_2) is revealed to all investors at t=2 which also induces investors to trade. The final part of the dividend (ϵ_3) is revealed to all investors at t=3. At t=1, orders in the market may not be balanced due to the delay of $(1 - \lambda)$ investors from Group b. Market makers offset temporary imbalances by taking positions. At t=2, all investors are present and market makers are able to unwind their positions.

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 asset units 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 $x_1^a + \theta$ of the risky asset. We use B_t^j to denote group j's holdings of the riskfree asset. Wealth at time t is given by $B_t^j + \bar{x}_{t-1}^j \tilde{P}_t$.

[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. We envisage $\sigma_3^2 >> \sigma_2^2$ so that date t=2 can be thought of as a shorter-term horizon while date t=3 represents a longer-time horizon.

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 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 is $-\frac{1-\lambda}{\lambda+2}\delta\sigma_2^2$ which we define to be price pressure and denote "s_1".

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

Our defined price pressure variable represents a deviation from the risk-adjusted price that would have been observed in a frictionless world (P_1^*). Intuitively, s_1 is the mass of trades that need to be cleared (by the market-markers) divided by the mass of agents in the market at t=1. Notice that s_1 is monotonically decreasing in magnitude as λ goes from zero to one. The price pressure also represents the premium charged by market makers as compensation for providing liquidity and clearing the market (a type of liquidity premium/discount).

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 total risk premium term.

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

$$\lambda \;=\; \frac{3\sqrt{\delta}}{\sqrt{2c}}\sigma_2 - 2$$

We provide some comparative statics for the expression above. As 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 participation costs $c > \frac{9}{8}\delta\sigma_2^2$, no individual investor participates at t=1. If $c < \frac{1}{2}\delta\sigma_2^2$, 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) There is 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.

With the above three notes in mind, the chart below displays the sign of six predicted relations from the model. The first six bullet points come directly from the chart. Bullet points 2, 3, 4, 5, 6, and 8 represent rather novel predictions of the model.

	Price Pressure 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	−	+	+

1. Price pressure 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 transitory prices fall (rise).

2. Price pressure is negatively related with individual investors' t=1 net trading imbalances: $s_1 = -\frac{1}{2}\left(1 + \Delta x_1^b\right)\delta\sigma_2^2$. This prediction supports empirical findings from Kaniel, Saar, and Titman (2008).

3. Price pressure is negatively related with individual investors' t=2 net trading imbalances: $s_1 = -\frac{1}{2}\Delta x_2^b \delta\sigma_2^2$. Price pressure is 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 "step-in" to help clear the market.

5. Market makers' inventories at t=1 are positively related with individual investors' net trading imbalances at t=2. Part of the 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). Some come the market at t=1 and buy (or sell). 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 $\Delta x_2^m = -\frac{1-\lambda}{\lambda+2}$. Part of 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 this 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 each month. The NYSE assigns one specialist per stock and a given specialist is responsible for approximately ten stocks.
- 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 the 2,357 common stocks 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 specialists' 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. Using end-of-month prices would infect/negate the explanatory role of trading variables (for transitory prices) in the Section 4 and 5 econometric models.

Importantly, our statistical group has an unmodeled third group—institutions. We drop this group due to adding up constraints 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 specialists' inventories (in both thousands of shares and dollars) and individuals' net trades. On average, specialists hold half a million U.S. dollars of inventory for large capitalization stocks. The positive average inventory values may be due to asymmetric costs and 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 specialists 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 participate actively at a monthly frequency.

3.2 Idiosyncratic Variables

Risks associated with market-wide return shocks can be hedged using highly-liquid index products. In addition, aggregate inventories of liquidity providers are exposed to market-wide return shocks. Therefore, our empirical analysis focuses almost entirely 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 D. For notational simplicity, we omit any subsricpts or superscripts referring to "idiosyncratic," and use $Spec_{i,t}$ to denote the idiosyncratic portion of the specialists' dollar inventories (for example).

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. See Appendix D. 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 (2,623.4 in thousands of dollars) and volatile net trades by individuals (39,505.0 also in thousands of dollars).

For completeness, we also report the standard deviations of idiosyncratic returns. As shown in Appendix D, $r_{i,t}^{idio}$ is stock i's residual from a regression on current and lagged innovations in the common return factor. Small stocks have an standard deviation of 13.74% while large stocks have a standard deviation of 10.31%.

3.3 Unit Root Tests

We test for mean-reversion of specialists' and individuals' positions. The augmented Dickey-Fuller test is performed on a stock-by-stock basis using the regressions below. Note that while $Spec_{i,t}$ and $\Delta Indv_{i,t}$ are used throughout the paper, $\Delta Spec_{i,t}$ and $Indv_{i,t}$ are used only for this test. All variables are defined explicitly in Appendix D.

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

Table 2 presents the results of the augmented Dickey-Fuller tests. The table reports the cross-sectional mean of the β coefficients and 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).[5] 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 estimation. We use a 10% critical value

[Insert Table 2]

We reject the existence of unit roots in the specialists' inventory positions at all conventional levels. A total of 862 of the 1,019 stocks reject the null. Our results indicate that NYSE specialists behave in a manner consistent with theoretical models of market making. After building a position, specialists quickly undo their trades and mean-revert inventories towards target levels.[6]

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. Our results indicate that, at the aggregate level, individuals do not mean revert their holdings. The numbers of significant $t-$values are available in the posted supplementary material.[7]

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

4 Price Decomposition—Base Case

This section presents the base case version of our state space (statistical) model. The base case only uses price and innovations to prices (i.e., no trading variables) when decomposing a stock i's (observed) price into two unobserved components. The first is called the "efficient

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

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

[7]See http://dl.dropbox.com/u/5179651/supplementarytables.pdf. We also test individual inventories using 5% critical values. However, the 10% threshold represents a weaker-than-normal test, that still ends with 968 out of 1,019 stocks failing to reject.

price" and reflects the stock's fundamental value. In our statistical model, the efficient price follows a martingale process and is denoted $m_{i,t}$ throughout the paper. The second component is called the "transitory price" and represents price pressure. The transitory component is denoted $s_{i,t}$ and is stationary.[8]

The model is estimated on a stock-by-stock basis. For estimation purposes, we use stock i's log price, expressed in basis points, after removing a required return. We denote this price as $p_{i,t}$. The required return is equal to the monthly risk free rate plus the stock's beta times a market risk premium of 6%. Appendix D provides details of the associated calculations. All values are at the end of a given month t. The base case state space model consists of the following three equations:

$$
\begin{aligned}
p_{i,t} &= m_{i,t} + s_{i,t} && (1)\\
m_{i,t} &= m_{i,t-1} + \beta_i f_t + w_{i,t} && (2)\\
s_{i,t} &= \phi_i s_{i,t-1} + \beta_{i,0} f_t + \ldots + \beta_{i,3} f_{t-3} + \epsilon_{i,t} && (3)
\end{aligned}
$$

Above, f_t represents the innovation of a common (market-wide) factor. Additional information about calculating f_t is given in Appendix D. 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. The f_t terms in the transitory price equation captures current and lagged adjustment to common factor innovation. $\epsilon_{i,t}$ is the idiosyncratic innovation of the stock's transitory price pressure.

Both $w_{i,t}$ and $\epsilon_{i,t}$ are assumed to be normal and independent in the base case estimation. We revisit this assumption in Section 5 when we include trading variables in the state space model. Price pressure persistence is accounted for by the auto-regressive term in the transitory ($s_{i,t}$) equation. The AR(1) coefficient, ϕ_i, is constrained to be nonnegative.

The model is estimated with maximum likelihood and exploits a Kalman filter. The estimation is implemented in Ox using standard optimization routines. The Kalman filter routines

[8]We are aware that the contemporaneous correlation between an efficient price innovation and a shock to the transitory component is not identified econometrically in the absence of trade information—see Menkveld, Koopman, and Lucas (2007) for an example. The base case model serves as exploratory analysis, sets the correlation to be zero, and effectively orthogonalizes the transients effects. In canonical microstructure models, the correlation is positive and identified by trade variables. For example, an unexpected buy carries both information and causes price pressure. Section 5 provides a full model with trading variables that identify the contemporaneous correlation.

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 three advantages associated with using a state space model. First, maximum likelihood estimation is asymptotically unbiased and efficient. Second, the statistical model offers a structural analysis that helps identify effects that would otherwise be unobserved. After estimation, the Kalman filter offers an in-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. Third, the Kalman filter helps to deal with missing observations in a simple way and without losing information. The model implies 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 do not consider such information.

Table 3 presents the base case estimates. Looking at all stocks, we see an estimated value of 849 basis points for the standard deviation of $w_{i,t}$. Transitory shocks are persistent as shown by the 0.35 value of ϕ_i. The fourth column shows the total standard deviation associated with transitory shocks. We calculate the total as $\left(\frac{\sigma(\epsilon)^2}{1-\phi_i^2}\right)^{\frac{1}{2}}$ and find it is equal to 452 basis points on average. The value of 452 basis points is key to analysis in Section 5 where we use the value as a point of comparison for the amount of idiosyncratic volatility that can be explained by our trading variables.

[Insert Table 3]

Table 3 shows the expected result that fundamental volatility is higher in smaller stocks. For the smallest quintile, $\sigma(w)$ is 1,059 bp; for the largest quintile, $\sigma(w)$ is 691 bp. Interestingly, the autocorrelation coefficient, ϕ_i, does not vary significantly across size quintiles.

To assess the economic importance of the (total) transitory shock, we calculate the ratio of transitory variance to efficient price variance. Using the numbers on the top row of Table 3, we see $\frac{452^2}{849^2} = 28.34\%$ suggesting price pressure is economically large at a monthly frequency.

The finding that transitory price variance is 28.34% the magnitude of efficient price variance at a monthly frequency represents the first empirical contribution of this paper.

4.1 Correlations of Trading and Price Variables

We use the estimated coefficients from Table 3 and a Kalman filter to extract estimated changes to a stock's efficient price as well as the estimated price pressure. We can also calculate the idiosyncratic portion of a stock's returns. We then correlate these return/price variables with the idiosyncratic portion of specialists' inventories and individuals' net trades.

The Kalman filter gives the conditional expectation of stock i's efficient price at time t. We denote this quantity as $\hat{m}_{i,t} = E\left[m_{i,t}|\mathcal{P}_{i,t}\right]$ where $\mathcal{P}_{i,t}$ represents the set containing all current and past prices.[9] We define the return (or change) of the efficient price and the price pressure of stock i for month t as:

$$\begin{aligned} \Delta\hat{m}_{i,t} &= E\left[m_{i,t}|\mathcal{P}_{i,t}\right] - E\left[m_{i,t-1}|\mathcal{P}_{i,t-1}\right] \\ \hat{s}_{i,t} &= p_{i,t} - \hat{m}_{i,t} \end{aligned}$$

We calculate a correlation matrix for each stock, across five variables, using current and lagged values, and using all 84 months of data. The five variables are: $Spec_{i,t}$, $\Delta Indv_{i,t}$, $r^{idio}_{i,t}$, $\Delta\hat{m}_{i,t}$, and $\hat{s}_{i,t}$. Appendix D provides details for all five variables.

Table 4 reports average correlation results—averaged across all stocks' correlation matrices. There are six main results we focus on. First, we note the negative autocorrelation of idiosyncratic returns confirms our conjecture about transitory price deviations. The first-order auto-correlation coefficient is -0.06 and can be found by looking in the top section of the table labeled "All" stocks 3^{rd} row (r^{idio}) and under "Lag 1 month" 3^{rd} column (r^{idio}_{-1}).

[Insert Table 4]

Second, using the -0.06 autocorrelation of r^{idio} along with the -0.03 (unreported) second-order autocorrelation, we can roughly calculate the implied ratio of transitory volatility and permanent volatility. The estimate is 31.58% and compares to the estimated value of

[9] Additional details about the Kalman filter are provided in Appendix B.

28.34% in the base-case state space model (see the end of the previous section.) Appendix C provides details of our implied ratio calculation. The estimate of 31.58% is important because its shows that, although autocorrelation coefficients appear small in magnitude (-0.06 and -0.03), they can still explain a large fraction of permanent volatility (31.58%).

Third, individuals' net trades are persistent as shown by the +0.31 first order autocorrelation coefficient. As discussed earlier, the positive autocorrelation indicates individual investors holdings do not mean-revert. To further support the finding, note that the (unreported) second-order auto-correlation coefficient is 0.16 for $\Delta Indv$.

Fourth, individuals' net trades at t-1 are positively correlated with idiosyncratic returns at time t (+0.03), net trades at time t are negative correlated with idiosyncratic returns at time t (-0.17), and net trades at time t+1 are negatively correlated with idiosyncratic returns at time t (-0.17). 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 (+0.03) than the contemporaneous price fall (-0.17).

Fifth, the correlation between specialist inventories and subsequent idiosyncratic returns is positive (0.05). The negative contemporaneous correlation between price pressure and specialist inventories (-0.09), suggests that the deviations from the specialists' optimal inventory positions are partially compensated by the temporary price deviation.[10] There is a negative contemporaneous correlation between efficient price change and specialist inventory (-0.23).

Sixth, the +0.07 coefficient shows that the specialists' inventory positions at t-1 are positively correlated with individual net trades at time t. This finding suggests that specialists (at least partially) unwind their positions by selling to individual investors.

We finish this section by emphasizing the general take-away from Table 4: The correlations between trading variables and price variables provide support for adding trading variables into the state space model.

[10] The compensation is complex. Hendershott and Menkveld (2010) show that price pressure can slow the arrival rate of traders which reduces the intermediarys revenues.

5 Trading Variables and Price Decomposition

This section uses measures of specialists' and individuals' trading as explanatory variables in the state space model. We begin by including only one group's trading variables at a time. Section 5.1 uses specialists' trading variables and Section 5.2 uses individuals' trading variables. Section 5.3 ends our analysis by presenting a statistical model that simultaneously considers both groups' trading variables. The full state space model with both groups' trading variables is given by:

$$
\begin{aligned}
p_{i,t} &= m_{i,t} + s_{i,t} \\
m_{i,t} &= m_{i,t-1} + \beta_i f_t + w_{i,t} \\
w_{i,t} &= \kappa_i^{spec} \tilde{S}pec_{i,t} + \kappa_i^{indv} \Delta \tilde{I}ndv_{i,t} + u_{i,t} && (4) \\
s_{i,t} &= \alpha_i^{spec} Spec_{i,t} + \alpha_i^{indv} \Delta Indv_{i,t} + \alpha_i^{D} D_{i,t} + \beta_{i,0} f_t + \ldots + \beta_{i,3} f_{t-3} + \epsilon_{i,t} && (5)
\end{aligned}
$$

Because Table 4 shows trading variables are negatively correlated with changes to the efficient price, we add the trading variables to the innovation of the efficient price in Equation (4). Our goal is to avoid a potential omitted variable bias. The tilde over the first letter of a variable indicates autocorrelation has been removed using an AR(1) regression. Appendix D provides details.

Including trading variables in Equation (4) is important if we believe these variables may be picking up informed trades. In this way, κ_i^{spec} and κ_i^{indv} help control for the possibility of informed trading.

Table 4 also provides intuition that transitory price deviations can be explained by inventories and net order balances. Therefore, we add specialist inventory positions and individual net trades to the transitory prices in Equation (5). $D_{i,t}$ is a dummy variable which takes a value of plus one (+1) if both $Spec_{i,t}$ and $\Delta Indv_{it}$ are positive and $Spec_{i,t}$ is in the top quartile of its distribution. $D_{i,t}$ takes a value of negative one (-1) if both variables are negative and $Spec_{i,t}$ is in the bottom quartile of its distribution. $D_{i,t}$ is zero (0) otherwise.

The dummy variable, $D_{i,t}$, allows us to estimate interaction effects between specialists' and individuals' trades. One could think of a dynamic model that is more complicated than the one presented in Section 2 and includes autocorrelated shocks to the non-traded risk. Such shocks might lead investors to start a trading period with inefficient positions. Alternatively, $D_{i,t}$ can be thought of as a proxy for times when funding constraints are likely to be binding.[11]

5.1 Specialist Trading Variables

We focus on the role of specialists' inventories by restricting $\kappa_i^{indv} = 0$ in Equation (4) and $\alpha_i^{indv} = 0$, and $\alpha_i^D = 0$ in Equation (5).

[Insert Table 5]

Table 5 reports our estimates. For both the efficient price equation and the transitory price equation, we report three facets of results. First, we see that κ_i^{spec} = -1.08 and the negative value indicates that specialists face adverse selection worries. Their inventories tend to be high as price 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^{spec} coefficient by the standard deviation of $\tilde{S}pec_{i,t}$. We see the total effect is 269 bp on average. In other words, a one standard deviation change in $\tilde{S}pec_{i,t}$ is associated with a 2.69% change in the efficient price.

Finally, to assess the economic magnitude of 269 bp, we compare the number to the 954 bp shown in third column. Specialists' trading can roughly explain $\left(\frac{269^2}{954^2}\right)$ or 7.95% of the permanent variance.

The key parameter in Table 5 is α_i^{spec}. The estimated value of -0.25 has the conjectured negative sign and signifies that a $100,000 deviation in a specialist's inventory is associated with a 0.25% transitory deviation in a given stock's monthly price. Specialists' inventories are high during times of temporary negative shocks. In other words, specialists absorb excess selling pressure and are partially compensated for providing liquidity via buying at temporarily low prices (with the proviso noted in Footnote 10). The α_i^{spec} coefficient is statistically significant as 263 of the 1,019 stocks produce significantly negative estimates, 683 are insignificant, and only 73 are significantly positive.

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

The average transitory price pressure is 158 bp as shown in the fifth column.[12] When making cross-sectional comparisons, note that the standard deviation of specialists' 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^{spec} might lead one to believe. As the table shows, estimated price pressure varies from 248 bp for small-cap stocks to 121 bp for large-cap stocks.

The magnitude of our price-pressure/specialists'-inventories result is larger than the related return predictability in Hendershott and Seasholes (2007). The earlier paper sorts stocks into quintiles based on specialists' 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 specialists' inventories. Our larger results suggest that there is a low frequency component to specialist inventories which is associated with substantial price distortions.

We end by comparing price pressure explained by specialists' inventories to the total transitory price movement of 452 bp shown in Table 3. For all stocks, we estimate that specialists' trading accounts for $\left(\frac{158^2}{452^2}\right)$ or 12.22% of temporary price variation. The value is 30.10% for small stocks.

5.2 Individual Trading Variables

We focus on the role of individuals' net trades by restricting $\kappa_i^{spec} = 0$ in Equation (4) and $\alpha_i^{spec} = 0$, and $\alpha_i^D = 0$ in Equation (5).

[Insert Table 6]

Table 6 reports our estimates. We see κ_i^{indv} is negative indicating that individuals' face adverse selection worries. While the slope coefficient is smaller in magnitude that the specialists' coefficient (-0.09 vs. -1.08) 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 268 bp effect. The 268 bp represents 8.3% of total variance calculated as $\frac{268^2}{929^2}$.

[12] One cannot calculate the 158 bp by multiplying the -0.25 coefficient by the standard deviation of $Spec_{i,t}$ shown in Table 1B due to correlation between transitory price pressure and inventory levels.

We focus again on the α_i^{indv} parameter, which is equal to -0.06 and has the conjectured negative sign. It is statistically significant as 264 of the 1,019 stocks estimates are significantly negative, 692 are insignificant and only 63 are significantly positive. 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 -0.17 for small-cap stocks to -0.01 for large-cap stocks. The average price pressure explained by individual investors' trades is 166 bp at a monthly frequency. The economic magnitude is similar to what is associated with specialists. We find individuals' net trades explain $\frac{166^2}{452^2}$ or about 13.49% of transitory price volatility (19.00% for small stocks).

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 earlier paper sorts 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. Our results may differ due to a somewhat different sample period and/or our focus on the idiosyncratic component of individuals' net trades.

5.3 Both Specialist and Individual Variables

Our final analysis includes both specialists' and individuals' trading variables in our state space model. The relevant parts of the full statistical model are shown in Equations (4) and (5). One goal of this section is to test whether one group's trading variables "drives out" the other group's variables. Or, do trading variables from both groups combine to explain stock price volatility?

[Insert Table 7]

Table 7 clearly shows that both groups' trading variables play an important role in our state space model. In the efficient price equation, both κ_i^{spec} and κ_i^{indv} remain negative with values of -0.96 and -0.09. The negative values imply that $\kappa_i^{inst} > 0$ indicating that institutional traders may have value-relevant information. Both groups buy as prices are falling and both groups tend to sell as prices are rising. The permanent volatility explained by specialists is

246 bp while the permanent volatility explained by individuals is 259 bp. These values can be compared to an average total permanent volatility of 930 basis points.

The transitory price equation clarifies the value of including both groups. Both α_i^{spec} 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^{spec} is -0.26 or 167 bp of price pressure (with 132 bp for large stocks and 263 bp for small stocks). Also, α_i^{indv} is -0.05 or 164 bp of price pressure (with 167 bp for large stocks and 196 bp for small stocks).

While Section 2 presents a single-shock model, a fully dynamic and recursive model in which market makers have funding constraints may lead to a non-linear relationship between price pressure and inventories. From Table 7, we notice that the interaction coefficient, α_i^D, is negative. The interaction coefficient indicates that price pressure is disproportionately large at times that specialists' inventories are high and individual investors are buying.

We calculate explained transitory price pressure using all the α estimates from the transitory price equation in Table 7. We also use variance-covariance matrix of the estimated α's although this matrix is not reported. Shown below are results for "All" stocks.

$$\begin{aligned}
\hat{\alpha}_{All} &= \begin{bmatrix} \alpha^{spec} \\ \alpha^{indv} \\ \alpha^{D} \end{bmatrix} = \begin{bmatrix} -0.26 \\ -0.05 \\ -65.42 \end{bmatrix} \\
\hat{\Sigma}_{All} &= Cov\left(\hat{\alpha}_{All}\right)
\end{aligned}$$

The volatility of the explained transitory price pressure is the square root of the variance calculated as: $\left(\hat{\alpha}'\hat{\Sigma}\hat{\alpha}\right)^{0.5} = 277.93$ basis points. When we look at the size quintiles, this volatility is 379.47 bp for small stocks and 241.08 bp for large stocks. To calculate the economic magnitude of the explained price pressure, we divide by the base-case variance of transitory price deviations from Table 3.

$$\frac{\hat{\alpha}'\hat{\Sigma}\hat{\alpha}}{452^2} = \frac{277.93^2}{452^2} = 37.81\%$$

The above represents the final contribution of our paper. We find specialists' and individuals' trading variables are 37.81% the magnitude of monthly transitory price variance. This finding is even stronger for small stocks as $\frac{379.47^2}{491^2} = 59.73\%$.

6 Conclusions

This paper provides a unified framework to better understand return dynamics, order flow dynamics, and return-flow dynamics. 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 simplicity, our framework produces numerous predictions. Some predictions support existing empirical results: a) Specialists' inventories are negatively correlated with transitory price movements; b) Individuals' net trades are negatively correlated with transitory price movements; and c) Specialists' inventories are negatively autocorrelated. 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) Specialists' 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 transitory price pressure. Estimating the model with monthly CRSP prices/returns and proprietary NYSE trading data allows us to ask: How large are transitory price deviations around fundamental values? Using our base case state space model, we estimate that transitory price pressure accounts for 28% of efficient price variation at a monthly frequency.

We use a Kalman filter to produce time-series estimates of the two unobservable components. We are able to estimate correlations of efficient price changes, transitory price pressures, and trading variables from two NYSE groups. We show specialists inventories (and individuals' net trades) are negatively correlated with past/current returns and positively correlated with future returns.

We add our trading variables to the state space model. The statistical framework allows us to control for the possibility that our trading variables pick up changes in a stock's fundamental value. This level of control allows us to better focus on transitory price pressure. The state space model produces a plethora of results. For example, we find a one standard deviation change in a specialist's inventories (or individuals' net trades) is associated with transitory volatility of 1.55% (or 1.66%). The results are larger for smaller stocks (2.48% or 1.97%). Together, trading variables from the two groups explain 37.81% of transitory variance (59.73% 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).

We end by noting directions for future research. First, we could solve a fully-recursive model with auto-correlated shocks to the non-traded risk. Second, our model could be expanded to include a fourth investor type. Perhaps institutions could be split into two groups such as pension funds and hedge funds. Modeling four groups would allow the statistical analysis to include trading variables from three groups of investors. Third, we could link price pressure to (mis)allocation of capital and the impact on investors' welfare. All directions are interesting; all represent considerable departures from this paper.

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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:

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

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

$$W_3^a = W_0 + (\tilde{P}_2 - \tilde{P}_1)x_1^a + (\tilde{P}_3 - \tilde{P}_2)x_2^a + \tilde{P}_3\theta + (\tilde{D}_3 - \bar{D}) \tag{6}$$

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,

$$\mathbb{E}_2\left[U(W_3^a)\right] = \exp\left\{ -\delta[W_2 - P_2\theta + (\mathbb{E}_2[\tilde{D}_3] - P_2)x_2^a + \mathbb{E}_2[\tilde{D}_3]\theta + \tilde{\epsilon}_1 - \frac{1}{2}\delta\sigma_3^2(x_2^a + \theta + 1)^2] \right\}$$

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 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 of risky assets are:

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

Market makers have the same utility function and initial endowment as other investor types, but they don't 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 express for P_2:

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

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 (6) 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

$$\begin{aligned} x_1^b(p) &= \frac{\bar{D} - \theta\delta\sigma_3^2 - P_1}{\delta\sigma_1^2} - (\theta - 1) \\ x_1^b(np) &= 0 \\ x_1^m &= \frac{\bar{D} - \theta\delta\sigma_3^2 - P_1}{\delta\sigma_1^2} - \theta \end{aligned}$$

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.

$$\mathbb{E}_1[U(W_3^b(p))] = \exp\big\{ - \delta[W_0 + (\mathbb{E}_1[\tilde{P}_2] - P_1)x_1^b(p) + (\mathbb{E}_1[\tilde{P}_3] - \mathbb{E}_1[\tilde{P}_2])x_2^b(p) + \mathbb{E}_1[\tilde{P}_3]\theta - c$$

$$-\frac{1}{2}\delta\sigma_2^2(x_1^b(p) + \theta - 1)^2 - \frac{1}{2}\delta\sigma_3^2(x_2^b(p) + \theta - 1)^2]\big\}$$

If individuals only participate at t=2, the expected utility of terminal wealth at t=1 is

$$\mathbb{E}_1\left[U(W_3^b(np))\right] = \exp\big\{ - \delta\big(W_0 + \Big(\mathbb{E}_1[\tilde{P}_3] - \mathbb{E}_1[\tilde{P}_2]\Big)\, x_2^b(np) + \mathbb{E}_1[\tilde{P}_3]\theta - \frac{1}{2}\delta\sigma_2^2(\theta-1)^2 - \frac{1}{2}\delta\sigma_3^2\left(x_2^b(np) + \theta - 1\right)^2\big)\big\}$$

B Likelihood Optimization

This section is referenced from Appendix B of Hendershott and Menkveld (2010). The likelihood of the state space model described by Equations (1), (2), and (3) is optimized in essentially three steps so as to minimize the probability of finding a local maximum. The optimization is implemented in Ox using standard optimization routines. It uses a Kalman filter from `ssfpack` which is an add-on package in Ox—see Koopman, Shephard, and Doornik (1999).

1. An OLS regression of log price difference on contemporaneous and lagged f_t yields starting values for β_i and $\beta_{i,0}, \ldots, \beta_{i,3}$. See Equations (2) and (3). These β estimates are fixed at these values until the final step.

2. The likelihood is calculated using the Kalman filter, see Durbin and Koopman (2001), and optimized numerically using the quasi-Newton method developed by Broyden, Fletcher, Goldfarb, and Shanno. In the optimization all parameters are free except for the βs and $(\sigma(\epsilon), \varphi)$. The latter runs over a nine by nine grid where φ ranges from 0.0 to 0.8 and $\sigma(\epsilon)$ ranges from 0 to a stock-specific upper bound that is calculated assuming that 80% of a stock's unconditional variance is price pressure. The likelihoods are compared across all 81 optimizations and the $(\sigma(\epsilon), \varphi)$ value that yields the highest likelihood is kept as starting value for the final optimization. The rationale for this step is to prevent numerical instability of the quasi-Newton optimization. That is, if all parameters are free on arbitrary starting values the optimization routine often runs off to a persistence parameter φ that approaches its upper bound of and price pressure variance approaches the stock's unconditional variance. The optimizer starts to load the observed price series on two nonstationary series, i.e., the efficient price and the price pressure, and becomes unstable.

   In the state space model, the distribution of the initial state $s_{i,0}$ follows $s_{i,0} \sim N(0, \frac{\sigma_\epsilon^2}{1-\phi^2})$ while the distribution of $m_{i,0}$ is unknown given the state is non-stationary. We follow the convention in Durbin and Koopman (2001) to represent $m_{i,0}$ as having a diffuse prior density, i.e., a random variable with infinite variance. Some people suggest an alternative approach which assumes that $m_{i,0}$ is an unknown constant and estimate it by maximum likelihood from the first observation $p_{i,0}$. In §5.7.3 of Durbin and Koopman (2001), they show that the diffuse initialization of the Kalman filter is the same as assuming that the initial state is fixed and unknown and estimating it from the first observation for the general linear Gaussian state space model. The reason for adopting diffuse initialization is that it is more efficient than the other approach in computation—see §5.7.5 of Durbin and Koopman (2001).

3. The likelihood is optimized where all parameters are free and starting values for: β_i, $\beta_{i,0}$, …, $\beta_{i,3}$, $\sigma(\epsilon)$, φ are equal to those found in steps 1 and 2.

This procedure proves numerically stable as we have strong convergence in the likelihood optimization for all of our stock-year samples, i.e., convergence both in (i) the likelihood elasticity with respect to its parameters and (ii) the one-step change in parameter values. They both become arbitrarily small.

C Estimating the Magnitude of Transitory Volatility

If the transitory price follows $s_t = \phi s_{t-1} + \epsilon_t$, the first and second order autocorrelation of midquote return are:

$$\rho_1 = \frac{-(1-\phi)\cdot\sigma(\epsilon)^2}{(1+\phi)\cdot\sigma(w)^2 + 2\sigma(\epsilon)^2}$$

$$\rho_2 = \frac{-\phi(1-\phi)\cdot\sigma(\epsilon)^2}{(1+\phi)\cdot\sigma(w)^2 + 2\sigma(\epsilon)^2}$$

The implied ratio of transitory volatility over permanent volatility is:

$$\begin{aligned}
\frac{\frac{\sigma(\epsilon)^2}{1-\phi^2}}{\sigma(w)^2} &= -\frac{\rho_1^3}{(\rho_1 + 2\rho_1^2 - \rho_2)(\rho_1 - \rho_2)} \\
&= -\frac{(-0.06)^3}{(-0.06 + 2(-0.06)^2 + 0.03)(-0.06 + 0.03)} \\
&= 31.58\%
\end{aligned}$$

D Variable Definitions

**	Indicates a variable used throughout the paper.
*	Indicates a variable used infrequently in Tables 2 to 7.

Price Variables:

	$P_{i,t}$	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.
	$p^{ln}_{i,t}$	Natural log of stock i's price at the end of month t.
**	$p_{i,t}$	Adjusted price of stock i's after subtracting its required return. Defined as: $p_{i,t} = p^{ln}_{i,t} - \delta_{i,t}$ where $\delta_{i,t}$ is defined below.
	$\hat{m}_{i,t}$	Estimate of the efficient price from the Kalman filter: $\hat{m}_{i,t} = E\left[m_{i,t} \vert \mathcal{P}_{i,t}\right]$ where $\mathcal{P}_{i,t}$ is the set containing all current and past prices.
*	$\hat{s}_{i,t}$	Estimate of the transitory price pressure: $\hat{s}_{i,t} = p_{i,t} - \hat{m}_{i,t}$.

Market Capitalizations and Weights:

$MktCap_{i,t}$	Market capitalization of stock i, in dollars, at the end of month t.
$\overline{MktCap}_i$	Average market cap.n of stock i, in dollars, over the sample period.
$\omega_{i,t}$	Weight of stock i in our "market" of 1,019 stocks: $\omega_{i,t} = \frac{\overline{MktCap}_i}{\sum_{i=1}^{N} \overline{MktCap}_i}$.

Return Variables:

	$r_{i,t}$	Return of stock i's over month t: $r_{i,t} = p^{ln}_{i,t} - p^{ln}_{i,t-1}$.
	$r_{f,t}$	Return of riskfree rate over month t and from Ken French's website.
	$r^{std}_{i,t}$	Standardized return of stock i's over month t: $r^{std}_{i,t} = \frac{r_{i,t} - \overline{r_{i,t}}}{std(r_{i,t})}$.
	r_t	Market-wide return or common factor. Equal to: $r_t = \sum_i \omega_{i,t} r^{std}_{i,t}$.
**	f_t	Innovation in market-wide returns. Defined as: $f_t = \xi_t$ from the regression: $r_t = \alpha + \phi_1 r_{t-1} + \phi_2 r_{t-2} + \phi_3 r_{t-3} + \phi_4 r_{t-4} + \xi_t$.
*	$r^{idio}_{i,t}$	Idiosyncratic portion of stock i's return. Defined as: $r^{idio}_{i,t} = \xi_{i,t}$ from the regression: $r_{i,t} = \alpha + \phi_0 f_t + \ldots + \phi_4 f_{t-4} + \xi_{i,t}$.
*	$\Delta\hat{m}_{i,t}$	Return of the estimated efficient (unobservable) price. Defined as: $\Delta m_{i,t} = E\left[m_{i,t} \vert \mathcal{P}_{i,t}\right] - E\left[m_{i,t-1} \vert \mathcal{P}_{i,t-1}\right]$.

Required Return Adjustment:

Step 1: Do a fixed-effects panel regression with all 1,019 stocks using the whole sample period: $r_{i,t} = \alpha + \beta_0 f_t + \beta_1 f_{t-1} + \beta_2 f_{t-2} + \beta_3 f_{t-3} + \beta_4 f_{t-4} + \varepsilon_{i,t}$.

Step 2: Do a stock-by-stock regression of the form:
$r_{i,t} = \alpha_i + \beta_{i,0} f_t + \beta_{i,1} f_{t-1} + \beta_{i,2} f_{t-2} + \beta_{i,3} f_{t-3} + \beta_{i,4} f_{t-4} + \varepsilon_{i,t}$.

Step 3: Calculate stock i's beta as: $\beta_i = \frac{\sum_{j=0}^{4} \beta_{i,j}}{\sum_{j=0}^{4} \beta_j}$.

Step 4: Calculate the required return as: $\delta_{i,t} = r_{f,t} + \beta_i \left(1.06^{\frac{1}{12}} - 1\right)$.

Specialists' Inventory Variables:

$Spec_{i,t}^{sh}$ Specialist's inventory (in shares) of stock i at the end of month t.

$Spec_{i,t}^{\$}$ Specialist's inventory (in dollars) of stock i at the end of month t
Defined as: $Spec_{i,t}^{\$} = Spec_{i,t}^{sh} \times \overline{P}_i$.

$Spec_{i,t}^{std}$ Standardized value of specialist's inventory of stock i's at the end of month t. Defined as: $Spec_{i,t}^{std} = \frac{Spec_{i,t}^{\$} - \overline{Spec_{i,t}^{\$}}}{std\left(Spec_{i,t}^{\$}\right)}$.

γ_t^{Spec} Common (market-wide) inventory factor at the end of month t.
Defined as: $\gamma_t^{Spec} = \sum_i \omega_i \times Spec_{i,t}^{std}$.

** $Spec_{i,t}$ Idiosyncratic part of specialist's inventory. Defined as: $Spec_{i,t} = \varepsilon_{i,t}$ from the regression: $Spec_{i,t}^{\$} = \alpha + \beta \cdot \gamma_t^{Spec} + \varepsilon_{i,t}$.

* $\Delta Spec_{i,t}$ Defined as: $Spec_{i,t} - Spec_{i,t-1}$.

* $\tilde{S}pec_{i,t}$ Defined as the residual from an AR(1): $\tilde{S}pec_{i,t} = \varepsilon_{i,t}$
from the regression $Spec_{i,t} = \phi_0 + \phi_1 Spec_{i,t-1} + \varepsilon_{i,t}$.

Individuals' Trading Variables:

	$Indv^{sh}_{i,t}$	Individuals' inventories/holdings (in shares) of stock i at the end of month t. Assumed to be zero at the beginning of the sample period.
	$Indv^{\$}_{i,t}$	Individuals' inventories/holdings (in dollars) of stock i at the end of month t. Defined as: $Indv^{\$}_{i,t} = Indv^{sh}_{i,t} \times \overline{P}_i$.
	$\Delta Indv^{\$}_{i,t}$	Individuals' net trading (in dollars) of stock i's at the end of month t. Defined as: $\Delta Indv^{\$}_{i,t} = Indv^{\$}_{i,t} - Indv^{\$}_{i,t-1}$.
	$Indv^{std}_{i,t}$	Standardized value of Individuals' inventories/holdings of stock i at the end of month t. Defined as: $Indv^{std}_{i,t} = \frac{Indv^{\$}_{i,t} - \overline{Indv}^{\$}_{i,t}}{std\left(Spec^{\$}_{i,t}\right)}$.
	γ^{Indv}_t	Common (market-wide) inventory factor at the end of month t. Defined as: $\gamma^{Indv}_t = \sum_i \omega_i \times Indv^{std}_{i,t}$.
	$\Delta\gamma^{Indv}_t$	Net trading of common factor over month t: $\Delta\gamma^{Indv}_t = \gamma^{Indv}_t - \gamma^{Indv}_{t-1}$.
*	$Indv_{i,t}$	Idiosyncratic part of individuals' inventory. Defined as: $Indv_{i,t} = \varepsilon_{i,t}$ from the regression: $Indv^{\$}_{i,t} = \alpha + \beta \cdot \gamma^{Indv}_t + \varepsilon_{i,t}$.
**	$\Delta Indv_{i,t}$	Idiosyncratic part of net trades. Defined as: $\Delta Indv_{i,t} = \varepsilon_{i,t}$ from the regression $\Delta Indv^{\$}_{i,t} = \alpha + \beta \cdot \Delta\gamma^{Indv}_t + \varepsilon_{i,t}$.
	$\tilde{I}ndv_{i,t}$	Defined as the residual from an AR(1): $\tilde{I}ndv_{i,t} = \varepsilon_{i,t}$ from the regression: $Indv_{i,t} = \phi_0 + \phi_1 Indv_{i,t-1} + \varepsilon_{i,t}$.
*	$\Delta\tilde{I}ndv_{i,t}$	Defined as the residual from an AR(1): $\Delta\tilde{I}ndv_{i,t} = \varepsilon_{i,t}$ from the regression: $\Delta Indv_{i,t} = \phi_0 + \phi_1 \Delta Indv_{i,t-1} + \varepsilon_{i,t}$.

Interaction of Specialists' and Individuals' Trading:

*	$D_{i,t}$	$= +1$ if $Spec_{i,t} > 0$, $\Delta Indv_{i,t} > 0$, and $Spec_{i,t} \in$ Q1
		$= -1$ if $Spec_{i,t} < 0$, $\Delta Indv_{i,t} < 0$, and $Spec_{i,t} \in$ Q4
		$= 0$ otherwise
		Q1 and Q4 represent the hi/lo quartiles of $Spec_{i,t}$'s distribution.

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
$Spec_{it}^{sh}$	Specialists' closing inventory	1,000 shares	NYSE	5.93	2.77	3.12	5.40	13.04	40.55
$Spec_{it}^{\$}$	" " "	\$ 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
$Spec_{i,t}$	Specialists' inventory	\$ 1,000	Mean-Avg	0.0	0.0	0.0	0.0	0.0	0.0
”	” ”	″	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	Mean-Avg	0.0	0.0	0.0	0.0	0.0	0.0
”	” ”	″	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	%	Mean-Avg	0.0	0.0	0.0	0.0	0.0	0.0
”	” ”	″	Std-Avg	13.74	12.23	11.62	11.22	10.31	11.88

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 specialists and individuals:

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

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

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 stocks 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.

		Specialists	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: Base Case State Space Model

This table reports estimates from the base case state space model. The first equation shows the observable log price (p_{it}). The second equation show the unobserved efficient price ($m_{i,t}$). The third equation shows the the unobserved transitory price deviations ($s_{i,t}$).

$$\begin{aligned} p_{i,t} &= m_{i,t} + s_{i,t} \\ m_{i,t} &= m_{i,t-1} + \beta_i f_t + w_{i,t} \\ s_{i,t} &= \phi_i s_{i,t-1} + \beta_{i,0} f_t + \ldots + \beta_{i,3} f_{t-3} + \epsilon_{i,t} \end{aligned}$$

Data are monthly starting January 1999 and ending December 2005. The table reports p-values in parentheses. These p-values are based on a test statistic that counts the number of significant t-values across all stocks in the bin. The test statistic is binomially distributed under the null. In the t-test, we use the 0.10 critical value if the cross-sectional mean is negative and the 0.90 critical value if the cross-sectional mean is positive.

	$\sigma(w)$	ϕ_i	$\sigma(\epsilon)$	$\left(\frac{\sigma(\epsilon)^2}{1-\phi_i^2}\right)^{\frac{1}{2}}$
All	849	0.35	324	452
	(0.000)	(0.000)	(0.000)	(0.000)
Q1 (Small)	1,059	0.33	365	491
	(0.000)	(0.000)	(0.000)	(0.000)
Q2	913	0.35	345	508
	(0.000)	(0.000)	(0.000)	(0.000)
Q3	790	0.34	348	466
	(0.000)	(0.000)	(0.000)	(0.000)
Q4	788	0.41	275	407
	(0.000)	(0.000)	(0.000)	(0.000)
Q5 (Large)	691	0.34	288	389
	(0.000)	(0.000)	(0.000)	(0.000)

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

Table 4: Correlations of Trading and Price Variables

This table presents correlations of idiosyncratic inventories of NYSE specialists ($Spec_{i,t}$), individuals' net trades ($\Delta Indv_{i,t}$), the idiosyncratic part of monthly returns ($r^{idio}_{i,t}$), estimated price pressures ($\hat{s}_{i,t}$), and the returns/changes to the estimated efficient price ($\Delta\hat{m}_{i,t}$). A full description of all variables is given in the text and in Appendix D. Efficient prices and price pressure are estimated by a Kalman filter using the statistical base-case model shown in the text. Correlations are calculated on a stock-by-stock basis using the entire January 1999 to December 2005 sample period. The table shows average matrices (across stocks). p-values are reported in parentheses and are based on a test statistic that counts the number of significant t-values across all stocks estimates in the bin. The test statistic is binomially distributed under the null. In the t-test, we use the 0.10 critical value if the cross-sectional mean is negative and the 0.90 critical value if the cross-sectional mean is positive.

		Lag 1 month			Contemporaneous			Fwd 1 month		
		$Spec_{-1}$	$\Delta Indv_{-1}$	r^{idio}_{-1}	$Spec$	$\Delta Indv$	r^{idio}	$Spec_{+1}$	$\Delta Indv_{+1}$	r^{idio}_{+1}
All	$Spec_t$	0.15			1.00			0.15		
		(0.000)			(0.000)			(0.000)		
	$\Delta Indv_t$	0.07	0.31		0.05	1.00		0.01	0.31	
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)	
	r^{idio}_t	0.05	0.03	-0.06	-0.22	-0.17	1.00	-0.04	-0.17	-0.06
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	$\Delta\hat{s}_t$	-0.06	-0.08	0.07	-0.09	-0.12	0.18	0.01	-0.06	-0.06
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	$\Delta\hat{m}_t$	0.04	0.03	0.01	-0.23	-0.17	0.83	-0.05	-0.18	-0.06
		(0.000)	(0.000)	(0.710)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q1 (Small)	$Spec_t$	0.30			1.00			0.30		
		(0.000)			(0.000)			(0.000)		
	$\Delta Indv_t$	0.12	0.32		0.07	1.00		0.03	0.32	
		(0.000)	(0.000)		(0.000)	(0.000)		(0.168)	(0.000)	
	r^{idio}_t	0.04	0.05	-0.06	-0.30	-0.13	1.00	-0.08	-0.19	-0.06
		(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	$\Delta\hat{s}_t$	-0.09	-0.10	0.07	-0.11	-0.13	0.17	0.01	-0.09	-0.06
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.021)	(0.000)	(0.054)
	$\Delta\hat{m}_t$	0.03	0.05	0.01	-0.30	-0.12	0.88	-0.09	-0.19	-0.06
		(0.000)	(0.000)	(0.994)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q2	$Spec_t$	0.12			1.00			0.12		
		(0.000)			(0.000)			(0.000)		
	$\Delta Indv_t$	0.08	0.28		0.06	1.00		0.02	0.28	
		(0.000)	(0.000)		(0.000)	(0.000)		(0.013)	(0.000)	
	r^{idio}_t	0.06	0.04	-0.04	-0.25	-0.17	1.00	-0.05	-0.17	-0.04
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	$\Delta\hat{s}_t$	-0.05	-0.08	0.07	-0.11	-0.12	0.19	-0.00	-0.06	-0.08
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.175)	(0.000)	(0.000)
	$\Delta\hat{m}_t$	0.04	0.04	0.02	-0.26	-0.16	0.84	-0.05	-0.19	-0.05
		(0.000)	(0.000)	(0.175)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

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		Lag 1 month			Contemporaneous			Fwd 1 month		
		$Spec_{-1}$	$\Delta Indv_{-1}$	r^{idio}_{-1}	$Spec$	$\Delta Indv$	r^{idio}	$Spec_{+1}$	$\Delta Indv_{+1}$	r^{idio}_{+1}
Q3	$Spec_t$	0.12			1.00			0.12		
		(0.000)			(0.000)			(0.000)		
	$\Delta Indv_t$	0.05	0.28		0.03	1.00		0.01	0.28	
		(0.000)	(0.000)		(0.001)	(0.000)		(0.000)	(0.000)	
	r^{idio}_t	0.06	0.03	-0.06	-0.19	-0.16	1.00	-0.02	-0.16	-0.06
		(0.000)	(0.388)	(0.000)	(0.000)	(0.000)	(0.000)	(0.081)	(0.000)	(0.000)
	$\Delta\hat{s}_t$	-0.06	-0.08	0.09	-0.09	-0.13	0.19	0.02	-0.06	-0.07
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.004)
	$\Delta\hat{m}_t$	0.05	0.03	0.00	-0.21	-0.16	0.81	-0.03	-0.17	-0.07
		(0.000)	(0.817)	(0.817)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Q4	$Spec_t$	0.11			1.00			0.11		
		(0.000)			(0.000)			(0.000)		
	$\Delta Indv_t$	0.07	0.32		0.05	1.00		0.01	0.32	
		(0.000)	(0.000)		(0.000)	(0.000)		(0.081)	(0.000)	
	r^{idio}_t	0.04	0.02	-0.04	-0.20	-0.19	1.00	-0.04	-0.18	-0.04
		(0.002)	(0.054)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	$\Delta\hat{s}_t$	-0.05	-0.07	0.06	-0.08	-0.10	0.15	0.02	-0.04	-0.06
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.921)	(0.000)	(0.081)
	$\Delta\hat{m}_t$	0.03	0.02	0.01	-0.21	-0.19	0.81	-0.05	-0.19	-0.05
		(0.021)	(0.000)	(0.388)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q5 (Large)	$Spec_t$	0.11			1.00			0.11		
		(0.000)			(0.000)			(0.000)		
	$\Delta Indv_t$	0.05	0.36		0.04	1.00		-0.00	0.36	
		(0.000)	(0.000)		(0.000)	(0.000)		(0.011)	(0.000)	
	r^{idio}_t	0.04	0.03	-0.07	-0.17	-0.22	1.00	-0.03	-0.16	-0.07
		(0.000)	(0.048)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)
	$\Delta\hat{s}_t$	-0.04	-0.07	0.05	-0.07	-0.12	0.18	0.00	-0.03	-0.05
		(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.109)	(0.001)	(0.011)
	$\Delta\hat{m}_t$	0.04	0.03	0.01	-0.18	-0.22	0.79	-0.03	-0.16	-0.07
		(0.000)	(0.000)	(0.370)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

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

Table 5: State Space Model with NYSE Specialists' Inventories

This table presents estimates from a state space model that includes NYSE specialists' 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 price deviation.

$$\begin{aligned} p_{i,t} &= m_{i,t} + s_{i,t} \\ m_{i,t} &= m_{i,t-1} + \beta_i f_t + w_{i,t} \\ w_{i,t} &= \kappa_i^{spec} \tilde{S}pec_{i,t} + u_{i,t} \\ s_{i,t} &= \alpha_i^{spec} Spec_{i,t} + \beta_{i,0} f_t + \ldots + \beta_{i,3} f_{t-3} + \epsilon_{i,t} \end{aligned}$$

Full descriptions and definitions of variables are given in Appendix D. 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. The table reports p-values in parentheses. These values are based on a test statistic that counts the number of significant t-values across all stocks. The test statistic is binomially distributed under the null. In the t-test, we use the 10% percentile if the cross-sectional mean is negative and the 90% percentile if the cross-sectional mean is positive.

	Efficient Price Equation			**Transitory Price Equation**		
	κ_i^{spec}	$\lvert\kappa_i^{spec}\rvert \cdot \sigma(\tilde{S}pec)$	$\sigma(w)$	α_i^{spec}	$\lvert\alpha_i^{spec}\rvert \cdot \sigma(Spec)$	$\sigma(\epsilon)$
All	-1.08	269	954	-0.25	158	159
	(0.000)			(0.000)		
Q1 (Small)	-3.16	441	1,171	-0.50	248	181
	(0.000)			(0.000)		
Q2	-1.08	281	1,025	-0.38	170	155
	(0.000)			(0.000)		
Q3	-0.53	212	909	-0.24	125	158
	(0.000)			(0.000)		
Q4	-0.44	226	893	-0.09	124	133
	(0.000)			(0.000)		
Q5 (Large)	-0.16	183	769	-0.05	121	169
	(0.000)			(0.000)		

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

Table 6: 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 price deviation.

$$\begin{aligned} p_{i,t} &= m_{i,t} + s_{i,t} \\ m_{i,t} &= m_{i,t-1} + \beta_i f_t + w_{i,t} \\ w_{i,t} &= \kappa_i^{indv} \Delta \tilde{I}ndv_{i,t} + u_{i,t} \\ s_{i,t} &= \alpha_i^{indv} \Delta Indv_{i,t} + \beta_{i,0} f_t + \ldots + \beta_{i,3} f_{t-3} + \epsilon_{i,t} \end{aligned}$$

Full descriptions and definitions of variables are given in Appendix D. 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. The table reports p-values in parentheses. These values are based on a test statistic that counts the number of significant t-values across all stocks. The test statistic is binomially distributed under the null. In the t-test, we use the 10% percentile if the cross-sectional mean is negative and the 90% percentile if the cross-sectional mean is positive.

	Efficient Price Equation			**Transitory Price Equation**		
	κ_i^{indv}	$\lvert\kappa_i^{indv}\rvert \cdot \sigma(\Delta \tilde{I}ndv)$	$\sigma(w)$	α_i^{indv}	$\lvert\alpha_i^{indv}\rvert \cdot \sigma(\Delta Indv)$	$\sigma(\epsilon)$
All	-0.09	268	929	-0.06	166	227
	(0.000)			(0.000)		
Q1 (Small)	-0.22	267	1,123	-0.17	197	269
	(0.000)			(0.000)		
Q2	-0.11	268	1,000	-0.06	176	241
	(0.000)			(0.000)		
Q3	-0.06	252	878	-0.03	133	234
	(0.000)			(0.000)		
Q4	-0.04	282	880	-0.01	157	187
	(0.000)			(0.000)		
Q5 (Large)	-0.01	271	762	-0.01	164	203
	(0.000)			(0.000)		

# of Obs: N × T = 1,019 × 84 = 85,586

Table 7: State Space Model with Both Specialists and Individuals

This table presents estimates from a state space model that includes NYSE specialists' 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 price deviation.

$$\begin{aligned} p_{i,t} &= m_{i,t} + s_{i,t} \\ m_{i,t} &= m_{i,t-1} + \beta_i f_t + w_{i,t} \\ w_{i,t} &= \kappa_i^{spec} \tilde{S}pec_{i,t} + \kappa_i^{indv} \Delta \tilde{I}ndv_{i,t} + u_{i,t} \\ s_{i,t} &= \alpha_i^{spec} Spec_{i,t} + \alpha_i^{indv} \Delta Indv_{i,t} + \alpha_i^D D_{i,t} + \beta_{i,0} f_t + \ldots + \beta_{i,3} f_{t-3} + \epsilon_{i,t} \end{aligned}$$

Full descriptions and definitions of variables (including the interaction dummy $D_{i,t}$) are given in Appendix D. 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. The table reports p-values in parentheses. These values are based on a test statistic that counts the number of significant t-values across all stocks. The test statistic is binomially distributed under the null. In the t-test, we use the 10% percentile if the cross-sectional mean is negative and the 90% percentile if the cross-sectional mean is positive.

	Efficient Price Equation					Transitory Price Equation					
	κ_i^{spec}	$\lvert\kappa_i^{spec}\rvert\times$ $\sigma(\tilde{S}pec)$	κ_i^{indv}	$\lvert\kappa_i^{indv}\rvert\times$ $\sigma(\Delta\tilde{I}ndv)$	$\sigma(w)$	α_i^{spec}	$\lvert\alpha_i^{spec}\rvert\times$ $\sigma(Spec)$	α_i^{indv}	$\lvert\alpha_i^{indv}\rvert\times$ $\sigma(\Delta Indv)$	α_i^D	$\sigma(\epsilon)$
All	-0.96 (0.000)	246	-0.09 (0.000)	259	930	-0.26 (0.000)	167	-0.05 (0.000)	164	-65.42 (0.000)	186
Q1 (Small)	-2.83 (0.000)	402	-0.22 (0.000)	253	1,132	-0.61 (0.000)	263	-0.15 (0.000)	196	-88.56 (0.000)	208
Q2	-0.94 (0.000)	261	-0.10 (0.000)	257	999	-0.33 (0.000)	173	-0.05 (0.000)	177	-92.55 (0.000)	187
Q3	-0.48 (0.000)	198	-0.07 (0.000)	253	877	-0.20 (0.000)	138	-0.02 (0.000)	129	-74.12 (0.000)	195
Q4	-0.38 (0.000)	205	-0.03 (0.000)	273	879	-0.12 (0.000)	130	-0.01 (0.012)	153	-37.59 (0.021)	162
Q5 (Large)	-0.14 (0.000)	161	-0.01 (0.000)	260	762	-0.05 (0.000)	132	-0.00 (0.000)	167	-33.83 (0.002)	176

# of Obs: N × T = 1,019 × 84 = 85,586