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Variations in Trading Volume, Return Volatility, and Trading Costs: Evidence on Recent Price Formation Models

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ABSTRACT

Patterns in stock market trading volume, trading costs, and return volatility are examined using New York Stock Exchange data from 1988. Intraday test results indicate that, for actively traded firms trading volume, adverse selection costs, and return volatility are higher in the first half-hour of the day. This evidence is inconsistent with the Admati and Pfleiderer (1988) model which predicts that trading costs are low when volume and return volatility are high. Interday test results show that, for actively traded firms, trading volume is low and adverse selection costs are high on Monday, which is consistent with the predictions of the Foster and Viswanathan (1990) model.

ACADEMICS, INVESTORS, AND REGULATORS alike are now intensively focused upon understanding the volatility of asset returns and its relation to trading volume. This interest was undoubtedly piqued by the market break of October 1987—a time during which volatility and trading volume reached unprecedented levels. But, even beforehand, researchers observed regular differences in the return process for various hours of the day and days of the week.

Research concerning temporal patterns in stock market volatility and volume falls in two groups—studies that document observed patterns and studies that develop models to predict patterns. Among the studies in the first group are Oldfield and Rogalski (1980), French and Roll (1986), Stoll and Whaley (1990), Harris (1986), and Wood, McInish, and Ord (1985), who report evidence on seasonalities in daily and weekly return variances. Among the regularities that have been documented using interday data is that volatility is higher when the market is open than when it is closed. Oldfield and Rogalski (1980), French and Roll (1986), and Stoll and Whaley (1990), for example, point out significant differences in return volatility between trading

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and nontrading intervals. Overnight volatility is proportionately less than volatility during the trading day and weekend volatility is proportionately lower than trading day volatility. Using intraday data, Wood, McInish, and Ord (1985) document a U-shaped pattern in return volatility during the trading day, that is, volatility is highest at the beginning and the end of the trading day. Similarly, Harris (1986) shows strong intraday patterns in return volatility and presents his results by firm size. Along a different but related dimension, Jain and Joh (1988) show that the trading volume is different within and across days. They provide evidence of an inverted U-shape in volume across days. Monday and Friday have the lowest volume, and the most active periods are in the middle of the week.

Studies in the second group attempt to model explicitly various patterns in return volatility. In two related papers, Admati and Pfleiderer (1988) and Foster and Viswanathan (1990) provide models to explain time-dependent patterns in securities trading. Both studies consider in detail how information is impounded in prices, and how different groups of investors may influence prices. By carefully considering the microstructure of trading between informed traders, a market maker, and liquidity traders, predictions of the form of inter- and intraday patterns in return volatility, trading volume, and trading costs are made.

To test these predictions, we need to document any systematic variation in the components of trading costs. Others, most notably Glosten and Harris (1988) and Stoll (1989) use price and spread data to decompose trading costs into the fixed, inventory, and adverse selection cost components; however, they do not consider whether the components vary through time. With a method that is related to Hasbrouck (1989, 1991a, 1991b), we estimate fixed and adverse selection cost components from transaction price changes and test whether systematic variations in these components exist. Linking trading cost estimates with patterns in return volatility and trading volume is crucial to our study. Admati and Pfleiderer and Foster and Viswanathan recognize the role of discretionary liquidity traders in accentuating inter- and intraday variations in volume and volatility. These traders adjust their transactions to avoid times when trading costs are highest. Hence, we use our estimates of trading costs to determine whether these costs change with volume and volatility in a manner consistent with the theories of Admati and Pfleiderer and Foster and Viswanathan. For Admati and Pfleiderer this means that trading costs are low when trading volume is high and prices are more volatile. Foster and Viswanathan predict that trading costs are low when trading volume is high and prices are less volatile.

The outline of the paper is as follows. In Section I, we review the underpinnings of the Admati and Pfleiderer and Foster and Viswanathan models, examine their predictions, and describe how the predictions are tested. Section II describes the stock market price and trading volume data that are used. Sections III and IV focus on inter- and intraday trading volume and return volatility patterns and how they relate to the predictions of the Admati and Pfleiderer and Foster and Viswanathan models. In Section V, price changes are decomposed into fixed cost and adverse selection cost components to examine their temporal variation. Section VI contains a summary.

I. Review of Price Formation Models

Both the Admati and Pfleiderer and Foster and Viswanathan models make use of a modeling structure first presented by Kyle (1985). In this framework, there is a market maker, informed traders, and liquidity traders. The market maker observes the order flow, and sets prices at which trade occurs. At no time does the market maker know who is informed or what information an informed trader may have. Rather, the market maker watches the order flow to infer the informed trader's beliefs and sets prices so that they best represent the true value of the asset. Hence, the model focuses on the adverse selection faced by the market maker; informed traders trade only when they profit from their knowledge. Without liquidity traders the market would collapse from this information asymmetry. Both Admati and Pfleiderer and Foster and Viswanathan note that while the liquidity traders have no specific advantage (information or otherwise), they may have some discretion over when they trade. Hence, when liquidity traders believe that the informed trader has superior information, they may choose to refrain from trading, so that it is less likely that they bear the costs of trading with an informed individual.

In the Admati and Pfleiderer model, discretionary liquidity traders are given the freedom to choose what time of day they trade; in equilibrium, all discretionary liquidity traders choose to trade at the same time of day. While this pooling of trades attracts informed traders, Admati and Pfleiderer show that this strategy minimizes the trading costs of discretionary liquidity traders. Admati and Pfleiderer predict patterns in the covariations of volume, the variance of price changes, and adverse selection costs (by adverse selection costs we mean the extent to which an order causes the market maker to adjust a security price away from its current level to reflect the new information in the order flow). Specifically, they show that for intraday transactions (their Hypotheses 1 and 2) high volume periods have low trading costs and more informative prices.

In a related model, Foster and Viswanathan analyze interday trading where an informed trader and a subset of the liquidity traders act strategically. In this model, the informed trader receives information each day, but this information becomes less valuable through time, because there is a public announcement of some portion of the private information each day. Hence, discretionary liquidity traders have an incentive to delay their transactions when they believe that the informed trader is particularly well-informed. By waiting they can learn from the trades that occur and the public signal that is released. The informed trader, knowing that there is a forthcoming public signal, trades more aggressively and so more information is released through trading. If more private information accumulates over a weekend than on a week night, and there is no equivalent increase in the precision of the public signal on the weekend, Foster and Viswanathan predict a weekend effect in trading volume and return volatility. They show that trading volume should be lower on Monday than Tuesday, and trading costs are highest on Monday.

Foster and Viswanathan predict these patterns to be more pronounced for firms with more and better public information, because for these firms it is more likely that the informed trader's advantage is eradicated by a publicly observed announcement. Here we allow for this possibility by dividing the stocks used in our tests into deciles based on the dollar value of shares traded in a year, the supposition being that more actively traded stocks are more closely followed and have a more regular and detailed public information source.

II. The Data

The tests in this study are performed using price, quote, and volume data provided by the Institute for the Study of Securities Markets (ISSM) for 1988. This source provides transaction and quote data for stocks listed on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX). In addition, quotes and transactions in NYSE and AMEX listed stocks from regional market centers (Boston, Cincinnati, Midwest, Instinet, Pacific, National Association of Securities Dealers, and Philadelphia) are incorporated in the data set (in 1988 there were approximately 52 million trades and quotes in the ISSM data base). The data have all information distributed by the Security Industry Automation Corporation (SIAC) and the data are reported in event time. There are a number of corrections made by SIAC because of reporting errors from the exchange floor; we use the data set after the SIAC modifications. In addition, ISSM passes the data through their own error filters. We use these filters to exclude transactions and quotes that appear to be wrong.[1]

All the securities in our sample are common stocks listed on the NYSE. To ensure that we have a sufficient number of observations in our sample, we require that the stocks trade on at least 200 out of the 253 trading days in 1988. We only use the quotes and transactions from the NYSE, and ignore data from the regional exchanges. We omit stocks that split, pay stock dividends, or pay dividends in rights. In our calculations of return variance, we adjust the price changes for the effects of cash dividend payments. Because we are interested in the interday variations of volume, trading costs, and return variances, we use only weeks that have trading on Monday

[1] ISSM uses filters that examine surrounding prices and quotes to spot unusual trades or quotes. For example a price of $4.00 when the surrounding trades and quotes are $40.00 would be determined to be in error. Further information regarding these filters can be obtained from ISSM at the Fogelman College of Business and Economics, Memphis State University, Memphis, Tennessee 38152.

through Friday, inclusive. That is, we omit weeks that have holidays so that we do not have to adjust our tests for the shifting that naturally occurs from a shorter trading week. This gives us 45 weeks of trading data, which translates into 225 trading days and 1575 trading hours for each firm. The NYSE is open from 09:30 to 16:00 (Eastern Time), so we count the first half hour of trading as a separate period, and have seven periods per day. Finally, we classify a transaction as being seller-initiated if the previous error-free quote from the NYSE has a bid price that is closer to the transaction price than the ask price.[2]

The Foster and Viswanathan model predicts sharp patterns in volume when the public information quickly reveals private information and less distinct patterns when public information is a poor substitute for private information. To proxy for the quality of public information, we use the average daily dollar value of transactions in 1988. Firms with a large dollar volume of trading activity should be more closely followed by public reporting agencies and thus better public information ought to be available to traders. Firms are ranked and formed into deciles (decile one being the least actively traded stocks, decile ten the most actively traded stocks). Next, to reduce the computational burden, we selected the first twenty firms that meet the screening criteria listed above from each decile in alphabetical order by ticker symbol (this should be a random selection). Of course, we form the trading activity deciles before applying our screening criteria to ensure that we get a proper representation of relative trading activity. Finally, we compute and report results for deciles one (least actively traded stocks), five (moderately actively traded stocks), and ten (most actively traded stocks) only.

III. Variations in Trading Volume

A. Background and Hypotheses

In this section we introduce tests to document changes in trading volume within and between days. To illustrate our techniques, we describe in detail our tests to determine if trading volume is evenly distributed across days of the week; we use an equivalent design to test whether volume is evenly distributed across hours of the day.

For the interday tests, the Foster and Viswanathan model predicts that, if public information is precise and the informed trader has more private information, then discretionary liquidity traders delay their trades. Because the informed trader's information advantage is short-lived, the delay tactic of discretionary liquidity traders leaves less liquidity in the market and makes it easier for the market maker to infer the informed trader's reasons for trading. As a consequence, the volume is lower, prices are more informative (volatile), and trading costs are higher. Knowing this, consider the conse-

[2] In keeping with Lee and Ready (1991), we use quotes that are at least five seconds old to classify the transactions.

quences if the trading break over the weekend produces a stronger adverse selection problem on Monday. We should see discretionary liquidity traders postpone their transactions, and Monday's volume should be the lowest of any day of the week. The better the public information released on Monday, the more likely it is for discretionary liquidity traders to delay their trades, which should result in a strong shift in volume from Monday to other days of the week. It is this pattern in interday volume that we test for in this section of the paper—larger stocks that have a more reliable flow of public information should be more likely to have lower volume on Monday.

For the intraday tests we have no a priori theory that predicts a particular pattern of intraday volume. Admati and Pfleiderer show that trading patterns emerge from the clustering of trades by the discretionary liquidity traders; however, they do not predict whether a concentration of trading volume occurs at the open, the middle of the day, or at the close. Hence, we test for whether some time of day has consistently more shares traded than any other.

For both the inter- and intraday specifications, we test the null hypothesis that the trading volume is uniform through time. For the interday case, if we allow for a basic level of trading volume, where differences in volume depend only on the day of the week, we have:

$$v_t = v + \sum_{i=2}^{5} 1_{d=i}\eta_i + \epsilon_t; \tag{1}$$

for a particular stock. We use $d = 1, 2, \ldots, 5$ (for the intraday tests this would be $h = 1, 2, \ldots, 7$) to represent Monday through Friday (9:30 to 10:00 through 15:00 to 16:00—we treat the first half hour of trading as a separate period and double the volume therein so that this half-hour period is comparable to the other one hour periods). The volume on day t, v_t, is composed of a fixed effect for Monday, v, an interday adjustment for days other than Monday, η_i, and an idiosyncratic error term with zero expected value, ϵ_t. The expression $1_{d=i}$ is an indicator function that takes on a value of one if the day of the week of observation t is equal to d, and has a value of zero otherwise. This provides dummy variables that give the day of the week on which the volume is realized. Expression (1) simply states that the average volume on each day of the week can be different. The coefficient v is the average Monday volume, η_2 is the amount by which the average Tuesday volume exceeds the average Monday volume and so on for η_i, $i = 3, 4, 5$.

B. Methodology

In this section we outline the procedure we use for estimating expression (1) (and other equations of the same form). The value of the coefficients of the dummy variables, η_i, are central to our tests for inter- and intraday variations in trading volume. Hence, in this section we also outline our techniques for determining whether these coefficients are significantly different from zero. In all of our tests we first assess the significance of the variations across all of the firms and days in each decile. Having determined that there are significant variations in the sample, we use additional tests to focus on specific firms or specific days (hours) to pinpoint the source of the variation. The use of a test of an initial multivariate hypothesis, followed by a test of a univariate hypothesis is an accepted procedure for avoiding finding spurious significance; see Savin (1980, 1984) and Scheffe (1977) for a discussion of this issue.[3]

Because trading volume is potentially correlated across firms (if one firm has heavy trading on some day, other firms may also be more actively traded), we estimate equation (1) simultaneously for all twenty firms in each decile, providing more efficient estimates by exploiting cross-correlations in the error terms. Because different firms have varying numbers of shares outstanding, however, there can be significant differences in the level of trading volume between firms. Hence, we divide the observed trading volume in each period by the number of shares outstanding (measured in thousands of shares) to get a turnover rate that has the same interpretation for all firms in the sample. With this turnover measure, we estimate expression (1) as a system of 20 equations, one equation for each firm. We employ Hansen's (1982) generalized method of moments (GMM) technique, using the Newey and West (1987) correction for serial correlation to estimate the system from expression (1), while allowing for arbitrary cross-correlations, serial correlation up to a finite lag length, and heteroskedastic errors.[4]

Hansen's GMM technique involves specifying a set of moment restrictions to estimate the unknown parameters. From expression (1), there are five unknown parameters for each firm, v, η_2, η_3, η_4, and η_5. We use the normal equations of the regression corresponding to expression (1) as the orthogonality conditions:

$$\begin{aligned} E[\epsilon_t] &= 0 \\ E[\epsilon_t 1_{d=i}] &= 0 \quad i = 2,3,4,5 \end{aligned} \tag{2}$$

For each firm, there are five orthogonality conditions (one for the fixed effect, and one for each day dummy) and five parameters to be estimated. For the system of twenty firms, there are one hundred parameters to be estimated with one hundred equations, so the system is just-identified. Let θ be a 100-vector of parameter values (the first five elements of θ are v and η_i, $i = 2,3,4,5$ from the first firm, and the coefficients for the remaining firms are stacked in the same order).

Following Hansen (1982), we assume that the error process is stationary and ergodic. Under these assumptions, for a large number of observations the sample moments should be close to the population moments. Let $g_T(\theta)$ be a 100-vector of the sample moments (T denotes the sample size, which is 225

[3] If we were to use univariate tests directly, we would have to partition the rejection region of the tests to account for the number of hypotheses we examine.

[4] MANOVA and other related methods do not allow these kinds of arbitrary cross- and serial-correlation.

(1575) for the interday (intraday) tests). For a specific firm, $g_T(\theta)$ contains:

$$g_T(\theta) = \frac{1}{T}\sum_{t=1}^{T}\begin{pmatrix} v_t - v - \Sigma_{i=2}^{5} 1_{d=i}\eta_i \\ (v_t - v - \Sigma_{i=2}^{5} 1_{d=i}\eta_i)1_{d=2} \\ (v_t - v - \Sigma_{i=2}^{5} 1_{d=i}\eta_i)1_{d=3} \\ (v_t - v - \Sigma_{i=2}^{5} 1_{d=i}\eta_i)1_{d=4} \\ (v_t - v - \Sigma_{i=2}^{5} 1_{d=i}\eta_i)1_{d=5} \end{pmatrix} \tag{3}$$

where $g_T(\theta) \to 0$ as $T \to \infty$.

To estimate v and η_i for each firm, we choose values that set the sample moment conditions as close to zero as possible. In general, we would minimize the quadratic form of $g'Wg$, where W is a symmetric weighting matrix (that incorporates the Newey and West (1987) correction for serial correlation). Hansen (1982) gives the form of a weighting matrix that yields consistent estimates that are asymptotically normally distributed. In our case, the system is just-identified, so we need only to solve for $g_T(\theta) = 0$; our GMM estimates are identical to those from OLS (however, their standard errors are different). If we define D_T to be the consistent estimator of $\frac{\partial g_T(\theta)}{\partial\theta}$ and define $\hat{\theta}$ to be estimates of θ, we have:

$$\sqrt{T}(\hat{\theta} - \theta) \sim N\left(0, [D_T'WD_T]^{-1}\right) \tag{4}$$

We use $\hat{\theta}$ and the distribution properties of expression (4) to test a number of hypotheses. First, we test the restriction that all eighty day dummies (four dummies for each of the twenty firms) in the multivariate system are zero. This is a direct test of whether there are any interday differences in trading volume. Second, we test to see which days have trading volume that is different from Monday. That is, we test whether the average η_i computed from the 20 firms is zero, for $i = 2, 3, 4, 5$. Third, we count the number of times that we reject the hypothesis that all of the day dummies are zero for a specific firm.

For our first test of whether at least one of the day dummies is not zero, let Σ be an 80×80 subset of the estimated variance-covariance matrix, $[D_T'WD_T]^{-1}$, where we have dropped terms associated with the fixed effects, v, for each firm. In addition, let $\hat{\mu}$ be an 80×1 vector of the estimated day effects for each firm, $\hat{\eta}_i$, stacked into a single vector. Under the null hypothesis that $\mu = 0$, we can rewrite expression (4) as:

$$\sqrt{T}\,\hat{\mu} \sim N(0, \Sigma) \tag{4a}$$

If we scale the left-hand side of expression (4a) by $\Sigma^{\frac{1}{2}}$ and square it, we get a quadratic form that is distributed as:

$$T\hat{\mu}'[\Sigma]^{-1}\hat{\mu} \sim \chi^2(80) \tag{5}$$

where the expression $\chi^2(80)$ refers to a χ^2 distribution with 80 degrees of freedom.

For our second test of whether the average day of the week coefficients are different from zero, we define S to be a 20×20 matrix that includes only those terms from the estimated variance-covariance matrix having to do with the day dummy being examined. Next, we define ν to be a 20×1 vector of the estimates for the given day dummy (one for each firm), and let R be a 1×20 vector where each element is 0.05. Using the null hypothesis that the average day dummy (across firms) is zero, we have a quadratic form similar to (5) above:

$$T(R\nu)'[RSR']^{-1}(R\nu) \sim \chi^2(1) \tag{6}$$

Note that there is a separate version of expression (6) for each of the day dummies.

In our third test, we examine the number of firms for which we reject the null hypothesis that there are no interday variations in trading volume, by considering whether the firm's day of the week dummy variable coefficients are all zero with a quadratic form similar to those used above. In this case, we compute 20 statistics that are χ^2-distributed with four degrees of freedom. This test simultaneously uses the four dummy coefficients for each firm and a 4×4 subset of the variance-covariance matrix (it includes only those elements associated with the dummy coefficients for a particular firm). A large χ^2 statistic means that at least one of the day dummy variables has a coefficient that is significantly different from zero.

C. Results

Table I contains the interday and intraday variations in trading volume, and many interesting results appear. First, with respect to interday trading volume tests, there is a significant variation in trading volume for at least one firm on at least one day of the week. We see from the first row of Panel A in the table that all deciles have χ^2 statistics that are significant at the 1% level (the least actively traded firms, decile one, have a χ^2 statistic of 181 and the most actively traded firms, decile ten, have a χ^2 statistic of 592).

The results in Table I also allow us to identify trading volume patterns by day of the week. The second through fourth rows of Panel A of Table I provide the average dummy coefficient value (across firms) and the χ^2 statistic for the test that the average coefficient is equal to zero. For example, on Tuesday the least actively traded securities have higher volume than Monday by 0.16. Remember that our trading volume is a turnover measure that has been divided by 1000, thus, on average, Tuesday volume is higher than Monday volume by 0.016% of the shares outstanding. The associated χ^2 statistic is 1.08 and is not statistically significant at the 5% level. For decile ten, the most actively traded firms, the Tuesday volume is higher than Monday volume, on average, by 0.055% of the shares outstanding. This difference has a χ^2 statistic of 4.30, which is significant at the 5% level. Notice that, with

Table I

Variations in Trading Volume for Sixty Firms Traded on the NYSE in 1988

Trading volume at time t, v_t, is measured as a fraction of the shares outstanding, and decile 1 refers to a sample of those firms least actively traded for the year, while decile 10 is a sample of the most actively traded firms in 1988. The following equation is estimated and three tests are reported:

$$v_t = v + \sum_{i=2}^{5} 1_{d=\iota}\eta_\iota + \epsilon_t; \tag{1}$$

where v is the reference volume based on Monday (the first half hour of) trading and ϵ_t is a zero mean error term. The first test examines whether all of the coefficients of the day (hour) dummy variables, η_ι, are zero for the firms in each decile, and a χ^2_{80} (χ^2_{120}) statistic is reported for the interday (intraday) test for each decile. The second test examines whether each day (hour) is different from Monday (the first half hour) for all firms in each decile. An ordered pair of the mean (across firms) dummy variable coefficient and the corresponding χ^2_1 statistic are reported for each day (hour). The third test lists the number of firms for which at lest one day (hour) dummy variable coefficient is different from zero at the 5% level.

Test	Decile 1	Decile 5	Decile 10
	Panel A. Interday Difference		
Overall significance	181†	171†	592†
η_2 (Tuesday)	0.16, 1.08	0.17, 0.83	0.55, 4.30*
η_3 (Wednesday)	0.10, 0.52	0.17, 0.89	0.75, 4.46*
η_4 (Thursday)	0.30, 1.72	0.30, 2.27	0.80, 2.79
η_5 (Friday)	0.23, 0.78	0.00, 0.00	0.54, 3.39
Number of significant coefficients	0	0	11
	Panel B. Intraday Differences		
Overall significance	735†	809†	1662†
η_2 (10:00)	−0.11, 6.32*	−0.19, 48.82†	−0.72, 15.05†
η_3 (11:00)	−0.14, 20.39†	−0.27, 91.36†	−0.83, 17.87†
η_4 (12:00)	−0.17, 55.23†	−0.33, 139.44†	−0.98, 24.23†
η_5 (13:00)	−0.22, 92.14†	−0.38, 192.87†	−1.02, 25.99†
η_6 (14:00)	−0.21, 105.32†	−0.31, 81.56†	−0.96, 23.21†
η_7 (15:00)	−0.15, 42.23†	−0.17, 31.36†	−0.79, 15.63†
Number of significant coefficients	18	20	19

*different from 0 at the 5% level.
†different from 0 at the 1% level.

this second test, the only significant interday variations in trading volume are for the most actively traded firms where the Tuesday and Wednesday volume is significantly higher than the Monday volume at the 5% level of significance.

Finally, we count the number of firms in each decile for which we could reject the hypothesis that none of the coefficients of the day dummy variables are zero, using a 5% significance cutoff. We report these values in the last row of Panel A of Table I. On a firm by firm basis, we cannot reject the hypothesis that there are no interday variations in trading volume for less actively traded firms (deciles one and five). In the tenth decile, we reject the null hypothesis of no interday variations in trading volume for 11 of the 20 firms. Hence, it appears that variations in trading volume are statistically significant for only the most actively traded firms. This finding is consistent with the Foster and Viswanathan model, where discretionary liquidity traders are more likely to alter their trades when there is a strong public information signal.

The intraday trading volume test results are reported in Panel B of Table I. Overall there is strong evidence of intraday variations in trading volume, with the volume being highest in the first half-hour of trading. In all three samples, there was at least one stock that had one hour where the coefficient of a dummy variable was statistically significantly different from zero at the 1% level.

We find that for more actively traded stocks (deciles five and ten) all of the average dummy variable coefficients are significantly different from zero at the 1% level, and that trading volume is highest in the first half hour of trading. For the least actively traded stocks, decile one, all but the 10:00 dummy variable coefficient, η_2, are significantly different from zero at the 1% level. The average of the 10:00 coefficient is -0.11 (as before this means that the trading volume in the 10:00 to 10:59 time period is lower by 0.011% of the shares outstanding than in the 9:30 to 9:59 period). Notice that in the middle of the day the trading volume is at its lowest level relative to the first half hour of trading for all reported deciles. These average coefficient values and their χ^2 statistics confirm the U-shaped pattern in interday trading volume observed by Jain and Joh (1988).

In the final row of Panel B in Table I, note the high number of instances where we reject the hypothesis of no intraday variations in trading volume. For example, with the least actively traded firms we find that there are 18 out of 20 firms where we reject the null hypothesis that there are no intraday variations in trading volume. For the firms in decile five, we reject the hypothesis of no intraday variations in trading volume for all firms, and for the most actively traded firms there are significant intraday variations in trading volume for 19 out of 20 firms.

In short, it appears that there are significant intraday variations in trading volume for all of the deciles that we report. There are significant interday variations in trading volume only for the most actively traded firms in our sample. These findings are consistent with both the models of Admati and Pfleiderer and Foster and Viswanathan. That is, we find that there is a concentration of volume in the opening half hour of trading with our intraday tests. For our interday tests we find that Monday trading volume is significantly lower than Tuesday and Wednesday trading volume for the most actively traded firms. Next, we examine whether changes in return volatility and trading costs move with these patterns in trading volume in a manner consistent with the models of Admati and Pfleiderer and Foster and Viswanathan.

IV. Variations in Return Volatility

A. Background and Hypotheses

In addition to patterns in the volume of shares traded, we are interested in variations in return volatility. Understanding patterns in volatility helps us to determine when prices are more informative, which in turn suggests various trading strategies to investors. This section contains tests on inter- and intraday variations in return volatility. We use the prices at the end of each day (hour) to compute the returns over the day (hour) and estimate the following expression:

$$r_t = r + \sum_{i=2}^{5} 1_{d=i}\zeta_i + u_t$$

$$\left(r_t - r - \sum_{i=2}^{5} 1_{d=i}\zeta_i\right)^2 = \omega + \sum_{i=2}^{5} 1_{d=i}\gamma_i + v_t \tag{7}$$

The first equation in expression (7) is an adjustment for interday (intraday) variations in mean returns. The second equation represents the variance of returns, using a mean that has been corrected for interday (intraday) variations.[5] We estimate expression (7) with a system of 40 equations (two equations for twenty firms) with GMM. As before, we use orthogonality conditions from the regression normal equations:

$$\begin{aligned} E[u_t] &= 0 \\ E[u_t 1_{d=i}] &= 0 \quad i = 2,3,4,5 \\ E[v_t] &= 0 \\ E[v_t 1_{d=i}] &= 0 \quad i = 2,3,4,5 \end{aligned} \tag{8}$$

Expression (8) gives us 200 equations and 200 unknowns, so the system is just-identified. With the parameter estimates and the variance-covariance matrix, we test for interday variations in exactly the same fashion as when we examined variations in the trading volume.[6] The coefficients of the day (hour) dummy variables in the second equation of expression (7), γ_i, give the interday (intraday) variations in return volatility. The value of these coefficients forms the basis of our tests.

[5]Recall that the first trading interval for the intraday tests is one half hour and the other intervals are one hour. To make all time periods comparable, we double the return for the 9:30 to 10:00 time period.

[6]This approach is similar to that of Harvey and Huang (1991).

B. Results

Table II presents the results of our tests on variations in return volatility. The first row of Panel A shows that all χ^2 values are significant at the 1% level; the χ^2 value for the least actively traded stocks is 281, and the χ^2 statistic for the most actively traded stocks is 310.[7] Beginning with the interday variation results, we see that at least one of the twenty stocks in each decile has a significant interday variation in return volatility.

Being able to distinguish between volatility on different days of the week is difficult, however. When we examine the averages (across firms) of each of the day dummy coefficients, we find that none of the averages of the coefficients is significantly different from zero for any decile. When we count the number of firms where we can reject the hypothesis that all of the day dummies have zero coefficients, we find that for only one of the least actively traded firms can we show a significant interday variation in return volatility. Two stocks in decile five have a significant interday variation in return volatility, and for the most actively traded shares only five of 20 stocks have significant interday variations in return volatility. Hence, it appears that while there are interday variations in return volatility only for the most actively traded stocks, the evidence does not appear to be strong.

The intraday differences in return volatility are reported in Panel B of Table II. Here, we find that there are significant variations in return volatility. The test of whether none of the coefficients of the hour dummy variables is different from zero among all 20 stocks in each decile is rejected at the 1% significance level for all deciles. That is, the χ^2 statistic for the less actively traded shares is 646, for the shares in decile five the statistic is 873, and for the most actively traded stocks the statistic is 622.

The hour-by-hour results are reported in Panel B of Table II. We see that in the first and tenth deciles all of the average hour dummy coefficients are nonzero at the 1% significance level. For example, for the 10:00 to 10:59 dummy we find that the variance of returns is lower by 0.0950 and the associated χ^2 statistic is 35.81 for the least actively traded firms. In decile five, we reject the hypothesis that the average hour dummy coefficients are zero at the 5% level of significance. For the fifth decile, the return variance drops by 0.0010 after the first half hour of trading and the χ^2 statistic is 4.56 for the 10:00 to 10:59 interval. Notice that the opening half hour is always more volatile than any other time of the day for all deciles.

When we check for intraday variations in return volatility on a firm by firm basis, we find that for all but five firms in the least actively traded decile we

[7]Because we are using transaction prices and not adjusting for the bid-ask bias, our estimate of the variances is too large (see Smith (1989)). As we document in Section V, there are time dependencies in the trading costs, so it is possible that these variance patterns are the result of variations in the bid-ask spread. In earlier drafts of the paper, we found that there was no difference in the variations in volatility when we used the midpoint of the bid-ask spread prior to the last transaction of each time period instead of the transaction price. Because other papers in the literature compute returns with transaction prices, we present our results in the same form.

Table II

Variations in Return Volatility for Sixty Firms Traded on the NYSE in 1988

Decile 1 refers to a sample of those firms least actively traded for the year, decile 10 is a sample of the most actively traded firms in 1988. The return on a stock at time t, r_t, is broken into a reference return based on Monday (the first half hour of) trading, r, an adjustment for the day of the week (hour of the day) (where the ζ_i are the coefficients of the day (hour) dummy variables), and a mean zero error term, u_t. The variance of the returns from this adjusted mean is computed. To do this the following pair of equations is estimated and three tests are reported:

$$r_t = r + \sum_{i=2}^{5} 1_{d=i}\zeta_i + u_t$$

$$\left(r_t - r - \sum_{i=2}^{5} 1_{d=i}\zeta_i\right)^2 = \omega + \sum_{i=2}^{5} 1_{d=i}\gamma_i + v_t; \qquad (7)$$

where the second equation gives estimates of interday (intraday) variations in the variance of return; ω is the reference volatility based on Monday (the first half hour of) trading, and v_t is a zero mean error term. The first test examines whether all of the coefficients of the day (hour) dummy variables, γ_i, are zero for the firms in each decile, and a χ^2_{80} (χ^2_{120}) statistic is reported for the interday (intraday) test for each decile. The second test examines whether each day (hour) is different from Monday (the first half hour) for all firms in each decile. An ordered pair of the mean (across firms) of the dummy coefficients and the corresponding χ^2_1 statistic are reported for each day (hour). The third test lists the number of firms for which at least one day (hour) dummy variable coefficient is different from zero at the 5% level.

Test	Decile 1	Decile 5	Decile 10
Panel A. Interday Differences			
Overall significance	281†	290†	310†
γ_2 (Tuesday)	−0.0006, 0.00	0.0000, 0.01	−0.00005, 2.96
γ_3 (Wednesday)	−0.0037, 0.08	−0.0002, 0.66	0.00001, 0.10
γ_4 (Thursday)	0.0042, 0.10	−0.0001, 0.25	0.00004, 0.60
γ_5 (Friday)	0.0072, 2.68	0.0005, 0.48	0.00016, 1.96
Number of significant coefficients	1	2	5
Panel B. Intraday Differences			
Overall significance	646†	873†	622†
γ_2 (10:00)	−0.0950, 35.81†	−0.0010, 4.56*	−0.00024, 102.67†
γ_3 (11:00)	−0.0990, 35.53†	−0.0010, 5.07*	−0.00026, 110.35†
γ_4 (12:00)	−0.0985, 37.72†	−0.0010, 5.35*	−0.00026, 118.02†
γ_5 (13:00)	−0.0954, 36.24†	−0.0010, 5.49*	−0.00026, 120.28†
γ_6 (14:00)	−0.0951, 35.88†	−0.0010, 5.32*	−0.00026, 113.45†
γ_7 (15:00)	−0.0927, 209.07†	−0.0010, 4.96*	−0.00023, 86.53†
Number of significant coefficients	15	20	20

*different from 0 at the 5% level.
†different from 0 at the 1% level.

can reject the null hypothesis that there are no intraday variations in return volatility.

An analysis of Tables I and II suggests that trading volume is high when volatility is high for the intraday case (volume is highest and returns are most volatile at the open), but not for the interday case (because we find no strong interday variations in return volatility). Additionally, we find that the interday variations in trading volume are weak, relative to the intraday variations in trading volume. To clarify this association, we regress the return volatility dummy coefficients on the trading volume dummy coefficients for the firms in each decile (these regressions are not reported in the tables). If the Admati and Pfleiderer prediction is correct, we should see a positive relation between the two sets of coefficients. For the Foster and Viswanathan model, we should see a negative relation between the interday return volatility and volume dummy coefficients. Under the Foster and Viswanathan model, the negative association should be most pronounced for the most actively traded firms; it is in this sample that the discretionary actions of liquidity traders are most effective. None of the regressions of the interday dummy variables coefficients yields a significant fit at the 5% level. Hence, we cannot reject the hypothesis that there is no relation between interday variations in volume and volatility for all three of our samples. For the intraday coefficients, we find that for deciles one and ten we reject the null hypothesis that there is no association between the volume and volatility dummy coefficients with p-values of 4.73% and 0.02%, respectively. For the fifth decile, there is no significant relation between the volume and volatility dummy variable coefficients at the 5% level. For the first and tenth deciles, the volume dummy coefficients are positively related to the return volatility dummy coefficients, which supports the prediction of Admati and Pfleiderer.

So far we have shown that, in keeping with Admati and Pfleiderer, trading volume is highest when returns are most volatile in the intraday tests. The lack of strong interday variations in return volatility and trading volume means that the tests of the Foster and Viswanathan model have little power. As a reminder, the significant difference between Admati and Pfleiderer and Foster and Viswanathan is that Foster and Viswanathan allow for a public signal between days that reveals some of the informed trader's private information. In this setting, a discretionary liquidity trader avoids days when there is a lot of private information. By waiting for the public signal, the discretionary liquidity trader lowers the trading volume on days with high return volatility. As we have shown, the only significant interday variations occur for the more actively traded stocks, which are likely to have regular, precise public information.

To test fully the Admati and Pfleiderer and Foster and Viswanathan models, we need to examine patterns in trading costs. In particular, the portion of the trading cost that is induced by the adverse selection faced by the market maker is of critical interest. Both the Admati and Pfleiderer and Foster and Viswanathan models claim that the adverse selection trading costs are lowest when trading volume is the highest. In the context of their models, discretionary liquidity traders shift their transactions only when they can reduce their costs by doing so. If the trading costs are high when trading volume is high we would reject these models. This restriction on the trading costs, trading volume, and return volatility is considered in the next section.

V. Variations in Trading Costs

A. Background and Hypotheses

In this section, we use transaction price changes to estimate fixed and adverse selection (or information) cost components. By documenting the inter- and intraday variations in these trading cost components, we gain a greater insight into the behavior of traders and discover whether the implications of the Admati and Pfleiderer and Foster and Viswanathan models are consistent with the data.

The Admati and Pfleiderer model (see Section 1 of their paper) predicts that trading costs are lowest in periods where the volume is highest. This cost reduction occurs because liquidity traders pool their trades in an effort to reduce their transaction costs. While more informed traders submit orders in response to this concentration of liquidity, competition among these traders ensures that adverse selection trading costs are even lower.

The Foster and Viswanathan model, on the other hand, predicts the adverse selection cost component to be highest on Monday. The magnitude of the difference between the Monday costs and the costs on other days depends on the precision of public information. Precise public information limits the ability of the informed agent to shift trades and creates the largest difference in the adverse selection costs. In contrast, poor public information places weaker restrictions on the informed trader's ability to transact, so the cost difference is lower. If total trading volume is a good proxy for the precision of available public information, the Foster and Viswanathan model predicts that differences in the adverse selection costs should be more pronounced for more actively traded stocks.

To estimate trading costs, we use transactions data and measure time, t, in terms of the number of transactions made in 1988. For our interday (intraday) tests we use dummy variables to recognize on which day of the week (hour of the day) each transaction occurs. Following Hasbrouck (1991a, 1991b), we model the market maker's price adjustment rule (in an interday setting) as follows:

$$q_t = \alpha + \sum_{i=2}^{5} \delta_i \mathbf{1}_{d_t=i} + \sum_{j=1}^{5} \beta_j dp_{t-j} + \sum_{k=1}^{5} \iota_k q_{t-k} + \tau_t$$

$$dp_t = 2c\left[1_{[\tilde{q}_{d,t} > 0]} - 1_{[\tilde{q}_{d,t-1} > 0]}\right] + \sum_{i=2}^{5} 2c_i\left[1_{[\tilde{q}_{d,t} > 0]} - 1_{[\tilde{q}_{d,t-1} > 0]}\right]1_{d_t = i} + \lambda\tau_t + \sum_{j=2}^{5} \lambda_j 1_{d_t = d_j}\tau_t + \nu_t, \tag{9}$$

where q_t is the quantity traded at time t and dp_t is the price change resulting from the portion of the order that was not expected at time t. The first equation of expression (9) gives a conditional expected value for the transaction size at time t. We use five lags of price changes, five lags of orders, an intercept, and a day of the week (hour of the day) dummy to compute the conditional expected trade size. The second equation of expression (9) gives the price change as a function of the order that was not expected by the market maker. Expression (9) differs from the model used by Hasbrouck (1991a, 1991b), who uses changes in the quote midpoint, whereas we are interested in price changes. As a consequence, we incorporate a fixed cost component, c, in our price adjustment equation. The fixed component of the price change has a special structure. The fixed costs are paid only when the price moves from a bid to an ask or vice versa. If the price moves from a buy (sell) to a sell (buy) order, the fixed cost term is negative (positive). The variable portion of the price change, λ, is the adverse selection cost component. This value represents the amount by which the market maker adjusts the transaction price for each share of unexpected order flow. Expression (9) also includes day (hour) dummies to estimate interday (intraday) variations in the fixed and adverse selection cost components of the price change.

Following Hasbrouck (1991a, 1991b) and Lee and Ready (1991), we determine the sign of the q_t (whether it was buyer or seller initiated) using bid and ask quotes that are at least five seconds old when the transaction occurs. Transactions at or closest to the bid are sell orders and are negative; prices at or closest to the ask are buy orders and are positive. Transactions occurring at prices exactly between the bid and ask are assumed to be crossed and are omitted.

Because of the large number of transactions for the frequently traded stocks, we are unable to use GMM (our computer system could not handle so large a problem). Instead, we estimate equation (9) for each firm using Ordinary Least Square (OLS) with White (1984) corrected standard errors. Also, because no two firms have an identical timing of transactions we cannot estimate expression (9) as a multivariate system across all firms.

For each firm, we first use the second equation of expression (9) to see whether all the fixed and adverse selection cost dummy coefficients are zero. Next, we more closely examine the value of the day (hour) dummy coefficient values. For the interday tests, we are most concerned about whether the trading costs on Tuesday are different from those on Monday; this tells us whether discretionary liquidity traders find it beneficial to delay their transactions from Monday to Tuesday in response to the private information accumulated over the weekend. In the intraday tests we are interested in whether the 10:00 and 15:00 hour trading cost dummy variables are zero, i.e., we want to know if trading costs change with the drop in volume and volatility after the open and whether the opening half hour is different than the closing hour.

To perform the tests described above, we compute a χ^2 statistic for each firm based on the null hypothesis that a particular coefficient or group of coefficients of dummy variables is zero using the White (1984) corrected variance-covariance matrix. From these χ^2 statistics, we report (for each decile): (i) the number of firms that have significant interday (intraday) variations in fixed and adverse selection trading costs; (ii) the average coefficient for the Tuesday (10:00 and 15:00) dummy variable and (iii) the number firms where the coefficients of the Tuesday (10:00 and 15:00) dummy variable coefficients are negative—this is to see whether trading costs are higher on Monday (in the first half hour of trading or at the close).

Much of our power in the volume and variance tests comes from the ability to aggregate across firms in a multivariate test. For our analysis of transaction costs, we would like to use simultaneously all of the cross-sectional data in each decile. Nonsynchronous trading does not allow this simultaneous estimation, so we aggregate across all firms using the p values from the χ^2 test, with a procedure advocated by Gibbons and Shanken (1987). The aggregated p-value is calculated as follows. First, $-2\log_e$ of the individual firm p-value is distributed χ^2 with 2 degrees of freedom. The sum of these transformed p-values is distributed as a χ^2 with twice the number of firms as its degree of freedom. An overall or aggregated p-value is then calculated from this new statistic.[8] Note that this technique ignores cross-correlations that may exists between firms.[9] Our tests on trading volume and return volatility suggest that we would find significant variations in trading costs more often with multivariate tests; we find these variations using the aggregated p-values as well.

B. Results

Table III lists the variation in fixed costs for inter- and intraday periods. While Table III does not include the estimates of the cost components, an example of the coefficient values is as follows. The average fixed cost for firms in decile five during 11:00 through 11:59 was \$0.0695. The average revision in prices due to the unexpected component of the order size (adverse selection cost) was \$0.0086 per thousand shares. These average fixed and adverse selection costs are lower than those reported by Glosten and Harris (1986); however, their estimation technique is based on the total order size, not just

[8] See Gibbons and Shanken (1987) for a discussion of the power of this test.

[9] For similar reasons Hasbrouck (1991a, 1991b) also aggregates tests statistics across firms without an explicit adjustment for cross-correlations.

its unpredictable component, does not use bid-ask data to sign trades, and ignores inter- and intraday variations.

The fixed cost component shows little significant interday variation. From the first row of Panel A of Table III, we see that only for 3 firms in decile five and for 6 of the most actively traded firms can we find evidence of significant interday variations in fixed trading costs. In the second rows of Panel A of Table III we report that the hypothesis that all Tuesday fixed cost dummies have a zero coefficient is rejected for two firms in the first decile, for no firms in the fifth decile, and for two firms in the tenth decile. The aggregated p-value reported in the fifth row of Panel A of Table III shows that there is no significant change in the fixed component of trading costs from Monday to Tuesday. Finally, we also note that for the least actively traded firms, the Tuesday dummy variable had a negative coefficient for 10 of the twenty firms examined. In deciles five and ten there were 9 and 7 negative Tuesday dummy variable coefficients, respectively.

From Table III, we see that the hypothesis that all the fixed cost dummies for the different hours are equal to zero is rejected in 16 out of 20 firms for the most actively traded firms, decile ten, but only for seven firms in the fifth decile and one of the least actively traded firms, decile one. For the tenth decile, using White-corrected χ^2 statistics, we find four rejections for the hypothesis that the 10:00 dummy had a coefficient other than zero. For both the first and fifth deciles, there is only one firm out of twenty for which we can reject the hypothesis that the 10:00 dummy coefficient is zero. For the 15:00 dummy, we find very few cases where we can reject the hypothesis that there are significant variations in the fixed costs. About half of the 10:00 and 15:00 dummy values are negative for all deciles. Consistent with these individual firm results, aggregated p-values are significant only for the 10:00 dummy coefficient for the most actively traded firms. Hence, there appears to be little significant intraday variation in the fixed cost component of price changes.

Tests for interday variations in adverse selection trading costs are reported in Panel A of Table IV. The test that all of the adverse selection dummy coefficients are zero is rejected in five cases for the least actively traded firms, decile one, 12 cases for the second decile, and 11 cases for the most actively traded firms, decile 10. Also, the Tuesday dummy coefficient is not significantly different from zero in the first decile, but is significantly different from zero for five firms in the fifth decile, and six firms in the tenth decile. The aggregated p-values suggest a significant interday effect for the fifth and tenth decile (the rejection is stronger for the tenth decile). Hence, it appears that adverse selection costs become lower on Tuesday for the most actively traded firms, a finding that is consistent with the Foster and Viswanathan model. For the fifth decile, however, the average coefficient of the Tuesday dummy is positive which is inconsistent with the Foster and Viswanathan model.

As a final check on the predictions of the Foster and Viswanathan model, we regress the coefficient of each adverse selection trading cost dummy

Table III
Variations in Fixed Trading Costs for Sixty Firms Traded on the NYSE in 1988

Decile 1 refers to a sample of those firms least actively traded for the year, decile 10 is a sample of the most actively traded firms in 1988. The fixed cost component of price changes is estimated with the following system:

$$
\begin{aligned}
q_t &= \alpha + \sum_{i=2}^{5} \delta_i 1_{d_t=i} + \sum_{j=1}^{5} \beta_j dp_{t-j} \\
&\quad + \sum_{k=1}^{5} \iota_k q_{t-k} + \tau_t \\
dp_t &= 2c[1_{[\tilde{q}_{d,t}>0]} - 1_{[\tilde{q}_{d,t-1}>0]}] \\
&\quad + \sum_{i=2}^{5} 2c_i[1_{[\tilde{q}_{d,t}>0]} - 1_{[\tilde{q}_{d,t-1}>0]}]1_{d_t=i} \\
&\quad + \lambda\tau_t + \sum_{j=2}^{5} \lambda_j 1_{d_t=d_j}\tau_t + \nu_t;
\end{aligned}
\tag{9}
$$

where c is the fixed cost component and c_i is a dummy variable that gives the interday (intraday) variations in the fixed costs. The first equation uses the current order, q_t, to estimate the unexpected order flow (defined to be τ_t, the residual variable of the regression) using a fixed effect, α, the past five price changes, dp_{t-j}, the past five orders, q_{t-k}, and an adjustment for the day (hour) at which the trade occurred (the coefficient of the day (hour) dummy variable is δ_i). The second equation splits the current price change, dp_t, into the fixed cost components and the portion that depends on the unexpected order flow (the adverse selection cost which is denoted by the variable λ). In addition, dummy variables (with coefficients λ_j) are included to account for interday (intraday) variations in the adverse selection cost component of the price change, and ν_t is a zero mean error term.

The first test examines whether the estimated coefficients of each day (hour) dummy variable are different from zero for a given firm. Here we report the number of firms where there is a significant interday (intraday) difference at the 5% level based on a χ^2 test with White (1984) corrected standard errors. Subsequent tests are concerned with the average of a particular day (hour) dummy coefficient value across the firms in the sample. The number of firms for which the coefficient is different from zero is reported (using a χ^2 test with White (1984) corrected standard errors), as is the average coefficient value, the number of firms with negative coefficients, and an aggregated p-value from the χ^2 test using the procedure outlined in Gibbons and Shanken (1987).

Test	Decile 1	Decile 5	Decile 10
Panel A. Interday Differences			
Number of firms with significant interday differences	0	3	6
Number of firms with significant Tuesday coefficients	2	0	2
Average value of the Tuesday coefficient	−0.0054	−0.0041	0.0022
Number of firms with negative Tuesday coefficients	10	9	7
Aggregated p-value for the Tuesday coefficient	0.299	0.393	0.108

Table III—*Continued*

Test	Decile 1	Decile 5	Decile 10
Panel B. Intraday Differences			
Number of firms with significant intraday differences	1	7	16
Number of firms with significant 10:00 coefficients	1	1	4
Average value of the 10:00 coefficient	−0.0012	−0.0039	0.0013
Number of firms with negative 10:00 coefficients	12	9	12
Aggregated p-value for the 10:00 coefficient	0.359	0.079	0.012
Number of firms with significant 15:00 coefficients	2	1	0
Average value of the 15:00 coefficient	0.0029	−0.0040	0.0063
Number of firms with negative 15:00 coefficients	10	9	8
Aggregated p-value for the 15:00 coefficient	0.298	0.066	0.297

against the coefficient of each trading volume dummy for all firms. In addition, we regress the sign (1 for positive values and -1 for negative values) of the adverse selection coefficients on the sign of the trading volume coefficients.[10] Using the value of the coefficients, we find no significant relation between variations in adverse selection trading costs and trading volume. Using signs of the coefficients, we find a significant (at the 1% level) negative relation between adverse selection trading costs and trading volume for the tenth decile, which is consistent with the Foster and Viswanathan model. Hence, it appears that low adverse selection trading costs occur at the same time as high trading volume for the most actively traded firms.

Panel B of Table IV reports the intraday variations in adverse selection trading costs. We find that the hypothesis that all of the adverse selection dummies have zero coefficients is rejected for eight firms in the first decile, 13 firms in the fifth decile, and 12 firms in the tenth decile. Few of the individual firm White-corrected χ^2 statistics show that the 10:00 and 15:00 dummy variables have nonzero coefficients. The aggregated p-values, however, suggest that there are significant intraday variations in the adverse selection costs, and these p-values become smaller for more actively traded firms.[11] At the same time, the number of firms for which the 10:00 and 15:00 dummy variables have negative coefficients increases with the trading activity.

Because the Admati and Pfleiderer model suggests that adverse selection trading costs are lowest at times when trading volume is high, the intraday pattern in adverse selection costs seems contrary to the Admati and Pfleiderer model. Hence, we repeat the regression of trading volume dummy coefficients on adverse selection trading cost dummy coefficients. As in the interday case, the regression with the coefficient values does not yield a

[10] In both regressions we do not use an intercept because fixed effects are already accounted for in the intercepts of the original regressions.

[11] McInish and Wood (1992) show that there is a similar pattern in the bid-ask spread during the day. Hasbrouck (1991b), using an impulse-response model, confirms this intraday pattern.

Table IV

Variations in Adverse Selection Trading Costs for Sixty Firms Traded on the NYSE in 1988

Decile 1 refers to a sample of those firms least actively traded for the year, decile 10 is a sample of the most actively traded firms in 1988. The adverse selection cost component of price changes is estimated with the following system:

$$\begin{aligned} q_t &= \alpha + \sum_{i=2}^{5} \delta_i 1_{d_t=i} + \sum_{j=1}^{5} \beta_j dp_{t-j} \\ &\quad + \sum_{k=1}^{5} \iota_k q_{t-k} + \tau_t \\ dp_t &= 2c[1_{[\tilde{q}_{d,t}>0]} - 1_{[\tilde{q}_{d,t-1}>0]}] \\ &\quad + \sum_{i=2}^{5} 2c_i[1_{[\tilde{q}_{d,t}>0]} - 1_{[\tilde{q}_{d,t-1}>0]}]1_{d_t=i} \\ &\quad + \lambda\tau_t + \sum_{j=2}^{5} \lambda_j 1_{d_t=d_j}\tau_t + \nu_t; \end{aligned} \tag{9}$$

where λ is the adverse selection cost component and λ_j is a dummy variable that gives the interday (intraday) variations in the adverse selection costs. The first equation uses the current order, q_t, to estimate the unexpected order flow (defined to be τ_t, the residual variable of the regression) using a fixed effect, α, the past five price changes, dp_{t-j}, the past five orders, q_{t-k}, and an adjustment for the day (hour) at which the trade occurred (the coefficient of the day (hour) dummy variable is δ_i). The second equation splits the current price change, dp_t, into its the fixed cost component, c, and the adverse selection costs. In addition, dummy variables (with coefficients c_i) are included to account for interday (intraday) variations in the fixed cost component of the price change, and ν_t is a zero mean error term.

The first test examines whether the estimated coefficients of each day (hour) dummy variable are different from zero in a given firm. Here we report the number of firms where there is a significant interday (intraday) difference at the 5% level based on a χ^2 test with White (1984) corrected standard errors. Subsequent tests are concerned with the average of a particular day (hour) dummy coefficient value across the firms in the sample. The number of firms for which the coefficient is different from zero is reported (using a χ^2 test with White (1984) corrected standard errors), as is the average coefficient value, the number of firms with negative coefficients, and an aggregated p-value from the χ^2 test using the procedure outlined in Gibbons and Shanken (1987).

Test	Decile 1	Decile 5	Decile 10
Panel A. Interday Differences			
Number of firms with significant interday differences	5	12	11
Number of firms with significant Tuesday coefficients	0	5	6
Average value of the Tuesday coefficient ($*10^5$)	−0.569	0.178	−0.042
Number of firms with negative Tuesday coefficients	11	9	14
Aggregated p-value for the Tuesday coefficient	0.776	0.001	0.000

Table IV—*Continued*

Test	Decile 1	Decile 5	Decile 10
Panel B. Intraday Differences			
Number of firms with significant intraday differences	8	13	12
Number of firms with significant 10:00 coefficients	2	2	4
Average value of the 10:00 coefficient ($*10^5$)	0.397	0.671	−0.123
Number of firms with negative 10:00 coefficients	9	11	19
Aggregated p-value for the 10:00 coefficient	0.051	0.030	0.001
Number of firms with significant 15:00 coefficients	2	2	4
Average value of the 15:00 coefficient ($*10^5$)	−0.128	0.848	−0.055
Number of firms with negative 15:00 coefficients	9	10	15
Aggregated p-value for the 15:00 coefficient	0.002	0.075	0.000

significant association between trading volume and adverse selection trading costs. Using the sign of the coefficients yields a significant (at the 5% level) positive relation between the adverse selection trading costs and trading volume for firms in the tenth decile. While this is a weak test, it indicates that the data appear to be inconsistent with the Admati and Pfleiderer model at this level.

Both the Admati and Pfleiderer and Foster and Viswanathan models cannot, in their current form, explain the fact that trading volume is highest when trading costs are high for the intraday tests. While the interday data supports the Foster and Viswanathan model, the use of discretionary liquidity trading in the Foster and Viswanathan model means that it too would predict low volume with high trading costs in an intraday setting. This particular rejection, however, gives some insights into why these models do not match the empirical record. High transaction costs when the volume is highest may result from the market maker's monopolistic power, greater inventory costs during this active period of trading, or intra-daily variation in the private and public information that makes the middle portion of the day fundamentally different than the open or close. Each of these possibilities should be explored in further research.[12]

VI. Summary

This study examines the empirical behavior of stock market trading volume, trading costs, and price change volatility and its implications regarding the Admati and Pfleiderer and Foster and Viswanathan models of discretionary liquidity trading. The evidence, garnered from inter- and intraday New York Stock Exchange data, shows that fixed trading costs have little intra- or interday variation. On the other hand, the adverse selection cost component of price change varies within the day and across days. In particu-

[12]As an example of this, see Brock and Kleidon (1992) who use a model where the market maker has monopolistic power.

lar, adverse selection costs are high in the first half hour of trading, fall during the middle of the trading day, and then increase again towards the close of trading. While the data are very noisy, high adverse selection costs are found at times of the day with higher trading volume, which is inconsistent with the Admati and Pfleiderer model. Adverse selection costs (trading volume) are higher (lower) on Monday than on other days, primarily for actively traded firms. This evidence is consistent with the Foster and Viswanathan model.

Our empirical work indicates that existing theoretical models based on the adverse selection faced by the market maker are broadly consistent with observed patterns in the volume-volatility relation. That is, intraday trading volume is high when returns are most volatile. We do not find, however, significant interday variation in return volatility. Neither model can explain the intraday phenomenon of high trading costs when trading volume is high —this effect appears to be inconsistent with the interests of discretionary liquidity traders. Perhaps further research that enriches the current models to allow for heterogeneity in the public and private information arrival process, inventory costs, or monopolistic rents to the market maker will explain this phenomenon.

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