Empirical Essays on Information Asymmetries

in Financial Markets

by

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Abstract

This thesis consists of three separate empirical studies of information asymmetries in financial markets.

The first essay, entitled "Information Asymmetries and Security Market Design: An Empirical Study of the Secondary Market for US Government Securities" examines the empirical implications of an information asymmetry between primary and secondary dealers in the US government securities market. This asymmetry arises because primary dealers are permitted to trade through *all* brokers operating in the marketplace while secondary dealers are restricted to trade through only a *subset* of brokers. Brokers distribute valuable information over video screens to their trading clients including dealers' up-to-date bid-ask spreads and recent transaction prices. As such, *all* brokers' video screen information is available to primary dealers, while only a *subset* of brokers' information is available to secondary dealers. Empirical results detect the resulting information asymmetry between primary and secondary dealers.

The second essay, entitled "Uncertainty, Collusion and Returns in a Multiple-Bid, Multiple-Unit Auction with Resale," analyzes bidding behavior in the Mexican Treasury debt auction for the period July, 1986 - August, 1989. Auction rules closely resemble those of the US Treasury: bidders submit multiple bids for multiple units. Purchased quantities are immediately resold. Results detect collusion between the six largest bidders who on average purchase 80% of new government debt. Results also detect information asymmetries between these six bidders and remaining participants. The majority of bidders account for the winner's curse.

Measures of *ex-ante* information disparities between bidders explain cross sectional variation in downward biases of winning bids. Demand for debt is inelastic in the range of the lowest winning bid prices suggesting that the Mexican Treasury should substitute noncompetitive for competitive quantities to increase auction revenues.

The third essay, entitled "An Empirical Examination of the Intraday Behavior of the NYSE Specialist," examines the intraday quote-setting behavior of specialists for 118 NYSE stocks. This essay is written jointly with Mitchell Petersen. We find that revisions in the midpoint of specialists' quoted spreads depend on transaction volumes, changes in quoted volumes, contemporaneous changes in market indices and the time elapsed between quote revisions. Trades which immediately precede requotation induce larger revisions than those which do not. Trades for volumes which exceed quoted volumes induce larger absolute and smaller marginal revisions than trades for volumes which are less than quoted volumes. The sensitivities of quote revisions to transaction volumes vary across trading periods but patterns are inconsistent with existing theory. Trading activity, return risk, and insider concentration explain cross-sectional variation in the sensitivity of quote revisions to transaction volumes.

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Essay <u>One</u>

INFORMATION ASYMMETRIES AND SECURITY MARKET DESIGN:

AN EMPIRICAL STUDY OF THE SECONDARY MARKET FOR US GOVERNMENT SECURITIES

I. Introduction

The secondary market for US Government Securities market is one of the largest and most efficient asset markets in the world. US government securities are traded worldwide, 24 hours a day. Average daily volume in the secondary market exceeds $40 billion. Virtually continuous auction markets exist in the most active government securities issues.

The nature of the secondary market trading system has a direct impact on interest rates required to issue new government debt. One would expect the improvement of resale opportunities to lower trading costs and investment risks and in turn lower the costs of debt issuance. One must therefore carefully evaluate secondary market design given the large sums of money -- $1.8 trillion in 1988 -- that the Treasury must raise each year to finance current budget deficits and refinance existing debt. For example, a reduction of 10 basis points (.1%) in the issuance rate of interest for a given year's $200 billion government budget deficit would lower the annual interest cost of servicing this deficit by $200 million.

The U.S. General Accounting Office (GAO) is currently evaluating the existing structure of the secondary market for US government securities in response to a mandate of the Government Securities Act of 1986. Efforts of the GAO have addressed concerns voiced by market participants regarding

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Analyses of intraday series of 566 two-year note and 1931 30-year long-term bond transactions detect information asymmetries between primary and secondary dealers. Point estimates indicate that secondary dealer price expectations lag those of primary dealers and that secondary dealers post wider bid-ask spreads.

Unfortunately, this paper does not address the case of *inactive* issues due to a lack of appropriate data. The set of inactive issues consists of all Treasury securities issued before the most recently executed Treasury auction that have yet to mature. Brokers' services are *completely unavailable* to secondary dealers in the case of inactive issues even though they are readily available to primary dealers. Given that I detect information asymmetries in trading of the two inactive issues examined in this paper, it is likely that even more substantial information asymmetries exist in the case of inactive issues.

The balance of the paper proceeds as follows. Section II describes the institutional structure of the secondary market for US government securities and highlights issues of regulatory interest. Section III provides a model of transaction price behavior in a perfectly integrated market in which all primary and secondary dealers enjoy identical access to broker trading privileges and video screen information. Section IV derives statistical properties of price changes in the presence of an information asymmetry between primary and secondary dealers. Section V describes the data. Section VI provides empirical results. Section VII provides concluding comments.

II. The Secondary Market for US Government Securities

This section describes the institutional structure of the secondary market for US government securities and highlights issues of regulatory interest.[1]

The US Treasury issues securities in the form of bills, notes, and bonds to refinance debt, to raise new funds to finance deficits, and to manage the government's cash flow. As the fiscal agent of the Treasury, the Federal Reserve auctions Treasury securities to the public. The majority of initial purchasers of these securities are large banks and securities firms which operate as government securities dealers. These dealers purchase securities for their own portfolios, on behalf of their customers or for resale in the secondary market. Dealers participating in issuance auctions are referred to as primary dealers.

Once purchased, government securities can be resold in the secondary market. The secondary market performs two basic functions. First, it distributes debt to private investors. These investors include state and local governments, insurance companies, banks, pension funds, other financial institutions, as well as individual investors. Second, the secondary market facilitates the resale of government securities when these investors decide to alter their government securities portfolios.

Insert Figure 1 Here

Dealers. There are three categories of dealers participating in the secondary market for US government securities -- primary dealers, aspiring primary dealers and secondary dealers. Primary dealers are dealers that

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[1]This section borrows liberally from GAO (1987).

participate in the issuance auctions in which Treasury securities are initially sold. Dealers volunteer to become primary dealers, and in turn are required to meet certain financial standards as well as provide information to the Federal Reserve Bank of New York (FRBNY) needed to monitor compliance with these standards. To maintain their status as primary dealers, these dealers must also participate actively in issuance auctions and open market operations. There were in total 40 primary dealers when the data for this study were collected.

Aspiring primary dealers, the second category, are dealers currently undergoing FRBNY evaluation as potential primary dealers. This evaluation procedure typically lasts over a year, after which most aspiring dealers are granted primary dealer status. Aspiring primary dealers are not required to maintain any official FRBNY-mandated financial standards during the period of evaluation, nor are they required to participate in Treasury securities issuance auctions. There were in total 13 aspiring primary dealers when the data for this study were collected.

Secondary dealers comprise the third category. For the purposes of this study, this category consists of all dealers that trade in the secondary market that are neither primary nor aspiring primary dealers. The category of secondary dealers thus includes securities firms, banks, pensions funds, state and local governments, financial institutions, and individual investors. There were several hundred secondary dealers when the data for this study were collected.

Brokers. Most trading in the secondary market does not occur in a centralized place such as a stock exchange. Rather, it occurs in a decentralized network of dealers and brokers connected by

telecommunications systems. Dealers either negotiate trades directly or conduct them through brokers. Brokers do not buy securities for their own account, but instead specialize in arranging trades for others. Roughly 50% of total secondary market trading volume is arranged by brokers. The remaining 50% of trading volume is exchanged in direct trades between dealers.

Brokered trading can be described as follows. Each broker installs video screens in customer offices which show the best prices available from his customers, the quantities that can be bought or sold at these posted prices, and the prices and quantities of the transactions the broker has most recently arranged. If a customer finds a price on given broker's screen attractive, he can telephone the broker and communicate his desire to initiate trade. The broker will then telephone the customer posting this price and consummate the transaction.

If a customer instead prefers to post his own price on a broker's screen, he can submit a price-quantity sale (ask) or purchase (bid) pair to the broker over the telephone. If a customer submits a sale order, the broker will post the customer's price-quantity pair as long his ask price is strictly less than the ask price already posted on the broker's video screen. Likewise, if the customer submits a purchase order, the broker will post the customer's price-quantity pair at the bid as long as the submitted bid price is strictly greater than the bid price already posted on the broker's screen.

Submitted price-quantity pairs which do not meet these criteria are held in queue until they expire. Price-quantity pairs, whether they be held in queue or posted on the broker's video screen, expire two minutes

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after they are submitted. If a posted ask order expires while on a broker's screen, the broker replaces the expired ask order with the ask order that has the lowest ask price in his queue. Likewise, if a posted bid order expires, the broker replaces the expired bid order with the bid order that has the highest bid price in his queue.

A quoted price on a broker screen represents 1/10,000 of the actual price at which the security in question will be exchanged in the event of a trade. The broker price grid is defined in increments of 1/32, although dealers are allowed to quote prices in finer increments of 1/64 and 1/128. The face value of all traded securities is $1 million. Dealers are required to post whole-number volumes. The minimum volume which dealers can post is therefore 1. As an example, a quoted price at the bid of 99+16/32 with an associated volume of 5 represents an offer to purchase 5 government securities with a total face value of $5 million at a price of $ 995,000 per security.

It is important to discuss the nature of the trading mechanism employed by brokers. The dealer posting a price-quantity pair for which trade has been initiated has the right of first refusal for additional trades at the posted price. If this dealer prefers to increase the volume of the transaction, he can communicate a proposal for a larger volume to his trading partner via the broker arranging the transaction. If the trading partner (i.e., the dealer who initiated trade in the first place) agrees, the volume of trade at the posted price will be increased to the newly proposed volume. The broker will then post the new trading volume on his screen. If the trading partner chooses not to accept to offer to increase the volume of trade, the broker will accept offers from other

dealers for the additional volume at the posted price. This process continues until the trading needs of the dealer initially posting the price - quantity pair are satisfied or no new dealers contact the broker to exchange additional transaction volumes. The final transaction volume is then posted on the broker's screen and all trade is consummated. Due to the nature of this mechanism, dealers quite often build up transaction volumes well above originally posted volumes. For example, it is not uncommon for dealers to build up to volumes $30 million in face value from initially posted volumes of $5 million.

As compensation for his services, the buyer and the seller each pay the broker 1/6400 of the total face value of arranged transactions. Charges are levied only on transacted volumes; posting orders and placing orders in queue are free of charge.

All brokerage activity is *anonymous*. Brokers do not divulge the identities of dealers who have executed transactions, posted price-quantity pairs on video screens or placed orders in queue. Dealers therefore remain uninformed of whom they've traded with until resettlement the day following the consummation of brokered transactions.

The feature of anonymity is designed to prevent strategic gaming which might otherwise arise in a transparent market in which market participants' identities are unveiled. For example, some argue that in a transparent market, participants could collectively force dealers constrained by inventory rebalancing requirements to trade at unfavorable prices.

Interdealer brokers adhere to the policy of restricting their customer bases exclusively to primary and aspiring primary dealers. The

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customer lists of interdealer brokers overlap considerably according to the GAO. There were in total seven interdealer brokers when the data for this study were collected.

Retail brokers serve secondary dealers as well as primary and aspiring dealers. Retail brokers indicate that secondary dealer transactions constitute the majority of their business activity.[2] There were in total two retail brokers when the data for this study were collected.

Interdealer brokers argue that they must restrict their customer base to primary and aspiring primary dealers due to the feature of anonymous trading. The argument is as follows. Interdealer brokers do not back the transactions which they broker as principals. Individual dealers must therefore bear principal risk when they transact. This gives rise to an adverse selection problem which could lead to a breakdown of trade. In particular, due to the blind brokerage feature, dealers do not know the identity of their trading partners. They must have confidence, however, that their trading partners are creditworthy and are able to honor their trading commitments. Otherwise, in the worst case, dealers could suffer substantial losses if a trading partner were to go bankrupt and fail to honor his trades.

Interdealer brokers argue that restricting their customer base to primary and aspiring primary dealers eliminates this adverse selection problem. The financial stability of primary dealers is regularly monitored by the FRBNY in association with issuance auctions and open market operations. Although aspiring primary dealers are not formally required

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[2] See GAO (1987).

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to meet the strict standards imposed on primary dealers, it is widely held that the FRBNY only grants aspiring primary dealer status to dealers maintaining financial standards similar to those of existing primary dealers.

Retail brokers, on the other hand, back the trades they arrange as principals. The issue of adverse selection of trading partners therefore does not arise in the case of retail brokering. Of course, retail brokers attempt to limit their exposure to principal risk by restricting their customer base to dealers whom they regard as creditworthy.

Many secondary dealers maintain creditworthiness standards comparable to those of primary dealers but would find it against their interests to meet the auction participation requirements necessary to acquire primary dealer status. These dealers argue that they deserve access to interdealer broker services and that the risk of expanding interdealer broker access is minimal given how well retail brokering currently functions.

Secondary dealers complain about the low quality of retail broker price information relative to interdealer broker price information. Some argue that retail broker prices fail to depict market conditions accurately due to the concentration of transacted order flows on interdealer broker screens. Others argue that transaction prices on retail screens are misleading because primary dealers "head and fake" and transact small volumes at off-the-market prices on retail screens in order to manipulate secondary dealers' price expectations. Secondary dealers also claim a disadvantage in grasping the overall market climate due to the heterogeneous information content of different brokers' video screen

information.

Furthermore, retail brokers do not arrange trades for *inactive* issues. Therefore, broker services are *completely unavailable* to secondary dealers in the case of inactive issues. The set of inactive issues consists of all Treasury securities issued before the most recently executed auction that have yet to mature. Interdealer brokers, however, do arrange trades for inactive issues. The video screen information of the seven interdealer brokers is therefore available to primary dealers, while no broker video information is available to secondary dealers. Secondary dealers thus complain that information asymmetries between primary and secondary dealers are even larger in the case of inactive issues.

Proponents of the existing system argue against the risks of changing a stable, well-functioning market system. They argue that that the quality of video screen information does not differ between interdealer and retail brokers. Some also suggest that primary dealers deserve special privileges with interdealer brokers as compensation for service as stable outlets for government debt.

III. A Structural Model of Transaction Prices

This section provides a model of the behavior of price changes in a perfectly integrated market. My initial set-up resembles that of of Garbade and Silber (1979) but also incorporates the insights of Glosten and Milgrom (1985) and Kyle (1985) on adverse selection in financial markets.

Throughout this section and the rest of this paper, I merge the

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categories of primary and aspiring primary dealers defined in the previous section into the category of "primary dealers" for convenience. Because primary and aspiring primary dealers possess exactly the same privileges with interdealer and retail brokers, no effective distinction exists between the two for the purposes of the remainder of this paper.

I use the term *market center* to distinguish between the broker access privileges of primary and secondary dealers. Primary dealers and interdealer brokers comprise the primary market center; primary dealers choosing to trade through retail brokers, secondary dealers and retail brokers comprise the secondary market center. Note that because primary dealers enjoy access to both interdealer and retail brokers, the primary and secondary market centers are not comprised of mutually exclusive sets of participants.

Assume all dealers transact in a costless, frictionless environment. Let E_k be the unobservable equilibrium value of the underlying asset at the time of the kth transaction in a given day (i.e., E_k is expectation of the security's end-of-trading cash value conditional on information available at the time of the k-th transaction). Let T_k^a be the observed transaction price of the kth transaction initiated by a *purchaser* of the security (where the superscript a represents the ask side of the market). I assume that the T_k^a is the sum of E_k and α_k^a, where α_k^a is a serially uncorrelated stochastic term with mean α, a lower bound of zero and finite variance σ_α^2. α_k^a can be loosely interpreted as an inventory cost/monopoly power component of the spread. T_k^a is thus:

$$T_k^a = E_k + \alpha_k^a \qquad \alpha_k^a \sim (\alpha, \sigma_\alpha^2) \geq 0 \qquad (1a)$$

A symmetric model applies to transactions initiated by *sellers* in the perfectly integrated market center. Let T_k^b be the observed transaction price of the kth transaction initiated by a seller (where the superscript b represents the bid side of the market.) T_k^b is thus:

$$T_k^b = E_k + \alpha_k^b \qquad \alpha_k^b \sim (-\alpha, \sigma_\alpha^2) \leq 0 \qquad (1b)$$

I assume changes in true value arise due to drift or due to the incorporation of information inherent in transacted volumes. Define Δ_k as the elapsed time between the kth and $k\text{-}1^{st}$ trades. Also define V_k as the observed volume exchanged in transaction k. One thus has $V_k > 0$ if transaction k occurs at the ask and $V_k < 0$ otherwise. E_k is thus:

$$E_k = E_{k-1} + \lambda *V_k + p_k \qquad\qquad E(p_k) = 0, \; E(p_k^2) = \Delta_k *\psi \qquad (2)$$

p_k is a normally distributed, serially uncorrelated stochastic innovation which I assume is uncorrelated with the α_k^as and α_k^bs. $\psi > 0$ is a constant which represents the variance of the drift term per unit of time (measured in minutes throughout this paper). ψ is assumed to be independent of Δ_k (i.e., ψ is not a function of the elapsed time between the k-1st and k-th transactions). λ represents the sensitivity of dealers' assessments of underlying asset values to transacted volumes.[3] Readers can interpret $\lambda*V_k$ as the volume-related adverse selection component of the bid-ask

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[3]Simplicity and the linear equilibrium of the Kyle (1985) model motivate the assumption that the true value varies linearly with transaction volumes.

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spread.[4,5]

The trading mechanism characterized by (2) is one in which the dealer posting the k-th transaction price on a broker screen knows with perfect certainty the volume V_k which he will exchange in the k-th transaction. Given V_k, the dealer is thus able forecast his revised assessment of the true value E_k perfectly. Recalling discussion from Section II, however, dealers are actually uncertain about the volumes they will transact in upcoming transactions when they post prices on broker screens. This is due to the uncertain nature of negotiations in which dealers build up ultimate transaction volumes above initially quoted volumes. In an ideal specification the dealer would post the k-th transaction price based on the volume he *expects* to exchange in the k-th transaction. (2) is therefore a misspecification to the extent that the realized transaction volume V_k will differ from this dealer's ex-ante expectation of the volume which is ultimately exchanged.

Data on expected transaction volumes of dealers posting price-quantity pairs on broker screens are of course unavailable. (2) is a reasonable approximation of the trading mechanism, however, as long as the volumes which dealers' expect to transact when they post prices on broker screens do not differ substantially from volumes which are

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[4]Admati and Pfleiderer (1988) and Foster and Viswanathan (1987) suggest that λ might exhibit patterns across trading periods. In exploratory regressions with my data, however, the estimated values of λ did not vary substantially across hours of the day or days of the week. I therefore assume λ is constant in the empirical analysis of this paper.

[5]$\lambda * V_k$ may measure inventory adjustment costs as well as adverse selection costs. For example, market makers' inventory costs may vary linearly with transaction volumes. All of the tests performed in this paper remain valid if this is the case as long as the magnitude of inventory costs do not differ across primary and secondary dealers.

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ultimately realized in trades.

Taking the difference between prices of two transactions executed on the ask side of the market yields:

$$T^a_k - T^a_{k-1} = (E_k + \alpha^a_k) - (E_{k-1} + \alpha^a_{k-1}) \qquad (3a)$$

$$= P_k + \alpha^a_k - \alpha^a_{k-1} + \lambda * V_k$$

where $E(T^a_k - T^a_{k-1}) = \lambda * V_k$. If the k-th and k-1st transactions are executed on the ask and bid sides of the market, respectively, one has:

$$T^a_k - T^b_{k-1} = (E_k + \alpha^a_k) - (E_{k-1} + \alpha^a_{k-1}) \qquad (3b)$$

$$= P_k + \alpha^a_k - \alpha^b_{k-1} + \lambda * V_k$$

where $E(T^a_k - T^b_{k-1}) = 2* \alpha + \lambda * V_k$.

Now define the dummy variable $SIDE_k$:

$SIDE_k$ = 1 if the k-th transaction is executed on the ask side of the market.

-1 if the k-th transaction is executed on the bid side of the market.

One can estimate α and λ with the following regression model:

$$T_k - T_{k-1} = \alpha * (SIDE_k - SIDE_{k-1}) + \lambda * V_k + \epsilon_k \qquad (4)$$

where $\epsilon_k = (\alpha_k - SIDE_k * \alpha) - (\alpha_{k-1} - SIDE_{k-1} * \alpha) + P_k$ and $E(\epsilon_k) = 0$. Note that I drop the superscripts a and b.

One can estimate σ^2_α and ψ with the following regression:

$$\hat{\epsilon}^2_k = 2 * \sigma^2_\alpha + \Delta_k * \psi + \xi_k; \quad E(\xi_k) = 0 \qquad (5)$$

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where $\hat{\epsilon}_k^2$ is the squared residual calculated with estimates of α and λ from (4). (I employ heteroscedastic-consistent, MA(1)-consistent covariance matrices in all regressions in the empirical section of this paper. As such the heteroscedastic and MA(1) components in the error structures of (4) and (5) do not invalidate hypothesis tests).

If the primary and secondary dealer market centers are perfectly integrated, parameter estimates of models (4) and (5) should not depend on the market centers in which the k-th and k-1st transactions employed to calculate $T_k - T_{k-1}$ are executed. This statement is the basis of tests proposed in the following section.

IV. Testable Implications of Information Asymmetries

In this section I derive implications of information asymmetries between primary and secondary dealers for estimation of models (4) and (5) of the previous section. I assume throughout that the actual process of intermarket center adjustment is driven by 1) the dissemination of information from primary dealers to secondary dealers through direct (i.e. non-brokered) primary-secondary dealer trade,[6] 2) intermarket center arbitrage performed by primary dealers trading through retail brokers and 3) public announcements which reveal the private information primary dealers.[7]

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[6] Recall that direct trade between dealers constitutes 50% of secondary market volume. In fact, several major securities firms have full-time sales/trading forces to execute direct trades over the telephone with other dealers. Most of these firms are primary dealers.

[7] A commonly used empirical methodology for examining lead-lag relationships such as the relationship I hypothesize between the primary

I assume that valuations of underlying assets of secondary dealers lag those of primary dealers deterministically:

$$E_k^s = E_k^p - p_k^\delta \qquad (5)$$

s and p distinguish between "true" values in the secondary and primary dealer market centers, respectively. p_k^δ denotes the *realized* drift in the primary dealer market center during the period beginning δ minutes before the k-th transaction and ending at the time of the k-th transaction. p_k^δ thus represents the additional information incorporated into primary market center prices during the period beginning δ minutes before the k-th transaction and ending at the time of execution of the k-th transaction. I also assume the "true" value is determined in the primary market center and follows the same stochastic process posited in the previous section:

$$E_k^p = E_{k-1}^p + \lambda_p * V_k + p_k \qquad (6)$$

if the k-th transaction is executed in the primary dealer market center and

$$E_k^p = E_{k-1}^p + \lambda_s * V_k + p_k \qquad (7)$$

if the k-th transaction is executed in the secondary dealer market center. The subscripts p and s denote the depth parameters of the primary and

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and secondary market centers employs Granger-Sims causality tests. Granger-Sims causality tests per se are not statistically valid tests of lead-lag relationships. In particular, the fact that a series y_t displays a phase lead of a series x_t is neither a necessary nor a sufficient condition for current or lagged y_ts to be of in predicting x_t. (See Sargent, Macroeconomic Theory (1986), pp. 271-273).

secondary dealer market centers, respectively. I make this distinction because the values of λ_p and λ_s will differ if primary and secondary dealers are indeed asymmetrically informed.

Now define the dummy variable $SIDE_k^P$ follows:

$SIDE_k^P$ = 1 if the k-th transaction is executed on the ask side of the market in the primary market center.

-1 if the k-th transaction is executed on the bid side of the market in the primary market center.

0 if the k-th transaction is executed in secondary market center.

Define $SIDE_k^s$ similarly where the superscript s of course refers to the secondary market center.

Incorporating (6) and (7) into (4) from the previous section yields the following regression model:

$$T_k - T_{k-1} = \alpha_p * (SIDE_k^P - SIDE_{k-1}^P) + |SIDE_k^P| * \lambda_p * V_k \qquad (8)$$
$$+ \alpha_s * (SIDE_k^s - SIDE_{k-1}^s) + |SIDE_k^s| * \lambda_s * V_k$$
$$+ \epsilon_k$$

where $E(\epsilon_k)$ = 0 and

$$\epsilon_k = (\alpha_k - SIDE_k^P * \alpha^P - SIDE_k^s * \alpha^s) - (\alpha_{k-1} - SIDE_{k-1}^P * \alpha^P - SIDE_{k-1}^s * \alpha^s) + P_k$$

| | denotes the absolute value operator. The dummies effectively select the proper parameterization of (8) according to the execution points of the k-th and k-1st transactions. Now define $\hat{\epsilon}_k^2$ as the squared residual calculated with the estimated values of α_p, α_s, λ_p and λ_s from (8).

Employing the fact that Var $(p_k^\delta) = \delta * \psi$ yields the following regression models with which one can estimate $\sigma_{\alpha p}^2$, $\sigma_{\alpha s}^2$, ψ and δ:

if $\delta < \Delta_k$,

$$\hat{\epsilon}_k^2 = (|SIDE_k^p| + |SIDE_{k-1}^p|) * \sigma_{\alpha p}^2 + (|SIDE_k^s| + |SIDE_{k-1}^s|) * \sigma_{\alpha s}^2 \qquad (9a)$$
$$+ (\Delta_k + \delta/2 * ([(|SIDE_k^p| - |SIDE_{k-1}^p|) - (|SIDE_k^s| - |SIDE_{k-1}^s|)]) * \psi + \xi_k$$

and if $\delta > \Delta_k$,

$$\hat{\epsilon}_k^2 = (|SIDE_k^p| + |SIDE_{k-1}^p|) * \sigma_{\alpha p}^2 + (|SIDE_k^s| + |SIDE_{k-1}^s|) * \sigma_{\alpha s}^2 \qquad (9b)$$
$$+ (1 - D_k^{ps}) * (\Delta_k + \delta/2 * [(|SIDE_k^p| - |SIDE_{k-1}^p|) - (|SIDE_k^s| - |SIDE_{k-1}^s|)]) * \psi$$
$$+ D_k^{ps} * (\delta - \Delta_k) * \psi + \xi_k$$

D_k^{ps} is a dummy which takes on the value of 1 if $|SIDE_k^s| + |SIDE_{k-1}^p| = 2$ and 0 otherwise (i.e., $D_k^{ps} = 1$ if the dependent variable of equation (8) used in the calculation of $\hat{\epsilon}_k^2$ is $T_k^s - T_{k-1}^p$ where the superscripts denote the execution points of transactions). The distinction between (9a) and (9b) arises because $E(\hat{\epsilon}_k^2) = \sigma_{\alpha s}^2 + \sigma_{\alpha p}^2 + Max[\ \Delta_k - \delta, \delta - \Delta_k\ ]$ for $\hat{\epsilon}_k^2$ s corresponding to $T_k^s - T_{k-1}^p$ observations. One must determine whether $\Delta_k - \delta \geq 0$ or $\Delta_k - \delta < 0$ in order to determine D_k^{ps} and avoid model misspecification for these $\hat{\epsilon}_k^2$ s.

In the empirical section of this paper I first consistently estimate δ of models (9a) and (9b) exclusively with the squared residual series $\hat{\epsilon}_k^2$ from model (8) which correspond to $T_k^p - T_{k-1}^p$, $T_k^s - T_{k-1}^s$, $T_k^p - T_{k-1}^s$ observations. I then compare Δ_k (which is measured in minutes) for each $\hat{\epsilon}_k^2$ which corresponds to a $T_k^s - T_{k-1}^p$ observation to this consistent estimate of δ to determine which of (9a) and (9b) applies. I then

reestimate (9a) and (9b) by augmenting initial regressions with these previously excluded $\hat{\epsilon}_k^2$ s.

The technique described in the preceding paragraph is legitimate as long as δ is truly a constant. If instead δ varies throughout my sample (but is positive so that my specification for the $\hat{\epsilon}_k^2$ s corresponding to $T_k^p - T_{k-1}^p$, $T_k^s - T_{k-1}^s$, $T_k^p - T_{k-1}^s$ observations remains legitimate), initial estimates of δ will represent will represent estimates of the *average* lag of secondary dealer valuations behind those of primary dealers. In such circumstances, my technique for categorizing the $\hat{\epsilon}_k^2$ s corresponding to $T_k^s - T_{k-1}^p$ observations will lead to model misspecification.[8]

I estimate parameters of models (9a) and (9b) both with and without the $\hat{\epsilon}_k^2$ s corresponding to $T_k^s - T_{k-1}^p$ observations in the empirical section of this paper. One must balance the benefits of increasing the power of parameter estimates with the potential cost of model misspecification when assessing the contribution of the introduction of the additional $\hat{\epsilon}_k^2$ observations to the estimation procedure. I employ all observations in the estimation of model (8) because in this case the preceding discussion of misspecification is irrelevant.

If the secondary market center lags the primary market center one expects to estimate $\delta > 0$ and $\lambda_s > \lambda_p$. The first implication arises from the intermarket adjustment between expectations of secondary and primary

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[8] For example, assume that δ varies across my sample and that I estimate an average δ of 2.5 minutes with ϵ_k^2 s which correspond to $T_k^p - T_{k-1}^s$, $T_k^s - T_{k-1}^s$ and $T_k^p - T_{k-1}^p$ observations. Now take a particular $T_k^s - T_{k-1}^p$ observation and assume that for this observation that $\Delta_k = 2$ minutes and that the true value of δ during the period of execution of the two transactions used to calculate this observation is 1.5 minutes. Using the technique put forth in the previous paragraph I would make the mistake of applying (9b) rather than (9a) to this observation.

dealers posited in (5), (6) and (7). The second is based on the conclusions of the literature on adverse selection in financial markets. That is, one expects to observe larger adverse selection components in spreads posted on retail brokers' screens due to information asymmetries between primary dealers executing intermarket center arbitrage in trades with uninformed secondary dealers serving as market makers.[9]

V. The Data

My data consist of transaction histories of 566 two-year note and 1931 30-year long-term bond (the long bond) transactions. Both the two-year note and the long bond were issued in the May, 1987 US Treasury auction. The two-year note was issued with a maturity of May, 1989 while the 30-year long bond was issued with a maturity of May, 2017. Both securities were *active issues* when these transaction histories were recorded. That is, these securities were the most recently issued Treasury securities with two-year and thirty-year maturities.

The data for the long bond were recorded over a period of 39 hours during the six trading days between July 17-24, 1987. The data for the two-year note were recorded over a period of 34 hours during the five trading days between July 20-24, 1987. All data were recorded during active trading hours, i.e., between between 9:00 a.m. and 4:00 p.m.

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[9] If information asymmetries between different secondary dealers are more substantial than those between different primary dealers, trading in the secondary market center will be thinner than in the primary market center regardless of the existence of intermarket center arbitrage efforts of primary dealers. As such, strictly speaking, the result that $\lambda_s > \lambda_p$ is consistent with but does not necessarily confirm the alternative hypothesis.

Eastern Standard Time.

Recall that there were in total seven interdealer brokers and two retail brokers in the secondary market for US government securities during the sampling period. The series I collected consist of transactions executed by *three* interdealer brokers (FBI, Garban, and RMJ) and *one* retail broker (Cantor-Fitzgerald). These transaction series therefore do not include transactions executed by the three remaining interdealer brokers and the additional retail broker. Since FBI, Garban, RMJ and Cantor-Fitzgerald arrange an estimated 80% of brokered two-year note and long bond transactions, the exclusion of the four remaining brokers is not necessarily a major source of concern.

I created the data series by merging transaction histories which originate from two different sources. The first source, the source for the interdealer broker transaction information, is the Merrill-Lynch Bloomberg computer system. The Bloomberg system records the volume, price, side of the market (i.e., whether the transaction occurred at the bid or ask) and the minute of execution of all transactions arranged by FBI, RMJ and Garban. The system sequences transactions executed within the same minute. Bloomberg data are available only to Merrill-Lynch, a primary dealer.

The second source, the source of retail broker transaction information, is my manual transcription of Cantor-Fitzgerald video screen information. The transcription includes the volume, price, side of the market and the minute of execution of transactions executed by Cantor-Fitzgerald. The timing mechanism, the clock on the Cantor-Fitzgerald screen, was synchronized with the timing mechanism of

the Bloomberg system.[10]

Time pressure generally did not interfere with efforts to record data accurately. This is because transaction information is typically posted for a period of at least twenty seconds subsequent to the initiation of trade on Cantor-Fitzgerald's screen.

Unfortunately, however, during periods of very active trading trading it was impossible to transcribe volumes of four long bond and two two-year note transactions. If the transaction for which the volume is unavailable is the last transaction executed in a pair used to calculate an observation, the observation is dropped from the sample in the empirical section of this paper. This is because the volume of the last transaction is an independent variable in regression models (8), (9a) and (9b).

The price of one long bond transaction was not transcribed. Obviously, no observations were constructed with this transaction.

Because the data originate from two sources and execution times are recorded in minutes, it is impossible to sequence transactions executed *within the same minute but in different market centers*. Since the actual

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[10]A potential problem arises due to the the fact that transaction times are recorded in minutes in the database. As an example, assume the recorded the time of transaction T_k is 12:02 p.m. while the recorded time of transaction T_{k-1} is 12:00 p.m.. The corresponding measured value of Δ_k (i.e., the value which I would calculate for my regression) in this example would be 2 minutes. These recorded transaction times, however, would simply indicate that T_k occurred between 12:00 and 12:01 and T_{k-1} occurred between 12:02 and 12:03. As such, the true value of Δ_k would lie somewhere between one and three minutes.

Preliminary regressions indicated that measurement error attributable to the use of recorded execution times as opposed to actual execution times is not a serious source of concern. In particular, I assumed that measurement error in the Δ_ks adhered an i.i.d. triangular distribution on the interval [0,2] and altered estimators of parameters accordingly to remove the resulting statistical bias. Estimates changed only slightly.

sequence of transactions is the basis of the tests proposed in this paper, no observations calculated with such transactions are included in the regressions in the next section.

A lag equal to the average time required to execute a transaction in the primary market center exists in the data series. In particular, the data series of Cantor-Fitzgerald transactions include transaction *initiation* times while the FBI, Garban and RMJ data series recorded by the Bloomberg system include transaction *completion* times. The duration of a typical two-year note or long bond transaction (i.e., the amount of time which expires between the initiation and completion of a transaction) is roughly thirty seconds. Under the null hypothesis of perfect market integration one thus expects to estimate (roughly) $\delta = -.5$ in both the long bond and two-year note series.

Observations constructed with successive transactions spaced in time by more than 5 minutes are dropped from the sample. This is done because the analysis is designed to focus on short-run trading behavior. (The inclusion of observations calculated with transactions spaced in time by more than 5 minutes induces only minor changes in results).

Insert Table I Here

Table I provides summary statistics on my database of broker transactions. The table is divided into two sections. The first section provides summary statistics on the entire database. The second section provides summary statistics on the observations used in regressions in the next section of the paper.

Referring to the first section of Table I, Cantor-Fitzgerald, the

retail broker isolated in this study, arranged almost half of the 1931 long bond transactions in the database but only 30% of the 566 two-year note transactions. The disparity in these proportions reflects the fact that Cantor-Fitzgerald is the dominant long bond broker in the market, but is a somewhat weaker player in the case of the two-year note. Transactions are essentially divided equally between hits and takes in both series.

Transactions prices vary more widely in the long bond series than the two-year note series. In particular, long bond prices vary between 98.97 and 102.77 (i.e., 98+31/32 and 102+49/64, respectively, in terms of the market price grid) with a standard error of 1.02. Two-year note prices vary between 99.79 and 100.07 (i.e., 99+101/28 and 100+9/128, respectively, in terms of the market price grid) with a standard error of .07.

Now refer to the section of Table I which provides summary statistics on the observations for regressions in the next section. A total of 757 long bond and 281 two-year note squared price differences met the criteria established for the sample in this section. The standard deviation of the dependent variable T_k-T_{k-1} is larger for the the long bond series, reflecting the long bond's higher volatility level. In the two-year note series, the shortage of observations constructed with two successive secondary market center transactions reflects Cantor-Fitzgerald's weaker market position as a two-year note broker.

$|V_k|$, the absolute value of the transaction volume regressor associated with the T_k-T_{k-1} series, is on average larger as well as more variable in the two-year note series. $|V_k|$ averages 10.09 units in the

two-year note series and 5.39 units in the long bond series. Associated standard deviations are 12.77 and 6.62 units, respectively.

Δ_k, the regressor representing the amount of time elapsed between the execution of k-th and k-1st trades, is also on average larger and more variable in the two-year note series. Δ_k averages 1.47 minutes in the two-year note series and 1.06 minutes in the long bond series. Associated standard deviations are 1.12 and 1.45, respectively.

Reader's should note that many dealers regard Cantor-Fitzgerald video screen information as the best information available in the market due to high proportion of brokered long bond trades which Cantor Fitzgerald arranges. As is reflected in my sample, Cantor-Fitzgerald arranges roughly 50% of the brokered long bond transactions executed in the secondary market for US government securities. As a result of this concentration of order flow, long bond bid-ask spreads and transaction prices are updated regularly on Cantor-Fitzgerald's video screen. Cantor-Fitzgerald's reputation as a broker of the two-year note is less distinguished.

It is difficult, however, to predict whether statistical tests are more likely to detect information asymmetries between primary and secondary dealers in the long bond or the two-year note series under the alternative hypothesis of imperfect market center integration. Based on the purported disparities in information quality between Cantor-Fitzgerald's long bond and two-year note video information, one would expect more pronounced information asymmetries in the case of the two-year note. One the other hand, due the higher variability of the long bond prices, one might expect larger information asymmetries in the case

of the long bond. In particular, more frequent price changes are likely to facilitate the exploitation of private information by primary dealers in trades with secondary dealers arranged by Cantor-Fitzgerald. The power of statistical tests is also likely to be greater in the case of the long bond due to the larger sample size as well as the wider variation in the dependent variable $T_k - T_{k-1}$.

V. EMPIRICAL RESULTS

This section discusses estimation of models (8), (9a) and (9b). I first apply ordinary least squares to model (8) to estimate α_s, α_p, λ_s and λ_p. I calculate the squared residual series $\hat{\epsilon}_k^2$ with these estimates and apply nonlinear least squares to models (9a) and (9b) to estimate $\sigma_{\alpha s}^2$, $\sigma_{\alpha p}^2$, ψ and δ. To determine which of (9a) and (9b) applies to each of the $\hat{\epsilon}_k^2$ s corresponding to $T_k^s - T_{k-1}^p$ observations I first obtain non-linear least squares estimates of δ exclusively employing the $\hat{\epsilon}_k^2$ s corresponding to $T_k^p - T_{k-1}^p$, $T_k^s - T_{k-1}^s$, $T_k^p - T_{k-1}^s$ observations. I then compare observed values of Δ_k to estimates of δ for each of the $\hat{\epsilon}_k^2$ s corresponding to $T_k^s - T_{k-1}^p$ observations. After determining which of (9a) and (9b) applies to these additional $\hat{\epsilon}_k^2$ s, I run nonlinear least squares employing the entire $\hat{\epsilon}_k^2$ series.

As I explained in Section IV, a potential problem of misspecification arises in regressions with the $\hat{\epsilon}_k^2$ s corresponding to $T_k^s - T_{k-1}^p$ observations if δ varies throughout my samples. Readers must therefore balance the benefit of the gain in statistical power attributable to the inclusion of additional observations with the potential costs of

introducing misspecification when assessing results. Regressions which exclude the additional $\hat{\epsilon}_k^2$ s are not subject to such misspecification as long as δ remains positive throughout my samples.

Table 2 summarizes ordinary least squares estimates of the parameters α_s, α_p, λ_s and λ_p of model (8). As is the case with all regressions in this section, I list heteroscedastic-consistent, MA(1) consistent t-statistics for this regression in parentheses.[11] The estimate of α_s is negative, a result which is not consistent with the predictions of the model. The estimate , however, is insignificant and very small in magnitude. The inaccuracy of the estimate is probably attributable to the scarcity of secondary market center transactions in the two-year note series. The estimate of α_p of 1.5×10^{-3} is economically plausible and has a t-statistic of 2.62. In particular, the magnitude of the estimate represents roughly .0015% of the average recorded transaction price in the two-year note series.[12] The estimate of λ_s of 1.4×10^{-4} is accurate (with a t-statistic of 2.19) and economically plausible as well. The estimate indicates that each additional unit of a buyer-initiated two-year note trade on average induces an upward revision in secondary market center valuations of .00014%. The estimate of λ_p of 4.5×10^{-6} is smaller

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[11]I employ a modified version of the White heteroscedastic-consistent robust variance-covariance estimator which is consistent in the presence of an MA(1) of unspecified form in the error structure. I refer interested readers to White (1984), pp. 132-161. I employ this estimator because GLS transformations of (8), (9a) and (9b) proved computationally impossible. (A footmote in a earlier draft explains why this is the case. This draft is available upon request).

[12]Two-year note spreads typically ranged between 0% (i.e., a locked market in which bid and ask prices did not differ) and .031% (i.e., 1 / 32 in terms of the market price grid) of outstanding two-year note prices during my   sampling period.

in magnitude, a result which is consistent with the alternative hypothesis. The restriction that $\lambda_s - \lambda_p$ is rejected at the 6 % level of significance. (The test statistic is distributed $\chi^2(2)$). The Durbin-Watson statistic exceeds 2 due to the negative serial correlation induced by the MA(1) in the error structure.

The model more accurately estimates parameters in the case of the long bond. Surprisingly, the estimate of α_p of 5.8 x 10^{-3} is twice as large as the estimate of α_s of 2.7 x 10^{-3}. T-statistics for estimates of α_p and α_s are 5.65 and 2.99. The estimate of λ_s of 6.9 x 10^{-4} exceeds the estimate of λ_p of 6.5 x 10^{-4} but the difference between these estimates is significant either economically or statistically. T-statistics for estimates of λ_s and λ_p are 6.57 and 4.33, respectively. The Durbin-Watson statistic again exceeds 2 due to the negative serial correlation induced by the MA(1) in the error structure.

Let us now turn to nonlinear least squares estimation of models (9a) and (9b) in Table III. I first discuss results of the regression for the two-year note which excludes $\hat{\epsilon}_k^2$ s corresponding to the 51 $T_k^s - T_{k-1}^p$ observations in the series. This model estimates a value of δ of 3.79. The estimate differs significantly from -.5, the value of δ under the null hypothesis. The model's estimate of $\sigma_{\alpha p}^2$ of 7.7 x 10^{-6} is substantially larger than its estimate of $\sigma_{\alpha s}^2$ of 1.8 x 10^{-6}. The estimate of $\sigma_{\alpha s}^2$, however, has a very large standard error. Again, this inaccuracy is probably attributable to the scarcity of secondary market center transactions in the two-year note series. The estimate of ψ of 1.1 x 10^{-5} has a t-statistic of 2.85. This result suggests a dependence between price variability and the elapsed time between trades. The Durbin-Watson

statistic is less than 2 due to the positive serial correlation induced by the MA(1) in the error structure.[13]

I next augment the sample for the regression discussed in the immediately preceding paragraph with the $\hat{\epsilon}_k^2$ s corresponding to 51 two-year note T_k^s - T_{k-1}^p observations. I apply models (9a) and (9b) to observations for which $\Delta_k \geq 4$ and $\Delta_k \leq 3$, respectively. (Recall that transactions times are recorded in minutes). Results suggest that the introduction of these observations induces model misspecification due to stochastic behavior in the parameter δ. In particular, the estimate of δ increases to 5.57 minutes and moves outside of the interval of 3-4 minutes employed to categorize the T_k^s - T_{k-1}^p observations in the first place. Estimates of $\sigma_{\alpha s}^2$ and $\sigma_{\alpha s}^2$ both increase to 1.2 x 10^{-5} while the estimate of ψ decreases by a third to 6.8 x 10^{-6}.

I now turn to the long bond regression which excludes the $\hat{\epsilon}_k^2$ s corresponding to 152 T_k^s - T_{k-1}^p observations in the long bond series. The estimate of δ is positive, as the alternative hypothesis would suggest, but does not differ significantly from -.5. Estimates of $\sigma_{\alpha s}^2$ and $\sigma_{\alpha s}^2$ of 1.8 x 10^{-4} and 1.2 x 10^{-4} are very similar. Both estimates achieve high levels of statistical significance. The estimate of ψ of 3.6 x 10^{-5} is not significant, suggesting that the dependence between price variability and time is not as strong in the long bond as in the two-year note series.

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[13] I employ ordinary least ordinary least squares estimates of models (9a) and (9b) as starting values for two-year note and long bond nonlinear least squares regressions which exclude the ϵ_k^2 s corresponding to the T_k^s - T_{k-1}^p observations. I employ parameter estimates of from theses nonlinear regressions as starting values for regressions which include the $\hat{\epsilon}_k^2$ s corresponding to the T_k^s - T_{k-1}^p observations. Each of the four regressions of Table III achieves convergence in three iterations.

The Durbin-Watson statistic is again less than 2 due to the positive serial correlation induced by the MA(1) in the error structure.

Results from the regression which includes the $\hat{\epsilon}_k^2$ s corresponding to 152 T_k^s - T_{k-1}^p observations suggest the introduction of misspecification, but to a lesser extent than in the case of the two-year note. The estimate of δ falls to .45 minutes, a figure which lies outside of the 1 - 2 minute interval employed to categorize the T_k^s - T_{k-1}^p observations in the first place. The inaccuracy of the estimate precludes rejection of the null hypothesis that δ = -5. Estimates of $\sigma_{\alpha s}^2$ and $\sigma_{\alpha s}^2$ are very similar to those in the regression discussed in the immediately preceding paragraph. The significance levels of these estimates rise largely due to the introduction of the additional observations. The estimate of ψ increases by a quarter to 4.5 x 10^{-5} and becomes statistically significant.

VI. Concluding Remarks

Results detect information asymmetries between secondary and primary dealers in the secondary market for US government securities in the case of the two active issues I examine. Secondary dealers' price expectations lag those of primary dealers by an estimated 2.2 and minutes and 4.3 minutes in the two-year note and long bond series. Relevant parameters of secondary dealer market center bid-ask spreads appear larger than those of primary dealer market center spreads. Statistical evidence against the null hypothesis is stronger in the case of the two-year note. This is probably due to Cantor-Fitzgerald's weaker market position as a two-year note broker.

Due to a lack of appropriate data I have been unable to address information asymmetries in inactive issue trading in this paper. Recall that in the case of inactive issues no broker video screen information is available to secondary dealers. Given that I detect information asymmetries in the two active issues examined in this paper, it is likely that substantial information asymmetries exist in the case of inactive issues.

This paper addresses only one of the many idiosyncrasies of US Treasury security trading. Others examples include Treasury security auction and resale procedures. Further research should examine such idiosyncrasies in light of their implications for the behavior of Treasury security prices and the employment of these prices by financial economists in capital budgeting problems and tests of asset pricing models.

REFERENCES

Admati, Anat and Paul Pfleiderer, "A Theory of Intraday Patterns: Volume and Price Variability." The Review of Financial Studies, 1 (1988), 3-40.

Amihud, Yakov and Haim Mendelson. "Dealership Market." Journal of Financial Economics, 8 (1980), 31-53.

Bagehot, Walter "The Only Game in Town." Financial Analysts Journal, 22 (1971), 12-14.

Beja, Avraham and Thomas S.Y. Ho, "Structure and Price Behavior in Multiple Market Systems." Working Paper No. 914/86, Tel Aviv University, (1986).

Foster, F. Douglas and S. Viswanathan, "Interday Variations in Volumes, Spreads and Variances: I. Theory." Working Paper, Duke University, (1987).

Garbade, Kenneth D. and William L. Silber, "Dominant and Satellite Markets: A Study of Dually-Traded Securities." The Review of Economics and Statistics, 61 (1979), 455-460.

Glosten, Lawrence R., "Components of the Bid-Ask Spread and the Statistical Properties of Transaction Prices." Journal of Finance, 42 (1987), 1293-1308.

_____ and Lawrence E. Harris, "Estimating the Components of the Bid-Ask Spread." <u>Journal</u> <u>of</u> <u>Financial</u> <u>Economics</u>, 21 (1988), 123-142.

———— and Paul Milgrom, "Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders." <u>Journal</u> <u>of</u> <u>Financial</u> <u>Economics</u>, 14 (1985), 71-100.

Ho, Thomas and Hans Stoll, "Optimal Dealer Pricing Under Transactions and Return Uncertainty." <u>Journal</u> <u>of</u> <u>Financial</u> <u>Economics</u>, 9 (1981), 47-73.

Kyle, Albert S., "Continuous Auctions and Insider Trading," <u>Econometrica</u>, 53 (1985), 1315-1335.

_____, "Market Structure, Information, Futures Markets, and Price Formation." <u>International</u> <u>Agricultural</u> <u>Trade</u>: <u>Advanced</u> <u>Readings</u> <u>in</u> <u>Price</u> <u>Formation</u>, <u>Market</u> <u>Structure</u>, <u>and</u> <u>Price</u> <u>Instability</u>, ed. by Gary G. Storey, Andrew Schmitz, and Alexander H. Sarris. Boulder and London: Westview Press, (1984), 45-64.

Rzepczynski, Mark S., "Comments on the Nature of the Current Trading System in the Secondary Market for U.S. Government Securities." Consulting report for the U.S. General Accounting Office, (1987).

U.S. General Accounting Office, "U.S. Government Securities: An Examination of Views Expressed About Access to Brokers' Services." United States General Accounting Office Report to the Congress, GAO/GGD-88-8,

(1987).

U.S. General Accounting Office, "U.S. Government Securities: Expanding access to Interdealer Brokers' Services." U.S. General Accounting Office Hearing, GAO/GGD-87-42, (1987).

White, Halbert, Asymptotic Theory for Econometricians. Orlando: Academic Press, (1984).

Figure 1

Access to Trade in the

Secondary Market For US Government Securities

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        ┌─────────────────────────────────────────────────────────────┐
        │                                                             │
   ┌─────────┐            ┌──────────┐              ┌──────────┐
   │ Primary │            │ Aspiring │              │Secondary │
   │ Dealers │────────────│ Primary  │──────────────│ Dealers  │
   │         │            │ Dealers  │              │          │
   └─────────┘            └──────────┘              └──────────┘


          ┌───────────┐              ┌──────────┐
          │Interdealer│              │  Retail  │
          │  Brokers  │              │  Brokers │
          └───────────┘              └──────────┘
```
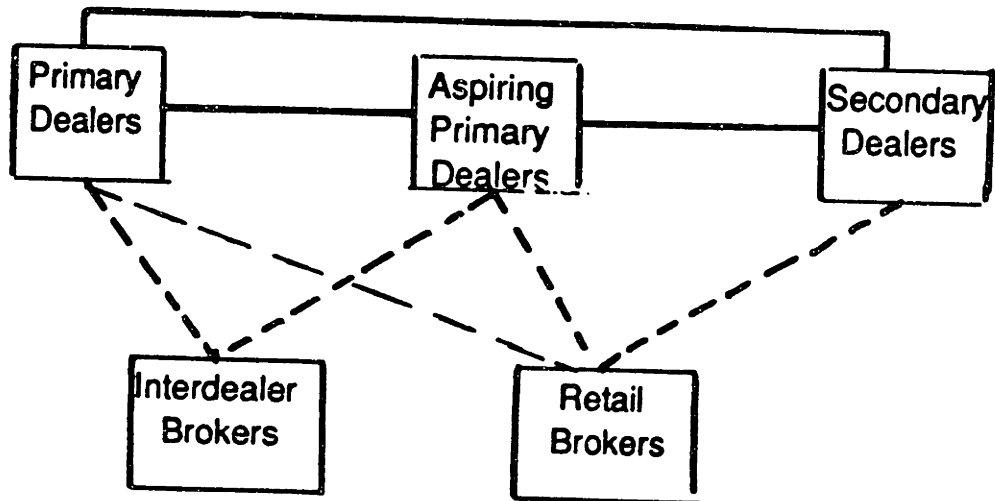
_____ denotes direct trading flow

_ __ __ _denotes broker access

A primary or aspiring primary dealer can execute trades with:

1) other primary and aspiring primary dealers
   -directly
   -through interdealer brokers
   -through retail brokers

2) secondary dealers
   -directly
   -through retail brokers

A secondary dealer can execute trades with:

1) other secondary dealers
   -directly
   -through retail brokers

2) primary and aspiring dealers
   -directly
   -through retail brokers

Table 1

SELECTED STATISTICS ON DATA SERIES OF BROKER TRANSACTIONS

	Long Bond	Two-Year Note
The Complete Data Series		
Division of Sample by Broker Type		
Retail Broker Transactions (i.e. Cantor-Fitzgerald)	929	171
Interdealer Broker Transactions (i.e., FBI, Garban and RMJ)	1002	395
Total	1931	566
Division of Sample by Transaction Type		
Hits (i.e, initiated by a seller)	948	277
Takes (i.e., initiated by purchaser)	983	281
Total	1931	566
Transaction Prices[a]		
Mean	100.38	99.28
Standard Error	1.02	.07
Minimum	98.97	99.79
Maximum	102.77	100.07

Observations Calculated for Empirical Estimation of Models (8), (9a) and (9b)[b]

	Long Bond	Two-Year Note
$T_k - T_{k-1}$		
Mean	.0012	-.0006
Standard Deviation	.0206	.0069
Minimum	-.0781	-.0023
Maximum	.0938	.0023
Transaction Pairs Used to Construct Observations		
T_k and T_{k-1} are primary and secondary market center transactions, respectively.	152	51
T_k and T_{k-1} are secondary and primary market center transactions, respectively	141	50
T_k and T_{k-1} are both primary market center transactions	208	159
T_k and T_{k-1} are both secondary market center transactions	256	21
Total	757	281
$|V_k|$		
Mean	5.93	10.09
Standard Deviation	6.62	12.63
Minimum	1.00	1.00
Maximum	50.00	81.00
Δ_k		
Mean	1.01	1.47
Standard Deviation	1.12	1.45
Minimum	0.00	0.00
Maximum	5.00	5.00

[a] The price of one transaction in the long bond series was not transcribed. This transaction was dropped from the sample when these price statistics were calculated.
[b] These observations were constructed with transactions which: 1) were spaced in time by no more than five minutes and 2) were not executed during minutes in which transactions were executed in both the primary and secondary market centers.

Table II.

ORDINARY LEAST SQUARES ESTIMATION ' F MODEL (8)[1,2]

Null Hypothesis: $\lambda_s = \lambda_p$

Alternative Hypothesis: $\lambda_s > \lambda_p$

Estimated Parameters[a,b,c]	Two-Year Note	Long Bond
λ_s	1.4×10^{-4}	6.9×10^{-4}
	(2.19)	(6.57)
λ_p	4.5×10^{-6}	6.5×10^{-4}
	(.20)	(4.33)
α_s	-7.5×10^{-5}	2.7×10^{-3}
	(.09)	(2.99)
α_p	1.5×10^{-2}	5.8×10^{-3}
	(2.61)	(5.65)
Observations	281	757
R-Squared	.04	.17
Durbin-Watson	2.28	2.15
$\chi^2(2)$ Test of $\lambda_s = \lambda_p$	3.47	.05
Significance Level of Test	.06	.82

[1] Observations for these regressions were constructed with transactions which: 1) were spaced in time by no more than five minutes and 2) were not executed during minutes in which transactions were executed in both the primary and secondary market centers.

[2] Heteroscedastic-consistent, MA(1)-consistent t-statistics are listed in parentheses.

TABLE III.

NONLINEAR LEAST SQUARES ESTIMATES OF MODELS (9a) AND (9b)[1]

Null Hypothesis: $\delta = -.5$

Alternative Hypothesis: $\delta > -.5$

	Two-Year Note		Long Bond	
	$\hat{\epsilon}^2_k$ s for $T^s_k - T^p_{k-1}$ Obs. Excluded	$\hat{\epsilon}^2_k$ s for $T^s_k - T^p_{k-1}$ Obs. Included	$\hat{\epsilon}^2_k$ s for $T^s_k - T^p_{k-1}$ Obs. Excluded	$\hat{\epsilon}^2_k$ s for $T^s_k - T^p_{k-1}$ Obs. Included
δ	3.78	5.58	1.63	.45
	(1.79)	(1.83)	(.69)	(.50)
σ_s	1.3×10^{-6}	1.3×10^{-5}	1.8×10^{-4}	1.8×10^{-4}
	(.27)	(1.79)	(4.66)	(5.74)
σ_p	7.7×10^{-6}	1.2×10^{-5}	1.2×10^{-4}	1.2×10^{-4}
	(2.40)	(3.51)	(4.75)	(5.47)
ψ	1.1×10^{-5}	6.5×10^{-6}	3.6×10^{-5}	4.5×10^{-5}
	(2.85)	(1.79)	(1.23)	(2.06)
R^2	.07	.04	.01	.01
Durbin-Watson	1.79	1.80	1.77	1.73
Observations	230	281	605	757

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[1]Heteroscedastic-consistent, MA(1)-consistent t-statistics are listed in parentheses.

Essay Two

Uncertainty, Collusion and Returns in a Multiple-Bid,

Multiple-Unit Auction with Resale

I.   Introduction

The auctions literature constitutes one of the most substantial contributions of modern economics.   See McAfee and McMillan (1987) and Wilson (1988) for recent surveys.   Only minimal empirical research on auctions exists, however.   This is the case despite the abundance of auction field data and the suitability of auctions as testing grounds for the validityof game-theoretic models of the strategic behavior of agents in environments characterized by imperfect and asymmetric information.

This paper takes a small step towards filling the empirical gap in the auctions literature by analyzing bidding behavior in weekly Mexican Treasury auctions for the period July 1986 - August, 1989.   As in US Treasury auctions, bidders submit multiple bids for multiple units. Purchased quantities are immediately resold in an active resale market. Unfortunately, no model of a multiple-bid, multiple-unit auction with resale exists.   I thus examine robust implications of single-unit, single-bid auctions heuristically rather than estimate an equilibrium model of bidding behavior.

Results detect collusion among the six largest bidders who purchase on average 80% of new Mexican Treasury debt.   Evidence of collusion is provided in two forms.   First, I calculate bidders'ex-post profitability with bid and resale price data.   The six largest bidders accountfor

immense shares of auction purchases and profits. Second, I analyze aggregate bidder profits in cross sectional regressions. Contrary to the predictions of the theory of competitive auctions, profits of the six largest bidders vary inversely with the dispersion of their bids.

Results detect information asymmetries between large and small bidders. I provide evidence of information asymmetries in two forms. First, I compare the *ex-post* profits and profit margins of large and small bidders. Large bidders' ex-post profits and profit margins exceed those of small bidders. Second, I examine the impact of entry of small bidders on the profitability of incumbent bidders in cross sectional regressions. Entry by small bidders to the auction fails to explain variation in aggregate, large bidder or small incumbent bidder profitability. This suggests that small bidders bid solely on the basis of public information.

Results confirm that bidders account for the winners' curse. First, aggregate auction profits are positive. Bidders earning negative profits appear to have been unlucky rather than ignorant of the winner's curse. Second, in cross sectional analysis the magnitude of the downward bias in bidsas estimates of resale values varies directly with measures of ex-ante disparities in bidders' value estimates.

Section II summarizes the rules and institutional details of the Mexican Treasury auction. Section III summarizes relevant implications of auction theory for bidding behavior. Section IV summarizes aggregate and bidder-specific Mexican Treasury auction results for the sampling period. Section V provides cross sectional analysis of auction profits. Section VI provides concluding remarks.

II. Auction Rules and Institutional Details

This section describes the rules and institutional details of the Mexican Treasury auction. Readers will note that the rules of the Mexican Treasury auction closely resemble those of the US Treasury auction.

On average over 40 bidders participate in weekly Mexican Treasury auctions. Bidders fall into one of four categories: government banks, private banks, stock brokerages and insurance companies. By Mexican standards bidders are large financial institutions. These bidders submit *competitive* sealed bids that are discount-quantity pairs. Discounts can be specified up to two decimal points. Discounts are converted to prices in the following manner:

$$Price = 100 - Discount*Maturity/360$$

The maturity is denominated in days.

Auction rules place no restrictions on the number of competitive bids which bidders can submit. Bidders thus typically submit multiple competitive bids. On average 25 bidders submit competitive bids each week.

Bidders can also submit a single noncompetitive bid that specifies a quantity but does not specify a discount. The Treasury guarantees that noncompetitive bidders win the quantities specified in their noncompetitive bids up to a prespecified maximum. The set of non-competitive and competitive bidders overlaps substantially; many bidders in practice submit both competitive and noncompetitive bids.

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Competitive bidders bid for the debt which is not allocated to noncompetitive bids in a discriminatory auction. (Because neither the number nor the aggregate quantity of noncompetitive bids is known in advance competitive bidders do not know exactly the amount of Treasury debt for which they are competing when they bid). Issued debt is allocated starting from the lowest submitted discount up until the entire offering is assigned. Competitive bidders pay the unit prices implied by the discounts of their winning bids for the quantities which they win. Bidders often pay different unit prices (i.e., receive different discounts) because they submit multiple bids. All of the noncompetitive bidders pay the quantity-weighted average price of the winning competitive bids.

Every Friday the Banco de Mexico (the fiscal agent for the Mexican Treasury) announces the quantity, the maturity and the guaranteednoncompetitive quantity of the next weekly issue. Participants must deliver both competitive and noncompetitive bids to the Banco de Mexico premises by 1:30 p.m. on Tuesday. On Wednesday morning the Banco de Mexico informs bidders of their winnings and announces auction results. The Treasury and winning bidders settle claims just before business opens on Thursday.

Most acquired debt is immediately resold on Wednesday afternoon to investors not participating in Tuesday auctions. Wednesday resale market transactions are settled just before business opens on Thursday. As a result of this resale feature, the length of the holding period for auction participants for large portions newly-issued debt is zero, i.e., participants immediately resell Mexican government debt without ever

possessing it.

The Mexican Treasury retains the right to cancel all or part of each weekly auction. Cancellation refers to a reduction in the quantity issued through the cancellation of competitive bids. Complete cancellation refers to the cancellation of all competitive bids. The Mexican Treasury cancels auctions with outcomes which it regards as unfavorable.[1] Quite often, for example, the Treasury cancels auctions in which bidders have colluded excessively.[2]

Until July, 1989, the auction rules dictated that no single competitive bidder could purchase more than 40% of the quantity offered to competitive bidders. This level was increased from 40% to 60% at the end of July, 1989.[3]

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[1] In the event of complete cancellation, noncompetitive bidders receive the cancellation discount specified in the Friday auction announcement. This discount is typically favorable (i e., higher than discounts implied by Friday market prices for comparable issues of outstanding government debt) to ensure the submission of noncompetitive bids. Partial cancellation refers to the cancellation of some (but not all) competitive bids. In the event of partial cancellation noncompetitive bidders receive the quantity-weighted mean discount of uncancelled winning competitive bids.

In the event of either partial or complete cancellation, the Treasury executes a "third round" in which it allocates debt to noncompetitive bids with quantities exceeding initially guaranteed quantities. Allocated quantities of third rounds are typically small since quantities of noncompetitive bids are rarely substantially greater than initially guaranteed quantities.

[2] Throughout a large portion of the sampling period the rules of the auctionrequired the cancellation of bids with discounts which exceeded either 1) the sum of the average bid discount and one standard deviation of the distribution of bid discounts or 2) the sum of the quantity-weighted average bid discount and one quantity-weighted standard deviation of the distribution of bid discounts. Because this requirement resulted in the cancellation of only several very small bids, it is ignored throughout the remaining discussion in this study.

[3] I ignore this regime change throughout this study because its implementation does not appear to have altered bidder behavior substantially during the sampling period. (The new regime, futhermore,

It is illegal for bidders to bid for more than 100 times the value of their capital bases. This capital constraint affords the largest bidders substantial market power.

50% of resale transactions are executed on the the Mexico City money market exchange. The money market exchange is comprised of representatives of approximately 40 different financial institutions. Each financial institution maintains a private booth on the 10000 square foot exchange floor. Exchange officials regulate trade, complete paperwork for executed transactions and operate electronic video equipment from a desk in the center of the exchange floor. All exchange trade is direct; floor traders negotiate terms of trade directly with each other without the assistance of intermediaries. Traders must register all consummated transactions with exchange officials.

The remaining 50% of secondary market volume is exchanged directly between representatives of financial institutions in trades negotiated over the telephone. These trades are not announced publicly.

An active overnight lending market exists in parallel with the secondary market for Treasury debt. The same institutions participating in issuance auctions and resale activities trade overnight debt instruments on the Mexico City money market exchange and over the telephone.

The resale market for new issues is competitive and efficient. Wednesday resale activity levels are high; the number of participants is large enough to ensure competitive behavior. For this reason weighted

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was only in place for one month of my sampling period (i.e., August, 1989). Any bias resulting from ignorance of the regime change is thus likely to be minimal).

average resale prices from the Mexico City money market exchange accurately estimate realized common values of Treasury debt. The overnight lending market is less efficient and competitive, but not markedly so. (Several large institutions account for disproportionate amounts of overnight lending activity).

The Mexican Treasury issues numerous debt instruments. This study focuses on auctions of one-month peso-denominated zero-coupon securities called CETES because data on auctions for other instruments are unavailable. Outstanding issues of one-month CETES constituted on average 25% of the face value Mexican Treasury debt during the sampling period.

Often the Treasury executes auctions for one-month CETES and other instruments simultaneously. In these instances most participants bid in auctions for both CETES and remaining instruments. Throughout this study I ignore the potential impact of the simultaneous execution of auctions for other instruments on bidding behavior in CETES auctions.

Readers will recall that Mexico experienced a foreign debt crisis, a moderate hyperinflation and a highly contested Presidential election during the 1986-1989 sampling period. Uncertainty associated with these events most certainly exacerbated the risks of bidding in Treasury auctions.

Auction participants openly acknowledge collusion between the six largest bidders. No legal deterrents to collusion exist; Mexican anti-trustlaw is extremely underdeveloped. Mexican financial circles are small and closely-knit. For example, two of the six largest participants in CETES auctions are owned by members of the same family. The concentrated, centralized character of the finance profession no doubt

facilitates collusive behavior.

Cartel members agree before each auction on the prices of bids and divide cartel purchases amongst themselves. Ceilings on purchases necessitate this mechanism rather than, say, a bid rotation scheme. (Recall that throughout the majority of the sample period auction rules required that no single bidder purchase more than 40% of the total competitive issue).[4] Capital constraints and disparities in the magnitudes of retail deposit bases across cartel members probably explain the uneven allocation of auction purchases across cartel members.[5]

Two particular features of CETES auction procedures provide ideal instruments for enforcing collusion. First, the Banco de Mexico provides detailed information regarding the joint distribution of bid discounts and quantities in its Wednesday announcements. Although this information does not specify identities of participants associated with bids, one can readily infer the ranges in which the bids of major participants lie. Second, Mexico City money market transactions are observable to money market exchange participants. Eavesdropping on transaction negotiations is widespread and permissible. Also, the exchange permits traders to examine the current day's transaction history upon request. This transaction history includes both prices and quantities of all transactions executedsince the opening of the exchange and the identities of traders who executed these transactions. Deviations from cartel

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[4]In fact, government officials indicate that several weeks after this 40% maximum was raised to 60% in July, 1989, the cartel replaced the quantity division procedure with a week-by-week bid rotation scheme.

[5]Recall that bidders are not allowed to bid for more than 100 times the value of the capital bases.

behavior are thus readily detectable.

Entry to the auction is restricted. First, the Mexican financial system lacks the capacity to outbid the cartel members and compete away profits; only several institutions maintain capital bases large enough to to make substantial purchases. Second, non-Mexican firms may not legally submit bids due to a ban on the foreign purchase of Treasury debt.

III. Auction Theory and Its Implications for Bidding Behavior in CETES Auctions

No model of equilibrium bidding behavior in a multiple-bid, multiple-unit auction exists. I therefore examine heuristically robust implications of equilibrium models single-bid, single-unit auctions rather than estimate of an equilibrium model.[6]

Auction theory distinguishes between two polar auction forms: independent private values (IPV) and common value auctions. In IPV

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[6]Wilson (1979) models a share auction in which bidders submit continuous demand schedules. Unfortunately, his model does not directly apply to the auction examined in this paper. First, Wilson models a uniform price auction while the CETES auction is discriminatory. Second, bidders' demand functions in Wilson's model are continuous while CETES bidders submit series of price-quantity pairs representing points on their demand curves. Third, Wilson models the behavior of competitive, symmetric bidders while CETES auction bidders collude and are asymmetrically informed. Fourth, the equilibria which Wilson discusses bear little resemblance to those observed in CETES auctions. In particular, Wilson's model predicts sale prices equal to one half of realized common values. As I indicate later, CETES prices fall on average only 2.5 basis points short of realized common values.

Bichkandani and Huang (1989) model T-Bill auctions. Their failure to incorporate the feature of multiple bids renders their model inapplicable to CETES auctions. Huang has indicated to me in a series of conversations that the extraordinary complexity of incorporating the multiple-bid feature was the basis for their decision to adhere to the single-bid, single-unit paradigm.

auctions   bidders' valuations are independently distributed. In common value auctions bidders share a single uncertain valuation. Auctions for art works are IPV auctions if bidders do not participate for investment purposes. Auctions for offshore oil field leases in which bidders' profits are determined by uncertain drilling activities for reserves sold at a common market price are common value auctions. The feature of resale ensures that weekly Mexican Treasury auctions are common value auctions.

The phenomenon of the winner's curse often arises in discussions of common value auctions. In common value auctions each bidder presumably obtains an unbiased estimate of the object being sold before bid submission. Winning bidders of auctions are those with the highest ex-ante estimates. Winning thus conveys bad news to winning bidders because it means that all losing bidders estimated the value of the object to be lower. If the winning bidder has bid his ex-ante estimate, he is almost certain to be "cursed." Studies of auctions for offshore oil rights suggest that the winner's curse does indeed exist (see, E.C. Cappen, R.V. Clapp and W.M. Campbell (1971) and Hendricks, Porter and Boudreau (1987)).

Models of equilibrium bidding behavior in common value auctions suggest that bidders must mark-down their bids from their ex-ante estimates to avoid the affliction of the winner's curse. The magnitude of this mark-down is an increasing function of disparities in ex-ante estimates of competing bidders. This mark-down ensures that in equilibrium bidders expect to earn positive profits conditional on winning.

Milgrom (1979a), Milgrom (1979b) and Wilson (1977) demonstrate that

under appropriate technical conditions, the downward bias in winning bids should disappear in the limit as the number of competitive bidders approaches infinity. In essence, competition should eliminate all profits and the prices of winning bids should converge to common values. When thenumber of bidders is finite, however, the net impact of the entry of additional bidders on the magnitude of the equilibrium mark-down in bids is ambiguous. An increase in the number of bidders exacerbates winner's curse considerations but increases competition and reduces the probability of winning. The former effect leads to an increase in bidders' mark-downs while the latter leads to a decrease. Depending on the nature of equilibrium bidding strategies and the distribution of private information, the net effect of the addition bidders can be either a decrease or an increase in bidders' mark-downs.

Englebrect-Wiggans, Milgrom and Weber (1983) model a common value auction in which the distribution of ex-ante is distributed asymmetrically, i.e., a subset of uninformed bidders' estimates are less precise than the estimates of their informed competitors. In equilibrium in their model the uninformed bidders bid more cautiously than their informed competitors. In an extreme example, if uninformed bidders' all bid on the basis of public information they earn zero expected profits in equilibrium and randomize their bidding decisions while informed bidders earn positive expected profits. In this extreme example the addition of uninformed bidders to the auction does not affect the profitability of either incumbent informed or uninformed bidders. Hendricks and Porter (1988) empirically confirm these implications in their study of bidding for OCS drilling rights.

IV. Auction Results and Bidder Profitability.

This section summarizes Mexican CETES auction outcomes and bidder profitability for the July, 1986 - August, 1989 sampling period. The Mexican Treasury executed a total of 156 auctions during the sampling period. 30 auctions were dropped from the sample because they were cancelled completely or partially. 5 auctions were dropped because data on submitted bids were unavailable. The final sample thus consists of 121 auctions.

The database consists of the complete set of participant-identified submitted competitive and noncompetitive bids, maximum winning discounts, the aggregate competitive and noncompetitive quantities allocated, and the quantity-weighted average discount of Wednesday Mexico City money market (i.e., resale market) transactions. With these data I reconstruct auction results entirely. I convert discounts to prices in the manner described in Section II. I convert quantity figures into August, 1989 US dollars for ease of interpretation.

Let us refer to Table I. The Mexican Treasury issued CETES with an average face value $210 million in the 121 auctions in the sample. On average $172 million was assigned to competitive bids; on average $38 million was assigned to noncompetitive bids. The ratio of the quantity-weighted average resale price to the quantity-weighted average auction price of winning competitive bids averaged 1.00023. The downward bias in bids, or the "cost" of the auction to the government thus averaged 2.3 basis points. (A basis point is 1/100 of a percentage point). This

result is consistent with the prediction of auction theory that winning bids are downwardly-biased estimates of common values.[7]

Insert Table I Here

How does one interpret the figure of 2.3 basis points? Commack (1986) calculates that the comparable figure for the US Treasury Bill auction is lessthan 1 basis point. Assumedly, the difference between the Mexican and the US figure is attributable differences in levels of 1) competition 2) ex-ante information disparities and 3) ex-ante uncertainty and risk aversion.

Bidders on average submitted 106 competitive bids in the 121 auctions included in the sample, but the number of submitted bids varied widely between the sample-wide minimum and maximum of 28 and 184. The number of competitive bidders averaged 25 and ranged between 14 and 33. The number of noncompetitive bidders averaged 38. The number of winning competitive bids averaged 44.5, but varied widely between a minimum of 2 and a maximum of 157. (In some cases several very large bids captured the entirety of the auction).

Both the variance and quantity-weighted variance of prices of winning bids exhibited substantial variation during tne sampling period. The variance of prices averaged .0009 and ranged between 0 and .0187.[8] The

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[7] I first inflate issued pesos to August, 1989 pesos using the monthly data on the Mexican Consumer Price Index. I then convert these figures to dollars using the August, 1989 peso/dollar exchange rate.

[8] I calculate the quantity-weighted variance as follows:

$$\text{Quantity-Weighted Variance} = \sum_{i=1}^{N} (b_i - \bar{b}_w)^2 * V_i / \sum_{i=1}^{N} V_i$$

where

b_i = the price of the i-th winning bid.

quantity-weighted variance of prices averaged .0008 and ranged between 0

and .0182.[9] I later attribute the variation in these two statistics to

1)variation in the levels ex-ante disagreement between bidders about the

values of CETES and 2) variation in the levels of collusion between

bidders. I then utilize these statistics as regressors in cross sectional

analysis of bidder profitability.

Now let us turn to calculations of ex-post profitability of

competitive bidders summarized in Table II. The first column of Table II

lists the profitability rankings of participants. (For legal reasons, the

Banco de Mexico would not divulge the names of participants). In total 50

bidders submitted winning competitive bids during the sampling period.[10]

Insert Table II Here

The second column of Table II lists the number of auctions in which

bidders submitted competitive bids. Approximately 20 bidders participated

in at least 110 auctions. The third column lists the average number of

competitive bids submitted in which bidders participated (i.e., auctions

in which bidders submitted either competitive or noncompetitive bids).

Bidders employed a variety of strategies: some averaged 5 competitive

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$$N = \text{the number of winning bids.}$$
$$V_i = \text{the quantity of the i-th winning bid.}$$
$$\bar{b}_w = \sum_{i=1}^{N} b_i * V_i / \sum_{i=1}^{N} V_i.$$

[9]In several auctions in which the number of winning bids was very low each
winning bid price was identical to the last cent.

[10]27 additional bidders submitted competitive bids during the sampling
period. None of the bids of these bidders won. I therefore exclude these
bidders from Table II.

bids per auction while others averaged fewer than one. Bidders who averaged fewer than one competitive bid per auction in general participated regularly as noncompetitive bidders but irregularly as competitive bidders.

The fourth column lists the number of auctions in which bidders submitted noncompetitive bids. Most competitive bidders usually submitted noncompetitive bids. One explanation for this is the profitability ofnoncompetitive bidding. (Recall that noncompetitive bidders pay the weighted average price of winning competitive bids).

The fifth column lists the cumulative auction purchases of individual bidders in thousands of August, 1989 US dollars. The concentration of purchases is striking: the six largest bidders purchased over 80% of the $20.9 billion aggregate volume.

The sixth column lists the cumulative profits of auction participants. I calculate these profits by subtracting bid prices from weighted-average Wednesday resale prices and multiplying by bid quantities.

Auction Profit = (Resale Price-Winning Bid Price) * Quantity of Bid

The concentration of profits is striking. The six largest bidders enjoyed almost 90% of total competitive auction profits. 13 bidders earned negative profits during the sampling period, but aggregate losses of these bidders were small. Bidder 50, the largest loser, lost a total $42 thousand.[11]

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[11]Those familiar with the auction can readily identify the bidding cartel from Table II. Members include three government banks (Banamex, Bancomer

The final column of Table II lists the margin (in basis points) earned by bidders on purchased CETES:

Margin = Cumulative Auction Profits/Cumulative Auction Purchases *10000

This figure is equivalent to the quantity-weighted average basis point spread earned by bidders purchasing and reselling CETES. The weighted-average margin for the entire sample is 2.6 basis points.

Results suggest the existence of information asymmetries between large and small bidders. The six bidders accounting for the majority of aggregate profits and purchases earned higher margins. Except for the case of bidder 7 who on average earned 1.3 basis points, each of these bidders earned over on ave#age 3 basis points on each purchased security. Aggregate profits of the 38 least profitable bidders amounted to $100 thousand -- a number remarkably close to zero. These results are consistent with a model in which larger bidders observe private signals but smaller bidders bid solely on the basis ofpublic information.[12]

I compared aggregate ex-post profitability of the 12 most profitable bidders to aggregate ex.posr profitability of the 38 least profitable bidders. In 26 auctions the 12 most profitable bidders earned positive

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and Finamex) and three brokerages (Inverlat, Probursa and Operadora de Bolsa). All six members fund large proportions of their auction purchases with deposits of retail clients. The fact that the deposits bases of the large banks exceed those of the brokerages in part explains the uneven allocation of purchases across the cartel.

[12] Information asymmetries are likely to arise for two reasons. First, larger bidders maintain private research staffs to gather private information about the term structure of interest rates while smaller bidders do not. Second, due to their influence in Treasury auctions large bidders enjoy more contact with government officials possessing valuable information regarding auction outcomes.

profits while the 38 least profitable bidders earned negative profits. In 5 auctions the reverse occurred. In 4 auctions both sets of bidders in aggregate lost money, while in 86 both sets earned aggregate profits. The fact the larger bidders tend to profit in auctions in which the uninformed bidders did not also confirms the hypothesis of information asymmetries.

V. Cross Sectional Regression Analysis of Auction Profitability

This section presents results of cross sectional regressions of aggregate auction profit margins against proxies for ex-ante information disparities, ex-an:e uncertainty and competition.

The first proxy I employ for ex-ante uncertainty and information disparities is the percentage change in the Mexican consumer price index realized during the month of auction execution (INFLATE). This proxy is imperfect to the extent that 1) realized and ex-ante expectations of inflation differ and 2) levels of ex-post and expected inflation differ across weeks of a given month. These concerns, however, do not warrant substantial discussion because this proxy provides little explanatory power in regressions.

The second proxy I employ for ex-ante uncertainty and information disparities is the variance of prices of one-month bonds implied by overnight lending rates over the five day period preceding and including of the day of auction execution (SECMKTVAR). (Recall that an overnight lending market exists in parallel with the resale market for Mexican Treasury bonds).[13] There is a strong correlation between investor behavior

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[13] I calculate these implied prices as follows:

in the the overnight lending market and the resale market for CETES. This correlation arises because the investors funding overnight loans serve as the ultimate source of demand for CETES issues. When the predictability overnight lending rates is low so is the predictability of demand for CETES.

The variance of secondary market prices is an imperfect proxy to the extent that one-month bonds created by continually rolling over overnight contracts differ from CETES. The strength of statistical results achieved with this proxy, however, suggests that this issue does not warrant substantial discussion.

I employ several proxies for the degree of competition. The first is the number of competitive bidders per unit of debt issued (BIDDERS). Research on auctions emphasizes that the number of porenrial bidders rather than the number of participating bidders determines the degree of auction competition. This is because reserve prices may prevent low-valuation bidders from submitting bids. Because no reserve prices are set in CETES auctions (i.e., bidders can submit bids with zero prices), this distinction is not relevant for this study.

Note that I normalize the number of competitive bidders by the volume of the auction. Recall that because bidders face capital constraints; a $30 million auction with 20 bidders is likely to be more competitive than a $300 million auction with 20 bidders.

Implied Price of One-Month Bond on Day $t = 100 \ / \ (1 + R_t)^{M_t/360}$

where
M_t = the maturity in days of the upcoming CETES issue.
R_t = the annualized weighted-average overnight lending rate on day t.

Recall from Table II that most variation in the number of bidders across the sampling period is attributable to entry and exit by smaller bidders. Based on discussion in Section III if these bidders are indeed less informed their participation should not affect the profitability of large bidders or other small bidders.

I also include the weighted average variance of winning bid prices as a proxy for the degree of competition (WTVARBID). On the one hand, if the auction is competitive, the ex.posr dispersion of bids will proxy for disparities in ex-ante estimates of bidders. On the other hand, a wider dispersion of prices may suggest partial or complete failure of cartel members to collectively rig their bids. If the latter effect is so strong that it completely offsets the former, a negative correlation will arise between the weighted variance of winning bids and auction profits.[14]

The third measure I employ as a proxy for competition is the aggregate competitive auction quantity (QUANTITY). A negative correlation between this proxy and auction profitability would suggest that collusion breaks down in larger auctions.

I also include the ratio of the noncompetitive quantity to the total auction quantity (i.e., the sum of competitive and noncompetitive quantities) as a regressor (NONCOMP). A negative correlation between this regressor and auction profitability would suggest that the Treasury should increase the prespecified maximum of noncompetitive bids to substitute

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[14]The cartel isolated in these regressions does not shift between distinctly competitive and collusive states in general. Rather, bidders rotate between
different subcoalitions which achieve varying levels of success in achieving collusive equilibria. As such, switching regression techniques designed to distinguish between collusive and competitive regimes such as those employed by Porter (1983) are inappropriate for this study.

noncompetitive for competitive quantities. In other words, this result would suggest that CETES demand is inelastic in the range of winning bid prices and the Treasury has not properly employed its monopoly power in raising auction revenues.[15]

My final regression model is:

$$PROFITS_t = CONSTANT + \beta_1 * INFLATE_t + \beta_2 * SECMKTVAR_t + \beta_3 * BIDDERS_t$$
$$+ \beta_4 * WTVARBID_t + \beta_5 * QUANTITY_t + \beta_6 NONCOMP_t + \epsilon_t,$$

where t, indexes auctions and

$PROFITS_t$ = Wtd Avg. Resale Price/Wtd Avg. Price of Winning Bids for the t-th auction.

I run regressions for three samples of bidders: the entire sample of bidders, the six hypothesized cartel members and the entire noncartel sample. Variables are identical across regressions except for the profitability and weighted average variance of winning bids variables. I calculate these two variables exclusively with the winning bids of bidders in the defined samples.

I drop observations in each regression for which the magnitude of the dependent variable exceeds 1.001 and is less than .9995. I drop three observations from the noncartel sample (but not the cartel and entire bidder samples) for auctions in which all noncartel bidders failed submit winning bids. In one auction the noncompetitive proportion is .56. This proportion is six times larger than the sample average proportion. I drop the observation for this auction from each of the three regression

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[15]Recall that the Banco de Mexico specifies maximum quantities for noncompetitive bids.

samples. In total, of the 121 auction observations I drop 7, 9 and 11 observations from the entire sample, the cartel sample and the noncartel sample regressions.

Columns of Table III summarize results. Coefficients for the monthly inflation rate are insignificant across regressions, suggesting that bidders' attention is focused on the behavior of the resale market rather than the macroeconomic climate. This result does not imply, however, that macroeconomic and political uncertainty experienced during the sampling period did not affect auction outcomes; periods of greatest political uncertainty coincided with the periods of highest overnight market volatility. The insignificance of the coefficients on the inflation rate attests to the informativeness of the behavior of the overnight lending market.[16]

Insert Table III Here

A consistent result is the positive correlation between auction profits and the variance of the prices of one-month bonds implied by

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[16] In preliminary regressions I employed two alternative proxies for general macroeconomic and political uncertainty: 1) the percentage change in the weighted-average maturity of outstanding CETES issues (including both one-month and three-month CETES issues) and 2) the expected peso/dollar exchange rate devaluation implied by peso-denominated 30-day forward contractsfor US dollars traded in Mexico City. The term structure of interest rates decreased in lengt# during periods in which hyperinflation appeared most imminent in Mexico. I hypothesized a negative correlation between auction profits and the percentage change in the weighted average maturity of outstanding CETES. Fears of exchange rate devaluation were highest during periods of political and macroeconomic uncertainty. I thus hypothesized a positive correlation between auction profits and the magnitude of the expectedexchange rate devaluation implied by prices of 30-day forward contracts for USdollars. Neither of the coefficients for these proxies was significant.

overnight lending rates. Coefficients for the variance of overnight bonds are positive and significant in each regression suggesting that bidders mark-down their bids from their estimates of CETES in response to uncertainty about resale values. If bidders are risk neutral, this result strongly confirms the hypothesis that they account for the winner's curse when calculating their bidding strategies. To the extent that bidders are risk averse, it is impossible to distinguish the portion of mark-downs attributable to risk aversion from that attributable to the avoidance of the winner's curse.

The insignificance of the coefficients for the number of competitive bidders (per unit of competitive volume sold) suggests that the entry of new bidders does not affect auction profitability. Recall that when the number of bidders is finite, the net effect of the addition of bidders to an auction is ambiguous: an increase in the number of bidders increases the degree of auction competition but exacerbates winners curse considerations. Also recallthe variation in the number of bidders is largely attributable to the entry of new, small bidders during the sampling period. The failure of entry of these bidders to affect the profitability of cartel members is consistent with the predictions of a model in which entering bidders bid solely on the basis of public information available to better-informed cartel members. The fact the entry does not affect the profitability of noncartel bidders is consistent with a model in which both incumbent and entering noncartel members bid solely on the basis of public information.[17]

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[17] As an experiment I employed the number of bidders as a regressor instead of number of bidders per unit of competitive volume. Coefficients for the number of bidders were positive and significant in regressions for the

The negative and statistically significant coefficient for the weighted average variance of winning bids in the regression for the entire sample of bidders is consistent with the hypothesis of cartel behavior. The fact that the coefficient on this variable is of greater magnitude (i.e., becomes more negative) in the regression for the six hypothesized cartel members further suggests that dispersion in the bids of the cartel members arises when collusive efforts are less successful. The coefficient in the regression for noncartel members is smaller than the coefficients in the other two regressions by an order of magnitude. Furthermore, this coefficient is highly insignificant. Recall that in a competitive auction one expects to observe a positive correlation between the dispersion of bids and auction profitability to the extent that the dispersion of bids is a proxy for ex-ante information disparities. The fact that the coefficient is this regression is negative suggests that some of the "noncartel" bidders may have attempted to rig bids with varying degrees of success.

The insignificance of the coefficients for the competitive quantity suggests that collusion does not break down during higher volume auctions.

Coefficients for the proportion of the noncompetitive quantity sold per auction are negative in regressions across samples. The coefficient is significant in the regression for the sample of cartel bidders and is almost significant in the other two regressions. Demand for CETES appears inelastic in the range prices of assigned bids, suggesting that the Banco

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entire sample and the cartel sample. This result may suggest that smaller, less-informed bidders drop out of auctions characterized by either high degrees of information asymmetries or ex-ante disparities in value estimates due to risk aversion.

de Mexico should substitute noncompetitive for competitive quantities.

VI. Concluding Remarks

Mexican policy makers should make efforts to discourage collusion. Suggestions include the enactment and implementation of stricter anti-trust measures and the easing of entry restrictions. Another possibility is the introduction of a uniform price auction. Research of Friedman (1960) and Bikhchandani and Huang (1989) on US Treasury auctions suggests that bidders have stronger incentives to reveal their true demand curves in uniform price auctions. Such incentives may indeed induce a breakdown in collusion by auction participants. The Banco de Mexico should consider withholding information regarding the joint distribution of bids and quantities currently announced with auction results[18] as well as restricting access of traders on the Mexico City Money Market exchange to information regarding daily transaction histories.

The Banco de Mexico should also consider increasing the prespecified guaranteed maxima of noncompetitive bids to increase auction revenues.

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[18] In the context of a competitive auction with resale, Bikhchandani and Huang (1989) argue that under certain conditions the public announcement of information regarding auction results provides bidders with incentives to increase the prices of their bids to signal high resale values to secondary market participants. The Mexican Treasury must consider the extent to which restrictions on the distribution of information regarding auction results will affect such signaling incentives.

REFERENCES

Bikhchandani, S. and Huang, C., "Auctions with Resale Markets: A Model of Treasury Bill Auctions," Review of Financial Studies, 1989.

Commack, E., "Evidence on Bidding Strategies and the Information Contained in Treasury Bill Auctions," University of Chicago, mimeo, 1986.

Capen, E. C., Clapp, R. V. and Campbell, W. M., "Competitive Bidding in High-Risk Situations," Journal of Petroleum Engineering, 23 (1971), 641-653.

Engelbrecht-Wiggans, R., Milgrom, P. R. and Weber, J. "Competitive Bidding and Proprietary Information," Journal of Mathematical Economics, 11 (1983), 161-169.

Feinstein, J. S., Block, M. K. and Nold, F. D., "Asymmetric Information and Collusive Behavior in Auction Markets," American Economic Review, (1985), 441-460.

Friedman, M., A Program for Monetary Stability, New York (1960).

Hendricks, K., and Porter, R. H. "An Empirical Study of an Auction with Asymmetric Information," American Economic Review, (1988). 865-883.

Hendricks, K., and Porter, R. H., "Collusion in Auctions," Northwestern University, mimeo (1989).

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Hendricks, K., Porter, R. H., and Boudreau, B., "Information, Returns, and Bidding Behavior in OCS Auctions: 1954-1969," _Journal of Industrial Economics_, 35 (1987), 517-542.

McAfee, R. P. and McMillan, J, "Auctions and Bidding," _Journal of Economic Literature_, 25 (1987), 708-747.

Milgrom, P. R., "A Convergence Theorem for Competitive Bidding with Differential Information," _Econometrica_, 47 (1979), 679-688.

—————————, _The Structure of Information in Competitive Bidding_, New York, (1979).

Milgrom, P. R. and Weber, R. J., "A Theory of Auctions and Competitive Bidding," _Econometrica_, 50 (1982), 1089-1122.

Paarsch, H.J., "Empirical Models of Auctions within the Independent Private Values Paradigm and an Application to the British Columbian Timber Sales," mimeo, University of British Columbia, (1989).

Parsons, J. and Raviv, A, "Underpricing of Seasoned Issues," _Journal of Financial Economics_, 14 (1985), 377-397.

Porter, R., "A Study of Cartel Behavior: The Joint Economic Committee, 1880-86," _Bell Journal of Economics_, 14 (1983), 301-314.

Wilson, R., "A Bidding Model of Perfect Competition," Review of Economic Studies, 44 (1977), pp. 511-518.

——————, "Auctions of Shares," The Quarterly Journal of Economics, 93 (1979), 675-89.

——————, "Strategic Analysis of Auctions, Stanford University, mimeo, 1988.

Table I. Summary Statistics on Auction Results

This table summarizes reconstructed results of 121 auctions CETES auctions executed during the August, 1986 - August, 1989 sampling period. Bid discounts were converted to prices in the manner suggested in Section II of this paper. Quantity figures are listed in millions of August, 1989 US dollars for ease of interpretation.

	Mean	Std. Dev.	Maximum	Minimum
Resale Price / Qty.-Wtd. Avg. Auction Price	1.00023	.0003	1.002	.9993
Competitive Quantity Assigned ($US millions)	172	76.9	356.9	16
Noncompetitive Quantity Assigned ($US millions)	38.0	22.2	97.4	7.1
# of Competitive Bids	106.1	30.79	184	28
# of Competitive Bidders	24.7	4.21	35	14
# of Winning Competitive Bids	41.3	29.7	157	2
# of Noncompetitive Bidders	37.9	6.7	57	21
Variance of Winning Bid Prices	.0009	.0025	.0187	0
Qty-Wtd. Variance of Winning Bid Prices	.0008	.0024	.0182	0

TABLE II. SUMMARY STATISTICS ON COMPETITIVE BIDDER PROFITS

Bidder	Auctions	Avg.# Bids	Avg # Win.Bids	Total Noncomp. Bids	000s $US Purchases	000s $US Profits	Basis Pt. Resale Margin
1	119	5.9	4.0	112	5378570	1601	3.0
2	119	4.9	2.2	98	2600904	928	3.6
3	112	5.7	2.8	80	1373577	569	4.1
4	117	2.4	1.1	82	1375550	511	3.7
5	118	3.9	2.3	116	3806808	503	1.3
6	113	2.9	1.5	108	1409585	436	3.1
7	112	3.1	1.0	67	621199	174	2.8
8	110	2.9	0.8	109	264237	124	4.7
9	120	2.8	1.2	104	708574	122	1.7
10	118	3.3	1.2	105	374770	113	3.0
11	116	5.2	2.3	112	386998	104	2.7
12	112	4.1	1.6	93	360455	103	2.9
13	120	4.3	2.0	114	334050	36	1.1
14	116	3.4	1.1	116	146498	19	1.3
15	54	4.9	0.9	47	79224	18	2.3
16	106	2.1	1.2	106	130521	13	1.0
17	114	2.9	0.6	114	93492	12	1.3
18	105	1.4	0.5	101	80418	9	1.1
19	93	3.7	0.6	78	33647	9	2.6
20	117	5.5	2.3	117	95272	8	0.8
21	112	4.0	1.2	110	69521	7	1.1
22	112	6.9	1.8	101	216030	7	0.3
23	104	2.2	0.7	103	59976	7	1.1
24	118	2.3	0.9	118	10982	4	4.1
25	27	3.0	1.6	15	234496	4	0.2
26	98	3.4	1.3	97	116926	4	0.3
27	34	1.0	0.4	34	101381	3	0.3
28	116	1.1	0.3	115	4032	1	2.2
29	33	0.7	0.1	27	952	0	1.6
30	52	0.4	0.1	51	2654	0	0.5
31	68	0.1	0.0	68	429	0	2.4
32	96	1.3	0.3	95	13951	0	0.1
33	59	0.1	0.1	59	1104	0	0.6
34	18	1.2	0.9	18	5312	0	0.1
35	64	0.1	0.0	62	107	0	2.3
36	77	0.4	0.2	77	1200	0	0.1
37	3	0.3	0.3	2	282	-0	-0.1
38	20	1.1	0.7	20	7633	-0	-0.1
39	23	0.2	0.1	23	1273	-0	-0.8
40	103	2.6	0.4	100	24339	-0	-0.1
41	18	2.2	0.7	8	11598	-0	-0.2
42	34	1.5	0.7	31	11758	-0	-0.2
43	56	2.4	0.7	56	11310	-1	-0.5
44	119	0.5	0.2	118	1984	-1	-2.9
45	61	0.7	0.2	60	7591	-1	-1.7
46	99	3.8	1.1	90	94701	-1	-0.1
47	111	1.5	0.5	106	13934	-3	-2.0
48	86	1.9	0.3	86	23126	-4	-1.8
49	87	1.9	0.7	87	52292	-7	-1.3
50	116	4.4	1.9	113	236075	-42	-1.8
TOTAL					20991301	5386	2.6

TABLE III. CROSS SECTIONAL ANALYSIS OF AUCTION PROFITABILITY[1]

$$\text{PROFITS}_t = \text{CONSTANT} + \beta_1 * \text{INFLATE}_t + \beta_2 * \text{SECMKTVAR}_t + \beta_3 * \text{BIDDERS}_t$$
$$+ \beta_4 * \text{WTVARBID}_t + \beta_5 * \text{QUANTITY}_t + \beta_6 \text{NONCOMP}_t + \epsilon_t$$

INFLATE	-.0005	-.0005	.0003
	(1.11)	(1.09)	(.527)
SECMKTVAR	.00015	.00023	.000057
	(3.22)	(4.87)	(3.92)
BIDDERS	.00043	.00043	.00023
	(1.53)	(1.65)	(.51)
WTVARBID	-.029	-.061	-.0028
	(2.96)	(3.60)	(.28)
QUANTITY	-2.02×10^{-7}	-1.35×10^{-7}	-3.87×10^{-7}
	(.49)	(.35)	(.72)
NONCOMP	-.0005	-.0005	-.0006
	(1.72)	(1.98)	(1.63)
Observations	114	112	110
R-Squared	.20	.27	.19

[1]T-statistics are listed beneath parameter estimates.

Essay Three[1]

An Empirical Examination of the Intraday Behavior of the NYSE Specialist

I.   Introduction

Existing research on market making focuses largely on two issues: adverse selection and inventory control.   Adverse selection models focus on the determination of optimal bid and ask prices by market makers exchanging assets with privately informed traders. These models suggest dealers must charge positive spreads to recoup losses in trades with informed traders.   The incidence of bid-ask spreads falls upon uninformed traders willing to incur transaction costs to rebalance their portfolios. See, for example, Bagehot (1971), Copeland and Galai (1983), Glosten and Milgrom (1985), Glosten (1989), Kyle (1984), Kyle (1985), and Easley and O'Hara (1987).

Further research suggests the significance of the adverse selection problem confronted by dealers varies across trading periods for two reasons.   First, uninformed traders can reduce their transaction costs by pooling their trades during specified periods to reduce information asymmetries.   By trading together, uninformed traders reduce the concentration of informed trading in the market and reduce the sensitivity of market maker's price expectations to transaction volumes.   Second, information disparities between dealers and traders vary in magnitude across, for example, days of the week.   Market makers will charge wider

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[1]This essay was written jointly with Mitchell Petersen.

bid-ask spreads when information disparities are widest because such information disparities attract informed trading to the marketplace. See Admati and Pfleiderer (1988) and Foster and Viswanathan (1989).

Inventory models suggest market makers post bid-ask spreads to prevent the accumulation of arbitrarily large cash and stock inventory positions. These models assume dealers limit deviations from "preferred" inventory levels due to inventory holding costs and nonegativity constraints. Dealers quote spreads to attract sales (purchases) when inventories exceed (are less than) preferred levels. See, for example, Garman (1976), Amihud and Mendelson (1980), Ho and Stoll (1981).

We develop a simple model of intraday NYSE specialist quote-setting behavior which incorporates institutional details of New York Stock Exchange (NYSE) trading and the implications of the inventory and adverse selection literatures. We estimate this model with intraday NYSE transaction data for 118 stocks. We find that revisions in the midpoint of specialists' quoted spreads depend on transaction volumes, changes in quoted volumes (the volumes the specialist quotes with his bid and ask prices), contemporaneous changes in aggregate market indices (the S&P 100 index) and the time elapsed between quote revisions. Trades which immediately precede requotation induce larger revisions than those which do not. Trades for volumes which exceed quoted volumes induce larger total and smaller marginal revisions than trades for volumes which are less than quoted volumes.

We find the sensitivities of quote revisions to transaction volumes vary across trading periods but patterns are inconsistent with existing theory. Revisions in the midpoint of quoted spreads do not increase

during inactive trading hours or on Mondays when information asymmetries are arguably largest.

We examine cross sectional variation in the sensitivity of quote revisions to transaction volumes estimated by our model. We find trading activity, return risk, and insider concentration explain variation across stocks.

Section I discusses our model of NYSE specialist quote-setting behavior. Section II discusses our data. Section III summarizes empirical results. Section IV provides concluding comments.

I. A Model of the Quote-Setting Behavior of the NYSE Specialist.

The NYSE is a continuous auction market with public limit orders and a designated market maker entitled the specialist. The NYSE requires the specialist to maintain prices at which he will buy (the bid) or sell (the ask) his stock. The specialist also quotes volumes with these prices. Quoted bid and ask volumes represent the maximum volumes the specialist guarantees to exchange at his quoted prices.

In this section we model the NYSE specialist's quote-setting behavior. As in Hasbrouck (1988), the specialist in our set-up posts take it or leave it bid and ask prices. We assume the specialist is endowed with monopoly power. We also assume the specialist cannot distinguish uninformed traders from informed traders. The specialist quotes his prices based on information which is publicly available, implicit in his limit order book, and implicit in the history of transactions he observes. Our set-up is entirely linear for ease of presentation. We allow for

nonlinearities in our empirical section.

The specialist quotes bid and ask prices which maximize his instantaneous expected profits. The t-th spread consists of the t-th quoted ask and bid prices q_t^A and q_t^B. (t indexes quotes as opposed to time. The elapsed time between the t-1st and the t-th quote will vary). The t-th transaction occurs subsequent to the quotation of the t-th bid and ask prices . A purchase by a floor trader thus occurs at q_t^A. z_t denotes the volume of t-th transaction. z_t is positive if the t-th trade is executed at the quoted ask price q_t^A (a specialist sale), z_t is negative if the t-th trade is executed at t-th quoted bid price q_t^B (a specialist purchase), and $z_t = 0$ if no trade precedes the specialist's decision to announce his t + 1st spread.

When he quotes his t-th spread, the specialist is uncertain about the volume z_t he will transact in the t-th transaction. He must choose q_t^A and q_t^B based on the volumes he expects to exchange in the t-th transaction (conditional on trade at the ask or the bid). The NYSE requires the specialist to exchange volumes which do not exceed (in absolute value) his quoted volumes.[2] We assume that both the adverse selection and inventory cost components in the specialist's quoted spread are linear in volume. The quoted prices q_t^A and q_t^B are formed as follows:

$$q_t^A = M_t + V_t + \lambda * E [z_t | A_t] + \alpha * (E [z_t | A_t] + I_t - \bar{I}_t) \quad (1a)$$

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[2] For example, assume the specialist quotes an ask price of 10 dollars and a volume at the ask of 1000 shares. If a floor trader arrives with an order to purchase 2000 shares, the specialist is required by the rules of the exchange to sell the 1000 shares at a price of 10 dollars per share. According to the NYSE rules, the specialist may then quote a new price before selling the next 1000 shares; or he can sell the entire order at his ask price of 10 dollars.

$$q_t^B = -M_t + V_t + \lambda * E [z_t | B_t] + \alpha * (E [z_t | B_t] + I_t - \bar{I}_t) \quad (1b)$$

where

M_t — the specialist's endowment of monopoly power.

V_t — the specialist's assessment of the "true" value of the security.

A_t — denotes the event that the t-th trade occurs at the ask price q_t^A.

B_t — denotes the event that the t-th trade occurs at the ask price q_t^B.

I_t — the inventory position of the specialist.

$\bar{I}_t$ — the specialist's preferred inventory position.

M_t represents the rent the specialist accrues by virtue of his endowment of monopoly power. $-M_t$ appears in (1b) because the specialist exercises monopsony power in seller-initiated transactions. λ measures market depth -- the sensitivity of the specialist's assessment of the true value of his asset to transaction volumes. λ is positive because informed traders initiate sales (purchases) when they anticipate price declines (increases). In our set-up, the specialist not only revises his assessment when he observes transaction volumes, but he rationally anticipates this revision when setting his quotes. $\lambda * E [z_t | A_t]$ and $\lambda * E [z_t | B_t]$ represent anticipated revisions in this assessment conditional on ask and bid trades.

The specialist also rationally anticipates future deviations from preferred inventory levels. $\alpha (E[z_t | A_t] + I_t - \bar{I}_t)$ and $\alpha (E [z_t | B_t] + I_t - \bar{I}_t)$ represent inventory costs the specialist expects to incur conditional on ask and bid trades.[3] α is positive because the specialist

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[3] Trades which enlarge deviations from from preferred inventory levels

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quotes bid and ask prices to favor sales when long $(I_t - \bar{I}_t < 0)$ and purchases when short $(I_t - \bar{I}_t > 0)$ of his preferred inventory position.

We assume that V_t is formed as follows:

$$V_t = V_{t-1} + \lambda * z_{t-1} + P_t \qquad (2)$$

P_t is a stochastic information shock with finite variance. P_t incorporates information arriving to the specialist from sources other than history of transactions. Because z_{t-1} denotes the *realized* transaction volume of the t-1st transaction, $\lambda * z_{t-1}$ represents the *realized* revision in the specialist's assessment arising from the t-1st transaction. Equation (2) captures the feature of NYSE trading that the specialist's realized transaction volumes differ from volumes he expects to transact when quoting his spreads.

Combining the above expression yields the following equation:[4]

$$\frac{1}{2} (q_t^A + q_t^B) - \frac{1}{2} (q_{t-1}^A + q_{t-1}^B) = (\lambda + \alpha) * z_{t-1}$$
$$+ \frac{1}{2}(\lambda + \alpha) * (E [z_t | A_t] - E [z_{t-1} | A_{t-1}])$$
$$+ \frac{1}{2}(\lambda + \alpha) * (E [z_t | B_t] - E [z_{t-1} | B_{t-1}])$$
$$+ P_t \qquad (3)$$

_____

induce positive inventory costs; trades which reduce deviations induce negative costs. For example, costs are positive in the event of a specialist purchase if the specialist is long.

[4]We also impose the assumption that $\bar{I}_t = \bar{I}_{t-1}$, i.e., the specialist's preferred inventory level does not change. Note that because we drop observations from our sample this this assumption does imply that the specialist's preferred inventory level remain constant across time. Rather, it implies that the preferred inventory level remain constant across periods during which we drop no observations.

The dependent variable is t-th revision in the midpoint of the quoted spread. Revisions in the midpoint of the quoted spread arise in (3) due to 1) changes in expected transaction volumes, 2) the arrival of new information about V_t and 3) marginal changes in inventory levels. The empirical difficulty of distinguishing between the adverse selection parameter λ from inventory parameter α is apparent in equation (3). Hasbrouck (1988) discusses this difficulty in detail.

According to equation (3) the specialist revises his quotes subsequent to each transaction. In practice, however, the specialist revises his quotes only intermittently due to the discreteness of transaction prices.[5] The exchange requires the specialist to quote his bid and ask prices in even eighths of a dollar. The specialist thus revises the position of his spreads only when optimal revisions implied by (3) exceed minimum permissible revisions.[6]

Due to price discreetness revisions in the quoted spread also depend on lagged transaction volumes.[7] Equation (3) depicts the desired revision in position of the specialist's quoted spread. When the specialist forgoes a revision in the midpoint of his quoted spread, the desired

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[5] Specialists revise the midpoints of their quoted spreads subsequent to 46% of the transactions on average in our sample.

[6] Take the example of a specialist sale for which (3) implies an increase in the midpoint of the specialist's quoted spread of three cents. The specialist will not revise the position of his spread because the minimum admissible revision in the midpoint of the spread is a sixteenth of a dollar (6.25 cents). If the specialist raises both the bid and the ask price by an eighth, the midpoint increases by an eighth. However, if only one price is raised, the midpoint only increases by a sixteenth.

[7] The discreteness of transaction prices may explain Hasbrouck's (1988) finding that lagged transaction volumes influence the specialist's decision to revise the position of his quoted spread.

change accumulates. Aggregating across trades executed between successive revisions in the position of the specialist's quoted spread, we derive an expression for the desired change in the midpoint of the spread:

$$
\frac{1}{2} (q_t^A + q_t^B) - \frac{1}{2} (q_{t-k}^A + q_{t-k}^B) = -(\lambda + \alpha) * \sum_{j=1}^{k} z_{t-j}
$$

$$
+ \frac{1}{2}(\lambda + \alpha)* (E [z_t \mid A_t] - * E [z_{t-k} \mid A_{t-k}])
$$

$$
+ \frac{1}{2}(\lambda + \alpha)* (E [z_t \mid B_t] - * E [z_{t-k} \mid B_{t-k}])
$$

$$
+ \sum_{j=0}^{k-1} P_{t-j} \tag{4}
$$

k denotes the number of trades executed by the specialist between successive quote revisions. Observed changes in the midpoint quoted spreads depend on volumes of transactions executed since the most recent revision.[8]

II. DATA AND EMPIRICAL PROCEDURES

A. Construction of the Quote Revision Data Set

We construct series of quote revisions and transaction volumes from the transcription of the NYSE ticker tape for the thirty trading day period September 1 - October 12, 1987.[9] Our original Institute for the Study of Security Markets (ISSM) database consists of chronological series of quoted and realized transaction prices and volumes.[10]

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[8] If the sum $(\lambda+\alpha)$ is large enough so that even small trades (i.e. one hundred shares) induce quote revisions this modification is irrelevant. In such circumstances, one will always observe k equal to 1; the specialist will revise his quotes after each trade.

[9] We excluded the last half of October, 1987 from our sample to preclude the influence of the events associated with the stock market crash on our results.

[10] The ISSM series also include regional exchange data. We ignore these

The specialist must quote bid and ask prices and volumes. Quoted bid and ask volumes represent the maximum volumes for which he guarantees his quoted bid and ask prices. Prices are not guaranteed for volumes exceeding the quoted limits. The specialist revises his quotes at will; he need not execute a transaction before revising his quotes. Existing quotes do not expire unless the specialist revises them.

Figure I: Structure of the Original ISSM Data Set
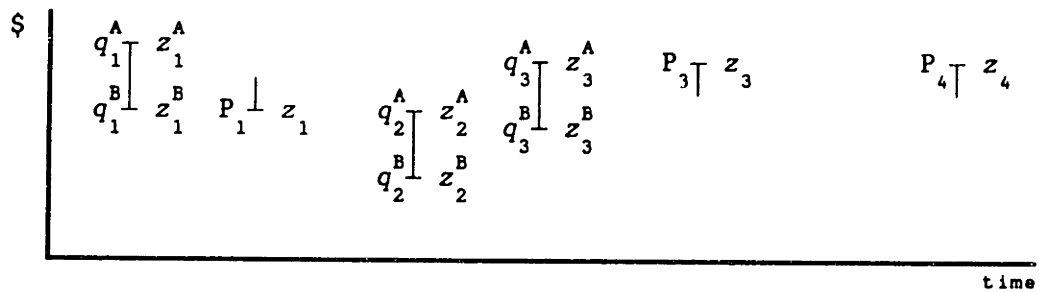
These procedures imply an alternation between quote and transaction data. Figure I provides an example of the chronology of the ISSM data for a given stock. In this example the specialist initially posts ask and bid prices (q_1^A, q_1^B) and volumes (z_1^A, z_1^B). He then buys $|z_1|$ shares at his bid price $(P_1 = q_1^B)$. He next revises his quotes to (q_2^A, q_2^B) and (z_2^A, z_2^B).[11] He replaces (q_2^A, q_2^B) and (z_2^A, z_2^B) with (q_3^A, q_3^B) and (z_3^A, z_3^B) without executing an intervening transaction. Perhaps the specialist is responding to information from an outside source such as a news service in this case. He executes the next two transactions at his third quoted ask

data because our focus is the NYSE. We also drop opening transactions from your sample because the NYSE specialist opens each trading day with a call auction.

[11] He may choose not to revise his quoted volumes. That is, he may set $z_1^A = z_2^A$ and $z_1^B = z_2^B$.

price (i.e., the specialist sells z_3 and z_4 at q_3^A). He chooses not to revise his quotes subsequent to the sale of z_3.

Figure II: Structure of the Modified Data Set
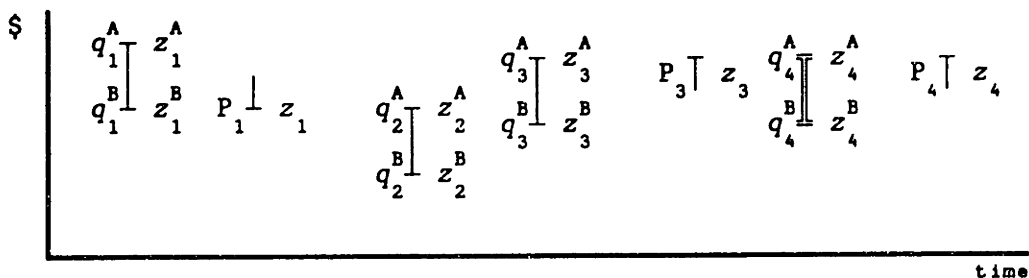
In constructing the data series of quote changes, we consider three distinct sequences of events.[12] Most often a quote revision follows a transaction, as in the quote revision from (q_1^A, q_1^B) to (q_2^A, q_2^B) in Figure II. In this case a non-zero traded volume is followed by a non-zero revision in the midpoint of the spread. The second case consists of two sequential trades uninterrupted by a quote revision.[13] In this case we superimpose the most recent quoted prices between the two transactions to create a quote revision of zero. Figure II illustrates how we implement this procedure in the context of the specialist sale of z_4 at the price P_4 = q_3^A. The third case consists of pairs of quotes uninterrupted by intervening trades. For example, in Figure II the specialist revises his quoted prices from q_2^A and q_2^B to q_3^A and q_3^B without executing a transaction.

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[12] The series of quotes (Q) and trades (T) produce four possible combinations: TQ, TT, QQ, and QT. A QT sequence does not produce an observation. If the specialist resets his quotes following a trade, we calculate a TQ observation. If the specialist chooses not to alter his quotes we calculate a TT observation.

[13] Instances in which the specialist revises his quoted volumes but does not revise his quoted prices fall into this category as well.

In this case we simply superimpose a transaction volume of zero ($z_i = 0$).

The ISSM database does not distinguish between buyer and seller-initiated trades. We impose the assumption that transactions executed at quoted ask and bid prices represent specialist sales and purchases. This assumption introduces an errors in variables problem if specialists cross their spreads in transactions (i.e., they buy at the ask or sell at the bid). We suspect such behavior is rare, however.[14]

We examined the validity this trade classification rule by comparing the probability distributions of midpoint changes executed immediately immediately subsequent to transactions we classify as purchases, sales, and zero-volume trades. Our model argues the specialist will revise his quotes downward after sales and upward after purchases by floor traders. The distributions we tabulate of midpoint changes subsequent to zero-volume transactions are symmetric around zero, skewed to the left for quote changes following purchases and to the right for quote changes following sales. These tabulations validate our classification scheme and suggest that specialists revise their quotes in response to transaction volumes. Figure III graphs the distributions of non-zero quote revisions for Brunswick Corporation, a representative stock from our sample.[15]

Some trades are executed at prices that lie within the quoted spread. We drop these trades from our sample because we cannot classify them as purchases or sales under plausible assumptions.[16] We suspect the majority

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[14] Spreads of one eighth are those most likely to be crossed.

[15] We examine the coefficient bias induced by classification errors in Appendix I.

[16] One can classify those trades at prices above and below the midpoint of the spread as specialist sales and purchases, but the accuracy of this classification method is questionable. The conditional probability

of these transactions are "match" trades between pairs of NYSE floor
traders or off the exchange traders.[17] In such trades the specialist plays
no direct role.

Figure III

CHANGE IN THE SPECIALIST'S QUOTES
CONDITIONAL ON TRANSACTION TYPE
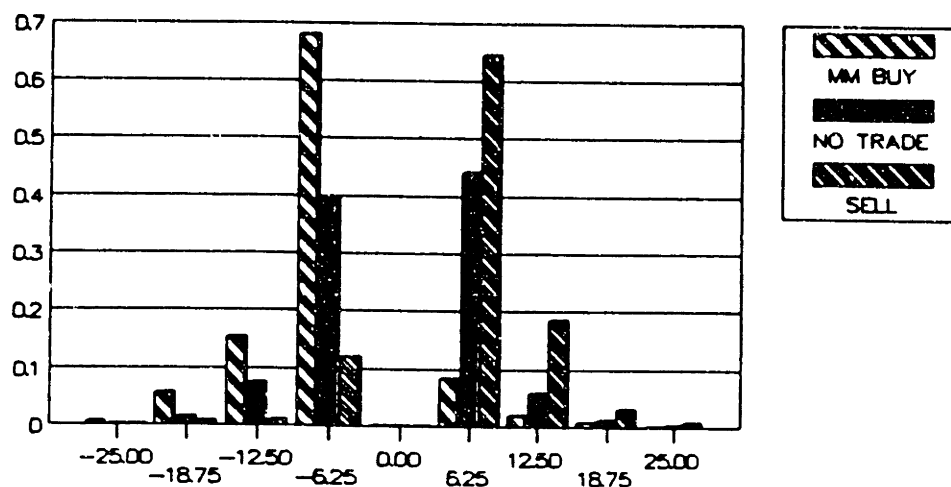
We tabulate this probability density of non-zero quote revisions
Brunswick Corp. data. We graph the distribution of the change in
the midpoint of the spread conditional on our classification of
immediately preceding trades. We include data only for
transactions executed at immediately preceding bid and ask prices
and express quote revisions in cents.

Other trades are executed at price that lie outside of the quoted
spread. We drop such trades from our sample as well. We suspect that
these trades are executed off the exchange floor which are reported with

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densities of quote revisions associated with these trades are essentially
symmetric around zero for both purchases and sales.

[17] Preliminary regressions suggested that transactions executed within the
quoted spread do not induce the specialist to revise the position of his
quotes.

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some delay. Such trades constitute roughly .1% of our sample. ISSM data series do not distinguish between transactions in which the specialist participates and those in which he does not. Examples of the latter include trades consummated off the NYSE floor and direct trades between floor traders. The specialist participated directly in twelve percent of 1987 trades and acted as an agent in another forty eight percent.[18] Lack of specialist participation invalidates our methodology to the extent that quote revisions arise due to inventory considerations alone. Whether or not the specialist participates in trades is irrelevant, however, when quote revisions arise due to the incorporation of information derived from observed trade.

We code volumes of buyer and seller initiated transactions at ask and bid prices as positive and negative throughout this paper. Positive volumes constitute specialist sales and represent reductions in the specialist's inventories. We denominate volumes in thousands of shares. A trade of one thousand shares is thus a unit trade.

B: Sample Selection

Our sample consists of 118 ISSM stocks for which Chicago Board of Exchange (CBOE) options existed in September, 1987. We started with the first 125 companies in an alphabetical listing. We then excluded the six stocks from this original list for which fewer than 1000 observations were available to ensure accurate estimation. We also exclude IBM due to computer memory limitations. Our final sample consists of 118 stocks.

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[18] The 12.1 percent figure represents the proportion of NYSE transactions in which specialists bought or sold for their own accounts. NYSE Fact Book, 1989, p. 14.

C: Estimating the Specialist's Quote Revision Rule

Measures of Transaction Volumes

We depart from our set-up in Section I and include both an intercept and a linear transaction volume component in our specification of the quote-revision rule to accommodate the possibility that the initiation of trade induces a quote revision independent transaction size. We implement this by adding a dummy to our regression model which takes on the values of one and negative one in the event of a specialist sales and purchases. We refer to this variable as the "side of spread dummy":

Side of Spread Dummy - 1 for specialist sale

--1 for specialist purchase

We implement this specification only for trades which immediately precede quote revisions (z_{t-1} in equation 4). The sum of this intercept and the transaction volume component will be positive because if the specialist indeed revises his quotes upward in response to purchaser-initiated trades.

The specialist quotes volumes which represent the maximum volumes for which he guarantees his prices. One suspects that he imposes volume limitations to preclude large losses to traders with superior information. Sometimes, however, the specialist transacts volumes which exceed his quoted volumes.[19] This suggests he believes such trades communicate less information than standard trades. Transaction volume component of the

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[19] The incidence of such transactions ranges from 2.0 percent to 85.2 percent across stocks. The median figure is 24.4 percent. We calculate these figures exclusively with volumes traded at quoted bid and ask prices.

quote revisions should be smaller. We distinguish between intercept and volume components of quote-revisions rules for transactions of volumes which strictly exceed and are less than quoted volumes. We make this distinction only for the the most recent trade. If quoted volumes are meaningless limits neither the constant nor the volume-related components of the quote revision will differ for transactions exceeding quoted volumes.

Recall from Section I that price discreetness induces quote revisions of zero even when desired changes are nonzero but small.[20] Price discreteness thus delays the incorporation of information from transactions into quotes. We include the cumulative sum of volumes of all transactions executed since the last quote revision, except for the most recent transaction (the cumulative sum is $\sum_{j=2}^{k} z_{t-j}$ from equation 4). If the information content of trades is homogeneous, quote revisions induced by the lagged volumes should not differ from those induced by trades which immediately precede quote revisions.

Other Determinants of the Specialist Quotes Revisions

As equation (4) suggests, changes in the specialist's expectations of future transactions volume should also induce quote revisions. If the specialist's expectations of future volumes do not vary across time or if the absolute values of expected volumes conditional on a trade at the ask and the bid do not differ the expected volume terms drop out of equation

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[20] In practice specialists frequently forgo quote revisions. The incidence of specialist quote revisions immediately subsequent to trade range across stocks between 1.3 percent and 46.8 percent in our sample. The median figure is 17.9 percent. (We calculate these figures exclusively with trades executed at quoted bid and ask prices).

(4).[21] In practice the specialist's expectations of future volumes do vary. For example, traders periodically inform the specialist of their future trading needs. On other occasions traders leave orders for the specialist to execute. We suspect much of the variability in the quoted volumes is attributable to such behavior. The specialist should incorporate information implicit in impending trades into the volumes he quotes with his bid and ask prices. On this basis, we employ changes in quoted volumes as proxies for changes in the expected volumes of the specialist

The specialist incorporates information he acquires observing the behavior of market indexes directly into his quotes. If market movements induce trading, excluding a market measure from our equation may bias our transaction volume coefficients.[22] The market indices of interest to specialists vary across stocks. We proxy for changes in market indices with the percentage change in the S&P 100 index realized during the elapsed time between successive quote revisions.[23] We calculate the percentage change in the index with the values which are outstanding just prior to quote revisions. All of our stocks have positive betas. For this

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[21] If volume expectations are constant across time (i.e., $E[z_t|A_t]$ = $E[z_{t-k}|A_{t-k}]$ and $E[z_t|B_t]$ = $E[z_{t-k}|B_{t-k}]$) or across the spread ($E[z_t|A_t]$ = - $E[z_t|B_t]$) then these terms drop out of equation (4).

[22] Assume that increases in the market index raise the optimally chosen quotes of the specialist. If upward movements in the market index also induce purchases by traders (i.e. increase the probability of a specialist sale), the coefficients for volumes will be biased upward because they will absorb effects of changes in the market index. If market movements do not influence volumes no bias will exist.

[23] Our choice was dictated by availability. We employ the intraday S&P 100 index recorded in the Berkeley Options Data base. Unfortunately, because the database records CBOE trading activity and the CBOE opens one half hour later than the NYSE, data are unavailable for the first half hour of trading in New York.

reason we expect to observe positive correlations between changes in the market index and quote revisions.

Although theoretical models do not distinguish between transaction and real time, the distinction may be important in practice. Shorter time intervals between quote revisions imply higher levels of trading intensity. Assuming trading intensity matters, a specialist purchase (sale) of given size will induce a larger downward (upward) revision in quoted prices if the time elapsed since the most recent quote revision is small. The inclusion of the elapsed time between successive quote revisions is incorrect. Such a specification would simply measure stocks' average per minute return.[24] The correct specification employs the product of the elapsed time variable with the sign of the most recently exchanged volume: Quote changes are more likely the shorter the time interval, but the sign of the change is determined by the type of transaction.[25] A negative coefficient for this variable would confirm our hypothesis.[26]

III: EMPIRICAL RESULTS

A. Estimation of the Specialist's Quote Revision Rule

We estimate the specialist's quote revision rule for our sample of

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[24] We estimated this specification for a subsample of firms. The coefficient signs on the elapsed time variable varied widely. Estimates, however, never differed significantly from zero.

[25] As a test of this hypothesis, for several stocks we estimated logit and probit models of the probability of specialist quote revisions subsequent to trade. Coefficient on elapsed time variables were consistently negative, confirming our hypothesis that the specialist is more likely to revise his quotes subsequent to trade as the elapsed time decreases.

[26] We also include a constant in our regression model. The constant varies in sign across stocks but is consistently insignificant.

118 stocks. We report results in Table I for Southern Company, a representative stock from our sample. As our model predicts, the Southern Company specialist revises his quotes downwards (upwards) subsequent to transactions at the bid (ask). The estimated intercept components of his revision rules are .558 and 2.54 cents for trades of in which volumes less than and greater than quoted volumes are exchanged. For both types of trades the specialist revises his quotes downward by an constant amount which is independent of trade size. The magnitude of this constant component is larger for trades for volumes which exceed quoted volumes. The estimated slope of the revision rule, however, is larger for transactions of vol:mes which do not exceed quoted volumes. Increases in trade sizes of 1000 shares induce marginal quote revisions of .558 and .021 cents for transactions of volumes less than and greater than quoted volumes. This suggests that the the Southern Company specialist has some ability to distinguish between information and liquidity trades.

Table I: Estimated Quote Revision Rule for Southern Company

Coefficient	Estimate	Stand Error	T-stat
Volumes ≤ Quoted Volumes			
Side of Spread Constant	0.484	0.052	10.70
Volume	0.239	0.058	3.84
Volumes < Quoted Volumes			
Side of Spread Constant	2.543	0.223	11.42
Volume	0.021	0.007	3.13
Cumulative Lagged Volume	0.002	0.002	0.90
Δ Quoted Volumes	0.069	0.012	5.66
% Δ in S&P 100	0.140	0.113	1.23
Δ Time * Side of Spread	-0.004	0.001	-8.19
Constant	0.024	0.035	0.69

R-Square = 0.195   No Observations = 4542   D.W. = 2.17

Side of spread is a dummy set equal to one for trades at the bid and negative one for trades at the ask We list heteroskedastic consistent standard errors and t-statistics. We calculate these statistics employing techniques of Wooldridge (1989). Transaction volumes are recorded in thousands of shares. Elapsed times are recorded in minutes.

Cumulative lagged volume contributes little explanatory power to the Southern Company regression; the coefficient for this variable is small and insignificant. Perhaps the specialist categorizes lagged trades as liquidity trades. Changes in quoted volumes are positively correlated with quote revisions as the model predicts. Quoted volumes apparently proxy for changes in expectations of future volumes. Changes in the market index are positively correlated with quote revisions as the model predicts. The significance level of the market index coefficient is low, however. The elapsed time between successive quote revisions(signed by the transaction volume of the trade immediately preceding the quote revision) is negatively correlated with the magnitude of the quote revision, suggesting that the specialist's quotes are more sensitive to transaction volumes during periods of active trading. The coefficient for this variable is highly significant.

Table II summarizes sample-wide results for the intercept and volume components of quote revision rules. The type of transaction (bid or ask) significantly affects the magnitude of the quote revision, independent of the size of the transaction for all of our stocks. As indicated in Table II, the coefficients for the side of the spread dummies are significant at the 0.1 percent level for all 118 firms. The ratio of side of spread coefficient to the average outstanding stock price during our sampling averages .058 across stocks in our sample.

We first refer to transactions of volumes not exceeding quoted volumes. The average marginal midpoint revision induced by a one thousand

Table II: Estimates of Volume Components of Quote Revision Rules

COEFFICIENT	TRADES ≤ QUOTED VOLUME SIDE OF SPREAD	VOLUME	TRADES > QUOTED VOLUME SIDE OF SPREAD	VOLUME
MEAN	3.222	0.489	5.341	0.132
MEDIAN	2.258	0.499	4.360	0.104
5 PERCENTILE	0.440	0.071	1.822	0.004
25 PERCENTILE	1.229	0.301	3.191	0.034
75 PERCENTILE	3.731	0.741	6.347	0.183
95 PERCENTILE	8.245	1.645	10.258	0.490
T-STATISTICS				
MEAN	14.15	4.83	13.49	2.79
MEDIAN	14.07	4.36	13.50	2.60
5 PERCENTILE	7.37	0.72	5.82	0.29
25 PERCENTILE	10.80	2.67	9.79	1.38
75 PERCENTILE	17.32	6.99	16.16	3.70
95 PERCENTILE	22.54	10.78	22.65	6.04
% Sig. at 1.0%	100.0	78.8	100.0	55.9
% Sig. at 0.1%	100.0	69.5	100.0	39.8

This table summarizes estimates of volume components of quote revision rules for our sample of 118 stocks. Our data span the thirty trading day period September 1 - October 12, 1987. Volumes are recorded in thousands of shares. We calculate T-statistics with heteroskedastic-consistent standard errors. We list signficance levels of one-sided T-tests.

share trade this type is 0.014 percent.[27] Average trade sizes typically exceed 1000 shares, however. Now define the *total quote revision* as follows:

Side of Spread Coefficient + Volume Coefficient *Mean [Volume]
———
Mean [Stock Price]

[27] The coefficients on volume are in cents per 1000 shares. For comparison across firms, we normalize coefficients by the average stock price during the sampling period. The normalized coefficients range between 0.007 and 0.197 percent. The median coefficient value is 0.050 percent.

where we calculate the mean stock price and volume figures with data from our sample. Total revision quote revisions range from .007 to .197 and average 0.069 percent in our sample of stocks. Although larger trades induce larger revisions, the existence of a positive intercept in the quote revision rule implies that quote revisions do not increase proportionally with volume. A two thousand share trade moves the quotes more than a one thousand share trade but less than two individual one thousand share trades. Estimated slope components differ significantly from zero at the one percent level for seventy eight percent of our stocks. T-statistics are less than one in the four cases in which the slope parameters are negative.

Now refer to estimates of revisions subsequent to transactions of volumes exceeding quoted volumes. Quote revision rules for these trades have larger intercept and smaller slope components. We graph quote revision rules for Southern Company in Figure IV. The quote revision rule flattens out for volumes exceeding the quoted volumes. Compared to quote revision rules for trades of volumes less than quoted volumes, both the side of spread and slope components are larger and smaller, respectively, for ninety eight percent of our stocks. In general differences in the intercept and slope estimates of revision rules associated with the two types of trades are statistically significant. The intercept coefficients are statistically larger for trades of volumes exceeding quoted volumes for eighty seven percent of our stocks. The slope coefficients are statistically smaller for sixty four percent of our stocks.[28]

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[28] Both tests are one sided t-tests calculated with robust standard errors and one percent levels of significance.

Figure IV

SPECIALIST'S QUOTE REVISION RULE
SOUTHERN COMPANY
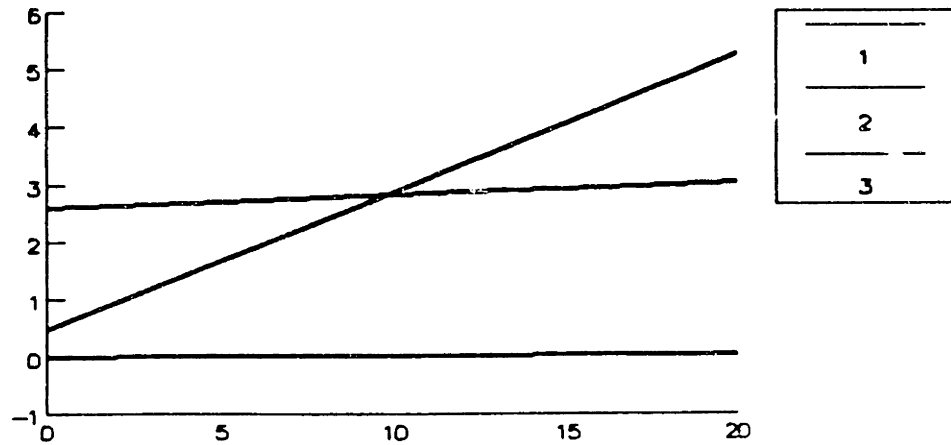
We graph quote revision rules for Southern Company. We record volumes in thousands of shares and quote revisions in cents. We distinguish between which immediately precede quote revisions and those which do not. For trades which immediately precede quote revisions we distinguish between trades in which volumes greater and less than quoted volumes are exchanged.

The side of the spread of initiated trade apparently conveys much more information than the actual volume in transactions of volumes exceeding quoted volumes. Transaction volumes provide additional information, but proportionally very little. A ten thousand share trade moves the quotes an average of 0.194 percent of the stock's average price during our sampling period whereas a twenty thousand share moves the quotes on average 0.330 percent.[29]

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[29] We calculate these numbers with the mean intercept and slope estimates.

Figure V: Estimated Total Quote Revisions Associated with Trades

in Which Volumes Greater and Less Than Quoted Volumes are Exchanged
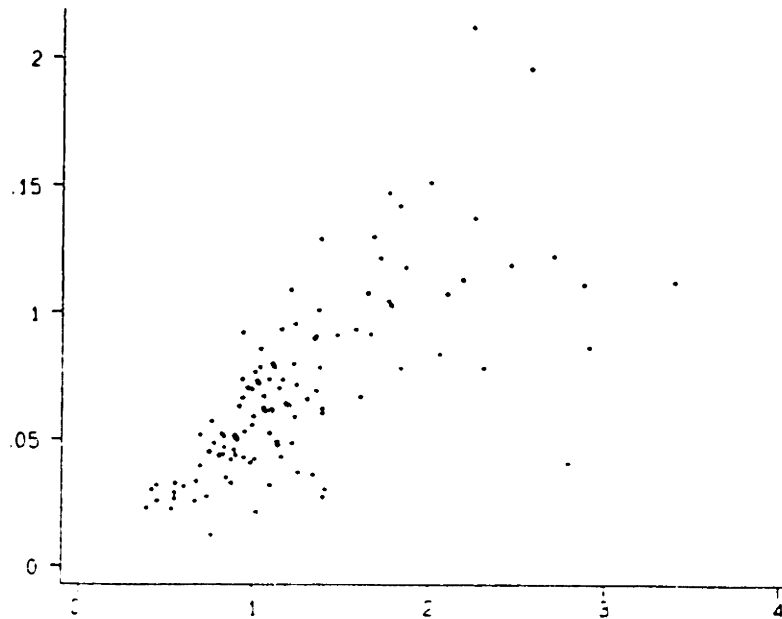
We graph estimated total quote revisions associated with trades in which volumes greater and less than quoted volumes are exchanged. We express estimated total quote revisions as percentages of average stock prices.

Our model suggests that inventory and adverse selection considerations determine the parameters of quote revision rules for both transactions of volumes greater and less than quoted volumes. On this basis total quote revisions associated with these types should be correlated. Figure V indicates that this is indeed the case. We graph on the two axes estimated total revisions associated with trades in which volumes greater and less than quoted volumes are exchanged. The correlation coefficient between these two types of revisions across stocks is 0.71.

Our model predicts that cumulative volumes will contribute to the

specialist's decision to revise his quotes. Empirical results, however, argue to the contrary. The magnitudes of coefficients for cumulative lagged volumes are much smaller than those for volumes of trades immediately preceding quote revisions. These coefficients are positive for only fifty six percent of our stocks; they are significant for only fourteen percent of our stocks (see Table III).[30] These results suggest that trades either induce large and immediate quote revisions or do not contribute to quote revisions at all. These results also suggest that the inventory component of the quoted spread is small and that the specialist has some ability to distinguish between information and liquidity trades.

Recall that we proxy for changes in expectations of future volumes with changes in quoted volumes. Coefficients for the changes in quoted volumes are positive as our model predicts for seventy four percent of our stocks. This suggests that the specialist incorporates information implicit in impending trades when determining the position of his spread. Changes in quoted volume induce smaller quote revisions than actual transaction volumes. Increases in quoted ask volumes of one thousand shares on average induce upward revisions in the quotes of 0.006 percent of average stock prices during our sampling period. This represents a tenth of the average movement induced by a one thousand share transaction. T-statistics of quoted volumes coefficients are small -- only fifty nine percent of the coefficients are statistically significant at the one percent level

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[30] We apply a one-sided t-tests with a cutoff point of one percent. Based on this the same test, this coefficient is significantly negative for five stocks in our sample.

Table III: Quote Revision Rule Coefficients

COEFFICIENT ESTIMATES	CUMULATIVE PAST VOL	Δ QUOTED VOLUME	% CHANGE IN S&P 100	TIME CHANGE
MEAN	-0.035	0.248	0.726	-0.048
MEDIAN	0.002	0.237	0.548	-0.027
5 PERCENTILE	-0.291	-0.287	0.024	-0.141
25 PERCENTILE	.011	-0.009	0.281	-0.056
75 PERCENTILE	0.034	0.437	0.955	-0.014
95 PERCENTILE	0.110	0.970	2.110	-0.004
T-STATISTICS				
MEAN	0.47	6.48	1.79	-5.59
MEDIAN	0.26	6.03	1.71	-5.57
5 PERCENTILE	-1.93	-2.25	0.04	-8.68
25 PERCENTILE	-0.89	-0.25	1.12	-6.90
75 PERCENTILE	1.74	12.21	2.63	-4.29
95 PERCENTILE	3.53	18.95	3.37	-2.43
% Sig. at 1.0%	14.4	59.3	33.1	96.6
% Sig. at 0.1%	9.3	57.6	8.5	90.7

This table summarizes coefficient estimates of equation (4) for 118 stocks. Our data span the thirty trading day period September 1 - October 12, 1987. We express volumes in thousands of shares and the elapsed time variable in minutes. We calculate T-statistics with heteroskedastic- consistent standard errors. Significance is based on one-sided T-tests.

Changes in the market index are positively correlated with specialist quote revisions for ninety six percent of our stocks. A one percent increase in the S&P 100 index realized during the time window between successive quote revisions on average induces increase upward revision in the midpoint of the quoted spread of 0.014 percent of the stock price. This effect is of the same order of magnitude as the effect of adding an additional thousand shares to a trade. Although coefficients are consistently positive across stocks, only thirty percent are statistically

significant at the one percent level.

The intensity of trade also influences the magnitude of quote revisions. Quote revisions are negatively correlated with the elapsed time between quote revisions. This is the case for every stock in our sample. Coefficients differ significantly from zero for ninety two percent of our stocks. Each additional elapsed minute on average reduces the expected revision in the specialist's quotes by about 0.0007 percent of the stock price. This result suggests that information asymmetries are widest during periods in which transaction orders arrive most frequently.

B: Variation in Quote Revision Rules Across Trading Periods

In this section we examine variation in the specialist's quote revision rule across hours of the trading day and days of the trading week. We reestimate our model we allowing the side of spread and transaction volume coefficients to vary across hours of the the trading day and days of the trading week.[31] Insufficient data were available for model estimation for four stocks from our original sample. We therefore exclude these stocks from the analysis of this section. We reject the null hypothesis that coefficients vary across the days of the week for fifty-six percent of the remaining stocks in our sample at the five percent level of significance. We reject the null that these parameters do not vary across hours of the trading day for thirty-four percent of our stocks.[32]

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[31] We do not have data on the S&P index for the 9:30 am to 10:00 am EST period. We therefore estimate coefficients exclusively for each of the six one hour periods between 10:00 am and 4:00 pm. We categorized the Tuesday following the Labor day holiday as a Monday.

[32] We employ a lagrange multiplier test which is robust to heteroskedasticity (see Wooldridge, 1989). A non-robust version of the test produces a higher proportion of rejections.

TABLE IV: Coefficient Estimates & Total Quote Revisions

Day of the Week Averages

	MON	TUE	WED	THUR	FRI
VOLUME > QUOTED VOLUME					
SIDE OF SPREAD	2.53	2.74	2.85	2.73	2.69
VOLUME	0.77	0.62	0.77	0.66	0.74
VOLUME > QUOTED VOLUME					
SIDE OF SPREAD	4.26	4.95	4.76	4.63	4.84
VOLUME	0.14	0.15	0.21	0.16	0.16
TOTAL QUOTE REVISION					
VOLUME < QUOTED VOLUME	0.067	0.069	0.072	0.069	0.068
VOLUME > QUOTED VOLUME	0.116	0.131	0.127	0.123	0.133

This table lists the average values of coefficients (in cents per thousand shares) and total quote revisions as percentages of average stock prices for each day of the week. We calculate these averages with 114 stocks. We calculate the total quote revisions with average transaction volumes and ignore the fact that these averages may differ across daysDue to a scarcity of observations we were unable to estimate parameters for four stocks.

We first examine patterns in the variation of coefficient estimates across days of the week. We display mean values of coefficient estimates and total quote revisions in Table IV. Variations in the coefficients are statistically significant but small in magnitude. Differences between mean total quote revisions are not statistically significant.[33]

The low variation in mean total quote revisions disguises the wide variation in total quote revisions across our sample of individual stocks. Define the percentage range in the total quote revision as:

$$\text{Percentage Range} = \frac{\text{Max[Total Quote Revision]} - \text{Min[Total Quote Revision]}}{\text{Mean[Total Quote Revision]}}$$

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[33] The F-statistics are 0.19 and 1.17 for total quote revisions subsequent to transactions for volumes less than and greater than quoted volumes.

To calculate this statistic we employ the maximum, minimum and mean of the five daily values of the total quote revision. For quote revisions subsequent to transactions for volumes less than quoted volumes the percentage range averages forty five percent in our sample. This means that the maximum quote revisions for average-sized trades typically exceed mean quote revisions by more than twenty percent. Minimum quote revisions fall more than twenty percent short of the mean. Maxima arise on Wednesday for twenty seven percent of our stocks and arise on Monday and Friday for eighteen and eleven percent. A Wednesday peak therefore is by no means a consistent result. Results for quote revisions subsequent to transactions for volumes exceeding quoted volumes lead to similar conclusions: the percentage range for these quote revisions averages forty one percent across stocks.[34] These results contradict the hypothesis of Foster and Viswanathan (1988) that market makers' sensitivities to transaction volumes are highest on Mondays when information asymmetries are arguably widest.

Admati and Pfleiderer (1988) argue that uninformed traders can reduce their transaction costs by pooling their trades during specified periods to reduce information asymmetries. By trading together, uninformed traders reduce the concentration of informed trading in the market and reduce the sensitivity of market maker's price expectations to transaction volumes. To test the validity of this hypothesis, we examine the

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[34] Despite the variation in estimates across days of the trading week, total quote revisions associated with the two types of trades maintain their high positive correlations. The correlations between the total quote revisions associated with transactions of volumes greater than and less quoted volumes are 0.69 for Monday, 0.65 for Tuesday, 0.64 for Wednesday, 0.58 for Thursday and 0.50 for Friday.

covariability of trading volume and estimated total quote revisions figures for different days of the trading week. Trading volume is lowest on Mondays and Fridays and peaks on Wednesday consistently across stocks in our sample.[35] This is precisely the pattern documented by recent empirical work (see Mulherin and Gerety 1989). Given the erratic patterns exhibited by estimates for individual stocks it is not surprising that we observe little relation between trading activity levels and total quote revisions. We first discuss results for total quote revisions subsequent to transactions of volumes less than quoted volumes. The correlations between average daily trading volumes and these total quote revisions average -0.23 across stocks; the minimum and maximum correlations are -0.97 and 0.99. Correlations differ significantly from zero at the five percent level for only 8 of our 114 stocks. Results are similar for total quote revisions subsequent to transactions of volumes exceeding quoted volumes: correlation coefficients average -0.16 and differ significantly from zero for only 4 stocks.

Examination of coefficient and total quote revision variation across hours of the trading day leads to qualitatively identical conclusions. We report mean coefficients and total quote revisions in Table V. Mean coefficients and mean total quote revisions exhibit little variation across hours of the day despite wide variation at the level of individual stocks. The percentage ranges average forty four percent and forty seven percent for total quote revisions subsequent to transactions for volumes less than and greater than quoted volumes. Trading volume again fails to

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[35] We calculate average daily trading volumes from our data set. Calculations are based on transactions executed at posted bid or the ask prices.

explain variation in estimates. The correlations between the total quote revision and average hourly trading volume have no consistent sign. For example, for revisions associated with trades for volumes which do not exceed quoted volumes, correlations average 0.13 and range between -0.92 and 0.93. These statistics differ significantly from zero at the five percent significance level for only six percent of our stocks.

TABLE V: Average Coefficient Estimates & Total Quote Revisions
Across Hours of the Trading Day Averages

	10am	11am	12am	1pm	2pm	3pm
VOLUME ≤ QUOTED VOLUME						
SIDE OF SPREAD	2.84	2.57	2.66	2.51	2.54	2.96
VOLUME	0.72	0.63	0.80	0.51	0.58	0.61
VOLUME > QUOTED VOLUME						
SIDE OF SPREAD	5.06	4.66	4.62	4.26	4.44	4.78
VOLUME	0.13	0.16	0.19	0.13	0.23	0.20
TOTAL QUOTE REVISION						
VOLUME ≤ QUOTED VOLUME	.072	.065	.069	.063	.064	.072
VOLUME > QUOTED VOLUME	.135	.126	.124	.114	.126	.122

This table lists the average values of coefficients (in cents per thousand shares) and total quote revisions (in percentages) for each day of the week. We calculate these averages with 114 stocks. Due to a scarcity of observations we were unable to estimate parameters for four stocks. We calculate the total quote revisions with average transaction volumes and ignore the fact that these averages may differ (albeit slightly) across days.

C: Cross Sectional Variation in Quote Revision Rules

Our estimates of quote revision rules vary widely across stocks. The likely sources of variation include stock specific determinants of specialist inventory and adverse selection concerns. This section isolates these determinants in cross sectional analysis of quote revision

rules.

Inventory risk provides one explanation of why the specialist revises his quotes subsequent to trade. Inventory risk should decrease with stock trading activity levels and increase with the riskiness of stock returns. In the former case, higher levels of trading activity reduce inventory adjustment costs. In the latter case, higher return risk implies greater risk for a given deviation from the preferred inventory level. For each stock we employ the average daily number of trades during our sampling period to proxy for trading activity (TRADES). We employ stock betas from the ISSM tape (BETA) and the standard deviation of daily returns for the January 1 - August 31, 1987 period (SD[RETURN]) as a proxies for stock return risk. Stock betas and returns standard deviations capture systematic and idiosyncratic risk.

Adverse selection may also explain why the specialist revises his quotes subsequent to trade. Quote revisions induced by adverse selection should increase with the intensity of informed trading and the magnitude of information asymmetries. To proxy for the intensity of informed trading we employ the ratios of holdings of institutional investors (INSTITUTION), five percent shareholders (FIVE PERCENT) and legally defined insiders (INSIDER) to total outstanding shares.[36] Most large institutional investors cannot be considered information traders. We thus expect to observe smaller quote revisions for stocks with larger proportions of institutional holdings. Arguably large shareholders and insiders (and traders in contact with these shareholders) are likely to possess private information about upcoming changes in asset values. We

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[36] We gathered this information from 1987 10-Qs and 10-Ks.

thus expect to observe larger quote revisions for stocks with larger proportions of five percent and insider holdings.

Information asymmetries between specialists and traders will be widest for stocks whose values are most frequently altered by announcements of new information. We expect to observe larger quote revisions subsequent to trades for such stocks. We employ the daily standard deviation of returns to proxy for the intensity of information arrival. We expect to observe larger quote revisions for stocks with larger standard deviations of returns. Recall that the standard deviation of returns also proxies for inventory risk. To the extent that inventory and adverse selection costs are correlated, we will be be unable to distinguish between these two phenomena with this proxy.[37]

We run individual regressions for total quote revisions subsequent to trades for volumes exceeding quoted volumes and trades for volumes which do not. Our regression model is:

$$\text{QUOTE REVISION}_i = \beta_0 + \beta_1 * \text{TRADES}_i + \beta_2 * \text{BETA}_i + \beta_3 * \text{SD[RETURN]}_i \qquad (5)$$

$$+ \beta_4 * \text{INSTITUTIONAL}_i + \beta_5 * \text{FIVE PERCENT}_i + \beta_6 * \text{INSIDER}_i + \epsilon_i$$

Table VI lists ordinary least squares results. For all coefficients we list heteroskedastic consistent t-statistics in parentheses. Results confirm the inventory risk hypothesis. The coefficient for the average number of daily transactions is negative and significant, suggesting that

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[37] We also included as regressors the number of Wall Street Journal citations for sample stocks during the January 1 - August 31, 1987 period and a dummy variable for takeover stocks. We intended to proxy for information asymmetries. Neither of these regressors explained variation in our dependent variable.

trading activity reduces inventory risk.[38] Coefficients for stock betas are positive and significant in both regressions, suggesting that inventory risks increase with systematic risk. The coefficients for the standard deviations of returns are positive in both regressions, suggesting that inventory risk increases with stock price variability. Only the coefficient in the regression for trades for volumes exceeding quoted volumes, however, is significant.

The Table VI: Cross Sectional Analysis of Quote Revision Rules

	VOLUME≤QUOTED VOLUME	VOLUME>QUOTED VOLUME
TRADES	-.000257 (8.15)	.000327 (7.89)
BETA	-.0043 (2.24)	-.068 (1.83)
SD[RETURN]	-.0014 (0.23)	-.0059 (2.78)
INSTITUTIONAL	-.0066 (0.20)	-.048 (2.47)
FIVE PERCENT	-.026 (0.01)	-.031 (0.17)
INSIDER	-.17 (0.32)	-3.71 (1.07)
R-Squared	0.51	0.49
Observations	118	118

The dependent variable is the total quote revision as calculated and graphed in Figure V and is expressed as a percent.

The coefficient for the proportion of institutional holdings is negative in both regressions but significant only in the regression for

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[38] We instrumented for TRADES with the number of outstanding shareholders. These two variables are highly correlated and it is safe to assume that the the number of shareholders is exogenous. 2SLS parameter estimates resembled our OLS results closely. Specification tests validated our assumption of the exogeneity of TRADES.

trades in which volumes exceed quoted volumes. This result confirms the hypotheses that quote revisions are lower for stocks with higher levels of liquidity trading. This result also suggests the significance of the proportion of liquidity trading as a determinant of the specialist's willingness to exchange volumes which exceed his quoted volumes. Coefficients for the proportions of five percent and insider holdings are negative and insignificant in both regressions. These regressors apparently provide poor gauges of the magnitudes of information asymmetries. The positive coefficients on the standard deviation of returns suggest that information asymmetries increase in magnitude with stock price variability.

IV. Concluding Remarks

Most notably we find a strong statistical correlation between transaction volumes and specialist quote revisions. The specialist raises and lowers his quotes subsequent to sales and purchases. This result holds across stocks and across trading periods. The sides of the market and volumes of transactions explain substantial portions of revisions in the positions of quoted spread. Other factors also explain quote revisions but to a lesser extent. These factors include changes in the market index, the elapsed time between trades and changes in quoted volumes.

Our results also suggest that the specialist has some ability to distinguish between informed and uninformed. For example, he occasionally agrees to trade volumes which exceed the his quoted volumes. Quote

revisions induced by these trades are proportionally smaller than those induced by transactions for volumes not exceeding quoted volumes. Also, the volumes of lagged transaction volumes induce smaller marginal quote revisions that those of trades immediately preceding quote revisions.

We hope our results focus future theoretical work on market micro structure on the development of models of more realistic trading mechanisms which incorporate of institutional features such as those examined in detail in this study.

Appendix I: Coefficient Bias Due to Trade Misclassification Errors.

The ISSM data series do not distinguish between specialist sales and purchases. Recall, however, that we classify transactions executed at quoted bid and ask prices as specialist purchases and sales. Our classification scheme may not be completely accurate. In this Appendix we examine the bias in coefficients induced by misclassification. For this analysis we employ a simplified model. We assume that only the transaction volumes induce revisions in the midpoint of the specialist's quotes:

$$\frac{1}{2} (q_t^A + q_t^B) - \frac{1}{2} (q_{t-1}^A + q_{t-1}^B) = \lambda\, z_{t-1} + \epsilon \qquad (6).$$

Assume that with probability α, an observation is misclassified -- i.e. the observed volume $(-1) *$ the true volume. The expected value of $\hat{\lambda}$ is:

$$\hat{\lambda} = E[\ (z_{t-1})^{-2}(z_{t-1} * \frac{1}{2} (q_t^A + q_t^B) - \frac{1}{2} (q_{t-1}^A + q_{t-1}^B))\ ]$$

$$= (1-\alpha)\ \lambda + E[\ (z_{t-1})^{-2}(\frac{1}{2} (q_t^A + q_t^B) - \frac{1}{2} (q_{t-1}^A + q_{t-1}^B) * \epsilon)]$$

$$+ \alpha\ (-\lambda) + E[\ (z_{t-1})^{-2}(\frac{1}{2} (q_t^A + q_t^B) - \frac{1}{2} (q_{t-1}^A + q_{t-1}^B) * \epsilon)]$$

$$= \lambda\ (1-2\alpha) \qquad (7)$$

Our coefficient is unbiased if there is no misclassification error. For misclassification error rates of less than fifty percent, our coefficient is biased towards zero. Each additional one percent of misclassification, biases our coefficient downwards by an additional two percent. This result describes the mean value of the coefficient. We simulate misclassification to characterize the entire coefficient distribution. We generate midpoint changes with the following equation:

$$\frac{1}{2} \left(q_t^A + q_t^B \right) - \frac{1}{2} \left(q_{t-1}^A + q_{t-1}^B \right) - \lambda \, z_{t-1} + 21.3 * \epsilon \qquad (8)$$

We employed the actual distribution of volumes for Brunswick Corporation.[39] We assumed that ϵ adhered to normally distributed with mean zero and variance one. Using the simulated data, we employed ordinary least squares to estimated λ. We ran the simulation one thousand times. We graph the empirical distribution of $\hat{\lambda}$ graphed in Figure VI.

Figure VI: Empirical Distribution of $\hat{\lambda}$ Under the

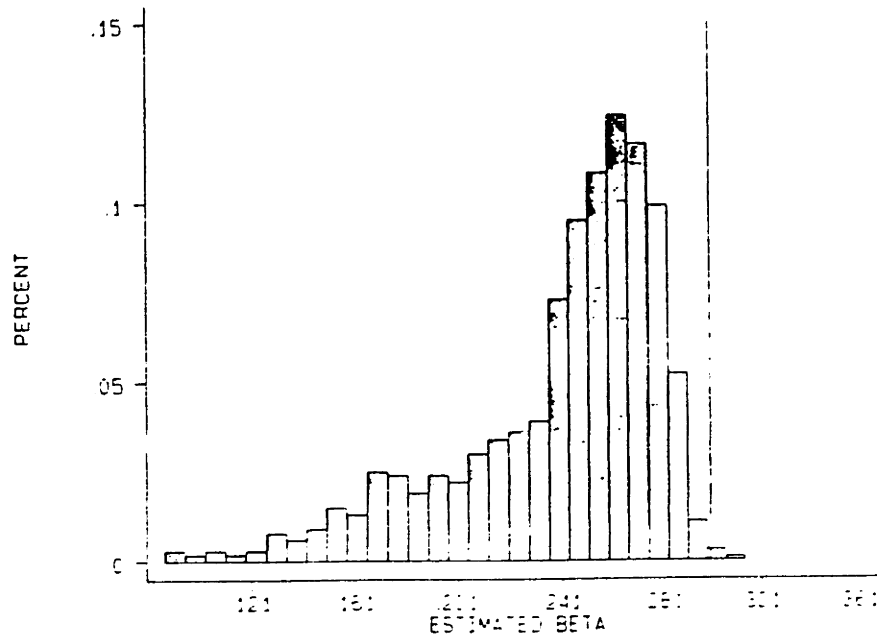Assumption of Zero Misclassification Error
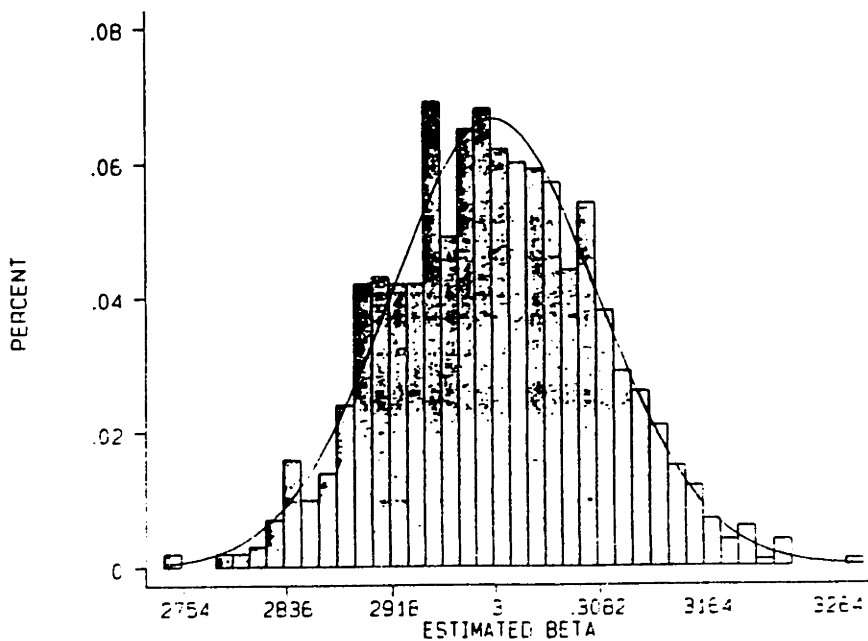
We plot the empirical frequency distribution of $\hat{\lambda}$ based on 1000 simulations of equation (8) under the assumption of zero misclassification error (i.e., $\alpha - 0$). We superimpose a normal density function with the same mean (0.300) and standard deviation (0.008) over the density.

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[39] There are 5062 transactions in the Brunswick data series. We chose the standard deviation of the residual to produce an R-squared of 0.20 roughly the average R-squared in regress for our sample of stocks.

We employed misclassification rates of five, ten, and fifteen percent. Each additional five percent of misclassification reduced the average estimate of λ by an additional ten percent. (The mean values of $\hat{\lambda}$ dropped to 0.271, 0.241, and 0.210). The skewness of the distributions towards zero increased with the degree of misclassification. (The median values of $\hat{\lambda}$ declined from 0.300 to 0.278, 0.253, and 0.222). Figure VII graphs the empirical distribution of $\hat{\lambda}$ for the case where $\alpha = .10$.

Figure VII: Empirical Distribution of $\hat{\lambda}$ Under the

Assumption of Ten Percent Misclassification Error

We plot the empirical frequency distribution of $\hat{\lambda}$ calculated in 1000 simulations of equation (8) under the assumption of ten percent misclassification error (i.e., $\alpha = .10$). The mean and standard deviations of of the empirical distribution are 0.241 and 0.040. The vertical line denotesthe true value of λ of 0.3.

REFERENCES

Admati, Anat and Paul Pfleiderer, "A Theory of Intraday Patterns: Volume and Price Variability." The Review of Financial Studies, 1 (1988), 3-40.

Amihud, Yakov and Haim Mendelson. "Dealership Market." Journal of Financial Economics, 8 (1980), 31-53.

Bagehot, Walter "The Only Game in Town." Financial Analysts Journal, 22 (1971), 12-14.

Constantinides, 1986, George, "Capital Market Equilibrium with Transactions Costs," Journal of Political Economy, 94(4), December, pp. 842-862.

Davis, Mark and A.R. Norman, 1987, "Portfolio Selection with Transactions Costs," Imperial College, September.

Easley, David and Maureen O'Hara, "Price, Trade Size, and Information in Securities Markets." Journal of Financial Economics, 1987, 69-90.

Foster, F. Douglas and S. Viswanathan, "Interday Variations in Volumes, Spreads and Variances: I. Theory." Working Paper, Duke University, (1987).

Glosten, Lawrence R., "Components of the Bid-Ask Spread and the Statistical Properties of Transaction Prices." Journal of Finance, 42 (1987), 1293-1308.

Glosten, Lawrence, "Insider Trading, Liquidity, and the Role of the Specialist." _Journal of Business_, 62 (1989), 211-235.

—————, and Lawrence E. Harris, "Estimating the Components of the Bid-Ask Spread." _Journal of Financial Economics_, 21 (1988), 123-142.

—————, and Paul Milgrom, "Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders." _Journal of Financial Economics_, 14 (1985), 71-100.

Harris, Lawrence, "Estimation of "True" Stock Price Variances and Bid-Ask Spreads form Discrete Observations." Mimeo, (1988).

Hasbrouck, Joel, "Trades, Quotes, Inventories, and Information." _Journal of Financial Economics_, 22 (1988), 229-252.

—————, and Thomas S. Y. Ho, "Order Arrival, Quote Behavior, and the Return-Generating Process." _Journal of Finance_, 42 (1987), 1035-1048.

Ho, Thomas S. Y. and Richard G. Macris, "Dealer Bid-Ask Quotes and Transaction Prices: An Empirical Study of Some AMEX Options." _Journal of Finance_, 39 (1984), 23-45.

—————, and Hans Stoll, "Optimal Dealer Pricing Under Transactions and Return Uncertainty." _Journal of Financial Economics_, 9 (1981), 47-73.

Holthausen, Robert W., Richard W. Leftwich and David Mayers, "The Effect of Large Block Transactions on Security Prices." *Journal of Financial Economics*, 19 (1987), 237-267.

Kyle, Albert S., "Continuous Auctions and Insider Trading," *Econometrica*, 53 (1985), 1315-1335.

Kyle, Albert S. 1984, "Market Structure, Information, Futures Markets, and Price Formation." *International Agricultural Trade: Advanced Readings in Price Formation, Market Structure, and Price Instability*, ed. by Gary G. Storey, Andrew Schmitz, and Alexander H. Sarris. Boulder and London: Westview Press, 45-64.

Roll, Richard, 1984, "A Simple Measure of the Effective Bid-Ask Spread in an Efficient Market." *Journal of Finance*, 39, 1127-1139.

Stoll, Hans, 1989, "Inferring the Components of the Bid-Ask Spread: Theory and Empirical Tests." *Journal of Finance*, 44, 115-134.

Wooldridge, J.M., 1989, "A Computationally Simple Heteroskedasticity and Serial Correlation Robust Standard Error for the Linear Regression Model," *Economic Letters*, 31, 239-43.

Wooldridge, J.M., 1989, "On The Application of Robust, Regression-Based Diagnostics to Models of Conditional Means and Conditional Variances," mimel, MIT, October, 1989.