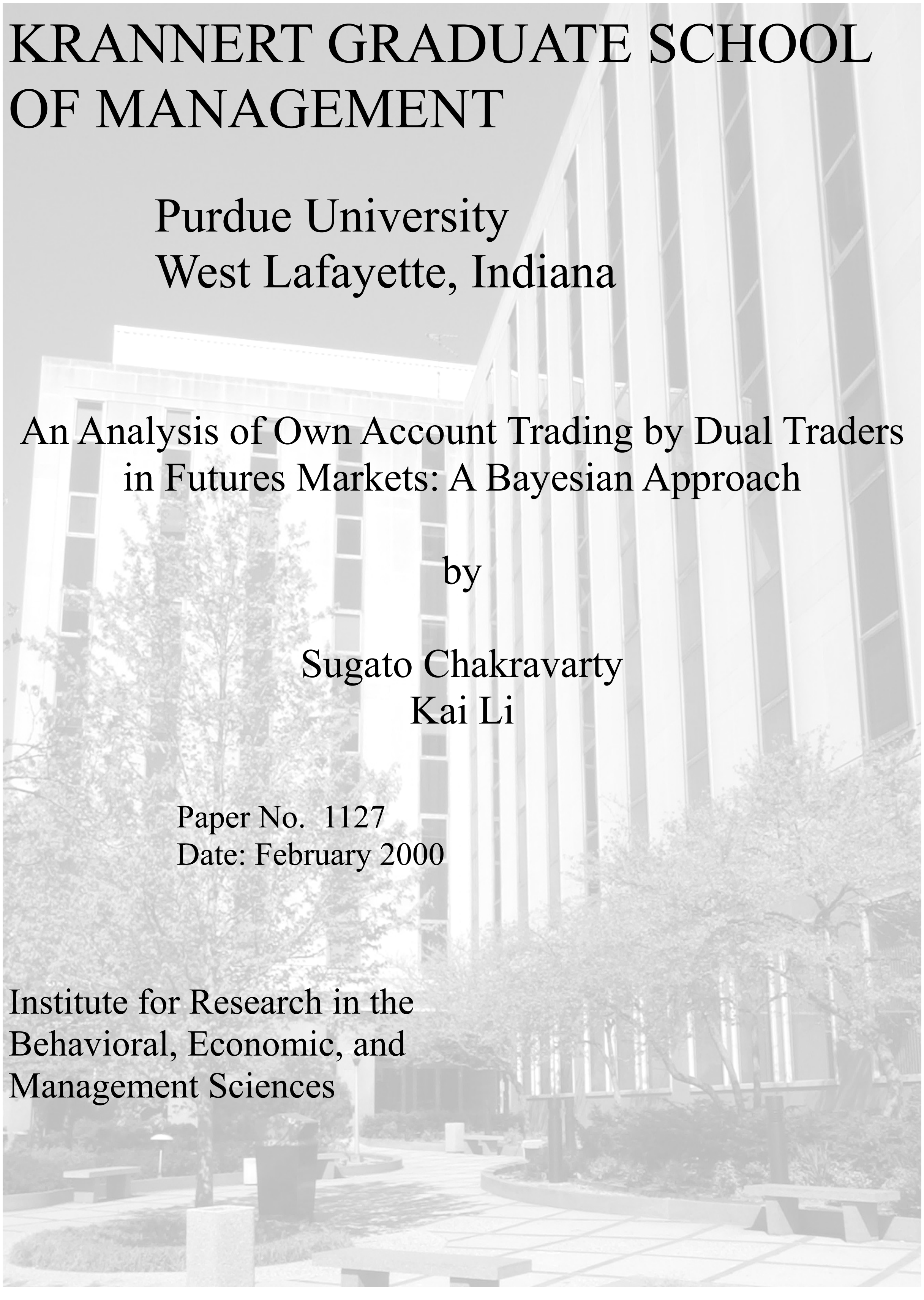

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An Analysis of Own Account Trading by Dual Traders in Futures Markets: A Bayesian Approach

by

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An Analysis of Own Account Trading by Dual Traders in Futures Markets: A Bayesian Approach[1]

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An Analysis of Own Account Trading by Dual Traders in Futures Markets: A Bayesian Approach

Abstract

Using an audit trail transaction data set compiled by the Commodity Futures Trading Commission (CFTC), we seek to ascertain directly the motives behind dual traders' own account trading and whether or not they are informed traders. We estimate our system of equations on *each* of the 101 most active dual traders in the data, using the Markov chain Monte Carlo (MCMC) method. We find that dual traders are informed traders who do not appear to piggyback off their customers' trades; whose own account trading reflects inventory control; and who appear to be liquidity suppliers. We also show that dual traders are heterogeneous in terms of their trading skills and other trade-related characteristics.

Keywords: informed trader, liquidity supplier, inventory control, endogeneity, heterogeneity, Markov chain Monte Carlo, simultaneous equations

JEL Classification: G20, G28, C11, C15, C35

An Analysis of Own Account Trading by Dual Traders in Futures Markets: A Bayesian Approach

1. Introduction

Regulators to Decide Own account Trading by Futures Brokers

U.S. regulators are gearing up to decide soon whether to limit a common trading practice on futures exchanges in Chicago that some critics say raises the potential for brokers to cheat their customers. ...... (If these trading limits are imposed) "We will lose some of our brokers, who say they need to supplement their income by trading for themselves as well as their customers," said Jim Sutter, who manages Cargill Inc.'s oilseeds and grain futures trading on the exchange.

- Excerpt from Bloomberg news wire release, July 22, 1999.

Dual trading is an age-old custom whereby some floor traders are allowed to trade both for themselves and for their customers.[2] As the above news release indicates, the debate over whether or not to ban dual trading on futures exchanges is alive and well. The supporters of the dual trading ban argue that through the unique role of these futures floor traders, they are in a position to have (private) information from observing their customers' trades and can sometimes take advantage of this information by trading on their personal account, either legally or illegally, through front running. In fact, an FBI sting in 1989 found that brokers were cheating customers, leading to dozens of arrests and a government ban, in 1992, on dual trading in major futures contracts. Interestingly, Congress banned the practice of dual trading but then left the door partially open by telling regulators they could decide on when to enforce it.

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[2] Dual trading, however, is not just restricted to the futures markets. In equity markets, for example, the market makers or specialists are also dual traders in that they can execute a customer order by matching a buyer with a seller while taking a residual portion of the order on personal account.

The opponents of the dual trading ban weigh in with the concern that some of the brokers affected by the ban might exit the market due to an inability to supplement their income from brokering by trading for themselves. Their exit could result in illiquid markets and higher trading costs. This view is consistent with Grossman (1989) who argues that allowing both brokering and dealing enables a dual trader to have less idle time and facilitates her switching from the activity in low demand to that in high demand.

Thus, the debate over the dual trading ban is in essence a debate over the relative importance of two competing roles played by a dual trader: as a liquidity supplier and as an informed trader. Which role is more prominent is ultimately an empirical question and is of obvious interest to regulators and academics alike. In this paper, we seek to provide some evidence to the ongoing debate by investigating the following questions at the *individual trader* level. What drives a floor trader's own account trading (versus brokering) decision? Are her own account trades motivated by information, liquidity, skill, inventory control and/or market timing? Are dual traders homogenous in the above mentioned characteristics?

Unfortunately, both the theoretical and empirical literature in dual trading, while providing numerous valuable insights, provides relatively little assistance in answering either of the above questions. Specifically, most of the theoretical literature on dual trading formalizes the intuition of dual traders piggybacking off the information inherent in customer trades, for personal profit (Grossman (1989), Roell (1990), Fishman and Longstaff (1992), Chakravarty (1994), and Sarkar (1995)). The empirical literature on dual trading can be broadly classified into two threads. The first thread focuses on the liquidity effects of various dual trading restrictions imposed on the futures markets, namely (1) the "top step rule" implemented by the Chicago Mercantile Exchange (CME) on the S&P 500 futures contract in June 1987; and (2) the

CME Rule 552 on all high volume futures contracts effective May 1991 (Smith and Whaley (1994), Chang, Locke and Mann (1994), Chang and Locke (1996), and Locke, Sarkar and Wu (1999)). The second thread of the empirical literature examines the microstructure of futures markets under competitive market making (Manaster and Mann (1996), and Ferguson and Mann (1998)).

While the latter group of the dual trading literature is somewhat related to the questions we raise above, there are a number of potential drawbacks with the existing empirical research. First, these studies all perform cross sectional analyses and important trader-specific effects are likely to be lost through aggregation. Second, there is potential simultaneity between a dual trader's choice of own account trading and her information, which is ignored by prior studies. Third and most importantly, our focal question of what, ex ante, drives a dual trader's own account trading (versus brokering) decision, as well as the issue of dual trader homogeneity, have never been directly investigated.

We jointly examine a dual trader's own account trading decision and her information by employing a simultaneous equation model with a binary endogenous variable (the decision of own account trading) and an information proxy. Since the dual trader's private information is unobservable, we use her profit from own account trading as a proxy for the unobservable information. The intuition is that if the floor traders have information through their dual trading activities, then their own account trading would, on average, increase trading profit. Fishman and Longstaff (1992) show that, for the floor traders in their sample, the average profit on dual trading days is significantly higher than that on own account trading days.

We estimate the system of equations using a Bayesian technique known as the Gibbs sampler.[3] Our Bayesian approach allows us to incorporate both parameter uncertainty and model uncertainty in a consistent manner, and, as we argue in the paper, provides us with more accurate parameter estimates than Heckman's (1976, 1979) two-step estimation technique. Finally, the Bayesian approach is easy to implement and, compared to Heckman's two-step estimators, the Bayesian estimates are full likelihood-based with nice finite sample properties.

The data used in the analysis are audit trail transaction records compiled by the Commodity Futures Trading Commission (CFTC). The data provide detailed information about trade time, price, quantity, trade direction (buyer or seller), the contract and the trader's identification and have been used within the CFTC for regulation and/or enforcement purposes.

The contribution of our paper is two-fold. First, we depart from the existing microstructure literature in that we directly investigate the determinants of a specific dual trader's decision to trade on her own account and her information in a simultaneous equation framework. By including variables that capture a dual trader's information gleaned from her customer trades, trading momentum, inventory, skills, and market timing, we are able to disentangle all these effects in a robust manner. Such a micro-level analysis of dual traders' behavior is absent in the literature, which has traditionally focused on the cross-section of dual traders and their aggregated impact on liquidity.

Second, we estimate our model on *each* of the 101 most active dual traders in the data, using the Bayesian approach. Specifically, our estimation technique allows us to adopt two alternative modeling approaches in examining dual traders' behavior: a single equation model

[3] Related references on the Bayesian estimation techniques in general and the Gibbs sampler (a special case of the Markov chain Monte Carlo method) in particular include Gelfand and Smith (1990), Casella and George (1992), and Chib and Greenberg (1996). Two recent microstructure papers adopting the Bayesian approach are Hasbrouck (1999) and Ball and Chordia (1999).

(the naïve model without considering the simultaneity of a dual trader's own account trading decision and her information) and a simultaneous equation model that accounts for the potential endogeneity. Our final Bayesian estimates are obtained as pooled estimates from the two contending models, where the pooling weights are determined endogenously from the data.

We find, first, that a dual trader's own account trading is inversely related to her customer trading (i.e., brokering) volume in the previous 5-minute time bracket. Second, a dual trader's own account trading is directly determined by her current inventory position. That is, a dual trader is more likely to trade if her inventory is away from the sleeping position (i.e., the zero contract holding). Third, we confirm the general belief that dual traders are informed traders in that their decision to trade on own account, on average, increases their personal trading profit.

Our first result on the existence of a substitution effect between a dual trader's own account trading and brokering implies that dual traders are not piggybacking off information from their customers' trades for personal profit. This result does not appear to support the idea modeled in the theoretical research on dual trading referred to earlier. Our second result on inventory control by dual traders supports the conclusion of Manaster and Mann (1996) and the key assumption made in inventory models of market microstructure. Finally, our result that dual traders are informed traders confirms street lore and the findings in Fishman and Longstaff (1992).

Estimation results on the remaining explanatory variables are mixed, showing different signs and statistical significance across the 101 dual traders examined. Overall, we find that dual traders' own account trading is mostly liquidity enhancing, positively related to their past own account trading, and are influenced, in varying degrees, by volatility, skill and trade timing variables. We present plots of the posterior distributions of the regression parameters across the representative dual trader in each of the futures contracts examined. These graphs show that the posterior distributions of the parameters are well dispersed across the traders without significant overlaps and provide some evidence of dual trader heterogeneity.

We also perform both parametric and nonparametric tests of equality of the parameter means and medians, respectively, across the representative dual trader in each futures contract. We are able to reject the null hypothesis of equality of the means (and medians) at the 1% level. We interpret these results as strong evidence of heterogeneity across dual traders. In contrast, the theoretical literature in market microstructure almost always invokes the assumption that informed traders are homogeneous (see O'Hara (1995) for a comprehensive survey). Understandably, this assumption results in tractable models. Our results, however, suggest the need to introduce heterogeneous informed traders into theoretical modeling.

In sum, the profile of a typical dual trader is that of an informed trader who does not appear to piggyback off her clients' information, and whose own account trading reflects her inventory position and her role as a liquidity supplier. There is also considerable heterogeneity across dual traders in their trading skills, market timing ability, and other trade-related characteristics.

Our results on the strong positive correlation between dual traders' own account trading and profits suggest that any drastic restrictions on dual traders' own account trading might adversely affect their revenue stream and hasten their exit, resulting in illiquid markets and higher trading costs. A potential policy recommendation, therefore, is against imposition of any drastic restrictions on own account trading by dual traders in futures markets.

The plan for the rest of the paper is as follows. Section 2 discusses the data and provides an overview of the sample of traders included in our analysis. Section 3 develops the two alternative modeling approaches in examining a dual trader's trading behavior and provides relevant details of the Bayesian approach. Section 4 introduces the set of explanatory variables. Section 5 reports our findings. Section 6 discusses robustness issues related to our results. Section 7 concludes.

2. Data Overview

Our data consist of audit trail transaction records of eight futures contracts traded at the CME during the first six months of 1992. These contracts are, respectively, live cattle, hogs, pork bellies, feeder cattle, lumber, Canadian Dollar, T-bill and S&P 400. Overall, there are over two million records that provide a detailed look at the complete trading history of all floor traders in eight different futures pits. We supplement the above data with the daily settlement price data for each of the contracts over the sample period in order to calculate the traders' personal trading profits.

The reason for focusing our attention on these eight futures contracts is that, since May 1991, the CME Rule 552 explicitly prohibits dual trading activities on the most active contracts on the exchange. According to Chang, Locke and Mann (1994), all the major currency contracts are affected by the rule. Given that our goal is to examine a dual trader's decision to trade on her own account, we only examine contracts that allow unrestricted dual trading.

Table 1 reports summary statistics on the dual traders selected for final analysis in each of the eight futures contracts. Specifically, our definitions of a dual trading day, dual traders, locals[4] and brokers follow Locke, Sarkar and Wu (1999). We calculate a trading ratio ***d*** as the proportion of a floor trader's own account trading volume over her total trading volume for the day she is active. For each floor trader, a trading day is a local day if $d > 0.98$, a broker day if $d < 0.02$, and a dual trading day if d lies on the closed interval [0.02, 0.98]. As Chang, Locke and Mann (1994) argue, when a broker makes a mistake in executing a customer order, the trade is placed into an error account as a trade for the corresponding broker's personal account. Thus, the 2% filter is used to allow for the possibility of error trading and appears reasonable from communications with the CFTC.

A floor trader with at least one dual trading day in the sample is defined as a dual trader. A floor trader with only local (broker) days in the sample is defined as a local (pure broker). The criterion for a specific floor trader to be included in our sample as an active dual trader is that the number of her dual trading days exceeds 50 (out of a maximum of 126 trading days during the first six months of 1992).

From table 1, we see that the live cattle contract has the largest number of active dual traders, while the S&P 400 contract has only one active dual trader included in our final analysis. Overall, active dual traders in each contract almost always carry out own account trading and trade both for customers and for their personal account on every single trading day. When less active on own account trading, these floor traders engage in pure brokerage activities, that is, trade exclusively for their customers on the remaining trading days.

The audit trail data record each transaction twice, once for each party to a trade. An

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[4] Locals are floor traders trading for their own accounts. It is well accepted in the literature that locals are important suppliers of liquidity in the futures markets. Locals trade frequently during the trading day by responding to short-run price movements. They hold minimal inventory levels, and trade in small amounts (see Working (1967), Silber (1984) and Smidt (1985)).

exchange algorithm called the computerized trade reconstruction (CTR) uses each trader's independently reported sequence of trades, in conjunction with the time and sales data, to time each trade within a minute. Since some timing errors are likely, we perform our analysis in 5-minute time intervals (defined as a time bracket).

In addition to trade time, the audit trail records provide price, quantity, specifics of the contract, and the trader's identification.[5] Unique to this data, each record also specifies the trade direction and a classification of the customer types for each side of a trade. There are four customer type indicators (CTI), labeled 1 through 4. The CTI 1 trades are market making trades for personal accounts (39% of the volume); CTI 2 trades are trades executed for the account of the trader's clearing member (6.2% of the volume); CTI 3 trades are trades executed for the account of any other exchange member (5.7% of the volume); and CTI 4 trades are the trades of outside customers (49.1% of the volume). These numbers are consistent with the statistics reported in Manaster and Mann (1996). Following Fishman and Longstaff (1992), Chang, Locke and Mann (1994), and Locke, Sarkar and Wu (1999), we drop both CTI 2 trades and CTI 3 trades from our analysis, since it is difficult to know the exact nature of those trades from the data available. Only CTI 1 trades (market-makers' trades for their personal accounts) and CTI 4 trades (trades for outside customers) are used in examining dual trading activities. Given that CTI 1 and CTI 4 trades comprise almost 90% of all transactions, we argue that there is no significant loss in information by deleting CTI 2 and CTI 3 trades.

[5] To protect trader privacy, however, the CFTC maps each trader's exchange badge number to a randomly selected number unique to the trader.

3. Empirical Design and Estimation Details

3.1 *Two Models*

The decision of a dual trader to trade on her own account and the effect of information on her trading decision can be analyzed within the context of a standard regression framework. A naïve (our benchmark) approach is to examine a dual trader's own account trading (versus her brokerage trading) decision and the impact of this decision on personal trading profit (the proxy for unobserved information) in two single equations. But, if dual traders do not choose own account trading randomly, but, rather, choose to do so on the basis of information, inventory position, and contract-specific characteristics, this non-randomness in the trading decision of dual traders would introduce a potential self-selection bias in our single equation framework. To eliminate the self-selection bias, we also model a dual trader's own account trading decision and her personal trading profit in a simultaneous equation system.

Consider $I_{i,t}^*$ to be the unobservable latent variable representing the added utility of dual trader *i* when she chooses own account trading over trading on behalf of her customers at time *t*. Let $I_{i,t}^* = E(I_{i,t}^*) + e_{1,it}$. Here we assume that $I_{i,t}^*$ is normally distributed with mean $E(I_{i,t}^*)$ representing the market's expectations of dual trader *i*'s utility increase through own account trading. The variable $e_{1,it}$ represents dual trader *i*'s unmeasured skills or information associated with her utility increase. For tractability, we assume a linear structure of the market's expectations. This implies that $E(I_{i,t}^*) = X_{1,it}\beta_{1,i}$, where $X_{1,it}$ is an $n \times k_1$ matrix of observable dual trader *i* characteristics and $\beta_{1,i}$ is a vector of k_1 parameters. Thus, we characterize dual trader *i*'s decision on own account trading over a 5-minute bracket *t* in a dual trading day as

$$I_{i,t}^* = X_{1,it}\beta_{1,i} + e_{1,it} \tag{1}$$

where, $I_{i,t}=1$, if $I_{i,t}^* > 0$. That is, dual trader i chooses to execute some own account trades (CTI 1 trades) during time interval t; and $I_{i,t} = 0$, if $I_{i,t}^* \leq 0$. That is, dual trader i chooses to execute trades on behalf of her customer (CTI 4 trades) during time interval t.

In our second equation, we examine the effect of dual trader i's own account trading decision on her personal trading profit,

$$\Pi_{i,t} = I_{i,t}\gamma_i + X_{2,it}\beta_{2,i} + e_{2,it}, \tag{2}$$

where $I_{i,t}$ is the binary choice variable on own account trading by dual trader i over time interval t, $X_{2,it}$ is an $n \times k_2$ matrix of observable dual trader i characteristics and $\beta_{2,i}$ is a vector of k_2 parameters. $\Pi_{i,t}$ is the trading profit for dual trader i, up to and including time bracket t, computed as in Fishman and Longstaff (1992). Specifically, the trading profit of dual trader i in time bracket t on day d is obtained as

$$\pi_{it,d} = \text{Buy Volume}_{it,d} \times (\text{Settlement Price}_d - \text{Purchase Price}_{it,d})$$
$$+ \text{Sell Volume}_{it,d} \times (\text{Sale Price}_{it,d} - \text{Settlement Price}_d)\,. \tag{3}$$

For the trading profit up to and including time bracket t, $\Pi_{i,t}$, we simply cumulate $\pi_{it,d}$ from the beginning of a trading day d up to and including time bracket t.

In sum, equation (1) models the own account trading decision of a dual trader as a function of relevant exogenous variables discussed in Section 4. Equation (2) models her information as a function of the own account trading choice variable ($I_{i,t}$) and relevant exogenous variables (also discussed in Section 4). The main purpose of equation (2) is to show whether dual traders are informed traders, through the sign and statistical significance of the coefficient associated with the binary choice variable $I_{i,t}$. Since the dual trader's private information is unobservable, we use her personal trading profit from own account trading, in equation (2), as a proxy for the unobserved information. This assumption is supported by Fishman and Longstaff (1992).

Our empirical setup implicitly assumes that dual traders are myopic. At first blush, this may seem contradictory to Kyle (1985), where the *single* informed trader is assumed to have long-lived private information. But in a significant extension of the basic Kyle framework, Holden and Subrahmanyam (1992) argue that Kyle's assumption of a single informed trader is strong and show that, in a world of *multiple* informed traders, there is aggressive competition which causes most of the informed traders' common private information to be revealed immediately. In addition, Manaster and Mann (1996) find evidence to suggest that if futures traders start the day with a zero inventory position, they generally end the day with a zero holding as well. Thus, both papers argue for informed traders with short-lived private information, as we have assumed in our empirical modeling.

Under the single equation approach, in which we assume no simultaneity, the error terms in equations (1) and (2) follow an independent and identical univariate normal distribution. Under the simultaneous equation approach, the error terms in equations (1) and (2) are postulated to have the following distributional characteristic. Specifically, $\begin{pmatrix} e_{1,it} \\ e_{2,it} \end{pmatrix}$ follows an independent and identical $\mathrm{BVN}(0,\Sigma)$, where BVN denotes a bivariate normal distribution and the variance-covariance matrix $\Sigma = \begin{pmatrix} 1 & \sigma_{e_1e_2} \\ \sigma_{e_2e_1} & \sigma_{e_2e_2} \end{pmatrix}$. Note that in Σ, $\mathrm{Var}(e_{1,it}) = 1$ because $I_{i,t}$ is only observed as a binary variable.

A priori, the single equation model and the simultaneous equation model are both of interest. Statistically, the difference between the two approaches is that the former model sets

σ_{e1e2} equal to zero while the latter leaves the covariance term σ_{e1e2} unconstrained. Economically, the key issue is whether dual trader i possesses unobserved information that is systematically related to her trading profit, after controlling for observables such as inventory effects, liquidity, trading skills, etc. In other words, the question is whether or not dual trader i's own account trading decision is exogenous to her personal trading profit (the information proxy).

To test for $H_0 : \sigma_{e1e2} = 0$ versus $H_1 : \sigma_{e1e2} \neq 0$, we compute the Bayes factor (BF_{01}) between the two models. The Bayes factor is the Bayesian version of the likelihood ratio test, which is obtained as the ratio of data densities under the model with zero covariance (H_0) and under the model with nonzero covariance (H_1), respectively (see Kass and Raftery (1995) for a survey). Noting that H_1 nests H_0, we employ the Savage-Dickey density ratio of Verdinelli and Wasserman (1995) to simplify the computation of the Bayes factor given by

$$BF_{01} = \frac{f(\sigma_{e1e2} = 0 \mid y)}{f(\sigma_{e1e2} = 0)}, \tag{4}$$

where $f(\sigma_{e1e2} \mid y) = \int\int f(\delta, \sigma_{e1e2}, \sigma_{e2e2} \mid y) d\sigma_{e2e2} d\delta$, $f(\sigma_{e1e2}) = \int\int f(\delta, \sigma_{e1e2}, \sigma_{e2e2}) d\sigma_{e2e2} d\delta$, $\delta = (\beta_1', \gamma, \beta_2')'$, the symbol "′" denotes a transpose and y represents the data.

According to Kass and Raftery (1995), there exists decisive evidence from the sample data against H_1 when BF_{01} exceeds 100. In practice, unless the data evidence overwhelmingly supports one particular formulation, for inference purposes, we can average out model uncertainty by pooling posterior densities under H_0 and H_1, respectively, according to Poirier (1995, pp. 604-605). More specifically, from the definition of the Bayes factor BF_{01}, the posterior probability that the single equation model holds true equals $\frac{BF_{01}}{1+BF_{01}}$, and the posterior probability that the simultaneous equation model holds true equals $\frac{1}{1+BF_{01}}$. Then the pooled posterior point estimate of any parameter is obtained as the weighted average of the corresponding posterior point estimates under the single equation model and the simultaneous equation model, using the two weights above.

3.2 *Estimation Details Using the Markov Chain Monte Carlo (MCMC) Method*

Under our simultaneous equation framework, there is a nontrivial covariance structure ($H_1 : \sigma_{e1e2} \neq 0$) between the error terms in equations (1) and (2). Due to the non-linearity in the likelihood function (caused by the binary own account trading choice variable I and the covariance σ_{e1e2}), full information maximum likelihood estimation is generally avoided in favor of the less efficient but computationally simpler estimation procedures such as the two-step algorithm developed by Heckman (1976, 1979). We discuss the Heckman approach in Section 3.3. In the current paper, we follow the method developed in Li (1998) to conduct a finite sample likelihood-based analysis of our empirical model in equations (1) and (2), using a combination of Gibbs sampling and data augmentation.[6]

Note that in a standard 2 x 2 variance-covariance matrix Σ, with four elements, there are three unique elements that need to be estimated, as the two off-diagonal elements are identical. In our case, since equation (1) is a probit, unity is imposed on the first diagonal element, for identification, leaving only two free parameters $\sigma_{e1e2}, \sigma_{e2e2}$ (the off-diagonal element and the second diagonal element) to be estimated. This creates complications in the estimation

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[6] Gibbs sampling is a simulation tool for obtaining marginal distributions from a non-normalized joint density (Casella and George (1992), Gelfand and Smith (1990)). Data augmentation is a scheme to augment the observed data in order to simplify the likelihood/posterior (Tanner and Wong (1987)). Both techniques are special cases of the Markov chain Monte Carlo approach (see Chib and Greenberg (1996) for a survey).

procedure and requires us to reparameterize Σ and to estimate the two free parameters separately.[7]

Decomposing the joint bivariate normal distribution for $\begin{pmatrix} e_{1,it} \\ e_{2,it} \end{pmatrix}$ in equations (1) and (2) into the product of the marginal distribution for $e_{1,it}$ and the conditional distribution $e_{2,it} \,|e_{1,it}$, we obtain

$$I^*_{i,t} = X_{1,it}\beta_{1,i} + e_{1,it}, \tag{5}$$

$$\Pi_{i,t} = I_{i,t}\gamma_i + X_{2,it}\beta_{2,i} + e_{1,it}\sigma_{e1e2} + v_{i,t}, \tag{6}$$

where $e_{1,it} = I^*_{i,t} - X_{1,it}\beta_{1,i}$, $\sigma^2 = \sigma_{e2e2} - \sigma^2_{e1e2}$, and $v_{i,t} \sim N(0,\sigma^2)$, $e_{1,it} \sim N(0,1)$ are independent. Conditional on the data and the regression parameter $\delta = (\beta_1', \gamma, \beta_2')'$ ($e_{1,it}, e_{2,it}$ are given), drawing σ_{e1e2}, σ^2 is like drawing from the posterior distribution of the univariate regression of $e_{2,it}$ on $e_{1,it}$,

$$e_{2,it} = e_{1,it}\sigma_{e1e2} + v_{i,t}, \qquad v_{i,t} \sim N(0,\sigma^2). \tag{7}$$

From here on, we focus on the reparameterized variance-covariance matrix $\Sigma = \begin{pmatrix} 1 & \sigma_{e1e2} \\ \sigma_{e2e1} & \sigma^2_{e1e2} + \sigma^2 \end{pmatrix}$.

We assume the following prior distribution

[7] The complication arises because when we have three free parameters to estimate in a 2x2 variance-covariance matrix Σ, from Zellner (1971, pp. 224-227) we know that, conditional on the data and the regression parameter vector, δ, the inverse of the variance-covariance matrix Σ^{-1} (with its three free parameters), follows a Wishart distribution; while conditional on the data and Σ, δ follows a multivariate normal distribution. But in our current setting, due to the probit equation (1), the variance of the error term in equation (1) is fixed at 1, which reduces the number of free parameters from three to two and precludes us from using the standard results discussed above.

$$f(\delta,\sigma_{e1e2},\sigma^{-2}) \propto f(\delta)\cdot f(\sigma_{e1e2})\cdot f(\sigma^{-2}), \tag{8}$$

where

$$f(\delta) \sim MVN(\delta_0, \Psi_0^{-1}),$$
$$f(\sigma_{e1e2}) \sim N(r_0, b_0^{-1}),$$
$$f(\sigma^{-2}) \sim G(\frac{v_0}{2}, (\frac{c_0}{2})^{-1}),$$

and MVN denotes a multivariate normal distribution, N denotes a univariate normal distribution, and G denotes a Gamma distribution (Poirier, 1995, p. 98).

Throughout the paper, we choose the following prior to report our final estimation results,

$$\delta_0 = 0_p, \Psi_0^{-1} = 10^8 \cdot I_p, r_0 = 0, b_0 = 2, v_0 = 4, c_0 = 1,$$

where p (= $k_1 + 1 + k_2$) is the dimension of the regression parameter δ, I_p denotes an identity matrix of rank p. The set of priors chosen has a fairly flat distribution on δ centered at a vector of zeros, and the prior mean for the variance-covariance matrix, Σ, is an identity matrix.

The Bayesian estimation approach is implemented as follows. First, we augment the observed data I with the unobservable (i.e., the incremental utility of dual trader i associated with her own account trading decision). This implies generating the latent incremental utility variable I^*, based on our observation of dual trader i's own account trading decision I. When the augmented data are generated consistently within the structure of the model, the distribution of the augmented data converges asymptotically to the distribution of the observed data. We then use the likelihood of both the observed data and the augmented data as a proxy for the likelihood of the observed data. Conditional on the observed and augmented data, approximate posteriors for the model parameters may be obtained using standard simulation methods. Next, we integrate out, using the Gibbs sampler (see, for example, Gelfand and Smith

(1990), and Hasbrouck (1999)), the uncertainty introduced by the involvement of unobserved data to get posteriors conditional only on the observed data (the actual choice of own account trading made by dual trader i). We then iterate between the data augmentation and the Gibbs sampler steps, and, our Bayesian estimates are obtained as sample averages of these Gibbs draws. The operations discussed above are collectively referred to as the Markov chain Monte Carlo (MCMC) method.

3.3 *The Heckman Two-Step Estimation Method*

Our simultaneous equation framework in equations (1) and (2) is a classic in the econometrics literature on limited dependent variables (Maddala (1983)). A slightly different model specification that does not include the endogenous dummy variable in the second equation has been extensively applied in conditional event studies in finance (see Prabhala (1997) for a survey)). Prabhala argues that when the endogenous event dummy variable is not included in the announcement effect equation (i.e., a different version of our equation (2)), consistent estimation may be achieved through a simple two-step procedure (Heckman (1976, 1979)). Below, we show why this approach is inappropriate in estimating our model, given by equations (1) and (2).

Following the bivariate normal assumption, the conditional mean of the error term $e_{2,it}$ can be shown as (see Heckman (1976))

$$\mathrm{E}(e_{2,it} \mid I_{i,t}=1, X_{2,it}) = \mathrm{E}(e_{2,it} \mid e_{1,it} > -X_{1,it}\beta_{1,i}, X_{2,it}) = \sigma_{e_1e_2}\frac{\phi(X_{1,it}\beta_{1,i})}{\Phi(X_{1,it}\beta_{1,i})}, \tag{9}$$

$$\mathrm{E}(e_{2,it} \mid I_{i,t}=0, X_{2,it}) = \mathrm{E}(e_{2,it} \mid e_{1,it} \le -X_{1,it}\beta_{1,i}, X_{2,it}) = -\sigma_{e_1e_2}\frac{\phi(X_{1,it}\beta_{1,i})}{1-\Phi(X_{1,it}\beta_{1,i})}, \tag{10}$$

where $\phi(X_{1,it}\beta_{1,i})$ and $\Phi(X_{1,it}\beta_{1,i})$ are, respectively, the standard normal density function and standard normal cumulative distribution function evaluated at $X_{1,it}\beta_{1,i}$. Based on the above observation, Heckman (1976, 1979) develops the so-called two-step estimation method. In the first step, the probit model in equation (1) is estimated by the maximum likelihood method. This step provides a consistent estimate $\hat{\beta}_{1,i}$ of $\beta_{1,i}$. $\hat{\beta}_{1,i}$ is then used to obtain estimates of $\frac{\phi(X_{1,it}\hat{\beta}_{1,i})}{\Phi(X_{1,it}\hat{\beta}_{1,i})}$ and $\frac{\phi(X_{1,it}\hat{\beta}_{1,i})}{1-\Phi(X_{1,it}\hat{\beta}_{1,i})}$. These estimates are used to rewrite equation (2) as

$$\Pi_{i,t} = I_{i,t}\gamma_i + X_{2,it}\beta_{2,i} + \sigma_{e_1e_2} I_{i,t}\frac{\phi(X_{1,it}\hat{\beta}_{1,i})}{\Phi(X_{1,it}\hat{\beta}_{1,i})} - \sigma_{e_1e_2}(1-I_{i,t})\frac{\phi(X_{1,it}\hat{\beta}_{1,i})}{1-\Phi(X_{1,it}\hat{\beta}_{1,i})} + u_{i,t}\,. \tag{11}$$

This second step regression, which can be estimated by OLS or WLS, provides estimates of $\beta_{2,i}$ and $\sigma_{e_1e_2}$.

In most cases of simultaneous equation models with limited dependent variables, the Heckman two-step approach provides a convenient way of obtaining consistent point estimates, but it is inappropriate in our particular model formulation. Specifically, our simultaneous equation model of equations (1) and (2) is different because the second equation in the system also contains the endogenous dummy variable $I_{i,t}$. Note that in equation (11), the dummy variable $I_{i,t}$ is a function of $X_{1,it}\hat{\beta}_{1,i}$ as well as the two added regressors $\frac{\phi(X_{1,it}\hat{\beta}_{1,i})}{\Phi(X_{1,it}\hat{\beta}_{1,i})}$ and $\frac{\phi(X_{1,it}\hat{\beta}_{1,i})}{1-\Phi(X_{1,it}\hat{\beta}_{1,i})}$, which causes multicollinearity among regressors. Given that the data are not able to distinguish between the dummy variable and the added regressors, the estimates of γ_i and $\sigma_{e_1e_2}$ would have large standard errors which, in turn, would make them unreliable.

In contrast, under the MCMC estimation approach, we do not need to introduce any additional regressors in equation (2), and our estimate of the covariance term $\sigma_{e_1e_2}$ is obtained as part of the variance-covariance matrix. By construction, the Bayesian approach does not suffer from multicollinearity.

4. The Dependent and Explanatory Variables

The dependent variable to capture a dual trader's own account trading decision in equation (1) is **TRADE DUMMY,** I, where I equals 1 if the dual trader trades on own account in time bracket t, and 0 otherwise. The dependent variable to capture a dual trader's own account trading profit in equation (2) (the information proxy) is **PROFIT,** Π, computed as her cumulative own account trading profit from the beginning of a trading day up to time bracket t within a day.

Our choice of a parsimonious set of exogenous variables, determining the trading decision of dual traders and their personal trading profit (the unobserved information proxy), is driven by the existing literature. The set of explanatory variables can be broadly classified into variables capturing market liquidity, information, trading momentum, contract risk, inventory effects, trading skills and timing of trades.

Walsh and Dinehart (1991), Smith and Whaley (1994), and Chang and Locke (1996) use the number of active liquidity suppliers, defined as the sum of the dual traders and other own account traders (locals), as one determinant of market liquidity. Their rationale for doing so is that the number of active liquidity suppliers provides actual competition not only through their trading but also because their presence in the pit (indicated by doing at least one trade during the session) provides additional potential competition among buyers and sellers. We use the number of pure locals (sole own account traders) over the prior 5-minute bracket, **lagNLOCAL**, as a proxy for market liquidity. If dual traders are liquidity suppliers, we would expect this variable to be positive and significantly correlated with dual trader *i*'s decision to trade on her own account.

We use dual trader *i*'s customer trading (i.e., brokering) volume as a fraction of her total trading volume in the 5-minute bracket prior to the current time bracket *t*, **lagFRACTI4,** as a proxy for her informational advantage. Fishman and Longstaff (1992), and Walsh and Dinehart (1991) conclude that dual traders possess superior information due to their brokerage trades. And Ito, Lyons and Melvin (1998) and Locke and Mann (1999) further note that the information sources associated with floor trader profitability are undoubtedly order-flow related, and, thus, of short duration. We expect that the more dual trader *i* trades for her customers in the previous time bracket, the more information she has about the market, and the more likely it is that she will trade on her own account in the current period. Such a scenario would be consistent with dual traders piggybacking off (the information in) their customers' trades and would imply a positive (and statistically significant) coefficient for lagFRACTI4.

We also hypothesize that there could be a momentum effect driving dual trader *i*'s own account trading. *Ceteris paribus*, she is more likely to trade in the current period if she has traded on her own account in the prior period. And the momentum effect could be different depending on the size of her previous CTI 1 trades. Accordingly, the variable, **lagVOLCTI1,** dual trader *i*'s own account trading volume in the prior 5-minute time bracket, is included in equation (1) as an explanatory variable. We expect that dual trader *i* is more likely to trade in the current period if she has traded on her own account the period before. Thus, we would expect a positive sign on the coefficient of lagVOLCTI1.

Both Walsh and Dinehart (1991) and Manaster and Mann (1996) postulate a relationship between the number of traders trading on own account and price volatility. We would like to know whether dual trader *i* is more likely to trade on own account in a volatile market environment. Accordingly, we construct our volatility measure following Manaster and Mann (1996). For each 5-minute bracket, we compute a quantity-weighted standard deviation for buy trade prices and another for sell trade prices. The price volatility, **lagVOLATILITY,** in the previous 5-minute time bracket is obtained as the maximum of the buy-price and sell-price standard deviations. The advantage of this measure is that it avoids the bid-ask bounce by exclusively using prices from one side of the transaction.

Following Fishman and Longstaff (1992) and Manaster and Mann (1996), we assume that all traders begin the trading day with a zero inventory position. Since we are interested in examining whether dual trader *i*'s own account trading decision is affected by her inventory position prior to the current 5-minute bracket *t*, we use an absolute inventory measure, **lagINVENTORY,** for our analysis.[8] Thus, for dual trader *i*, **lagINVENTORY,** is computed as her CTI 1 buy trades minus CTI 1 sell trades, cumulated from the beginning of a trading day to time bracket *t-1*, assuming that dual trader *i* only has full control of her CTI 1 trades. According to the inventory control literature (see O'Hara (1995)), *ceteris paribus*, dual trader *i* is more likely to trade if her (absolute) inventory position is away from zero (the sleeping position). We would, therefore, expect a positive sign on the coefficient of lagINVENTORY.

Leuthold, Garcia, and Lu (1994) find that large traders in pork bellies futures contracts

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[8] Manaster and Mann (1996) employ the measure of relative inventory to explain traders' execution skills. Relative inventory is the difference between a trader's actual inventory and the average inventory of all traders in a pit. It is unclear how the direction of causality runs.

generate significant profits and conclude that they possess significant forecasting ability. Their results suggest that certain large traders can accumulate experience and knowledge of the market, which permit them to generate consistent forecasts and accumulate considerable wealth. Manaster and Mann (1996) include a skill variable to capture the locals' abilities to transact at desirable prices. Following Manaster and Mann, we compute dual trader *i's* **SKILL** as the difference between her volume-weighted mean buy price (sell price), and the volume-weighted mean buy price (sell price) for *all* other floor traders, during each 5-minute bracket. Thus, for all dual trader *i's* purchases within a time bracket *t*, SKILL is positive (negative) when she purchases (both CTI 1 and CTI 4 trades) at a price lower (higher) than the average purchase price for all trades in that time bracket. Likewise, for all dual trader *i's* sales, SKILL is positive (negative) when she sells (both CTI 1 and CTI 4 trades) at a price higher (lower) than the average sale price for all trades in that time bracket. When dual trader *i* has both buy and sell transactions in time bracket *t*, our skill variable is a volume-weighted measure of the buy-price skill and the sell-price skill. For a given dual trader *i* in time bracket *t*, we use the lagged variable, **lagSKILL,** as a proxy to capture her trading skill up to time bracket *t-1*. If dual trader *i* does not trade at all during any 5-minute bracket, we use the most recently computed SKILL value instead.

Walsh and Dinehart (1991) suggest that the number of own account traders is greater in the first two hours and the final half-hour of each day, because these periods offer more profit opportunities. Consistent with this intuition, Ferguson and Mann (1998) find a U-shaped bid-ask spread over the trading day. Hence, we introduce a trade timing dummy, **HOT,** which equals 1 if the 5-minute bracket in which dual trader *i* trades on her own account (CTI 1 trades only) belongs to the first two hours or the final half-hour of a trading day, and 0 otherwise.

In summary, the variables explaining a dual trader's own account trading decision, TRADE DUMMY, in equation (1), are lagNLOCAL, lagFRACTI4, lagVOLCTI1, lagVOLATILITY, lagINVENTORY, lagSKILL, and HOT. The corresponding variables explaining the dual trader's own account trading profit, PROFIT, in equation (2), are TRADE DUMMY, VOLATILITY, SKILL, and HOT. By construction, PROFIT has a high serial correlation. We, therefore, include a lagged profit variable, **lagPROFIT**, in the right hand side of equation (2), to ameliorate the problem.

Equations (1) and (2) are first estimated as two independent equations (the naïve model) and then simultaneously, recognizing the possible correlation in the error terms. The model comparison results (as captured by the Bayes factor, BF_{01}, in table 4.3) indicate that neither model formulation is predominantly favored by the data. To take into account model uncertainty, the final estimates are obtained by pooling the estimates from the two models, with the pooling weights obtained endogenously within the estimation process (see Section 3.1). We repeat this exercise for each of the 101 active dual traders in our sample.

5. Results

5.1 *Overall Scheme of Presenting the Results*

As stated earlier, our final coefficient estimates for equations (1) and (2) are pooled estimates of the naïve model and the simultaneous equation model. Because we have 101 separate sets of coefficient estimates, one for each dual trader, we first present, in tables 2 and 3, the fractions of positive and negative coefficients as well as the fractions of positive and statistically significant (at the 5% level) and negative and statistically significant (at the 5% level) coefficient estimates in equations (1) and (2), respectively. Other details are discussed in Section 5.2.

We then present estimation results of the *median* dual trader in each of the eight contracts examined in the paper. The median dual trader in each contract is the trader whose number of dual trading days is the median of the dual trading days of all selected dual traders in that contract. The estimation results of all other dual traders are omitted for brevity, but are available from us on request.

The results for the median dual trader in each of the eight contracts are provided in tables 4.1, 4.2 and 4.3. Specifically, table 4.1 reports the single equation estimates, with the corresponding posterior standard deviations in parentheses, of equations (1) and (2); table 4.2 reports the simultaneous equation estimates, with the corresponding posterior standard deviations in parentheses, of equations (1) and (2); and table 4.3 reports the pooled estimates, where the pooling weights are derived from the Bayes factor reported in panel C of table 4.3. Note that in the first row of tables 4.1 to 4.3, the number after the futures contract denotes the specific median dual trader in that contract whose posterior estimates are provided right beneath. Thus, "Hogs 08" denotes that the median dual trader in the hogs futures is trader 08. The corresponding trade-related summary statistics of trader 08 in the hog futures is provided in table 1. Other contracts follow similarly.

An examination of tables 4.1, 4.2 and 4.3 reveals that the final coefficient estimates obtained from pooling (in table 4.3) are more precise than the corresponding estimates in either of tables 4.1 and 4.2. This is quite intuitive because by averaging across the two contending models, we take into account model uncertainty and the resulting pooled estimates have smaller posterior standard deviations.

We also estimated our simultaneous equation model using the Heckman two-step method (not reported, but available on request). The estimation results for the probit model in equation (1) are almost identical across different estimation methods, which is not surprising given that our Bayesian estimates do not indicate strong simultaneity between equations (1) and (2). The Heckman two-step method, however, gives us very different results for equation (2). Most noticeably, the coefficients associated with the TRADE DUMMY *(I)* and the added regressors (see discussion in Section 3.3) tend to have much larger standard errors than those of the corresponding Bayesian estimates, and the values of these two coefficients (γ_i and $\sigma_{e_1 e_2}$) also tend to differ in sign, which are typical symptoms of multicollinearity. This supports our argument in Section 3.3 about the inappropriateness of using Heckman's two-step method to estimate our simultaneous equation model.

5.2 *Discussion of Results*

From table 2, we find several dominating factors driving a dual trader's own account trading (versus customer account trading) decision. First, a dual trader is more likely (less likely) to trade on own account if she has not (has) traded much for her customers in the prior 5-minute time bracket. This follows from a large fraction of negative (and statistically significant) coefficients on lagFRACTI4 in all eight contracts and provides strong evidence that dual traders do not piggyback off the information from their customer traders for personal profit. The above result appears to contradict the intuition widely modeled in the theoretical dual trading literature cited earlier.

Second, a dual trader is also more likely to trade for her personal account if her inventory is away from the sleeping position (i.e., the zero contract holding). The coefficient associated with lagINVENTORY is overwhelmingly positive and significant in all eight contracts. This result is consistent with the intuition from the inventory control literature.

The remaining coefficients in equation (1) display varying degrees of significance, both within the same contract and across the different contracts. We interpret these results to indicate the presence of heterogeneity (in terms of skills and other trade-related characteristics) across dual traders and investigate this issue more formally in the next section. We find that the coefficient associated with lagNLOCAL (the liquidity proxy) is more likely to be positive than negative, indicating that dual traders' own account trades are more likely to be positively correlated with greater market liquidity. This provides reasonably strong evidence that dual traders' own account trades are liquidity providing and lends support to the opponents of the dual trading ban. We also find that, as postulated, the coefficient associated with lagVOLCTI1 (the momentum proxy) is more likely to be positive, which indicates the existence of a momentum effect in a dual trader's own account trading. The coefficient associated with lagVOLATILITY (the contract risk proxy) is more likely to be negative, indicating that a dual trader is less likely to indulge in own account trading in a volatile market environment. The coefficient associated with lagSKILL is more likely to be positive indicating that a dual trader's own account trading is associated with her innate skills as a trader. Finally, the coefficient associated with HOT is more likely to be positive, indicating that dual traders time their own account trades by trading during the beginning and at the end of the trading day.

The important variable in equation (2) is TRADE DUMMY. We find that the corresponding coefficient is overwhelmingly positive in all contracts. Furthermore, up to a third (or more) of the dual traders significantly increase their profits every time they trade on their personal accounts. Only for one trader, in the live cattle contract, do we find the opposite to be the case, i.e., personal trading actually decreases own account trading profit. Our result provides strong empirical support for the long-held belief, also extensively modeled in the theoretical dual trading literature, that dual traders are informed traders.

The estimation results of the *median* dual trader in each contract are presented in tables 4.1 to 4.3, to provide the reader with a sense of the magnitude of individual coefficients for a representative dual trader in each of the eight contracts.

To investigate the goodness-of-fit of our simultaneous equation model, we compute the Bayes factors comparing the simultaneous equation model with a model that contains an intercept term only, for dual traders in all eight contracts. The resulting Bayes factors are well over 100 (not reported), indicating that our current model formulation provides a good fit of the data.

In summary, a dual trader is both a liquidity supplier and an informed trader who does not appear to piggyback off her customer trades, and whose own account trading reflects inventory control.

5.3 *Dual Trader Heterogeneity*

The fact that we get a spectrum of signs and statistical significance for the majority of the regression parameters, both within a contract and across contracts, indicates the heterogeneous nature of the dual traders.

Under Bayesian inference, the unknown parameters are treated as random variables, and through Bayes' theorem, we obtain their respective posterior distributions. Thus, an effective way to investigate if the reported posterior means (and standard deviations) of a given parameter are (potentially) distinct, across dual traders, is to examine the corresponding posterior distributions of the parameter.

In figures 1 through 8, we plot the posterior distributions of the parameters corresponding to the seven explanatory variables in equation (1) (excluding the intercept term) and TRADE DUMMY in equation (2), for the median dual trader in each contract. As before, the number at the end of each contract in each graph identifies the specific median dual trader in that contract whose posterior estimates are provided in tables 4.1 to 4.3. From these figures, it is clear that the posterior distributions are well dispersed without significant overlaps, indicating distinct posterior means and dispersions across the median dual traders. Overall, these graphs provide evidence of heterogeneity of the dual traders.

To provide further support for dual trader heterogeneity, we also conduct statistical tests on the difference in the location of the parameters across the median dual traders. Assuming that the posterior distributions of the parameters follow independent normal distributions, the standard procedure for comparing the means of two normal distributions, is the two-sample t-test. If, however, the normality assumption is considered too strong, we can compare the medians of two posterior distributions using the nonparametric Wilcoxon test, and the medians of multiple posterior distributions using the nonparametric Kruskal-Wallis test.

Table 5 reports the test results. For the pair-wise comparison, the null hypothesis is that there is no difference in the means (t-test) or in the medians (Wilcoxon) of the posterior distributions of the parameters. There are eight median traders, one from each of the eight contracts, and, thus, twenty-eight unique pairs. We present the fraction of the corresponding test statistic with a p-value below 0.01 in table 5. For the simultaneous comparison, the null hypothesis is that there is no difference in the medians of the posterior distributions of the parameters, across all eight dual traders (Kruskal-Wallis). We present the p-value associated with the test statistic. As table 5 indicates, regardless of the test employed, each parameter is distinctly different across the eight median dual traders and, thus, provides further support of dual trader heterogeneity.

6. Robustness

In this section we discuss the various sensitivity analyses performed with our data to ensure that our results are not driven by the peculiarities of sample selection and/or the estimation process.

Recall that we use the 2% filter rule to distinguish between a broker day and a dual trading day. As this is somewhat arbitrary, we replicated all our analysis, successively, with 5% and 10% filter rules. That is, for each floor trader, a trading day is a broker day if d (defined in Section 2) < 0.05 ($d < 0.10$), and a dual trading day if d lies in the closed interval [0.05, 0.95] ([0.10, 0.90]). Upon re-estimation, our results remain qualitatively similar in each case.

We also experiment with the cutoff value on the number of dual trading days used to select the dual traders in our sample. To ensure that the conclusions reached from analyzing 101 dual traders are representative of the market as a whole, we experiment with a number of cutoff values below 50 dual trading days, to include progressively more dual traders in our sample. Upon re-estimation of our model in each case, the results remain similar and conclusions unchanged.

We consider only transactions in the nearest maturity contracts at any point in time and find that our results are virtually unchanged. We also experiment with various time brackets greater or less than five minutes and obtain results similar to the ones reported here.

Finally, we choose different prior specifications of the model parameters, and obtain similar results. Specifically, Section 3.2 gives the set of parameter values of the prior distribution function that we use to carry out our analysis. In addition, we use several different combinations of prior parameter values and obtain posterior distributions of the regression coefficient estimates that are similar to one another. Thus, the data appears to be informative about the model parameters.

In summary, our conclusions appear robust to the various sample selection rules and prior specifications.

7. Conclusions

Using detailed audit trail transaction data compiled by the Commodity Futures Trading Commission, we investigate if dual traders are informed traders and what motivates dual traders to trade on their own accounts. These questions are important in light of renewed interest in Congress as it gears up to consider legislation to impose limits on dual trading activities.

Our study goes significantly beyond the existing research. We recognize, and account for, the potential endogeneity between the own account trading decision of a dual trader and her unobserved information that drives the trading decision. At the same time, we acknowledge that whether or not these two variables are correlated with each other, is ultimately an empirical question. Toward that end, our final parameter estimates are obtained as weighted averages of the corresponding parameter estimates of two models: one of which recognizes the correlation while the other one (the naïve approach) does not. The weights themselves are determined endogenously within the estimation process. The estimation of our model is performed for *each* dual trader in our sample, using a Markov chain Monte Carlo (MCMC) method, which, as we argue, is the appropriate estimation technique to use, given our empirical setup.

We find that dual traders are informed traders who do not appear to piggyback off their customers' trades; whose own account trading reflects inventory control; and who appear to be liquidity suppliers. We also uncover strong evidence that dual traders are heterogeneous in terms of their trading skills and other trade-related characteristics.

An implication of our results is that any drastic restrictions on dual traders' own account trading are likely to adversely affect their role as liquidity providers, resulting in illiquid markets and higher trading costs. Policy makers may want to consider this last point before imposing additional restrictions on own account trading by dual traders in futures markets.

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Table 1: Summary Statistics for Our Sample of 101 Dual Traders

This table provides summary statistics for our sample of 101 dual traders in eight futures contracts. The first column lists the specific futures contract and also the selected dual traders in this contract with a distinct two-digit identifier. Total Trading Days gives the number of valid trading days by a floor trader. To categorize each trading day, we calculate a trading ratio for each floor trader for the day she is active. Specifically, we define d as the proportion of a floor trader's own account trading volume over her total trading volume on a day. For each floor trader, a trading day is a local trading day if $d > .98$, a broker trading day if $d < .02$, and a dual trading day if d lies on the closed interval [.02,.98]. Dual Trading Days is the number of trading days when a floor trader is a dual trader. Local Trading Days is the number of trading days when a floor trader is a local. Broker Trading Days is the number of trading days when a floor trader is a broker. Total Volume is the total number of contracts traded by a floor trader during the sample period. Total CTI 1 Volume is the number of contracts she trades on her own account. Total CTI 4 Volume is the number of contracts she trades for her clients. Number of Transactions gives the sample size for each trader used in our later analysis. Number of CTI 1 Transactions gives the number of times the floor trader trades on her own account. Number of CTI 4 Transactions gives the number of times the floor trader trades for her customers. The criterion to include a dual trader in our sample is that the number of her dual trading days exceeds 50.

Trader	Total Trading Days	Dual Trading Days	Local Trading Days	Broker Trading Days	Total Volume	Total CTI 1 Volume	Total CTI 4 Volume	Number of Transactions	Number of CTI 1 Transactions	Number of CTI 4 Transactions
					Live Cattle					
Live Cattle 01	123	121	0	2	57001	7322	49679	2499	915	1584
Live Cattle 02	122	118	0	4	10427	229250	75022	4204	2041	2163
Live Cattle 03	116	116	0	0	65713	27540	38173	2801	1723	1078
Live Cattle 04	121	115	0	6	21207	4526	16681	2320	948	1372
Live Cattle 05	126	114	2	10	14632	1805	12827	2329	667	1662
Live Cattle 06	115	113	1	1	48347	11975	36372	2733	1509	1224
Live Cattle 07	121	112	1	8	46381	20388	25993	2430	1033	1397
Live Cattle 08	120	108	3	9	8840	3699	5141	1055	609	446
Live Cattle 09	112	107	0	5	65396	7648	57748	3660	1316	2344
Live Cattle 10	107	107	0	0	33034	29314	3720	3764	3542	222
Live Cattle 11	112	106	0	6	26784	5693	21091	1352	558	794
Live Cattle 12	108	104	0	4	27428	5179	22249	1499	727	772
Live Cattle 13	126	103	0	23	29161	2113	27048	2936	643	2293
Live Cattle 14	115	103	0	12	13424	2726	10698	1410	606	804
Live Cattle 15	110	102	0	8	48132	6066	42066	3293	828	2465
Live Cattle 16	116	102	1	13	20113	4973	15140	1703	620	1083

Table 1 continued

Trader	Total Trading Days	Dual Trading Days	Local Trading Days	Broker Trading Days	Total Volume	Total CTI1 Volume	Total CTI4 Volume	Number of Transactions	Number of CTI1 Transactions	Number of CTI4 Transactions
Live Cattle 17	99	98	0	1	59617	18237	41380	3064	1624	1440
Live Cattle 18	125	97	28	0	69885	59290	10595	3141	2912	229
Live Cattle 19	116	96	16	4	42326	13774	28552	1865	1368	497
Live Cattle 20	122	91	0	31	28321	3280	25041	1769	781	988
Live Cattle 21	112	91	0	21	15447	4183	11264	1447	429	1018
Live Cattle 22	124	88	9	27	3735	873	2862	480	230	250
Live Cattle 23	122	87	28	7	20729	2065	18664	1179	562	617
Live Cattle 24	110	87	23	0	8698	7901	797	1079	950	129
Live Cattle 25	117	86	1	30	26839	1458	25381	1007	451	556
Live Cattle 26	118	85	0	33	60358	5924	54434	2817	478	2339
Live Cattle 27	108	74	33	1	7196	4484	2712	461	302	159
Live Cattle 28	112	69	0	43	113102	4877	108225	2642	493	2149
Live Cattle 29	122	69	1	52	17113	950	16163	898	232	666
Live Cattle 30	106	62	0	44	20958	867	20091	946	223	723
Live Cattle 31	113	62	0	51	9984	621	9363	682	154	528
Live Cattle 32	121	62	55	4	6986	5820	1166	857	740	117
Live Cattle 33	67	61	0	6	21033	3645	17388	1083	359	724
Live Cattle 34	116	60	0	56	40019	1750	38269	1577	257	1320
Live Cattle 35	117	58	0	59	93674	2322	91352	1782	171	1611
Live Cattle 36	122	57	1	64	59382	2297	57085	854	377	477
Live Cattle 37	82	56	0	26	42600	4318	38282	1256	304	952
Live Cattle 38	121	55	0	66	7044	425	6619	595	118	477
Live Cattle 39	95	53	13	29	4434	3008	1426	493	303	190
Live Cattle 40	67	50	14	3	8528	5050	3478	716	430	286
Hogs										
Hogs 01	118	117	0	1	90439	30692	59747	4522	2931	1591
Hogs 02	119	116	0	3	22732	2386	20346	3007	1025	1982
Hogs 03	117	115	1	1	32224	13886	18338	2889	1732	1157
Hogs 04	119	115	0	4	29337	10634	18703	3201	1470	1731
Hogs 05	111	100	2	9	35065	3850	31215	1763	447	1316
Hogs 06	122	99	11	12	6979	1885	5094	1245	745	500
Hogs 07	102	98	0	4	25623	5209	20414	2140	778	1362

Table 1 continued

Trader	Total Trading Days	Dual Trading Days	Local Trading Days	Broker Trading Days	Total Volume	Total CTI1 Volume	Total CTI4 Volume	Number of Transactions	Number of CTI1 Transactions	Number of CTI4 Transactions
Hogs 08	123	97	26	0	8056	5759	2297	1969	1642	327
Hogs 09	117	93	11	13	17049	2682	14367	1111	405	706
Hogs 10	110	92	18	0	41301	29803	11498	2392	1955	437
Hogs 11	114	89	0	25	72303	5600	66703	3026	1070	1956
Hogs 12	122	85	0	37	41070	1698	39372	2493	438	2055
Hogs 13	108	83	0	25	13768	1848	11920	1302	550	752
Hogs 14	116	67	0	49	47119	1643	45476	2129	292	1837
Hogs 15	122	55	54	13	5733	2424	3309	669	458	211
Pork Bellies										
Pork Bellies 01	124	124	0	0	34203	5684	28519	3623	1562	2061
Pork Bellies 02	115	114	0	1	14306	6174	8132	2621	1080	1541
Pork Bellies 03	120	112	0	8	31939	2002	29937	3533	1133	2400
Pork Bellies 04	117	110	7	0	45660	17329	28331	3714	2326	1388
Pork Bellies 05	113	109	3	1	10322	3473	6849	1858	994	864
Pork Bellies 06	118	107	0	11	42069	5750	36319	3670	1469	2201
Pork Bellies 07	112	103	9	0	9088	2953	6135	1494	744	750
Pork Bellies 08	123	97	0	26	36610	2227	34383	2553	626	1927
Pork Bellies 09	121	95	1	25	15665	1553	14112	1780	588	1192
Pork Bellies 10	123	93	0	30	35687	1210	34477	2912	626	2286
Pork Bellies 11	113	91	0	22	19300	1110	18190	2318	520	1798
Pork Bellies 12	111	80	29	2	7255	4611	2644	1368	1097	271
Pork Bellies 13	91	73	1	17	5466	1053	4413	1043	468	575
Pork Bellies 14	100	71	27	2	19874	14742	5132	1468	1035	433
Pork Bellies 15	105	69	34	2	14597	13130	1467	1046	875	171
Pork Bellies 16	119	53	66	0	16295	14410	1885	1040	918	122
Pork Bellies 17	102	51	49	2	5008	4280	728	277	213	64
Pork Bellies 18	114	51	63	0	4869	3919	950	804	657	147
Feeder Cattle										
Feeder Cattle 01	111	106	5	0	25606	20291	5315	2360	2057	303
Feeder Cattle 02	113	101	0	12	26343	2602	23741	2776	769	2007
Feeder Cattle 03	126	83	0	43	39813	1557	38256	2489	387	2102
Feeder Cattle 04	116	50	1	65	24479	654	23825	1246	267	979

Table 1 continued

Trader	Total Tradin g Days	Dual Trading Days	Local Trading Days	Broker Trading Days	Total Volume	Total CTI1 Volume	Total CTI4 Volume	Number of Transactions	Number of CTI1 Transactions	Number of CTI4 Transactions
Lumber										
Lumber 01	126	122	0	4	8725	1422	7303	2156	622	1534
Lumber 02	120	115	5	0	9521	1747	7774	2156	1093	1063
Lumber 03	122	112	0	10	4814	940	3874	1477	550	927
Lumber 04	113	105	0	8	16109	2075	14034	2357	631	1726
Lumber 05	119	102	8	9	7269	1209	6060	1435	468	967
Lumber 06	110	100	3	7	3900	1165	2735	1064	393	671
Lumber 07	119	100	8	11	3069	1229	1840	779	446	333
Lumber 08	116	94	1	21	15439	1609	13830	2055	466	1589
Lumber 09	112	88	0	24	13176	706	12470	1933	427	1506
Lumber 10	121	88	21	12	2510	847	1663	718	354	364
Canadian Dollars										
Cdn Dollars 01	124	116	0	8	70394	12541	57853	3650	1581	2069
Cdn Dollars 02	115	114	0	1	96237	16153	80084	5410	2625	2785
Cdn Dollars 03	119	113	0	6	68373	7244	61129	3744	1436	2308
Cdn Dollars 04	117	112	0	5	69225	11099	58126	3802	1576	2226
Cdn Dollars 05	125	99	0	26	57571	2854	54717	3620	787	2833
Cdn Dollars 06	114	99	12	3	38962	7909	31053	2156	1009	1147
Cdn Dollars 07	126	51	0	75	81370	1804	79566	2257	258	1999
T-bill										
T-bill 01	118	116	1	1	51350	15774	35576	2359	1459	900
T-bill 02	121	110	0	11	29746	4503	25243	1829	659	1170
T-bill 03	108	106	1	1	53584	12700	40884	3150	1916	1234
T-bill 04	121	105	0	16	19303	5158	14145	1794	576	1218
T-bill 05	109	86	23	0	62242	43958	18284	2077	1453	624
T-bill 06	123	72	2	49	28880	2963	25917	829	217	612
S&P 400										
S&P 400 01	91	73	2	16	3231	502	2729	838	247	591

Table 2: Bayesian Estimates of the Dual Trader's Own Account Trading Equation

This table provides an overview of the Bayesian estimates of equation (1) across our sample of 101 dual traders in eight futures contracts. For each futures contract, the first row gives the fractions of positive (+ve) and negative (-ve) coefficient estimates; the second row gives the fractions of significantly positive and negative coefficient estimates, at the 5% significant level. The estimation results are obtained by pooling the single equation model and the simultaneous equation model. The dependent variable in equation (1) is **TRADE DUMMY** (*I*), which equals 1 if dual trader *i* trades on her own account in time bracket *t*, 0 otherwise. **LagNLOCAL** is the number of pure locals (sole own account traders) in the 5-minute bracket prior to the current time bracket *t*. **LagFRACTI4** is dual trader *i*'s customer-trading volume as a fraction of her total trading volume in time bracket *t-1*. **LagVOLCTI1** is dual trader *i*'s own account trading volume in time bracket *t-1*. **LagVOLATILITY**, in time bracket *t-1* is obtained as the maximum of the buy-price and sell-price standard deviations. **LagINVENTORY**, is computed as dual trader *i*'s CTI 1 buy trades minus CTI 1 sell trades, cumulated from the beginning of a trading day to time bracket *t-1*. **LagSKILL** is a proxy to capture dual trader *i*'s trading skill up to time bracket *t-1*. **HOT** is a trade timing dummy that equals 1 if the 5-minute bracket in which dual trader *i* trades on own account belongs to the first two and final half-hour trading periods of a trading day, and 0 otherwise.

	INTERCEPT		LagNLOCAL		LagFRACTI4		LagVOLCTI1		LagVOLATILITY		LagINVENTORY		LagSKILL		HOT	
Pit	+ve	-ve	+ve	-ve	+ve	-ve	+ve	-ve	+ve	-ve	+ve	-ve	+ve	-ve	+ve	-ve
Live Cattle	78.4%	21.6%	59.5%	40.5%	0.0%	100.0%	67.6%	32.4%	32.4%	67.6%	75.7%	24.3%	67.6%	32.4%	64.9%	35.1%
	64.9%	8.1%	32.4%	27.0%	0.0%	97.3%	32.4%	0.0%	13.5%	43.2%	54.1%	10.8%	13.5%	5.4%	27.0%	8.1%
Hogs	73.3%	26.7%	73.3%	26.7%	0.0%	100.0%	80.0%	20.0%	33.3%	66.7%	86.7%	13.3%	40.0%	60.0%	73.3%	26.7%
	60.0%	13.3%	53.3%	13.3%	0.0%	100.0%	60.0%	13.3%	0.0%	20.0%	53.3%	0.0%	6.7%	6.7%	53.3%	13.3%
Pork Bellies	77.8%	22.2%	77.8%	22.2%	0.0%	100.0%	77.8%	22.2%	27.8%	72.2%	72.2%	27.8%	55.6%	44.4%	77.8%	22.2%
	55.6%	16.7%	38.9%	5.6%	0.0%	100.0%	50.0%	0.0%	11.1%	50.0%	50.0%	11.1%	5.6%	5.6%	50.0%	5.6%
Feeder Cattle	50.0%	50.0%	75.0%	25.0%	0.0%	100.0%	50.0%	50.0%	25.0%	75.0%	75.0%	25.0%	75.0%	25.0%	75.0%	25.0%
	25.0%	50.0%	25.0%	0.0%	0.0%	100.0%	25.0%	0.0%	0.0%	0.0%	75.0%	0.0%	25.0%	25.0%	25.0%	0.0%
Lumber	50.0%	50.0%	70.0%	30.0%	0.0%	100.0%	40.0%	60.0%	70.0%	30.0%	90.0%	10.0%	40.0%	60.0%	40.0%	60.0%
	20.0%	40.0%	30.0%	0.0%	0.0%	90.0%	20.0%	30.0%	10.0%	20.0%	70.0%	0.0%	20.0%	0.0%	20.0%	30.0%
Canadian Dollar	71.4%	28.6%	57.1%	42.9%	0.0%	100.0%	100.0%	0.0%	14.3%	85.7%	85.7%	14.3%	71.4%	28.6%	71.4%	28.6%
	57.1%	28.6%	0.0%	28.6%	0.0%	100.0%	57.1%	0.0%	0.0%	28.6%	71.4%	0.0%	28.6%	14.3%	42.9%	14.3%
T-bill	66.7%	33.3%	16.7%	83.3%	0.0%	100.0%	50.0%	50.0%	66.7%	33.3%	100.0%	0.0%	83.3%	16.7%	66.7%	33.3%
	66.7%	16.7%	0.0%	33.3%	0.0%	100.0%	0.0%	16.7%	33.3%	16.7%	83.3%	0.0%	33.3%	0.0%	50.0%	16.7%
S&P 400	100%	0%	100%	0%	0%	100%	0%	100%	0%	100%	100%	0%	0%	100%	100%	0%
	0%	0%	100%	0%	0%	100%	0%	100%	0%	0%	100%	0%	0%	100%	0%	0%

Table 3: Bayesian Estimates of the Dual Trader's Profit Equation

This table provides an overview of the Bayesian estimates of equation (2) across our sample of 101 dual traders in eight futures contracts. For each futures contract, the first row gives the fractions of positive (+ve) and negative (-ve) coefficient estimates; the second row gives the fractions of significantly positive and negative coefficient estimates, at the 5% significant level. The estimation results are obtained by pooling the single equation model and the simultaneous equation model. The dependent variable is equation (2) is **PROFIT** (Π), which is computed by cumulating dual trader *i*'s personal trading profit from the beginning of a trading day up to time bracket *t*. **TRADE DUMMY** equals 1 if dual trader *i* trades on her own account in time bracket *t*, 0 otherwise. **VOLATILITY,** in time bracket *t* is obtained as the maximum of the buy-price and sell-price standard deviations. **SKILL** is a proxy to capture dual trader *i*'s trading skill up to time bracket *t*. **HOT** is a trade timing dummy that equals 1 if the 5-minute bracket in which dual trader *i* trades on own account belongs to the first two and final half-hour trading periods of a trading day, and 0 otherwise. **LagPROFIT** is the trading profit up to and including time bracket *t-1*.

	INTERCEPT		TRADE DUMMY		VOLATILITY		SKILL		HOT		LagPROFIT	
Pit	+ve	-ve	+ve	-ve	+ve	-ve	+ve	-ve	+ve	-ve	+ve	-ve
Live Cattle	54.1%	45.9%	62.2%	37.8%	51.4%	48.6%	86.5%	13.5%	40.5%	59.5%	100.0%	0.0%
	8.1%	5.4%	21.6%	2.7%	8.1%	8.1%	32.4%	2.7%	2.7%	2.7%	100.0%	0.0%
Hogs	46.7%	53.3%	93.3%	6.7%	53.3%	46.7%	53.3%	46.7%	53.3%	46.7%	100.0%	0.0%
	13.3%	13.3%	46.7%	0.0%	6.7%	6.7%	0.0%	13.3%	0.0%	6.7%	100.0%	0.0%
Pork Bellies	50.0%	50.0%	100.0%	0.0%	66.7%	33.3%	44.4%	55.6%	55.6%	44.4%	100.0%	0.0%
	0.0%	0.0%	38.9%	0.0%	5.6%	5.6%	0.0%	5.6%	0.0%	0.0%	100.0%	0.0%
Feeder Cattle	25.0%	75.0%	75.0%	25.0%	75.0%	25.0%	100.0%	0.0%	0.0%	100.0%	100.0%	0.0%
	0.0%	0.0%	25.0%	0.0%	0.0%	0.0%	75.0%	0.0%	0.0%	0.0%	100.0%	0.0%
Lumber	40.0%	60.0%	100.0%	0.0%	70.0%	30.0%	60.0%	40.0%	80.0%	20.0%	100.0%	0.0%
	20.0%	0.0%	80.0%	0.0%	10.0%	0.0%	10.0%	0.0%	0.0%	0.0%	100.0%	0.0%
Canadian Dollar	71.4%	28.6%	85.7%	14.3%	42.9%	57.1%	28.6%	71.4%	57.1%	42.9%	100.0%	0.0%
	0.0%	0.0%	57.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	14.3%	100.0%	0.0%
T-bill	50.0%	50.0%	66.7%	33.3%	50.0%	50.0%	66.7%	33.3%	83.3%	16.7%	100.0%	0.0%
	0.0%	0.0%	16.7%	0.0%	16.7%	0.0%	66.7%	16.7%	16.7%	0.0%	100.0%	0.0%
S&P 400	100.0%	0.0%	100.0%	0.0%	100.0%	0.0%	0.0%	100.0%	0.0%	100.0%	100.0%	0.0%
	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%	100.0%	0.0%

Table 4.1: Bayesian Estimates for the Median Dual Trader under the Single Equation Model

This table reports the single equation estimates for the median dual trader in each of our eight futures contracts with the corresponding posterior standard deviations in parentheses. Note that the number after the futures contract in each column denotes the specific median dual trader in that contract whose posterior estimates are provided right beneath. The dependent variable in equation (1) is **TRADE DUMMY** (*I*), which equals 1 if dual trader *i* trades on her own account in time bracket *t*, 0 otherwise. The explanatory variables in equation (1) are as follows. **LagNLOCAL** is the number of pure locals (sole own account traders) in the 5-minute bracket prior to the current time bracket *t*. **LagFRACTI4** is dual trader *i*'s customer-trading volume as a fraction of her total trading volume in time bracket *t-1*. **LagVOLCTI1** is dual trader *i*'s own account trading volume in time bracket *t-1*. **LagVOLATILITY**, in time bracket *t-1* is obtained as the maximum of the buy-price and sell-price standard deviations. **LagINVENTORY**, is computed as dual trader *i*'s CTI 1 buy trades minus CTI 1 sell trades, cumulated from the beginning of a trading day to time bracket *t-1*. **LagSKILL** is a proxy to capture dual trader *i*'s trading skill up to time bracket *t-1*. **HOT** is a trade timing dummy that equals 1 if the 5-minute bracket in which dual trader *i* trades on own account belongs to the first two and final half-hour trading periods of a trading day, and 0 otherwise. The dependent variable in equation (2) is **PROFIT** (Π), which is computed by cumulating dual trader *i*'s personal trading profit from the beginning of a trading day up to time bracket *t*. The explanatory variables in equation (2) are: **TRADE DUMMY; VOLATILITY; SKILL; HOT;** and **LagPROFIT**, which is the trading profit up to and including time bracket *t-1*.

	Live Cattle 20	Hogs 08	Pork Bellies 09	Feeder Cattle 02	Lumber 05	Canadian Dollar 04	T-bill 03	S&P 400 01
Panel A. Probit Regression – Explaining the Own Account Trading Decision								
INTERCEPT	.9399 (.1596)	1.365 (.2005)	.0808 (.1217)	.0504 (.1226)	-.1201 (.1355)	.2897 (.0599)	.3001 (.0678)	.0310 (.1726)
LagNLOCAL	-.0688 (.0100)	.0200 (.0172)	.0572 (.0203)	.0165 (.0189)	.0033 (.0214)	.0192 (.0165)	-.0049 (.0171)	.0782 (.0516)
LagFRACTI4	-.7394 (.0890)	-1.121 (.0931)	-1.192 (.0913)	-.9474 (.0946)	-1.113 (.1025)	-.8186 (.0570)	-.4951 (.0539)	-1.120 (.1490)
LagVOLCTI1	.0018 (.0132)	.0054 (.0202)	.0245 (.0173)	-.0025 (.0141)	-.0400 (.0222)	.0071 (.0034)	.0009 (.0036)	-.0707 (.0518)
LagVOLATILITY	-.0062 (.0036)	-.0052 (.0055)	-.0016 (.0033)	-.0002 (.0032)	.0042 (.0041)	-.0010 (.0026)	.0013 (.0019)	-.0031 (.0129)
LagINVENTORY	.0321 (.0076)	.0101 (.0079)	.0435 (.0182)	.0252 (.0082)	.1218 (.0301)	.0123 (.0024)	.0082 (.0019)	.1399 (.0402)
LagSKILL	-.00013 (.00005)	.00003 (.00005)	.00004 (.00008)	.00002 (.00005)	-.00011 (.00009)	.00022 (.0012)	.00004 (.00006)	-.00145 (.0007)
HOT	.0923 (.0719)	-.0916 (.0801)	.2104 (.0732)	.0547 (.0581)	.4251 (.0827)	-.1890 (.0456)	.2705 (.0474)	.1508 (.0992)
R-Squared	13.0%	12.2%	13.7%	5.1%	13.4%	8.1%	4.0%	13.6%
Panel B. Explaining the Trading Profit								
INTERCEPT	10.236 (39.316)	-23.280 (36.067)	19.611 (20.410)	-.8295 (15.017)	11.860 (28.109)	11.343 (16.792)	-46.396 (35.930)	48.338 (34.851)
TRADE DUMMY	-7.418 (18.290)	29.878 (16.471)	7.236 (15.799)	15.467 (9.875)	33.886 (21.914)	35.642 (16.659)	30.074 (29.226)	35.186 (31.268)
VOLATILITY	.1493 (.9393)	.6250 (.9396)	-.2854 (.7051)	.5763 (.5159)	.2522 (1.130)	.7279 (.9794)	1.856 (1.197)	2.165 (3.767)
SKILL	.0154 (.0122)	.0030 (.0082)	-.0241 (.0177)	.0127 (.0078)	-.0087 (.0239)	-.0343 (.0454)	.1363 (.0346)	-.3346 (.1738)
HOT	-34.655 (19.009)	8.797 (12.916)	-4.566 (16.104)	-7.254 (9.426)	4.320 (21.986)	-29.160 (16.831)	58.166 (28.523)	-6.613 (28.574)
LagPROFIT	.9585 (.0083)	.9863 (.0060)	.7873 (.0149)	.9265 (.0076)	.8381 (.0148)	.9650 (.0052)	.9843 (.0050)	.7111 (.0244)
R-Squared	87.9%	93.2%	62.0%	84.3%	69.2%	90.5%	92.6%	51.2%
Panel C. The Variance-Covariance Matrix Σ								
σ_{e2e2}	141415.59 (4829.75)	74503.10 (2399.08)	97105.45 (3316.59)	53215.10 (1442.76)	146967.71 (5522.07)	258787.99 (5887.36)	629522.95 (15712.27)	170020.80 (8237.45)

Table 4.2: Bayesian Estimates for the Median Dual Trader under the Simultaneous Equation Model

This table reports the simultaneous equation estimates for the median dual trader in each of our eight futures contracts with the corresponding posterior standard deviations in parentheses. Note that the number after the futures contract in each column denotes the specific median dual trader in that contract whose posterior estimates are provided right beneath. The dependent variable in equation (1) is **TRADE DUMMY** (*I*), which equals 1 if dual trader *i* trades on her own account in time bracket *t*, 0 otherwise. The explanatory variables in equation (1) are as follows. **LagNLOCAL** is the number of pure locals (sole own account traders) in the 5-minute bracket prior to the current time bracket *t*. **LagFRACTI4** is dual trader *i*'s customer-trading volume as a fraction of her total trading volume in time bracket *t-1*. **LagVOLCTI1** is dual trader *i*'s own account trading volume in time bracket *t-1*. **LagVOLATILITY,** in time bracket *t-1* is obtained as the maximum of the buy-price and sell-price standard deviations. **LagINVENTORY,** is computed as dual trader *i*'s CTI 1 buy trades minus CTI 1 sell trades, cumulated from the beginning of a trading day to time bracket *t-1*. **LagSKILL** is a proxy to capture dual trader *i*'s trading skill up to time bracket *t-1*. **HOT** is a trade timing dummy that equals 1 if the 5-minute bracket in which dual trader *i* trades on own account belongs to the first two and final half-hour trading periods of a trading day, and 0 otherwise. The dependent variable in equation (2) is **PROFIT** (Π), which is computed by cumulating dual trader *i*'s personal trading profit from the beginning of a trading day up to time bracket *t*. The explanatory variables in equation (2) are: **TRADE DUMMY; VOLATILITY; SKILL; HOT;** and **LagPROFIT**, which is the trading profit up to and including time bracket *t-1*.

	Live Cattle 20	Hogs 08	Pork Bellies 09	Feeder Cattle 02	Lumber 05	Canadian Dollar 04	T-bill 03	S&P 400 01
Panel A. Probit Regression – Explaining the Own Account Trading Decision								
INTERCEPT	.9429 (.1605)	1.372 (.2108)	.0754 (.1212)	.0473 (.1241)	-.1167 (.1357)	.2920 (.0613)	.3004 (.0680)	.0338 (.1709)
LagNLOCAL	-.0691 (.0098)	.0195 (.0171)	.0572 (.0202)	.0168 (.0186)	.0036 (.0217)	.0195 (.0165)	-.0052 (.0174)	.0762 (.0524)
LagFRACTI4	-.7414 (.0890)	-1.120 (.0936)	-1.189 (.0912)	-.9457 (.0954)	-1.119 (.1038)	-.8185 (.0569)	-.4968 (.0543)	-1.119 (.1474)
LagVOLCTI1	.0016 (.0132)	.0065 (.0204)	.0253 (.0177)	-.0023 (.0140)	-.0409 (.0230)	.0071 (.0035)	.0009 (.0037)	-.0706 (.0509)
LagVOLATILITY	-.0061 (.0035)	-.0053 (.0056)	-.0017 (.0033)	-.0002 (.0033)	.0042 (.0042)	-.0012 (.0026)	.0013 (.0019)	-.0036 (.0128)
LagINVENTORY	.0321 (.0075)	.0099 (.0080)	.0431 (.0183)	.0254 (.0082)	.1224 (.0300)	.0123 (.0024)	.0081 (.0019)	.1405 (.0400)
LagSKILL	-.00013(.00005)	.00003 (.00005)	.00004 (.00008)	.00002 (.00005)	-.00011 (.00009)	.00022 (.0001)	.00004 (.00006)	-.0015 (.0065)
HOT	.0913 (.0733)	-.0949 (.0799)	.2138 (.0734)	.0543 (.0569)	.4250 (.0839)	-.1910 (.0466)	.2715 (.0479)	.1511 (.0995)
Panel B. Explaining the Trading Profit								
INTERCEPT	10.271 (39.280)	-23.680(35.627)	20.035 (20.650)	-.6346 (14.817)	12.170 (28.124)	11.413 (16.703)	-46.905 (35.802)	48.026 (34.767)
TRADE DUMMY	-7.080 (18.365)	29.961 (16.421)	7.088 (15.600)	15.511 (9.952)	33.618 (22.000)	35.611 (16.854)	30.759 (29.040)	35.930 (31.559)
VOLATILITY	.1536 (.9336)	.6404 (.9307)	-.2831 (.7094)	.5709 (.5184)	.2425 (1.128)	.7191 (.9820)	1.858 (1.204)	2.209 (3.812)
SKILL	.0155 (.0122)	.0032 (.0081)	-.0241 (.0176)	.0127 (.0078)	-.0095 (.0240)	-.0347 (.0454)	.1354 (.0344)	-.3352 (.1770)
HOT	-34.780 (19.035)	8.711 (12.981)	-4.783 (16.242)	-7.290 (9.338)	4.503 (21.961)	-29.456 (16.762)	58.004 (28.586)	-6.411 (28.820)
LagPROFIT	.9585 (.0084)	.9862 (.0061)	.7869 (.0149)	.9264 (.0075)	.8377 (.0147)	.9650 (.0052)	.9844 (.0050)	.7104 (.0241)
Panel C. The Variance-Covariance Matrix Σ								
σ_{e1e2}	.0030 (.7115)	.0408 (.7045)	.0694 (.7090)	.0161 (.7083)	-.0067 (.7050)	-.0079 (.7128)	-.0124 (.7108)	.0154 (.7108)
σ_{e2e2}	141358.05 (4737.17)	74526.41 (2359.28)	96990.48 (3243.71)	53180.04 (1434.23)	146975.79 (5495.61)	258892.90 (5983.89)	629278.16 (16010.76)	170017.68 (8324.81)

Table 4.3: Pooled Bayesian Estimates for the Median Dual Trader in Each Futures Contract

This table reports the pooled estimates for the median dual trader in each of our eight futures contracts with the corresponding pooled posterior standard deviations in parentheses. Note that the number after the futures contract in each column denotes the specific median dual trader in that contract whose posterior estimates are provided right beneath. The pooled estimates are obtained as weighted averages of the corresponding parameter estimates from the single equation model (table 4.1) and the simultaneous equation model (table 4.2) respectively, based on the Bayes factor values presented below. The Bayes factor (BF_{01}) compares the single equation model with the simultaneous equation model. According to Kass and Raftery (1995), there exists decisive evidence from the sample data against H_1 when BF_{01} exceeds 100.

	Live Cattle 20	Hogs 08	Pork Bellies 09	Feeder Cattle 02	Lumber 05	Canadian Dollar 04	T-bill 03	S&P 400 01
Panel A. Probit Regression – Explaining the Own Account Trading Decision								
INTERCEPT	.9414 (.1126)	1.3684 (.1461)	.0781 (.0848)	.0489 (.0870)	-.1184 (.0952)	.2909 (.0428)	.3002 (.0484)	.0324 (.1197)
LagNLOCAL	-.0689 (.0070)	.0198 (.0122)	.0572 (.0144)	.0167 (.0133)	.0035 (.0153)	.0194 (.0117)	-.0050 (.0123)	.0772 (.0367)
LagFRACTI4	-.7404 (.0631)	-1.120 (.0664)	-1.190 (.0638)	-.9460 (.0670)	-1.116 (.0728)	-.8186 (.0405)	-.4959 (.0381)	-1.120 (.1040)
LagVOLCTI1	.0017 (.0094)	.0060 (.0144)	.0249 (.0125)	-.0024 (.0101)	-.0405 (.0160)	.0071 (.0025)	.0009 (.0026)	-.0707 (.0360)
LagVOLATILITY	-.0062 (.0025)	-.0052 (.0039)	-.0016 (.0023)	-.0002 (.0023)	.0042 (.0029)	-.0011 (.0018)	.0013 (.0014)	-.0033 (.0091)
LagINVENTORY	.0321 (.0054)	.0100 (.0056)	.0433 (.0130)	.0253 (.0058)	.1221 (.0211)	.0123 (.0017)	.0081 (.0013)	.1402 (.0284)
LagSKILL	-.00013(.00003)	.00003 (.00003)	.00004 (.00005)	.00002 (.00003)	-.00011(.00006)	.00022 (.00008)	.00004 (.00004)	-.0015 (.0005)
HOT	.0918 (.0517)	-.0933 (.0568)	.2121 (.0520)	.0545 (.0403)	.4251 (.0591)	-.1900 (.0327)	.2710 (.0337)	.1510 (.0701)
Panel B. Explaining the Trading Profit								
INTERCEPT	10.253 (27.453)	-23.480(25.422)	19.823 (14.571)	-.7322 (10.655)	12.015 (20.000)	11.378 (11.887)	-46.651(25.264)	48.182 (24.596)
TRADE DUMMY	-7.249 (12.985)	29.920 (11.588)	7.162 (11.169)	15.489 (7.042)	33.752 (15.462)	35.626 (11.905)	30.417 (20.632)	35.558 (22.243)
VOLATILITY	.1515 (.6537)	.6327 (.6684)	-.2843 (.5011)	.5736 (.3711)	.2473 (.7999)	.7235 (.6941)	1.857 (.8501)	2.187 (2.688)
SKILL	.0155 (.0086)	.0031 (.0057)	-.0241 (.0124)	.0127 (.0055)	-.0091 (.0169)	-.0345 (.0319)	.1359 (.0247)	-.3349 (.1237)
HOT	-34.717(13.401)	8.754 (9.1365)	-4.674 (11.366)	-7.267 (6.596)	4.411 (15.426)	-29.308(12.003)	58.085 (19.949)	-6.512 (20.234)
LagPROFIT	.9585 (.0059)	.9863 (.0042)	.7871 (.0105)	.9265 (.0053)	.8379 (.0103)	.9650 (.0037)	.9844 (.0035)	.7107 (.0171)
Panel C. The Variance-Covariance Matrix Σ								
σ_{e1e2}	.0015 (.3557)	.0204 (.3524)	.0348 (.3549)	.0080 (.3537)	-.0033 (.3525)	-.0039 (.3564)	-.0062 (.3554)	.0077 (.3555)
σ_{e2e2}	141386.83 (3403.63)	74514.76 (1680.63)	97047.90 (2298.99)	53197.59 (1014.42)	146971.75 (3896.59)	258840.43 (4213.76)	629400.55 (11110.70)	170019.24 (5857.32)
BF_{01}	1.00044 (.000029)	.99919 (.000056)	.99766 (.000122)	1.00279 (.000166)	1.00009 (.000026)	1.00033 (.000032)	.99999 (.000019)	.99987 (.000019)

Table 5: Tests of Heterogeneity across the Median Dual Traders

This table provides evidence on the heterogeneity across the median dual trader in each of our eight futures contracts. For pair-wise comparison, we employ both the standard two-sample t-test and a nonparametric procedure (Wilcoxon) to test that the posterior distributions of the parameters have the same location across two distinct traders. With eight traders, one from each of the eight contracts, we perform a total of twenty-eight (7x8/2) pair-wise comparisons. For each parameter, the number under T-test (Wilcoxon) provides the fraction of the corresponding test statistic with a p-value below .01 for the null hypothesis of equality of the means (medians) across each pair. For a simultaneous comparison of the medians of a given parameter, across all eight dual traders, we employ the nonparametric Kruskal-Wallis test. For each parameter, the number under Kruskal-Wallis provides the p-value associated with the test statistic for the null hypothesis of equality of the eight medians. **LagNLOCAL** is the number of pure locals (sole own account traders) in the 5-minute bracket prior to the current time bracket *t*. **LagFRACTI4** is dual trader *i*'s customer-trading volume as a fraction of her total trading volume in time bracket *t-1*. **LagVOLCTI1** is dual trader *i*'s own account trading volume in time bracket *t-1*. **LagVOLATILITY**, in time bracket *t-1* is obtained as the maximum of the buy-price and sell-price standard deviations. **LagINVENTORY**, is computed as dual trader *i*'s CTI 1 buy trades minus CTI 1 sell trades, cumulated from the beginning of a trading day to time bracket *t-1*. **LagSKILL** is a proxy to capture dual trader *i*'s trading skill up to time bracket *t-1*. **HOT** is a trade timing dummy that equals 1 if the 5-minute bracket in which dual trader *i* trades on own account belongs to the first two and final half-hour trading periods of a trading day, and 0 otherwise. **TRADE DUMMY** equals 1 if dual trader *i* trades on her own account in time bracket *t*, 0 otherwise.

	LagNLOCAL		LagFRACTI4		LagVOLCTI1		LagVOLATILITY		LagINVENTORYY		LagSKILL		HOT		TRADE DUMMY	
Test	T-test	Wilcoxon	T-test	Wilcoxon	T-test	Wilcoxon	T-test	Wilcoxon	T-test	Wilcoxon	T-test	Wilcoxon	T-test	Wilcoxon	T-test	Wilcoxon
	96.4%	96.4%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	96.4%	96.4%
	Kruskal-Wallis		Kruskal-Wallis		Kruskal-Wallis		Kruskal-Wallis		Kruskal-Wallis		Kruskal-Wallis		Kruskal-Wallis		Kruskal-Wallis	
	.0001		.0001		.0001		.0001		.0001		.0001		.0001		.0001	

Figure 1. Posterior Distribution of the Coefficient Associated with LagNLOCAL in Equation (1)

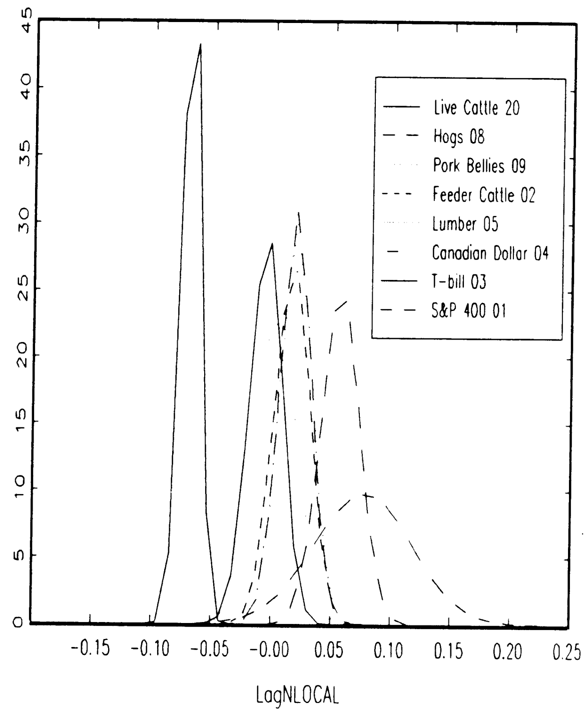


Figure 2. Posterior Distribution of the Coefficient Associated with LagFRACTI4 in Equation (1)

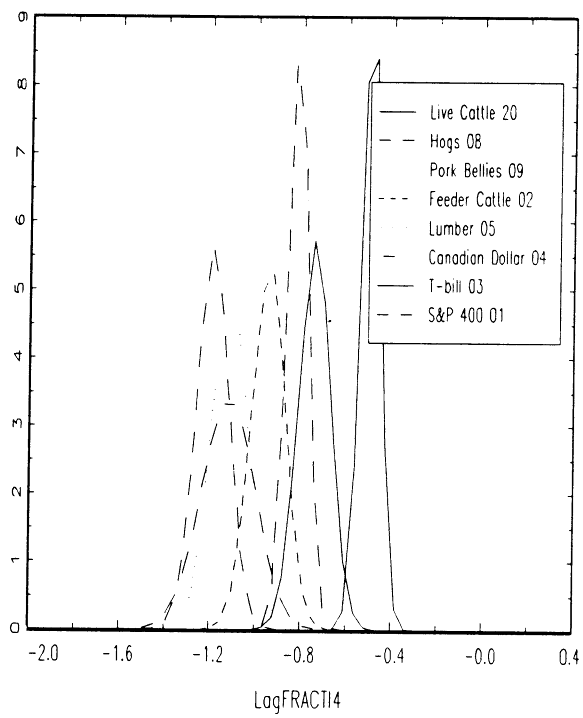


Figure 3. Posterior Distribution of the Coefficient Associated with LagVOLCTI1 in Equation (1)

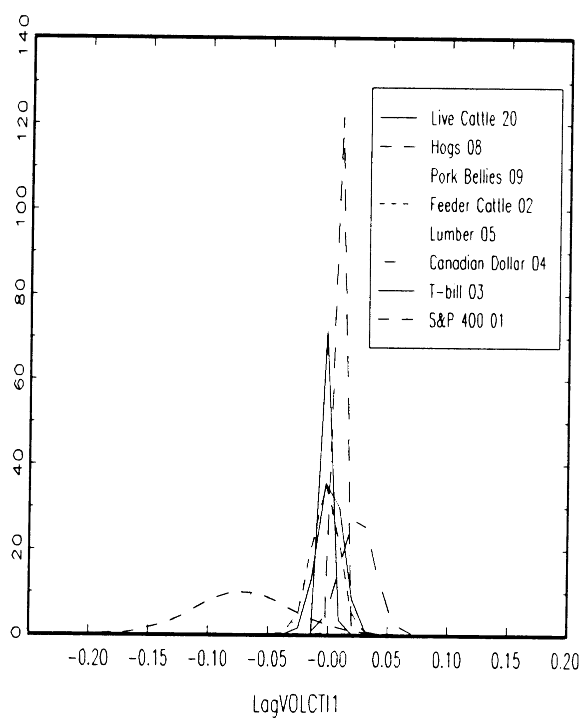


Figure 4. Posterior Distribution of the Coefficient Associated with LagVOLATILITY in Equation (1)

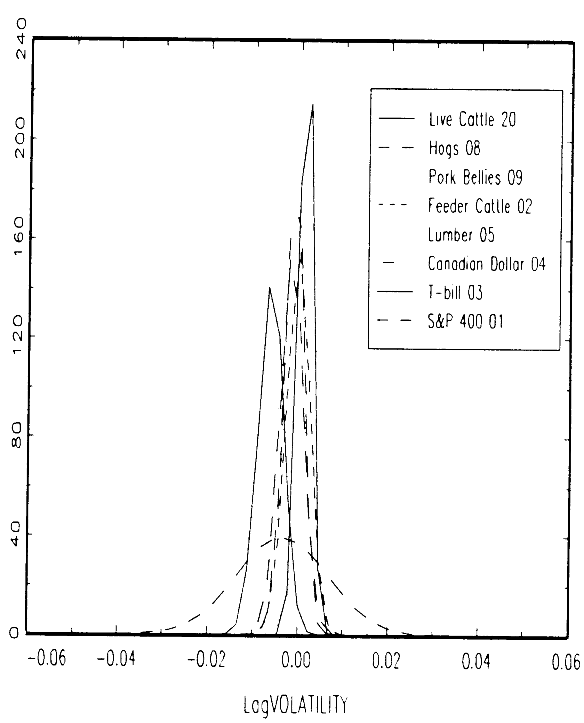


Figure 5. Posterior Distribution of the Coefficient Associated with LagINVENTORY in Equation (1)

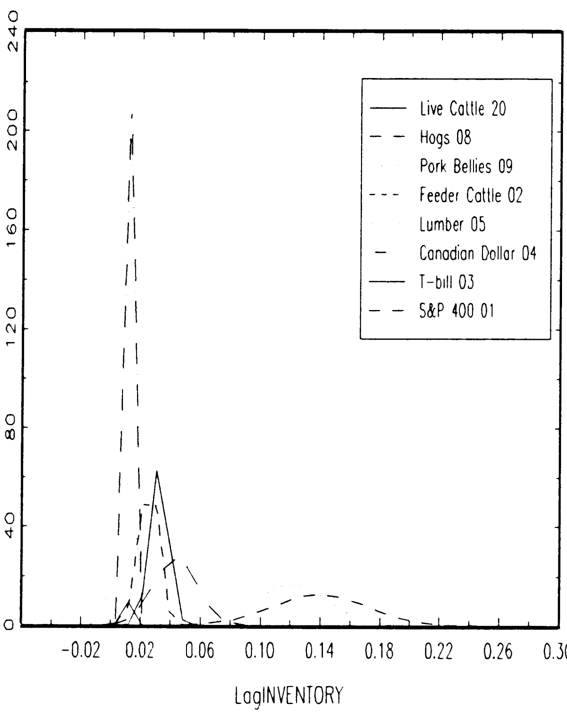


Figure 6. Posterior Distribution of the Coefficient Associated with LagSKILL in Equation (1)

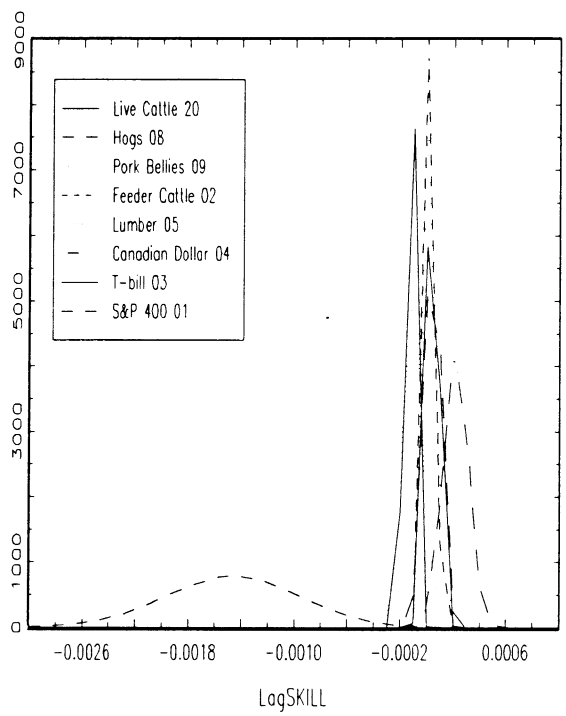


Figure 7. Posterior Distribution of the Coefficient Associated with HOT in Equation (1)

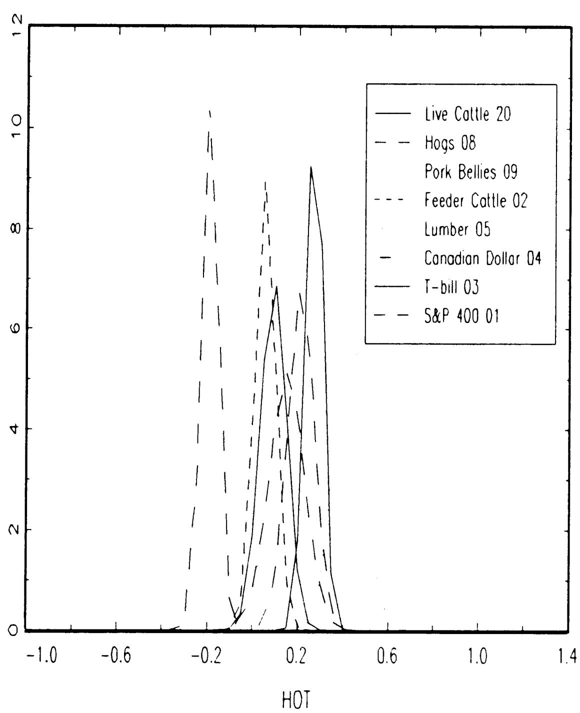
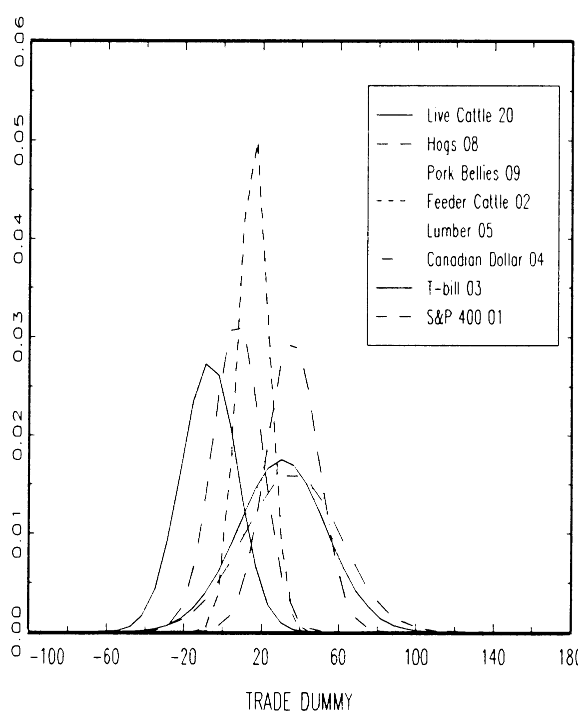


Figure 8. Posterior Distribution of the Coefficient Associated with TRADE DUMMY in Equation (2)



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