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A Bayesian analysis of dual trader informativeness in futures markets

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Abstract

We take a closer look at the question of whether dual traders in futures markets are indeed informed traders. Underpinning this question is the intuition that a dual trader's decision to trade on his own account is not random, but is *endogenously* determined by his expectations of trading profits related to this decision. We employ a simultaneous equations model with two endogenous variables: (1) the binary decision of own account trading (or not), and (2) the trading profit resulting from his own account trading. Our test of whether dual traders are informed traders comprises of estimating the correlation between the error terms of the two equations in our model, where one error term proxies for a dual trader's unobserved private information and the other captures his abnormal profit. Upon estimating the model, using the Bayesian approach, we find no evidence of significant correlation between a dual trader's private information and his abnormal profit. Overall, dual traders appear to be uninformed traders with distinct trade-related characteristics.

JEL classification: G20; G28; C11; C15; C35
Keywords: Endogeneity; Heterogeneity; Informed trader; Markov chain Monte Carlo; Private information; Simultaneous equations

1. Introduction

In the wake of the seminal work by Kyle (1985), Glosten and Milgrom (1985), and Easley and O'Hara (1987), there has developed a large body of research examining how informed traders impact asset prices and market liquidity (see O'Hara, 1995 for a summary).

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Unfortunately, the implications from this body of work are difficult to test, due to the simple fact that informed trading is unobservable. Consequently, empirical researchers have had to resort to inferring informed trading through indirect means, such as through trading profits (Fishman and Longstaff, 1992), through trade sizes (Barclay and Warner, 1993), through trade sizes and trader types (Chakravarty, 2001), and through the timing of trades (Lee et al., 1993).

In the current paper, we adopt a new empirical technique to investigate if dual traders are informed traders. Dual trading is an age-old custom in futures markets whereby some floor traders are allowed to trade both for themselves and for their customers. Our investigation is motivated by an ongoing Congressional debate on whether dual traders should enjoy such a privilege (see Chakravarty and Li, 2001) and the extant literature, both theoretical and empirical, that is silent on the specific question addressed here.[2] Underpinning the Congressional debate is the issue of whether these traders can (and do) take advantage of their privileged position of observing their customers' orders to make personal trading profits.

We employ a simple, yet powerful, test to investigate if dual traders are informed traders. In particular, we jointly examine a dual trader's own account trading decision and profitability by employing a simultaneous equations model with a binary endogenous variable—the decision of whether to trade on his own account—and a trading profit variable. In the own account trading equation, the error term captures the dual trader's (unobservable) private information. In the profit equation, the error term captures his abnormal profit. A significant correlation between the error term in the own account trading decision equation and the error term in the profit equation would indicate that the dual trader possesses (unobservable) private information that leads to abnormal profit. An important feature of our modeling framework is that we isolate the abnormal trading profit associated with a dual trader's personal trades from his overall trading profit and correlate the abnormal profit with the unobserved private information (if any) of the dual trader. In contrast, Chakravarty and Li (in press) examine if dual traders are informed traders by regressing their own account trades on variables capturing information (derived from observing their customers' orders), liquidity supply, and inventory control, while Fishman and Longstaff (1992) infer dual traders' information from the overall trading profit associated with their personal trades.

Our data are time series of audit trails at the Chicago Mercantile Exchange (CME) during the first half of 1992 compiled by the Commodity Futures Trading Commission (CFTC). The data provide information on trade time, price, quantity, trade direction (buyer or seller) and the trader's identification. They are used internally by the CFTC for regulation

[2] Specifically, the theoretical literature on dual trading, for example, starts with the basic assumption that dual traders are informed traders and then investigates the effects of their trading strategies (through piggybacking and/or front running) on market liquidity and the informativeness of prices (see, for example, Grossman, 1989; Roell, 1990; Fishman and Longstaff, 1992; Chakravarty, 1994; Sarkar, 1995). The empirical literature on dual trading can be broadly classified into three themes. The first theme focuses on the liquidity effects of various dual trading restrictions imposed on the futures markets (Smith and Whaley, 1994; Chang et al., 1994; Chang and Locke, 1996; Locke et al., 1999). The second theme of the empirical literature examines the microstructure of futures markets under competitive market making (Manaster and Mann, 1996; Ferguson and Mann, 2001). The third theme, represented by Chakravarty and Li (in press), examines the timing and determinants of own account trading by dual traders.

and enforcement purposes. We estimate our system of equations on *each* of the 101 most active dual traders in the data using Bayesian techniques.

We find weak evidence, at best, to suggest dual traders are informed traders. That is, there is no significant correlation between a dual trader's abnormal trading profit and his unobservable private information. We, however, identify an inventory control effect in dual traders' own account trading. That is, dual traders are more likely to buy for (sell from) their personal account if their inventory level is below (above) zero. We also find that not all of dual traders' own account trades are correlated with positive trading profits. Finally, there is strong evidence to suggest that dual traders are distinctly heterogeneous in their trade-related characteristics. Overall, our results imply that dual traders are uninformed—a finding that has important policy implications, in light of the ongoing Congressional debate on imposing personal trading restrictions on dual traders.

Our research is most closely related to, and supports the conclusions of, Chakravarty and Li (in press) who examine, at the individual trader level, the *timing* and the *determinants* of dual traders' personal trades. Using correlation statistics and time series regressions, Chakravarty and Li find that there is an absence of any trade timing by dual traders in relation to the execution of their customers' orders, and the determinants of dual traders' personal trades appear to be liquidity supply and inventory rebalancing. In this paper, we focus specifically on the informativeness of dual traders, by estimating the statistical correlation between the private information of dual traders and their abnormal trading profits.

The plan for the rest of the paper is as follows. Section 2 describes the empirical model used to examine dual trader informativeness and provides relevant details on Bayesian estimation. Section 3 introduces the data and defines the explanatory variables. Section 4 reports our findings. Section 5 concludes.

2. Methodology

2.1. The simultaneous equations model

We model a dual trader's decision to trade on his own account and the effect of this decision on his profit in two separate equations. The (own account) trading decision is discrete and is modeled using a probit regression. The endogeneity of the own account trading decision (if any) is reflected in the model by the explicit inclusion of a covariance term between the error of the probit equation, capturing the dual trader's unobservable private information, and the error of the profit equation, capturing his abnormal profit. If this covariance is positive, we infer that the dual trader possesses significant private information that leads to abnormal trading profit.[3]

[3] We have attempted to address possible functional misspecification in our modeling framework in the following way. First, based on the research in Chakravarty and Li (in press), we have streamlined our choice of explanatory variables in both equations. Second, we have normalized the trading profit variable (in terms of thousands of dollars) so that the estimates from both equations are of similar magnitude. Finally, we have experimented with different choices of prior parameters and our results appear to be robust to these different specifications.

Consider $I^*_{i,t}$ to be the unobservable latent variable representing the added utility of dual trader i when he chooses own account trading over trading on behalf of his customers in time interval 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. For tractability, we assume a linear structure for $E(I^*_{i,t})$ in that $E(I^*_{i,t})=X_{1,i}\beta_{1,i}$, where $X_{1,it}$ is an $n\times k_1$ matrix of relevant explanatory variables and $\beta_{1,i}$ is a vector of k_1 parameters. We assume that the information of dual trader i consists of an unobservable component—his private information—captured by the error term $e_{1,it}$, and a second component originating from observing his customers' (abnormal) trading volume. Formally, we characterize dual trader i's decision on own account trading in time interval t as

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

In practice, $I^*_{i,t}$ is unobservable. What we observe is a dummy variable $I_{i,t}$ defined by $I_{i,t}=1$, if $I^*_{i,t}>0$, that is, dual trader i chooses to execute some trades in his personal account in time interval t, and $I_{i,t}=0$, if $I^*_{i,t}{}^*\leq 0$, that is, dual trader i does not trade in his personal account and/or chooses to execute trades on behalf of his customers in time interval t. $X_{1,it}$ captures dual trader i's short-term order-flow-based information.

In our second equation, we examine the effect of dual trader i's own account trading decision on his 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 in time interval t, $X_{2,it}$ is an $n\times k_2$ matrix of observable trader and market characteristics, $\beta_{2,i}$ is a vector of k_2 parameters and $e_{2,it}$ is the error term capturing the abnormal profit in time interval t. $\pi_{i,t}$ is the trading profit of dual trader i, in time interval t, computed as in Fishman and Longstaff (1992). Specifically, the trading profit of dual trader i in time interval t on day d is obtained as[4]

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

In summary, Eq. (1) models the own account trading decision of a dual trader as a function of his unobservable private information, his customer order-flow-based information, and other relevant exogenous variables, discussed in Section 3.2. Eq. (2) models the trading profit of the same dual trader as a function of his own account trading choice variable ($I_{i,t}$) and relevant exogenous variables, also discussed in Section 3.2. Any possible correlation between a dual trader's own account trading profit and his own account trading

[4] The reason for having a trading day subscript "d" is that the settlement price differs from day to day and we emphasize this fact by adding the subscript in Eq. (3). In contrast, in Eqs. (1) and (2), our primary focus is on the own account trading decision and trading profit of a dual trader in time interval t, thus, we omit the subscript "d" to simplify the notation.

decision can be analyzed through the sign and statistical significance of the coefficient associated with the binary choice variable $I_{i,t}$ in Eq. (2).

Under our simultaneous equations modeling approach, the error terms in Eqs. (1) and (2), $\begin{pmatrix} e_{1,it} \\ e_{2,it} \end{pmatrix}$, are postulated to follow an independent and identical bivariate normal distribution BVN $(0,\mathbf{\Sigma})$, with mean zero and the variance–covariance matrix $\mathbf{\Sigma} = \begin{pmatrix} 1 & \sigma_{12} \\ \sigma_{12} & \sigma_{22} \end{pmatrix}$. Note that in $\mathbf{\Sigma}$, $\mathrm{Var}(e_{1,it}) = 1$ because $I_{i,t}$ is only observed as a binary variable, leaving only two free parameters σ_{22}, σ_{12} (the off-diagonal element and the second diagonal element) to be estimated. This creates complications in the estimation procedure and requires us to reparameterize $\mathbf{\Sigma}$ and to estimate the two free parameters separately.[5] In particular, we decompose the joint bivariate normal distribution for $\begin{pmatrix} e_{1,it} \\ e_{2,it} \end{pmatrix}$ in Eqs. (1) and (2) into the product of the marginal distribution for $e_{1,it}$, and the conditional distribution $e_{2,it}|e_{1,it}$, and obtain

$$I^*_{i,t} = X_{1,it}\beta_{1,i} + e_{1,it}, \tag{4}$$

$$\pi_{i,t} = I_{i,t}\gamma_i + X_{2,it}\beta_{2,i} + e_{1,it}\sigma_{12} + v_{i,t}, \tag{5}$$

where $e_{1,it} \sim N(0,1)$, $v_{i,t} \sim N(0, \sigma^2)$, $\sigma^2 = \sigma_{22} - \sigma_{12}^2$, and $e_{1,it}$, $v_{i,t}$ 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_{12}, σ^2 is like drawing from the posterior distribution of the univariate regression of $e_{2,it}$ on $e_{1,it}$,

$$e_{2,it} = e_{1,it}\sigma_{12} + v_{i,t}, \quad v_{i,t} \sim N(0, \sigma^2). \tag{6}$$

From here on, we focus on the reparameterized variance–covariance matrix

$$\mathbf{\Sigma} = \begin{pmatrix} 1 & \sigma_{12} \\ \sigma_{12} & \sigma_{12}^2 + \sigma^2 \end{pmatrix}.$$

A priori, a single-equation model, where Eqs. (1) and (2) are estimated separately, and our simultaneous equations model, are both of interest. Statistically, the difference between the two approaches is that the former sets the covariance term σ_{12} equal to zero while the latter leaves σ_{12} unconstrained. Economically, the key issue is whether dual trader i

[5] The complication arises because when we have three free parameters to estimate in a 2×2 variance–covariance matrix, $\mathbf{\Sigma}$, 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 $\mathbf{\Sigma}^{-1}$ (with its three free parameters), follows a Wishart distribution; while conditional on the data and $\mathbf{\Sigma}$, δ follows a multivariate normal distribution. Unfortunately, in our current setting, due to the probit Eq. (1), the variance of the error team in Eq. (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.

possess unobservable private information that is systematically related to his abnormal trading profit, after controlling for observables such as inventory effects, liquidity, etc. Put differently, the question is whether or not a dual trader's own account trading decision is exogenous to his personal trading profit.

To test for H_0:$\sigma_{12}=0$ versus H_1:$\sigma_{12}\neq 0$, we compute the Bayes factor (BF_{01}) between these 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.[6] 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

$$\mathrm{BF}_{01}=\frac{f(\sigma_{12}=0\,|\,y)}{f(\sigma_{12}=0)}, \tag{7}$$

where $f(\sigma_{12}|y)=\int\int f(\delta,\ \sigma_{12},\ \sigma_{22}\,|\,y)d\sigma_{22}d\delta$, $f(\sigma_{12})=\int\int f(\delta,\ \sigma_{12},\ \sigma_{22})d\sigma_{22}d\delta$, $\delta=(\beta_1',\ \gamma,\ \beta_2')'$, and y represents the data.

Stacking the time series observations and letting $Z_1=X_1$, $\delta_1=\beta_1$, $Z_2=(I,\ X_2)$, and $\delta_2=(\gamma,\beta_2')'$, Eqs. (1) and (2) are expressed as

$$\begin{pmatrix} I^* \\ \pi \end{pmatrix}=\begin{pmatrix} Z_1 & 0 \\ 0 & Z_2 \end{pmatrix}\begin{pmatrix} \delta_1 \\ \delta_2 \end{pmatrix}+\begin{pmatrix} e_1 \\ e_2 \end{pmatrix}. \tag{8}$$

For simplicity, we rewrite Eq. (8) as follows

$$Y^*=Z\delta+U, \quad E(UU')=\mathbf{\Sigma}\otimes I_n, \tag{9}$$

where $Y^*=(I^{*\prime},\pi')'$, $Z=\mathrm{diag}(Z_1,\ Z_2)$, $U=(e_1',e_2')'$, δ, $\mathbf{\Sigma}$ are defined, $\otimes$ denotes the Kronecker product, and n is the sample size.

2.2. Estimation using the Markov Chain Monte Carlo (MCMC) method

We assume the following prior distribution

$$f(\delta,\sigma_{12},\sigma^{-2})\propto f(\delta)\cdot f(\sigma_{12})\cdot f(\sigma^{-2}), \tag{10}$$

where

$$f(\delta)\sim \mathrm{MVN}(\delta_0,\Psi_0^{-1}), \quad f(\sigma_{12})\sim N(r_0,b_0^{-1}), \quad f(\sigma^{-2})\sim G\left(\frac{v_0}{2},\left(\frac{c_0}{2}\right)^{-1}\right),$$

MVN denotes a multivariate normal distribution, N denotes a univariate normal distribution, and G denotes a Gamma distribution (Poirier, 1995, pp. 98–99).

Throughout the paper, informative priors $f(\delta)\sim \mathrm{MVN}(\delta_0,\Psi_0^{-1})$ are used for the regression parameter δ, and we vary our choices of the prior parameters δ_0,Ψ_0 to ensure that our posterior estimates are insensitive to the prior. Given that we do not have any strong

[6] According to Kass and Raftery (1995), there exists some support from the data for H_0 when BF_{01} exceeds 1, and strong evidence against H_1 when BF_{01} exceeds 10.

belief about whether dual traders are informed or not, it is reasonable to choose the prior mean r_0 of the covariance term σ_{12} to be zero. Choosing the prior parameters b_0, v_0 c_0 can be more challenging, however. In general, the smaller the values of b_0,v_0, the less informative are the priors on σ_{12},σ^{-2}. We also take into account two implementational considerations as in Li (1998, 1999) when selecting the values of b_0,v_0,c_0. First, given, $r_0 = 0$ the prior mean of σ_{22} ($=\sigma_{12}^2 + \sigma^2$) equals $b_0^{-1} + c_0/(v_0 - 2)$. Given that the variance of the error term $e_{1,it}$ in the probit Eq. (1) is fixed at 1, to obtain a balanced variance–covariance matrix Σ, we need to choose the prior parameters b_0,v_0,c_0 in a way that the resulting prior mean of σ_{22} is around 1, albeit with a large variance. Second, the key for the choice of prior parameters b_0,v_0,c_0 is to allocate correctly the variation in $\sigma_{12}^2 + \sigma^2$ ($=\sigma_{22}$) to the two components of the sum. That is, we need to have comparable variability for both $\sigma_{12}^2$and σ^2. Consequently, we choose the following set of prior parameter values to report our final estimation results,

$$\delta_0 = 0_p, \quad \Psi_0^{-1} = 100 \cdot I_p, \quad r_0 = 0, \quad b_0 = 1, \quad v_0 = 4, \quad c_0 = 2,$$

where p ($=k_1 + 1 + k_2$) is the dimension of the regression parameter δ, and I_p denotes an identity matrix of rank p. The prior distribution characterized by this set of values is reasonably flat on δ, centered at a vector of zeros, and the mean for the variance–covariancematrix, Σ, is close to an identity matrix.[7]

We follow the method developed in Li (1998) to conduct a Bayesian analysis of our empirical model in Eq. (9). The Bayesian techniques involved are data augmentation and the Gibbs sampler. Data augmentation is a scheme to argument the observed discrete data, such as the binary choice of dual traders' own account trading decision I, by the unobservable continuous data, such as dual traders' latent incremental utility I^*, in order to simplify the calculation of the likelihood/posterior (see Tanner and Wong, 1987). Gibbs sampling is a simulation tool for obtaining marginal distributions from a non-normalized joint density (Casella and George, 1992; Gelfand and Smith, 1990). Both techniques are special cases of the Markov chain Monte Carlo (MCMC) approach (see Chib and Greenberg, 1996 for a survey).[8]

In particular, the Bayesian estimation proceeds as follows.

(1) Conditional on I, π, Z, δ, σ_{12}, σ^2,

$$I^* \sim \mathrm{CN}(\mu_{1|2}, \sigma_{1|2}), \quad \mu_{1|2} = Z_1\delta_1 + \frac{\sigma_{12}}{\sigma_{12}^2 + \sigma^2}(\pi - Z_2\delta_2),$$

$$\sigma_{1|2} = 1 - \frac{\sigma_{12}^2}{\sigma_{12}^2 + \sigma^2}, \tag{11}$$

where CN denotes the censored normal distribution, and I^* is censored to be either above or below zero depending on the value of the binary variable I.

[7] To ensure that our results are not driven by the particular set of values chosen for the prior distribution, we also experiment with other sets of values for b_0,v_0,c_0. For instance, b_0 varies from 0.1 to 10, v_0 varies from 2 to 10, and c_0 varies from 0.5 to 4. Overall, our posterior estimates and the findings of this paper are robust to different choices of the prior parameters. These results are available upon request.

[8] Two recent market microstructure papers using the Bayesian approach are Hasbrouck (2001) and Ball and Chordia (in press).

(2) Conditional on Y^*, Z, σ_{12}, σ^2,

$$\delta \sim \mathrm{MVN}(\tilde{\delta}, \tilde{\Psi}^{-1}), \quad \tilde{\Psi} = Z'(\boldsymbol{\Sigma}^{-1} \otimes I_n)Z + \Psi_0,$$
$$\tilde{\delta} = \tilde{\Psi}^{-1}[Z'(\boldsymbol{\Sigma}^{-1} \otimes I_n)Y^* + \Psi_0\delta_0]. \tag{12}$$

(3) Conditional on Y^*, Z, δ, σ^2, U=(e_1', e_2')$'$ being known,

$$\sigma_{12} \sim N(\tilde{r}, \tilde{b}^{-1}), \quad \tilde{b} = e_1'e_1\sigma^{-2} + b_0, \quad \tilde{r} = \tilde{b}^{-1}[e_2'e_1\sigma^{-2} + b_0 r_0]. \tag{13}$$

(4) Conditional on Y^*, Z, δ, σ_{12}, U=(e_1', e_2')$'$ being known,

$$\sigma^{-2} \sim G\left(\frac{\tilde{v}}{2}, \left(\frac{\tilde{c}}{2}\right)^{-1}\right), \quad \tilde{v} = n + v_0,$$
$$\tilde{c} = (e_2 - e_1\sigma_{12})'\,(e_2 - e_1\sigma_{12}) + c_0. \tag{14}$$

These four full conditionals, including one data augmentation step in Eq. (11), complete the MCMC algorithm. Some intuition of these four steps is offered as follows. In Step 1 (Eq. (11)), we augment the observed discrete data I with the unobservable continuous data I^* (i.e., the incremental utility of dual trader i associated with his 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. In 2 Steps 3 Steps 4 (Eqs. (12)–(14)), conditional on the observed and augmented data, approximate posteriors for the model parameters may be obtained using Gibbs sampling. We iterate between the data augmentation and the Gibbs sampler steps, and our Bayesian estimates of the model parameters δ,σ_{12},σ^2 are obtained as sample averages of these Gibbs draws.

3. Data and explanatory variables

3.1. The data

Our data consist of audit trail transaction records of eight futures contracts traded at the CME during the first 6 months of 1992 and are also used in Chakravarty and Li (2001, in press). The contracts are live cattle, hogs, pork bellies, feeder cattle, lumber, Canadian dollars, T-bills, and S&P 400. The two million plus transaction records provide a detailed look at the complete trading history of all floor traders in these eight 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 audit trail data record each transaction twice, once for each party to a trade. An exchange algorithm, called the computerized trade reconstruction, 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-min time intervals.

In addition to trade time, the audit trail records provide price, quantity, specifics of the contract, and the trader's identification. Unique to this data, each record also specifies the trade direction and a classification of the customer types on each side of a trade. There are four customer type indicators (CTI), labeled 1 through 4, we focus on the market making trades for personal account (CTI 1) and trades of outside customers (CTI 4). Our definitions of a dual trading day and dual traders follow Locke et al. (1999) and Chakravarty and Li (2001, in press). In particular, we calculate a trading ratio d as the proportion of a floor trader's personal trading (CTI 1) volume over the sum of his personal (CTI 1) and his customers' (CTI 4) trading volumes for each day he is active. For each floor trader, a trading day is a local[9] 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]. The criterion for a specific floor trader to be included in our sample as an active dual trader is that the number of his dual trading days exceeds 50, out of a maximum of 126 trading days during the first 6 months of 1992. With this filter, we obtain a total of 101 active dual traders in our sample across the eight futures contracts. These 101 traders account for well over half the total volume in our original data. Other details of the data are provided in Chakravarty and Li (2001).

3.2. The explanatory variables

The dependent variable which captures a dual trader's own account trading decision in Eq. (1) is *trade dummy*, I, which equals 1 if the dual trader trades on own account in time interval t, and 0 otherwise. The dependent variable which captures a dual trader's own account trading profit in Eq. (2) is *profit*, π, computed using Eq. (3).

Our choice of a parsimonious set of exogenous variables, determining the trading decision of dual traders and their personal trading profit, is based on the existing literature.[10] The set of explanatory variables can be broadly classified into variables capturing inventory effects, liquidity, and information inherent in the order flow. Thus, *inventory* is defined as an dual trader's own account buy trades minus his own account sell trades, cumulated from the beginning of a trading day to time interval t, assuming that a dual trader only has full control of his own account trades. *Customer netbuy*, our proxy for liquidity demand by the customers of dual traders, is defined as the difference between a dual trader's customer buy volume and his customer sell volume in time interval t. The information-related variables are captured through inclusion, in the regression model, of a dual trader's customer netbuy during time intervals $t-3$ up to $t-1$, NLAG1–NLAG3, and those in lead periods $t+1$ to $t+3$, NLEAD1–NLEAD3. The lagged (lead) variables should capture the case where a dual trader may trade personally after (before) executing his customers' orders.

In sum, the variables explaining a dual trader's own account trading decision, in Eq. (1), are inventory, customer netbuy, NLAG1–NLAG3, and NLEAD1–NLEAD3. The

[9] Locals are a group of futures floor traders who supply liquidity and rarely hold open positions overnight. Because of their liquidity-providing role, they are also known as market makers (Manaster and Mann, 1996).

[10] See, for example, Walsh and Dinehart (1991), Fishman and Longstaff (1992), Leuthold et al. (1994), Smith and Whaley (1994), Chang and Locke (1996), Manaster and Mann (1996), Ferguson and Mann (2001), and Chakravarty and Li (2001, in press).

corresponding variables explaining the dual trader's own account trading profit, in Eq. (2), are trade dummy, NLAG1–NLAG3, and NLEAD1–NLEAD3. Eqs. (1) and (2) are estimated for the 101 active dual traders in our sample.

4. Results

4.1. Dual trader informativeness

There are 101 sets of coefficient estimates, one for each dual trader in our sample. We present, in Tables 1 and 2, the numbers of positive and negative coefficients, as well as the numbers of positive coefficients that are two standard deviations above zero, and the numbers of negative coefficients that are two standard deviations below zero, respectively.

From Table 1, we find that dual traders are more likely to trade on own account when their inventory level is away from zero. This is shown by the either positive or negative coefficients on inventory. There is also sporadic evidence to suggest that dual traders either trade before or after executing their customers' orders, a result consistent with Chakravarty and Li (in press).

From Table 2, we find that while there is some evidence to suggest that dual traders earn positive profit through own account trading—as illustrated by the sign of the coefficient on trade dummy—the evidence is weak at best. Moreover, there is similar weak evidence to suggest that dual traders in our sample possess significant private information that bring them abnormal trading profits, as shown by the estimate of correlation coefficient ρ_{12} $(=\sigma_{12}/\sqrt{\sigma_{22}})$.

The results for the median dual trader in each of the eight contracts are provided in Table 3, to provide a sense of the magnitude of the estimated regression coefficients for a typical trader. For a given contract, the median dual trader is a trader whose number of dual trading days is closest to the median value of dual trading days among 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. Table 3 reports the posterior means of the coefficients, with the corresponding posterior standard deviations in parentheses. The Bayes factors in Table 3, Panel C indicate that for each median dual trader, the data strongly favor a model with a zero covariance term (except for the T-bill trader).[11] This result is consistent with our findings on the correlation coefficient ρ_{12} $(=\sigma_{12}/\sqrt{\sigma_{22}})$ (also shown in Table 3, Panel C) that the posterior estimates of the correlation coefficient are all close to zero with large standard deviations, and implies that we could simplify our model to the single-equation model where each of Eqs. (1) and (2) is estimated separately. Economically, these results imply that dual traders do not possess private information that leads to abnormal trading profits.

[11] We also conduct various sensitivity analyses to ensure that the peculiarities of sample selection and/or the estimation procedure do not drive our results. In all cases, our main conclusions appear robust to the various sample selection rules and prior specifications.

Table 1
Bayesian estimates of the dual trader's own account trading equation

	Intercept		Inventory		Customer netbuy		NLAG1		NLAG2		NLAG3		NLEAD1		NLEAD2		NLEAD3	
	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–
Live cattle	16 (14)	24 (22)	19 (8)	21 (8)	17 (1)	23 (3)	16 (0)	24 (1)	18 (0)	22 (2)	17 (0)	23 (1)	23 (0)	17 (2)	22 (0)	18 (3)	20 (1)	20 (0)
Hogs	6 (6)	9 (8)	8 (2)	7 (2)	8 (1)	7 (0)	11 (2)	4 (0)	8 (1)	7 (0)	9 (1)	6 (1)	5 (0)	10 (0)	8 (2)	7 (0)	10 (0)	5 (0)
Pork bellies	8 (8)	10 (7)	7 (3)	11 (7)	7 (1)	11 (2)	7 (0)	11 (1)	9 (1)	9 (0)	10 (0)	8 (0)	6 (0)	12 (0)	9 (0)	9 (0)	5 (0)	13 (1)
Feeder cattle	1 (1)	3 (3)	4 (0)	0 (0)	0 (0)	4 (0)	1 (0)	3 (0)	2 (0)	2 (0)	2 (0)	2 (0)	2 (0)	2 (0)	1 (0)	3 (1)	2 (0)	2 (0)
Lumber	2 (2)	8 (7)	5 (2)	5 (1)	7 (1)	3 (0)	5 (0)	5 (1)	8 (0)	2 (0)	3 (1)	7 (0)	7 (0)	3 (0)	6 (0)	4 (1)	6 (0)	4 (0)
Canadian dollars	1 (1)	6 (5)	3 (2)	4 (3)	4 (0)	3 (0)	4 (0)	3 (0)	1 (0)	6 (0)	1 (0)	6 (0)	3 (0)	4 (0)	3 (0)	4 (2)	2 (0)	5 (0)
T-bills	3 (3)	3 (3)	2 (1)	4 (2)	4 (1)	2 (0)	5 (0)	1 (0)	3 (0)	3 (1)	3 (1)	3 (1)	3 (0)	3 (0)	4 (0)	2 (0)	2 (0)	4 (0)
S&P 400	0 (0)	1 (1)	0 (0)	1 (1)	0 (0)	1 (0)	1 (0)	0 (0)	1 (0)	0 (0)	0 (0)	1 (0)	1 (0)	0 (0)	1 (0)	0 (0)	1 (1)	0 (0)

This table provides an overview of the Bayesian estimates of Eq. (1) across our sample of 101 dual traders in eight futures contracts. For each futures contract, the first row gives the numbers of positive (+ve) and negative (– ve) coefficient estimates; the second row gives the numbers of positive coefficient estimates that are two standard deviations above zero, and the numbers of negative coefficient estimates that are two standard deviations below zero, respectively. The dependent variable in Eq. (1) is own account trade dummy (I), which equals 1 if dual trader i trades on his own account in time interval t, 0 otherwise. Inventory is the cumulative difference between a dual trader's own account buy trades and his own account sell trades, from the beginning of a trading day to time interval $t-1$. Customer netbuy is the difference between a dual trader's customer buy volume and his customer sell volume in time interval t and is the liquidity proxy. NLAG1–NLAG3 are a dual trader's customer netbuy in time intervals $t-1$ up to $t-3$; and NLEAD1–NLEAD3 are a dual trader's customer netbuy in time intervals $t+1$ up to $t+3$. These lead and lag variables are the information proxies.

Table 2
Bayesian estimates of the dual trader's profit equation

	Intercept		Trade dummy		NLAG1		NLAG2		NLAG3		NLEAD1		NLEAD2		NLEAD3		ρ_{12}	
	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–	+	–
Live cattle	25 (11)	15 (9)	18 (9)	22 (11)	14 (3)	26 (2)	18 (3)	22 (1)	19 (0)	21 (2)	21 (0)	19 (2)	15 (0)	25 (2)	20 (0)	20 (0)	25 (12)	15 (9)
Hogs	12 (6)	3 (2)	5 (3)	10 (6)	11 (0)	4 (0)	9 (0)	6 (1)	7 (1)	8 (0)	10 (0)	5 (0)	8 (1)	7 (1)	8 (0)	7 (0)	10 (6)	5 (2)
Pork bellies	7 (5)	11 (6)	13 (6)	5 (4)	11 (1)	7 (0)	9 (0)	9 (1)	9 (0)	9 (1)	11 (1)	7 (0)	10 (0)	8 (1)	6 (1)	12 (0)	10 (5)	8 (6)
Feeder cattle	2 (1)	2 (0)	2 (0)	2 (1)	1 (1)	3 (0)	1 (0)	3 (0)	1 (0)	3 (0)	2 (0)	2 (0)	2 (0)	2 (1)	1 (0)	3 (1)	3 (1)	1 (0)
Lumber	5 (1)	5 (1)	9 (2)	1 (1)	5 (0)	5 (1)	6 (1)	4 (0)	5 (0)	5 (3)	4 (0)	6 (0)	4 (0)	6 (0)	4 (0)	6 (0)	5 (1)	5 (1)
Canadian dollars	4 (3)	3 (0)	3 (1)	4 (3)	4 (1)	3 (0)	3 (0)	4 (0)	4 (0)	3 (1)	5 (0)	2 (0)	5 (1)	2 (0)	3 (0)	4 (1)	4 (3)	3 (1)
T-bills	2 (1)	4 (3)	4 (3)	2 (1)	1 (0)	5 (1)	4 (1)	2 (0)	2 (0)	4 (1)	4 (0)	2 (0)	2 (0)	4 (0)	3 (0)	3 (0)	2 (1)	4 (3)
S&P 400	1 (0)	0 (0)	1 (0)	0 (0)	0 (0)	1 (0)	1 (0)	0 (0)	0 (0)	1 (0)	1 (0)	0 (0)	0 (0)	1 (0)	0 (0)	1 (0)	1 (0)	0 (0)

This table provides an overview of the Bayesian estimates of Eq. (2) across our sample of 101 dual traders in eight futures contracts. For each futures contract, the first row gives the numbers of positive (+ve) and negative (– ve) coefficient estimates; the second row gives the numbers of positive coefficient estimates that are two standard deviations above zero, and the numbers of negative coefficient estimates that are two standard deviations below zero, respectively. The dependent variable in Eq. (2) is own account trading profit (π). Trade dummy equals 1 if dual trader i trades on his own account in time interval t, 0 otherwise. NLAG1–NLAG3 are a dual trader's customer netbuy in time intervals $t-1$ up to $t-3$; and NLEAD1–NLEAD3 are a dual trader's customer netbuy in time intervals $t+1$ up to $t+3$. These lead and lag variables are the information proxies.

4.2. Dual trader heterogeneity

In this section, we investigate if dual traders are homogeneous or whether they have distinct observable characteristics (i.e., heterogeneous). Our investigation is motivated by the theoretical literature on informed trading that treats (multiple) informed traders as homogeneous (see, for example, Holden and Subrahmanyam, 1992) and uninformed traders collectively as nonstrategic traders suffering losses from trading against the informed traders (see O'Hara, 1995). In addition, Manaster and Mann (1996) report that locals in the futures markets appear to have varying inventory adjustment rates and that, over time, traders, long (short) in futures contracts, appear to display relatively greater (a relative lack of) skills at selling (buying) and a relative lack of (relatively greater) skill at buying (selling). The authors argue that their evidence is inconsistent with the assumption of homogeneous information and homogeneous risk aversion among dual traders. Locke et al. (1999), in fact, suggest that traders could be heterogeneous with respect to trading skills, and that the aggregate measures of trading costs, such as average bid–ask spreads, could be misleading. Consistent with the above, they develop a theoretical model based on dealer heterogeneity.

Before embarking on a formal test of dual trader heterogeneity, we see, from Table 3, that the coefficient estimates vary significantly across the eight median traders in our sample—an indication of possible differences across traders. To rigorously test for heterogeneity, however, we obtain the marginal likelihood of the unrestricted model based on the 101 individual dual trader models of Eqs. (1) and (2), and the marginal likelihood of the restricted model based on pooling the time series observations from all 101 traders and estimating Eqs. (1) and (2). The resulting Bayes factor far exceeds 10, indicating that there is significant heterogeneity among the dual traders in our sample.[12]

Our findings have important implications for theoretical research that tends to treat all traders, especially uninformed liquidity traders, collectively as automatons.[13] That is, the extant theoretical research includes uninformed traders simply to obtain equilibria where an informed trader will trade and uses the resultant equilibria to compute comparative statics related to market liquidity and informativeness of prices. Our evidence on trader heterogeneity indicates that this approach may be an over-simplification of reality.

In sum, we do not find strong evidence to suggest that dual traders possess private information that leads to their making abnormal trading profits through personal trading. There is weak evidence, at best, to support a direct and positive connection between own account trading by dual traders and their profits. We also provide direct evidence of dual trader heterogeneity with respect to their trade-related characteristics.

[12] We thank an anonymous referee for suggesting this approach to test for heterogeneity among the dual traders in our sample. One caveat to our finding of trader heterogeneity is that there are many coefficients which are imprecisely estimated (high posterior standard deviations), which could be set equal to 0. However, it suffices that a few of these coefficients are very precisely estimated to provide the strong evidence of heterogeneity.

[13] Thus, uninformed traders are provided with no objective functions and are included solely to provide valuable cover for the informed strategic traders (see, for example, Kyle, 1985; Glosten and Milgrom, 1985; Easley and O'Hara, 1987).

Table 3
Bayesian estimates for the median dual trader under the simultaneous equations model

	Live cattle	Hogs	Pork bellies	Feeder cattle	Lumber	Canadian dollars	T-bills	S&P 400
Panel A. Dual traders' own account trading decision								
Intercept	– 0.4804	– 0.4030	– 0.6845	– 0.6083	– 0.5909	– 0.2811	– 0.7558	– 0.5752
	(0.0384)	(0.0320)	(0.0353)	(0.0353)	(0.0441)	(0.0223)	(0.0661)	(0.0625)
Inventory	0.8278	0.3950	0.3675	0.7554	– 5.4405	– 0.5842	1.1081	– 9.8667
	(0.2225)	(0.2391)	(0.7422)	(0.6721)	(2.7690)	(0.2230)	(0.3681)	(3.6160)
Customer netbuy	0.0887	0.0081	0.1136	– 0.4805	– 0.5303	0.0431	– 0.3538	– 1.2625
	(0.3869)	(0.3543)	(0.3105)	(0.3307)	(1.2290)	(0.0970)	(0.2108)	(1.4998)
NLAG 1	– 0.0476	0.2775	– 0.5762	0.2030	0.2362	0.0535	0.0528	1.2885
	(0.3767)	(0.3635)	(0.3136)	(0.3117)	(1.1310)	(0.0960)	(0.2192)	(1.3815)
NLAG 2	– 0.3336	– 0.3932	– 0.0337	0.1385	– 1.8683	– 0.0985	0.0166	0.7839
	(0.3867)	(0.3412)	(0.2858)	(0.2994)	(1.2375)	(0.0899)	(0.2159)	(1.2350)
NLAG 3	– 0.4880	– 0.4925	– 0.1326	– 0.0142	0.9347	– 0.0234	0.0657	– 0.8927
	(0.3307)	(0.2946)	(0.2191)	(0.2536)	(0.9621)	(0.0778)	(0.1967)	(1.0892)
NLEAD 1	– 0.2413	– 0.0011	– 0.4073	– 0.0764	0.4078	0.1832	– 0.2969	2.4510
	(0.3965)	(0.3597)	(0.3062)	(0.3226)	(1.2167)	(0.0947)	(0.2125)	(1.3897)
NLEAD 2	0.0245	– 0.0988	0.2109	– 0.6562	– 2.5140	– 0.0487	0.0577	1.1184
	(0.3667)	(0.3672)	(0.2671)	(0.3133)	(1.2133)	(0.0885)	(0.2067)	(1.3112)
NLEAD 3	– 0.3548	0.0493	– 0.0052	0.3440	– 2.1725	– 0.1615	– 0.2936	2.9798
	(0.3787)	(0.3295)	(0.2401)	(0.3163)	(1.1630)	(0.0833)	(0.1974)	(1.4151)
Panel B. Dual traders' trading profit								
Intercept	– 0.0025	0.0006	– 0.0027	0.0001	– 0.0012	0.0003	0.0330	0.0065
	(0.0236)	(0.0232)	(0.0126)	(0.0082)	(0.0194)	(0.0213)	(0.0857)	(0.0249)
Trade dummy	0.0443	– 0.0122	0.0411	0.0214	0.0196	0.0110	– 0.0083	0.0324
	(0.0608)	(0.0595)	(0.0348)	(0.0213)	(0.0551)	(0.0517)	(0.2565)	(0.0676)

NLAG 1	0.0184	− 0.0768	0.1392	− 0.0387	0.0115	− 0.0292	− 0.1408	− 0.4504
	(0.1282)	(0.1143)	(0.0816)	(0.0492)	(0.3138)	(0.0300)	(0.1861)	(0.3304)
NLAG 2	− 0.0231	− 0.0225	0.0914	− 0.0436	− 0.1893	0.0001	0.1828	0.2449
	(0.1273)	(0.1148)	(0.0750)	(0.0491)	(0.3311)	(0.0290)	(0.1973)	(0.2879)
NLAG 3	0.0044	0.3008	− 0.1495	− 0.0082	0.3086	− 0.0139	− 0.1102	− 0.1709
	(0.1148)	(0.0957)	(0.0566)	(0.0407)	(0.2655)	(0.0257)	(0.1778)	(0.2446)
NLEAD 1	− 0.1726	− 0.0247	0.0646	0.0096	0.0072	0.0461	0.0625	0.3938
	(0.1345)	(0.1172)	(0.0809)	(0.0528)	(0.3181)	(0.0306)	(0.1866)	(0.3289)
NLEAD 2	− 0.0604	− 0.0909	0.0142	0.0672	− 0.3649	0.0432	− 0.0291	− 0.2025
	(0.1230)	(0.1210)	(0.0729)	(0.0517)	(0.3110)	(0.0279)	(0.1863)	(0.3183)
NLEAD 3	0.0109	− 0.0468	0.0080	0.0188	− 0.0025	− 0.0307	0.2563	− 0.5367
	(0.1197)	(0.1110)	(0.0625)	(0.0516)	(0.3075)	(0.0266)	(0.1815)	(0.3314)
Panel C. The variance–covariance matrix $\boldsymbol{\Sigma}$								
ρ_{12} $(=\sqrt{\sigma_{12}}/\sqrt{\sigma_{22}})$	− 0.0082	0.0073	0.0040	0.0027	− 0.0157	0.0015	0.0855	0.0357
	(0.0741)	(0.0777)	(0.0455)	(0.0504)	(0.0800)	(0.0740)	(0.0979)	(0.1097)
σ_{22}	0.2031	0.1869	0.1383	0.0480	0.1295	0.1719	1.6417	0.1039
	(0.0084)	(0.0067)	(0.0044)	(0.0014)	(0.0061)	(0.0045)	(0.1089)	(0.0069)
BF_{01}	29.17	31.57	58.70	93.52	34.90	36.56	5.68	27.30
	(0.6227)	(1.2939)	(1.2530)	(1.2327)	(0.7115)	(1.8027)	(0.2110)	(0.8720)
Sample size	1209	1655	2068	2271	940	3179	481	484

This table reports the posterior estimates for the median dual trader in each of our eight futures contracts with the corresponding posterior standard deviations in parentheses. The dependent variable in Eq. (1) is own account trade dummy (I), which equals 1 if dual trader i trades on his own account in time interval t, 0 otherwise. Inventory is the cumulative difference between a dual trader's own account buy trades and his own account sell trades, from the beginning of a trading day to time interval $t-1$. Customer netbuy is the difference between a dual trader's customer buy volume and his customer sell volume in time interval t and is the liquidity proxy. NLAG1–NLAG3 are a dual trader's customer netbuy in time intervals $t-1$ up to $t-3$; and NLEAD1–NLEAD3 are a dual trader's customer netbuy in time intervals $t+1$ up to $t+3$. These lead and lag variables are the information proxies. The dependent variable in Eq. (2) is own account trading profit (π). Trade dummy equals 1 if dual trader i trades on his own account in time interval t, 0 otherwise. BF_{01} gives the Bayes factor comparing the model with a zero covariance term (the null H_0) to the model where the variance–covariance matrix is unconstrained (the alternative H_1).

5. Conclusion

Using detailed audit trail transaction data compiled by the CFTC and a simultaneous equations modeling framework, we investigate if dual traders are informed traders. Our study goes significantly beyond existing research. In particular, we recognize and account for the potential endogeneity between the own account trading decision of a dual trader and his trading profit. Our methodology also allows us to isolate the abnormal trading profit associated with a dual trader's personal trades and to compute its correlation with the unobserved private information (if any) of the dual trader.

The estimation of our simultaneous equations model is performed on *each* of the 101 dual traders in our sample, using the MCMC method. Most significantly, we find that dual traders do not possess any significant private information. We also uncover strong evidence that dual traders are heterogeneous in terms of trade-related characteristics. Overall, our results have important policy implications in that they cast doubt on the notion that dual traders are informed traders. Rather, dual traders appear to be observationally distinct and uninformed.

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References

Ball, C.A., Chordia, T., 2002. True spreads and equilibrium prices. Journal of Finance 56, 1801–1836.

Barclay, M.J., Warner, J., 1993. Stealth trading and volatility: which trades move prices? Journal of Financial Economics 34, 281–305.

Casella, G., George, E., 1992. Explaining the Gibbs sampler. American Statistician 46, 167–174.

Chakravarty, S., 1994. Should actively traded futures contracts come under the dual-trading ban? Journal of Futures Markets 6, 661–684.

Chakravarty, S., 2001. Stealth trading: which traders' trades move stock prices? Journal of Financial Economics 61, 289–307.

Chakravarty, S., Li, K., 2001. Dual trading in futures markets: a closer look. Proceedings of the Chicago Board of Trade 13th Annual European Futures Research Symposium. Chicago Board of Trade, http://www.cbot.com/cbot/www/cont_detail/0,1493,14+61+276+1855,00.html.

Chakravarty, S., Li, K., 2002. An examination of own account trading by dual traders in futures markets. Journal of Financial Economics (in press).

Chang, E.C., Locke, P., 1996. The performance and market impact of dual trading: CME Rule 552. Journal of Financial Intermediation 5, 23–48.

Chang, E.C., Locke, P., Mann, S., 1994. The effect of CME Rule 552 on dual traders. Journal of Futures Markets 14, 493–510.

Chib, S., Greenberg, E., 1996. Markov chain Monte Carlo simulation methods in Econometrics. Econometric Theory 12, 409–431.

Easley, D., O'Hara, M., 1987. Price, trade size, and information in securities markets. Journal of Financial Economics 19, 69–90.

Ferguson, M., Mann, S., 2001. Execution costs and their intraday variation in futures markets. Journal of Business 74, 125–160.

Fishman, M.J., Longstaff, F., 1992. Dual trading in futures markets. Journal of Finance 47, 643–671.

Gelfand, A.E., Smith, A., 1990. Sampling-based approaches to calculating marginal densities. Journal of the American Statistical Association 85, 398–409.

Glosten, L.R., Milgrom, P.R., 1985. Bid, ask, and transaction prices in a specialist market with heterogeneously informed traders. Journal of Financial Economics 13, 71–100.

Grossman, S.J., 1989. An economic analysis of dual trading, Rodney L. White Center for Financial Research Paper 33–89, The Wharton School, University of Pennsylvania.

Hasbrouck, J., 2001. Liquidity in the futures pits: inferring market dynamics from incomplete data, working paper, New York University.

Holden, C.W., Subrahmanyam, A., 1992. Long-lived private information and imperfect competition. Journal of Finance 47, 247–270.

Kass, R.E., Raftery, A.E., 1995. Bayes factors. Journal of the American Statistical Association 90, 773–795.

Kyle, A.S., 1985. Continuous auctions and insider trading. Econometrica 53, 1315–1335.

Lee, C.M.C., Mucklow, B., Ready, M.J., 1993. Spread, depths, and the impact of earnings information: an intraday analysis. Review of Financial Studies 6, 345–374.

Leuthold, R.M., Garcia, P., Lu, R., 1994. The returns and forecasting ability of large traders in the frozen pork bellies futures market. Journal of Business 67, 459–473.

Li, K., 1998. Bayesian inference in a simultaneous equations model with limited dependent variables. Journal of Econometrics 85, 387–400.

Li, K., 1999. Exchange rate target zone models: a Bayesian evaluation. Journal of Applied Econometrics 14, 461–490.

Locke, P.R., Sarkar, A., Wu, L., 1999. Market liquidity and trader welfare in multiple dealer markets: evidence from dual trading restrictions. Journal of Financial and Quantitative Analysis 34, 57–88.

Manaster, S., Mann, S.C., 1996. Life in the pits: competitive market making and inventory control. Review of Financial Studies 9, 953–975.

O'Hara, M., 1995. Market Microstructure. Blackwell, Cambridge, MA.

Poirier, D.J., 1995. Intermediate Statistics and Econometrics: A Comparative Approach. MIT Press, Cambridge, MA.

Roell, A., 1990. Dual capacity trading and the quality of the market. Journal of Financial Intermediation 1, 105–124.

Sarkar, A., 1995. Dual trading: winners, losers and market impact. Journal of Financial Intermediation 4, 77–93.

Smith, T., Whaley, R.E., 1994. Assessing the costs of regulation: the case of dual trading. Journal of Law and Economics 37, 329–336.

Tanner, M.A., Wong, W.H., 1987. The calculation of posterior distributions by data augmentation. Journal of the American Statistical Association 82, 528–540.

Verdinelli, I., Wasserman, L., 1995. Computing Bayes factors using a generalization of the Savage–Dickey density ratio. Journal of the American Statistical Association 90, 614–618.

Walsh, M.J., Dinehart, S.J., 1991. Dual trading and futures market liquidity: an analysis of three Chicago Board of Trade contract markets. Journal of Futures Markets 11, 519–537.

Zellner, A., 1971. An Introduction to Bayesian Inference in Econometrics. Wiley, New York.