Market-Making Behavior in Futures Markets

by

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Practitioner's Abstract

This paper examines voluntary market-making behavior, namely scalping, in futures markets. Specifically, this paper studies what factors determine scalpers' entry and exit, and how scalping affects market liquidity and price volatility. The data used for the analysis are time-stamped electronic transaction data marked with traders' identities from the Dalian Futures Exchanges in China. The contributions of this paper are: (1) to give detailed analysis of scalping behavior and its impact on market liquidity; (2) to develop new econometric tools for analyzing time-series count data; (3) to propose a new measure of liquidity.

Keywords: Liquidity, Market-Making, Futures Markets, Scalpers, Autoregressive Conditional Intensity (ACI), Volatility.

I. Introduction

This paper is a study of voluntary market-making behavior, scalping, in futures markets. Specifically, this paper examines why scalping arises in futures markets, what factors determine scalpers' entry and exit, and how scalping affects market liquidity and price volatility. In futures exchanges, a scalper is usually identified as someone who makes frequent purchases and sales during the day, yet ending the day without any outstanding position. Collectively, scalpers voluntarily approximate the role of market-makers, providing the liquidity so essential to futures markets. We believe that the study of scalpers is of significant importance because the existence of scalpers in futures markets provides an ideal opportunity for us to study spontaneously emerged market-making behavior and its effects on market performance in a competitive continuous auction environment, free of any exchange regulations on market-making. In particular, we focus on the liquidity aspect of market performance.

The earliest work on scalpers is by Working (1954, 1967, 1977), who studied two months of trading records for "Mr. C", a leading floor trader on the New York Cotton Exchange in 1952. Working presented descriptive statistics and discussions on scalping behavior in his papers, and in particular suggested that scalping contributes to market "fluidity", and that scalpers "derive income from hedgers through temporarily absorbing hedging orders that are not immediately absorbed otherwise". Working (1967) also touched on the issue that scalping profit is positively related to trading frequency and negatively related to trade size. Silber (1984) analyzed six weeks of trading records from "Mr. X", a "representative scalper" on the New York Futures Exchange during 1982-1983, and derived similar conclusions regarding scalping strategy and profit. By studying the Computerized Trade Reconstruction (CTR) records of twelve active futures from the Chicago Mercantile Exchange (CME) from July through September 1990, Kuserk and Locke (1993) identified scalpers for each contract, and find that scalping revenue varies across commodities, and that scalpers tend to specialize in a particular commodity.

Both Working (1967, 1977) and Silber (1984) base their discussion on only one or two scalpers, and the CTR data analyzed by Kuserk and Locke (1993) are complied from paper records at the end of a trading day and time stamped accurate only to a 15-minute bracket. Thanks to the implementation of electronic trading systems, we have obtained all the transaction records of soybean futures from the Dalian Futures Exchange in China for the period June through December 1999 and April 2000. The data are time stamped to the second and each transaction record is marked with the trader's identity. This code for the trades reveals not just the broker but also the individual customer. While previous studies of scalpers are mostly descriptive, this paper presents formal econometric tests of three hypotheses: 1) scalpers are attracted to the market by liquidity; 2) scalpers' trading contributes to the liquidity of the market; 3) scalpers' trading has a negative effect on price volatility.

Liquidity is an important concept of market performance. The greater the liquidity, the smaller the price effects of trades, and thus the smaller the trading cost and the greater the ability of traders to hedge their price risks. There are two conventional measurements of liquidity: one method is to use bid-ask spreads as a proxy, the smaller the bid-ask spread, the more liquid the market; the other approach, proposed by Kyle (1984), is to regress price changes on order flows. The coefficient on order flow measures the price impact of trades, consequently, the smaller this coefficient, the greater the liquidity. This paper reexamines the concept of liquidity and suggests a new statistical measurement for it.

At the short interval over which scalping matters, the number of scalpers and the number of scalper's trades are both small integers. A new class of models, termed autoregressive conditional intensity (ACI) processes, allows one to generate dynamic forecasts of a time-series count model. We focus on how liquidity and scalping profit affect the number of scalpers that participate in trading in a fixed time interval. Using an ACI model, we specify a distribution for the count variable, which is the number of scalpers in this case, and the mean of the count variable conditioning on exogenous and predetermined variables, such as the past information on liquidity, profit, and the number of scalpers participating in trading. In futures markets, there are in general several contracts of the same commodity with different maturity dates, and it is common to find two or more contracts that are actively traded at the same time. To take into account this simultaneity effect, a bivariate ACI model is introduced to study how liquidity and profit affect scalpers' participation across two of the most active contracts in the Dalian Futures Exchange during our sample period. The model is estimated by maximizing the likelihood of the joint probability distribution of a bivariate count variable. The results suggest that greater liquidity and larger realized spread encourage scalping in contracts, but discourage scalping across contracts. We also find that both scalpers and non-scalpers contribute to liquidity in the market, but non-scalpers are the source of price volatility.

The organization of this papers is as follow. Section II presents the issues and hypotheses, and discusses the concept of liquidity and proposes a new measurement for it; Section III develops the ACI model and discusses its broader application as a time-series count model. A GARCH model is also specified in this section to study the heterogeneous price effects of trading by scalpers and non-scalpers. Estimation results are reported as well. Section IV concludes the paper.

II. Issues and Hypotheses

The existence of scalpers in futures markets provides an ideal opportunity for studying the effects of self-styled market-making behavior in a competitive continuous auction market. There are several issues we would like to address in this paper. First, why does voluntary market-making behavior, scalping, arise in futures market? What factors determine scalpers' entry and exit? Second, who provides liquidity to the market? Third, does scalping affect the price volatility of the market, and if so, how? The hypotheses corresponding to these questions are,

Hypothesis 1. Liquidity of a market attracts scalpers, and the number of scalpers is also positively related to scalpers' realized spread;

Hypothesis 2. Scalpers' trading increases the liquidity of the market;

Hypothesis 3. Scalpers' trading has a stabilizing effect on price, i.e., scalpers' participation negatively affects price volatility.

The remainder of this session discusses the concept of liquidity and introduces a new measure for it.

Liquidity

Why does scalping arise in futures markets? In any competitive market, be it a financial market, the housing market, or the used cars market, there are urgent buyers and sellers. According to Working (1954, p.4), "in markets where there are *frequent* purchases and sales for whatever the market will bring, some people make a more or less regular business of buying from urgent sellers in order to sell to urgent buyers." As long as there are enough market orders demanding immediate execution, there will be demand and payoff for a matching business in this market. Market-makers on NASDAQ, specialists on NYSE, and scalpers in futures markets can all be considered as providers of this matching service. By buying and selling frequently, scalpers serve the need of urgent buyers and sellers, no matter whether purposefully or unconsciously. If a trader needs to buy immediately, he is likely to pay a higher price to transact now than waiting until later; while a urgent seller would have to accept a lower offer if he is impatient. Such price differences paid by urgent buyers and sellers are costs of immediate execution, or the "price of immediacy" (Demsetz, 1968; Grossman and Miller, 1988); from the perspective of scalpers, they derive their profit by providing this liquidity service to impatient traders.

Whether formal exchanges or informal dealer networks, markets provide liquidity through the provision of the lowest cost trading. From the perspective of a market's users, the costs of trading fall into two broad categories, explicit costs, such as commissions and clearing fees, and implicit costs, such as "execution costs". There are two ways to understand the "execution cost". One way is to consider it as the "cost of immediate transaction", which is the price difference paid by urgent buyers and sellers. If a market-maker or a scalper crosses an urgent "buyer's price" and an urgent "seller's price" at the same time, then the price difference is the market-maker or the scalper's realized *spread*. Lower spreads correspond to lower trading costs, hence a more liquid market. Bid-ask spreads have been widely used as a conventional proxy for liquidity. Strictly speaking, the spread is considered as an appropriate measure of liquidity only if the market maker crosses a trade at a bid and an ask simultaneously (Grossman and Miller, 1988). The drawback of the spread as a measure of liquidity is that if price varies with trade size, the spread for large trades may be larger than the small trade spread, which creates difficulty for comparing the liquidity of different markets (O'Hara, 1995).

Another way to understand "implicit costs" is to consider the "price impact" of trades. If it happens that the price drops sharply immediately after a trader places a market order to sell, or the price rise suddenly after he places a market order to buy, his implicit trading costs are high, perhaps higher than his explicit trading costs, indeed perhaps so high that he ceases trading on that exchange. These trading costs reflect the market's illiquidity. To measure the "price impact" of trades, Kyle (1984) proposed a linear model regressing price changes on order flow, where the parameter on order flow is defined as λ. The λ measures price impact of trade, so the smaller the λ, the more liquid the market. Kyle also suggests that λ is closely related to bid-ask spread.

Despite the simplicity of Kyle's model, liquidity is interpreted only in the context of a linear model. A single statistic for liquidity would provide more flexibility for econometric modeling and testing. Recognizing this need, we introduce here a new measurement of liquidity. A market is said to be liquid if traders are able to make large transactions with minimal impact on price. One can see from this description that there are two dimensions to liquidity, one is volume, the other is price effect. Price effect can be measured by changes in price or price volatility. Incorporating these two factors into one statistic, liquidity can be defined as

$$liquidity = \frac{volume}{\sigma} \tag{1}$$

where σ is the standard deviation of price. This measurement of liquidity represents how much volume it takes to move price by one unit, in this case, one standard deviation. The inverse of this statistic measures the price impact of trading volume, the smaller the price impact, the greater the liquidity. In this paper, we focus on this measurement of liquidity, and study the relationship between scalping and liquidity in the futures market.

In summary, a liquid market provides low-cost trading, which attracts market orders, and as long as there are enough market orders demanding immediate execution, there will be a demand and payoff for scalpers' services. Scalpers' participation in turn works like a catalysis to trades, which increases the ability of the market to absorb large order imbalance in order flow with a minimal impact on price. In this sense, scalpers' trading decreases the trading costs for other traders, and increases the liquidity of the market. The entry and exit of scalping (market-making) business depends on the profit made by scalpers (market-makers), which is positively related to scalping volume and scalpers' (market-makers') realized spread. Notice that a drop in realized spread does not necessarily discourage scalping (market-making) - one may argue that smaller spread is a sign of more liquidity, and a more liquid market attracts higher volume of market orders, which in turn attracts scalping (market-making) business. For example, studies on the impact of recent market reforms on NASDAQ have found that the average number of dealers that make a market in a stock increases from 21 to about 25 despite the decrease in bid-ask spread after the new regulations are implemented (Weston, 2000). This phenomenon can be well explained by the fact that the post-reform NASDAQ, a much more liquid market, attracts more volume, thus more market makers. These discussions rationalize our first two hypotheses.

Price Volatility

Another issue we would like to explore is how scalping affects price volatility. Because price changes are caused by the shocks of order imbalance, if scalpers' trading indeed absorbs part of this shock, one can expect to see a less volatile market with the participation of scalpers. For instance, at one point of time, if buy orders exceed sell orders in size, prices will tend to rise for the short-term. A scalper could step in and offer to sell, and the offer from the scalper with the lowest ask will get executed. In this case, scalping tends to release some pressure of price increasing. Working (1977) noted that there is "price jiggling" in the futures market, i.e., small price changes in one direction immediately followed by a price change in the opposite direction. Working attributes this price pattern to the imbalance of market orders at a point of time. Working (1967) also suggests that scalping tends to restrict the size of price jiggling. Garbade and Silber (1979) also touch on the issue that scalpers' participation in a continuous auction reduces the volatility of transaction prices around the true (temporarily integrated) equilibrium price. Daigler and Wiley (1999) find that clearing members in the futures market who observe the order flow reduce the volatility of their own trades. Thus, our third hypothesis is intended to study the heterogeneous price effects of trading by scalpers and non-scalpers.

III. Empirical Tests and Results

Data

During a visit to the Dalian Futures Exchange in summer 2000, we obtained eight months of transaction records of soybean futures for the period of June 1999 through December 1999, and April 2000. Each transaction record is marked with broker and customer identities, transaction price and volume, a buy or sell indicator, an indicator of opening or closing positions, as well as a time stamp. There are six soybean futures contracts on the Dalian Futures Exchange, namely January, March, May, July, September, and November expirations. A contract expires in its delivery month, and the trading of this contract usually ends around the middle of the delivery month. For example, trading on July 2000 futures contract started mid July 1999, and ended mid July 2000. The trading of a contract gains a lot of momentum usually two months after its first trading date, and remains active for about another two months before the volume declines dramatically, but the trend of the trading activity also depends on the season as well as the trading on the spot market (Figure 1). In the Dalian Futures Exchange, soybeans futures are most active during the period of September through following January, when trading is heavy and price is volatile. The futures prices determined during this period set up the leadership for the rest of the season (Dalian Futures Exchange, 2000).

An analysis of the transaction records reveals several key facts. There are approximately 170 member firms trading in the sample period, and most of these member firms are brokerage firms representing approximately 2500-5000 individual customers, as well as a few member firms, called "locals", who trade for their own accounts (Table 1). By the regulations of the Dalian Futures Exchange, a brokerage firm is prohibited from trading for its own account; and those member firms trading for their own account cannot have brokerage business. For instance, in April 2000, there are 145 members firms in total, 130 of them are brokerage firms, which have 5,122 distinctive customers in all.[1] The remaining 15 are member firms trading only for their own accounts, each of whom has one seat.[2] A member firm can have several seats on the exchange floor, and it can also apply for a distance trading seat, and trade directly off the exchange. Sometimes, one of the member

[1] A customer is not allowed to open accounts with more than one brokerage firm.
[2] The annual fee of a seat is RMB20,000, which is regulated by the exchange.

firm's seats serves only one customer.[3] Among the 130 brokerage firms, one has four seats, eight have three seats, 38 have two seats, and the remaining 83 have one seat (Table 2 &3).

Scalpers

How to identify scalpers among over five thousand customers? Remember that scalpers are those who trade frequently during the day, and who rarely hold any significant overnight positions. There is only one two-and-a-half-hour morning session from 9:00am to 11:30am during a trading day in the Dalian Futures Exchange before April 2000. We define "frequent" as making at least one trade within every 15 minutes on average, which is equivalent to placing at least 10 orders a day. For example, there are 20 trading days in June 1999, if in any day, a customer places at least 10 orders of any contract, and holds an zero inventory at the end of the day, he becomes a candidate for scalper. If he trades with such a pattern for at least six or seven days in this month, he is considered as a scalper. These two selection criteria filter out about 10 scalper candidates each month from June to December 1999. There are some final justifications to these scalper candidates. Some traders are selected by these two criteria, but their trading pattern is characterized by placing many one-side orders at one point of time, and half-an-hour or an hour or so later, they liquidate their positions by placing many opposite-side orders. These traders are considered as day traders, and they are excluded from the scalpers' group. Another justification we make is that a trader has been consistently selected as a scalper for most of time in the sample, but in one month, he trades actively and holds a zero position at the end of day for only four or five days. In this case, he is still considered as a scalper for this month. Starting from April 2000, the Dalian Futures Exchange added an afternoon session from 1:30pm to 3:00pm. The total trading time is four hours. Using the same criteria of trading frequency and the overnight position discussed above, seven traders are classified as scalpers. The number of scalpers over time is reported in Table 1. It is worth pointing out that the three most active scalpers are new entries in April 2000. Due to lack of data for the first three months of the year 2000, one cannot judge when these three scalpers enter the market-making business. Three of the remaining four scalpers have been in the market since June 1999, and they have been identified as scalpers consistently. Scalper's volume accounts for about 6% to13% of the total trading volume of each contract depending on the contract's activity level and its time to maturity (Table 4).

Variables

We aggregate the transaction data at five-minute intervals, and there are 30 five-minute intervals between 9:00am and 11:30am. Those transactions recorded as having happened between 11:30am and 11:31am, are aggregated into the 31st five-minute interval. A scalper usually closes his position within several minutes. A five-minute interval is long enough to measure some relevant statistics, and short enough for us to observe the microstructure of the trading. Within each five-minute interval, volume is measured as the total sum of the volume for each pair of transactions; Price volatility is measured as the standard deviation of price (σ); Scalpers' realized spread is the volume-weighted average profit made by scalpers, which is the average sales price minus the average purchase price; Number of scalpers and number

[3] In some cases, such a customer trades much like a scalper.

of traders that have participated in trading are also calculated for each five-minute interval. Following (1), liquidity is defined as volume/σ, where the unit of volume is 100,000 ton.

In order to illustrate the intraday trading patterns, 31 time-of-the-day dummy variables are defined corresponding to each five-minute interval. Using data of May 2000 soybean futures contract, linear models with only these dummy variables as dependent variables are estimated for liquidity, volatility, and the number of scalpers. The coefficient estimates of the dummies are plotted in Figure 2. We can see from these charts that liquidity tends to be high right after the opening of the market and right before market closing. There is a break from 10:15am to10:30am on the exchange, and liquidity picks up a little right before 10:15am and right after 10:30am. The intraday seasonality plot of liquidity shows a U-shape pattern, we call it liquidity smile. Well-documented volatility smile is also shown in Figure 2. The intraday pattern of the number scalpers demonstrates similar characteristic.

Models

A Univariate ACI Model

It has been discussed in part III that scalpers' entry and exit are determined by scalpers' profit, which is affected by scalpers' realized spread and market liquidity. To test the first two hypotheses raised in part III, we propose a model that incorporates the dynamics of the number of scalpers as a function of liquidity and realized spread. The number of scalpers (x_t) present in a five-minute interval is a time-series count variable. One natural assumption is that the number of scalpers (x_t) is Poisson distributed after adjusting for intraday seasonality. Some examples that can be assumed to have the Poisson process are, arrivals of customers at a service facility, arrivals of phone calls at a switchboard, fatal automobile accidents at a busy intersection, emissions of α-particles from radioactive substance, and so on. All of these are "rather infrequent events that occur at 'random times'- with irregular spacing, occasionally close together, sometimes far apart, and with no apparent periodicities. Over any two long periods of time of equal length there are about the same number of occurrences, so the rate of occurrence is constant over time" (Berry and Lindgren, 1996).

Under the Poisson assumption, the distribution of (x_t) can be written as

$$P(x_t = j | x_{t-1}, Z_{t-1}) = \frac{e^{-\lambda_t} \lambda_t^{\,j}}{j!} \qquad \forall \quad j = 0,1,2,... \tag{2}$$

where λ_t is the conditional intensity of the Poisson process, in our application, the average number of scalpers in a unit interval [t, t-1). Z_{t-1} is a vector of exogenous and predetermined variables,

$$Z_{t-1} = (liq_{t-1}, \quad spread_{t-1})'$$

where $liq_{t\text{-}1}$ is liquidity measured as in (1), and $spread_{t\text{-}1}$ is the volume-weighted average realized spread of scalpers between [t-1, t-2). The conditional intensity λ_t can be specified as

$$\log(\lambda_t) = \sum_{i=1}^{31} \tau_i d_{it} + \beta x_{t-1} + \gamma Z_{t-1} \tag{3}$$

where d_{it} is a time-of-the-day dummy variable, and d_{it}=1 $\forall$ t$\in$ ith interval. The intraday seasonal pattern illustrated in Figure 2 is captured with the set of 31 time-of-the-day dummies in (3).

Jorda and Marcellino (2000) recognize the need for a dynamic model and then introduce an Autoregressive Conditional Intensity (ACI) model for the conditional intensity, which is,

$$\log(\lambda_t) = \sum_{i=1}^{31} \tau_i d_{it} + \alpha \log(\lambda_{t-1}) + \beta x_{t-1} + \gamma Z_{t-1} \tag{4}$$

where $\log(\lambda_{t\text{-}1})$ characterizes the autoregressive nature of the model. The term $x_{t\text{-}1}$ captures the dynamic effect of surprises in the count variable x_t. The role of the term $x_{t\text{-}1}$ is similar in nature to the moving average term in a typical ARMA model. It is therefore natural to name the model in (4) as an *autoregressive conditional intensity* model, ACI(1,1), where the first term in parentheses refers to the presence of a first-order autoregressive term, and the second term in parentheses refers to the presence of a first-order moving average term. The application of the ACI model is not limited to the problems we present here. Rather, it is a general formulation for dynamic time-series count-data problems.

A Bivariate ACI Model

There are six soybean futures contracts with different maturity dates in the Dalian Futures Exchange. We find that scalpers tend to participate in the two most actively traded contracts during a trading day. It is common practice for a scalper to concentrate on the trading of one contract for one or two hours and then switch to the trading of another contract. It is reasonable to assume that a scalper's participation in the trading of the second most active contract is dependent on his participation in the trading of the most active contract. A bivariate ACI model can be specified to incorporate this simultaneity effect of scalpers' trading. Let y_t denote the number of scalpers in the dominant contract, and x_t the number of scalpers in the second contract. Without loss of generality, the joint distribution of (x_t, y_t) can be decomposed as

$$f(x_t, y_t \mid x_{t-1}, y_{t-1}, Z^*_{t-1}) = g(x_t \mid y_t, x_{t-1}, y_{t-1}, Z^*_{t-1}) \bullet h(y_t \mid x_{t-1}, y_{t-1}, Z^*_{t-1}) \tag{5}$$

where $g(x_t \mid y_t, x_{t-1}, y_{t-1}, Z^*_{t-1})$ is the conditional probability density of x_t given y_t, and $h(y_t \mid x_{t-1}, y_{t-1}, Z^*_{t-1})$ the marginal probability density of y_t; and

$$Z^*_{t-1} = (liq_{1,t-1}, spread_{1,t-1}, liq_{2,t-1}, spread_{2,t-1})'.$$

Each probability density is assumed to be a Poisson distribution,

$$g(x_t | y_t, x_{t-1}, y_{t-1}, Z^*_{t-1}) = P(x_t = j | y_t, x_{t-1}, y_{t-1}, Z^*_{t-1}) = \frac{e^{-\lambda_{1t}} \lambda_{1t}^{\;j}}{j!} \quad \forall \quad j = 0,1,2,...$$

$$h(y_t | x_{t-1}, y_{t-1}, Z^*_{t-1}) = P(y_t = k | x_{t-1}, y_{t-1}, Z^*_{t-1}) = \frac{e^{-\lambda_{2t}} \lambda_{2t}^{\;k}}{k!} \quad \forall \quad k = 0,1,2,... \quad (6)$$

The parameterization of the conditional intensities is

$$\log(\lambda_{1t}) = \sum_{i=1}^{31} \tau_i d_{it} + \alpha_{11} \log(\lambda_{1,t-1}) + \beta_{11} x_{t-1} + \alpha_{12} \log(\lambda_{2,t-1}) + \beta_{12} y_{t-1} + \gamma_1 Z^*_{t-1} + \delta \log(\lambda_{2t}) + \phi y_t$$

$$\log(\lambda_{2t}) = \sum_{i=1}^{31} \tau_i d_{it} + \alpha_{21} \log(\lambda_{1,t-1}) + \beta_{21} x_{t-1} + \alpha_{22} \log(\lambda_{2,t-1}) + \beta_{22} y_{t-1} + \gamma_2 Z^*_{t-1} \quad (7)$$

Another issue of our interest is to find out who provides liquidity. By differentiating scalpers' and non-scalpers' volume, we are able to examine the heterogeneous effect of trading volume on liquidity. A linear model is specified as the following,

$$liq_t = \sum_{i=1}^{31} \tau_i d_{it} + \varphi_1 v_t + \varphi_2 \rho_t + \xi_t \quad (8)$$

where v_t is the average trading volume per scalper, and ρ_t is the average trading volume per non-scalper.

<u>Modeling Price Volatility</u>

The GARCH(1,1) model proposed by Bollerslev (1986) has become a benchmark to model financial asset return volatility. It is specified as

$$p_t = c + \phi_1 p_{t-1} + \phi_2 p_{t-2} + ... + \phi_s p_{t-s} + \varepsilon_t \text{, where } \varepsilon_t \sim N(0, \sigma_t^2) \quad (9)$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (10)$$

where p_t is the average price within each five-minute interval. The conditional variance σ_t^2 is the one-period ahead forecast variance based on past information, it has three components: 1). The mean ω; 2). News about volatility from the previous period, measured as the lag of the squared residual from the mean equation, ε_{t-1}^2, which is the ARCH term; 3). Last period's forecast variance, σ_{t-1}^2, which is the GRACH term. This specification is interpreted as a trader predicting this period's variance by forming a weighted average of a long term average (the constant), the forecasted variance from last period, and information about volatility observed in the previous period.

To study the heterogeneous effect of trading by scalpers and non-scalpers on price volatility, the conditional variance equation (10) may be modified to allow for the inclusion of exogenous regressors, Φ,

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \pi\Phi_t \qquad (10')$$

where $\Phi_t=(svol_t, nsvol_t, p_t^2)$, $svol_t$ is the trading volume by scalpers, and $nsvol_t$ is the trading volume by non-scalpers.

Estimation and Results

Maximum likelihood is used to estimate the ACI in (4). The ACI model is estimated using transaction data for May and July 2000 soybean futures contracts for the period June 1999 through December 1999. The advantage of the ACI specification over the Poisson specification of the conditional intensity is highlighted by the reduction of the absolute value of the log-likelihood, which is 48% for May 2000 contract and 43% for July 2000 contract (Table 5).

The estimates of the ACI model are reported in Table 6. For both May and July 2000 contracts, the coefficient estimates on liquidity are positive and significant, which implies that a more liquid markets attract scalpers. The argument supporting this conclusion is that liquidity attracts market orders demanding immediate execution, which in turn provides order flow for scalpers. The coefficient estimates on scalpers' realized spread are also positive as well as significant, implying scalpers are also attracted to the market by their profit per unit of volume. The coefficients on the autoregressive term of the conditional intensity $log(\lambda_{t-1})$ are positive and significant, and the coefficients on the term x_{t-1} are also positive as well as significant. The sum of the coefficient estimates on $log(\lambda_{t-1})$ and x_{t-1} is close to one, which emphasis the high persistence of scalpers' trading. In comparison, the Poisson model fails to capture the first order autoregressive nature of the conditional intensity.

The bivariate ACI model is estimated by maximizing the log-likelihood of the joint probability density in (5) with the marginal densities defined in (6) and conditional intensities specified in (7). The transaction of data of May 2000 and July 2000 futures contracts for the period of August 1999 through December 1999 are used. The estimation results are reported in Table 7. The May 2000 contract is considered as the dominant contract here because its volume is higher than that of July 2000 contract during most of our sample period (Figure 1). The advantage of the bivariate ACI model is obvious. The sum of the log-likelihood of the two univariate ACI models is –11706, while the log-likelihood of the bivariate ACI model is –8309, which is a 30% reduction of total value of the univariate log-likelihoods (Table 5).

Let us first examine the coefficient estimates in the May 2000 contract equation. The coefficient estimates of time-of-the-day dummy variables are plotted in Figure 3. The own liquidity and spread terms have positive and significant coefficient estimates, while the corresponding cross terms have negative and significant coefficient estimates. These results imply that scalpers are attracted to the trading of the May 2000 contract due to the liquidity and the realized spread they can make in this contract; Scalpers turn away from the trading of the May 2000 contract due to the liquidity of the July 2000 contract and the realized spread they can make in the trading of the July 2000 contract. Specifically, if the liquidity of the May 2000 contract increases by one unit, the average number of scalpers participating in the trading of this contract will increase by 6.90 in each five-minute interval. However, if the liquidity of the July 2000 contract rises by one unit, the average number of scalpers participating in the trading of the May 2000 contract will decrease by 4.92 in each five-minute interval. The estimation results of the July 2000 contract equation reflect consistent relationship. Namely, if the liquidity of the July 2000 contract increases by one unit, the average number of scalpers trading this contract will increase by 11.38 in each five-minute interval; This figure will decrease by 7.62 if the liquidity of the May 2005 contract increases by one unit. The coefficient estimates on $\log(\lambda_{2t})$ and y_t are both positive and significant, implying scalpers' participation in the trading of these two contracts is positively contemporaneously correlated. In summary, these results support Hypothesis 1 that liquidity of a market attracts scalpers, and the number of scalpers is also positively related to scalpers' realized spread.

Equation (8) is estimated by OLS using data of May 2000 futures contract, and coefficient estimates of the time-of-the-day dummies are plotted in Figure 4. The coefficients on both scalpers' volume and non-scalpers' volume are positive and significant, implying that both scalpers and non-scalpers contribute to the liquidity of the market (Table 8). This result supports Hypothesis 2 that scalping increases the liquidity of the market.

The GARCH(1,1) model specified in (9) and (10') is estimated for the May 2000 contract, and the results are reported in Table 9. The coefficient estimate on scalpers' volume is negative but insignificant, while the coefficient estimate on non-scalpers' volume is positive and significant. These results imply that the major source of price volatility is non-scalpers' trading. While this result does not support hypothesis 3 that scalpers' trading decreases price volatility, it at least confirms that scalpers do not contribute to price volatility.

IV. Conclusions

By using the transaction data from the Dalian Futures Exchange, we have studied why scalping arise in futures market, and how scalpers' trading affects liquidity and price volatility. A bivariate autoregressive conditional intensity (ACI) model is estimated for two most actively traded contracts during our sample period, and the results suggest that scalpers are attracted to the market by liquidity as well as scalpers' realized spread. We have also tested while both scalpers and non-scalpers contribute to the liquidity of the market, non-scalpers' trading is the source of price volatility.

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Table 1. Trader Statistics in the Dalian Futures Exchange.

	Number of Brokers	Number of Traders	Number of Scalpers
Jun-99	156	2545	8
Jul-99	158	2420	7
Aug-99	164	3053	8
Sep-99	161	4119	8
Oct-99	161	4122	8
Nov-99	169	5390	9
Dec-99	173	4371	5
Apr-00	145	5137	7

Table 2. Demographics of Member Firms in the Dalian Futures Exchange (April 2000).

Member firms doing brokerage			
one trading seat		83	
two trading seats			
two seats on the trading floor	26		
one seat on the trading floor, one distance trading seat	12	38	
three trading seats		8	
four trading seats		1	130
Members trading for their own account			15
Total			145

Table 3. Member Firms, Customers, and Scalpers in the Dalian Futures Exchange (April 2000).

Member Firms		Customers	Apparent Scalpers
Brokerage Firms	130	5122	6
Members trading for their own account	15	15	1
Total	145	5137	7

Table 4. Trading Volume on the Dalian Futures Exchange.

	All Contracts			Jan. 2000 Contract			March 2000 Contract		
	Total Volume	Scalpers' Volume	(%)	Total Volume	Scalpers' Volume	(%)	Total Volume	Scalpers' Volume	(%)
Jun-99	990046	102859	10.39%	162060	21173	13.06%	106591	9774	9.17%
Jul-99	733573	39918	5.44%	33961	3113	9.17%	27569	1762	6.39%
Aug-99	1122148	82822	7.38%	22620	3112	13.76%	16434	1942	11.82%
Sep-99	1231253	71995	5.85%	5600	732	13.07%	8702	988	11.35%
Oct-99	929039	70424	7.58%	2987	180	6.03%	3393	314	9.25%
Nov-99	2086658	235387	11.28%	2920	200	6.85%	6496	372	5.73%
Dec-99	735863	91746	12.47%	1152	125	10.85%	1579	324	20.52%
Apr-00									

Table 4. Continued.

	May 2000 Contract			July 1999 Contract			July 2000 Contract		
	Total Volume	Scalpers' Volume	(%)	Total Volume	Scalpers' Volume	(%)	Total Volume	Scalpers' Volume	(%)
Jun-99	594468	61866	10.41%	5147	218	4.24%			
Jul-99	646750	33742	5.22%	4769	10	0.21%	581	316	54.39%
Aug-99	1034810	74164	7.17%				25519	2123	8.32%
Sep-99	1088857	62004	5.69%				117641	7629	6.48%
Oct-99	462941	28711	6.20%				373450	32349	8.66%
Nov-99	434305	33518	7.72%				853646	100590	11.78%
Dec-99	19849	744	3.75%				76114	12089	15.88%
Apr-00	8918	300	3.36%				5736	471	8.21%

Table 4. Continued.

	Sept. 1999 Contract			Sept. 2000 Contract			Nov. 1999 Contract		
	Total Volume	Scalpers' Volume	(%)	Total Volume	Scalpers' Volume	(%)	Total Volume	Scalpers' Volume	(%)
Jun-99	84876	6772	7.98%				36904	3056	8.28%
Jul-99	13118	554	4.22%				6825	421	6.17%
Aug-99	14516	762	5.25%				8249	719	8.72%
Sep-99	1695	34	2.01%	4741	384	8.10%	4017	224	5.58%
Oct-99				84331	8820	10.46%	1937	50	2.58%
Nov-99				772588	99297	12.85%	841	0	0.00%
Dec-99				573784	68403	11.92%			
Apr-00				394617	24960	6.33%			

Table 4. Continued.

	Nov. 2000 Contract			Jan. 2001 Contract			March 2001 Contract		
	Total Volume	Scalpers' Volume	(%)	Total Volume	Scalpers' Volume	(%)	Total Volume	Scalpers' Volume	(%)
Jun-99									
Jul-99									
Aug-99									
Sep-99									
Oct-99									
Nov-99	15862	1410	8.89%						
Dec-99	63385	10061	15.87%						
Apr-00	312370	25003	8.00%	410309	26130	6.37%	19638	1843	9.38%

Table 5. Comparison of Poisson, Univariate ACI, and Bivariate ACI Models.

Model	Log-Likelihood	# of Dummy Variables	# of Parameters	% of Reduction in Loglikelihood
Poisson				
May 2000 Contract	-12727.90	30	33	
July 2000 Contract	-8931.09	27	30	
Univariate ACI				
May 2000 Contract	-6636.28	30	34	48% (Compared to Poisson)
July 2000 Contract	-5070.16	27	31	43% (Compared to Poisson)
Total	-11706.44	57	65	
Bivariate ACI	-8309.29	39	57	30% (Compared to Univariate ACI)

Table 6. Estimation Results of the Univariate ACI Model.

Variables	Coefficient	Std. Error	z-Statistic	Prob.
May 2000 Soybean Futures				
$\log(\lambda_{t-1})$	0.9688	0.0011	844.2395	0.0000
x_{t-1}	0.0277	0.0010	27.4005	0.0000
liq_{t-1}	2.3000	0.2000	11.4844	0.0000
$spread_{t-1}$	0.0063	0.0015	4.1735	0.0000
Log likelihood	-6636.28	Akaike info criterion		1.2958
Avg. log likelihood	-0.64	Schwarz criterion		1.3197
Number of Coefs.	34	Hannan-Quinn criter.		1.3039
July 2000 Soybean Futures				
$\log(\lambda_{t-1})$	0.9924	0.0005	2151.1380	0.0000
x_{t-1}	0.0068	0.0007	10.3650	0.0000
liq_{t-1}	1.2320	0.1998	6.1686	0.0000
$spread_{t-1}$	0.0034	0.0017	2.0058	0.0449
Log likelihood	-5070.16	Akaike info criterion		1.4032
Avg. log likelihood	-0.70	Schwarz criterion		1.4325
Number of Coefs.	31	Hannan-Quinn criter.		1.4133

Table 7. Estimation Results of the Bivariate ACI model.

Variables	Coefficient	Std. Error	z-Statistic	Prob.
Equation 1 (July 2000 Soybean Futures)				
$\log(\lambda_{1,t\text{-}1})$	0.7892	0.0211	37.3323	0.0000
$x_{t\text{-}1}$	0.0786	0.0083	9.4990	0.0000
$liq_{1,t\text{-}1}$	11.3800	2.1600	5.2867	0.0000
$spread_{1,t\text{-}1}$	0.0176	0.0079	2.2160	0.0267
$\log(\lambda_{2t})$	0.8187	0.1284	6.3764	0.0000
y_t	0.1146	0.0081	14.1410	0.0000
$\log(\lambda_{2,t\text{-}1})$	-0.6385	0.1145	-5.5784	0.0000
$y_{t\text{-}1}$	-0.1914	0.0116	-16.5428	0.0000
$liq_{2,t\text{-}1}$	-7.6200	1.2620	-6.0449	0.0000
$spread_{2,t\text{-}1}$	-0.0190	0.0073	-2.5949	0.0095
Equation 2 (May 2000 Soybean Futures)				
$\log(\lambda_{1,t\text{-}1})$	0.1145	0.0085	13.4693	0.0000
$x_{t\text{-}1}$	-0.0345	0.0040	-8.6506	0.0000
$liq_{1,t\text{-}1}$	-4.9200	1.2780	-3.8587	0.0001
$spread_{1,t\text{-}1}$	-0.0109	0.0050	-2.1966	0.0281
$\log(\lambda_{2,t\text{-}1})$	0.8814	0.0078	113.6572	0.0000
$y_{t\text{-}1}$	0.0528	0.0038	13.7748	0.0000
$liq_{2,t\text{-}1}$	6.9000	0.7240	9.5224	0.0000
$spread_{2,t\text{-}1}$	0.0164	0.0045	3.6100	0.0003

Log likelihood	-8309.2880	Akaike info criterion	2.3013
Avg. log likelihood	-1.1428	Schwarz criterion	2.3553
Number of Coefs.	57.0000	Hannan-Quinn criter.	2.3199

Table 8. Estimation Results in Equation (8).

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ν_t	10.9516	1.1758	9.3145	0.0000
ρ_t	91.5747	3.1303	29.2544	0.0000

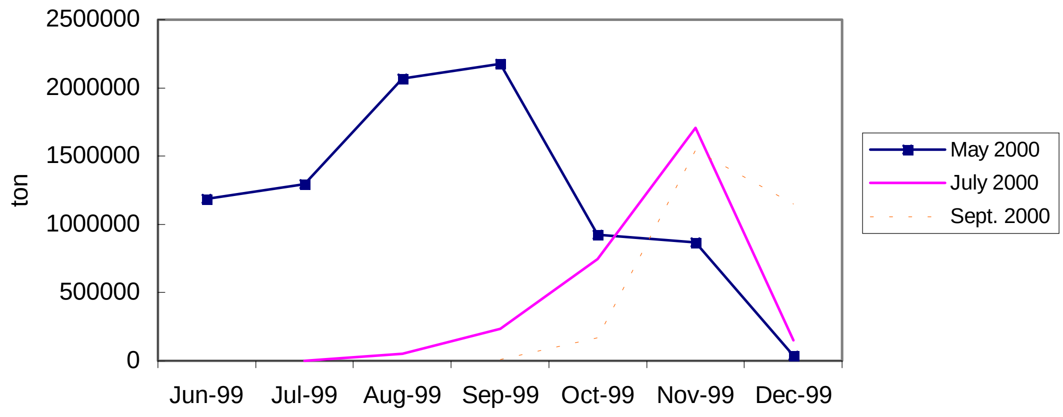
R-squared	0.3952	Mean dependent var	0.0116
Adjusted R-squared	0.3886	S.D. dependent var	0.0086
S.E. of regression	0.0067	Akaike info criterion	-7.1583
Sum squared resid	0.1165	Schwarz criterion	-7.0932
Log likelihood	9381.3800	Durbin-Watson stat	1.4325

Table 9. Estimation Results of GARCH(1,1).

	Coefficient	Std. Error	z-Statistic	Prob.
Constant	1.2373	19.6203	0.0631	0.9497
p_{t-1}	0.7123	0.0070	101.7949	0.0000
	Variance Equation			
Constant	169521.8000	4199.1520	40.3705	0.0000
ε_{t-1}^2	0.7517	0.0078	95.7673	0.0000
σ_{t-1}^2	-0.0829	0.0014	-58.1871	0.0000
$svol_t$	-5.2839	195.7793	-0.0270	0.9785
$nsvol_t$	31.6275	8.4970	3.7222	0.0002
p_t^2	0.1008	0.0037	27.3862	0.0000

R-squared	0.6649	Mean dependent var	743.7728
Adjusted R-squared	0.6647	S.D. dependent var	986.2558
S.E. of regression	571.1125	Akaike info criterion	15.0360
Sum squared resid	3360000000	Schwarz criterion	15.0416
Log likelihood	-77389.9000	F-statistic	2915.9570
Durbin-Watson stat	1.4274	Prob(F-statistic)	0.0000

Figure 1. Trading Volume in the Dalian Futures Exchange.



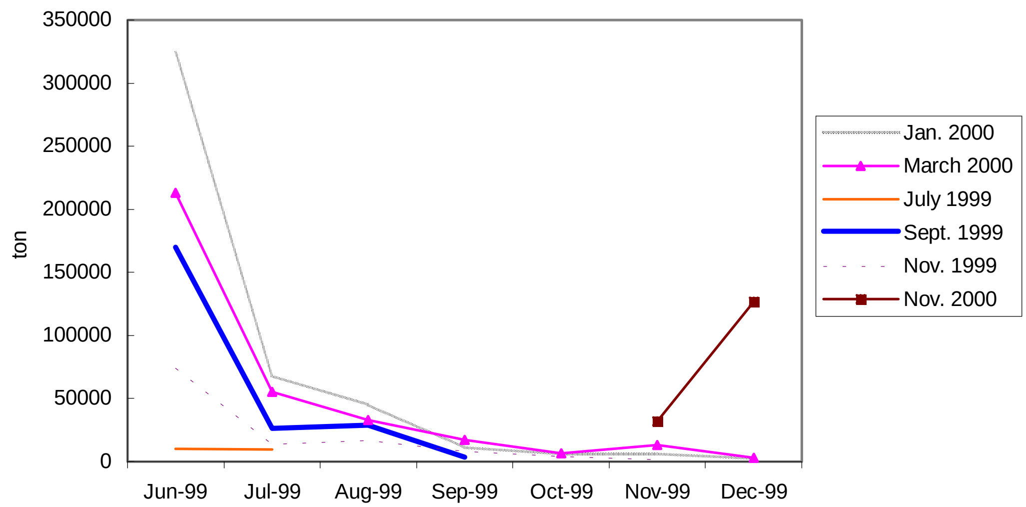


Figure 2. Intraday Seasonal Pattern of Liquidity, Volatility and Number of Scalpers in the Dalian Futures Exchange (May 2000 Soybean Futures).

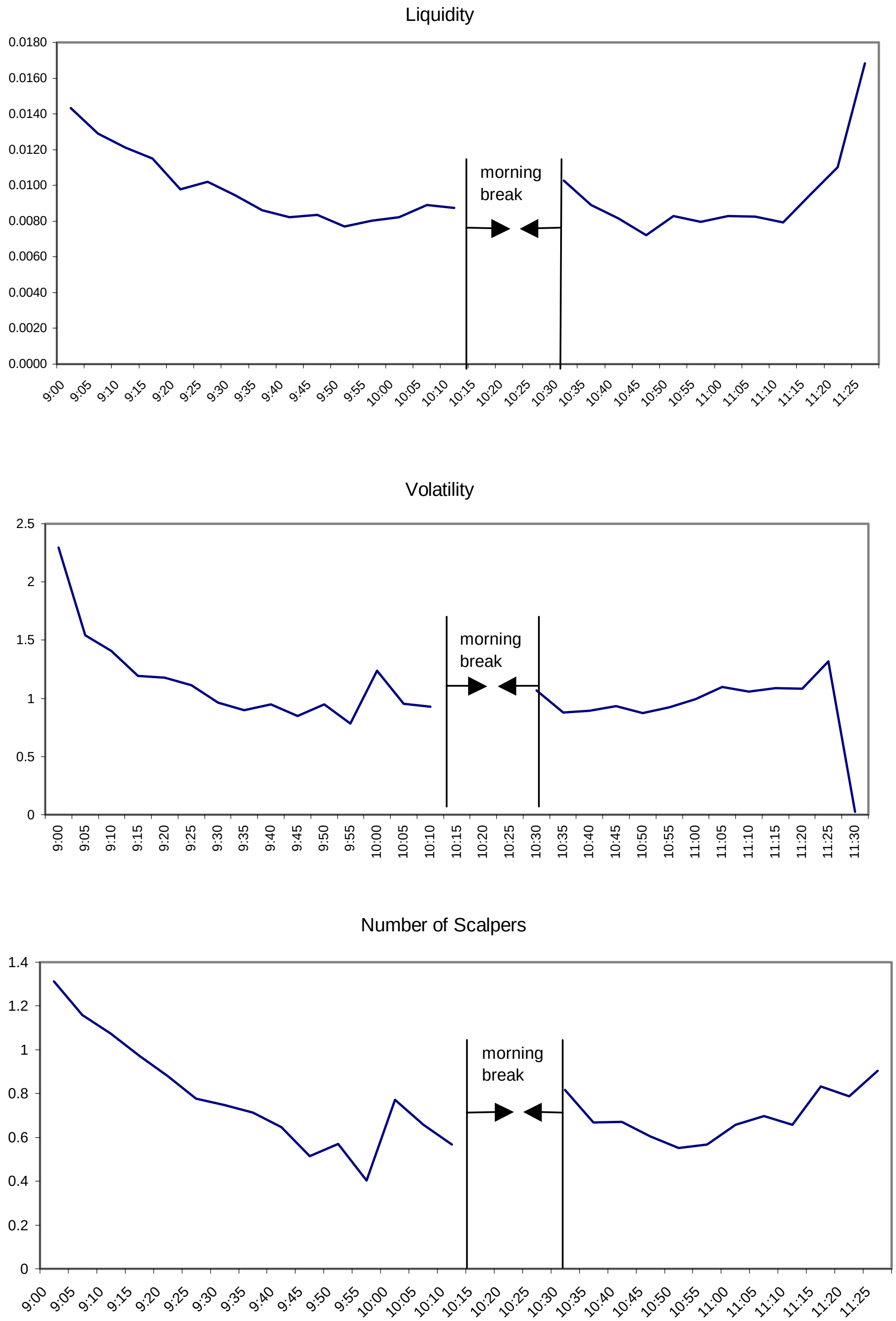
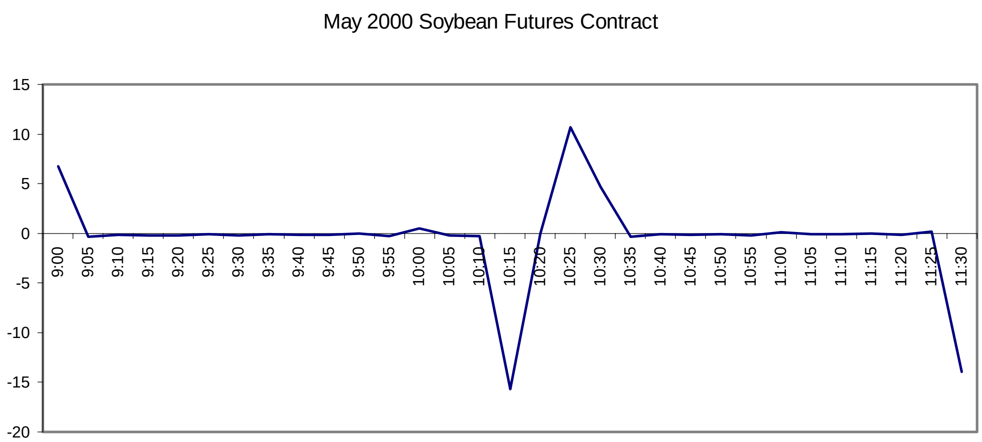


Figure 3. Estimates of Dummy Variables in the Bivariate ACI model.



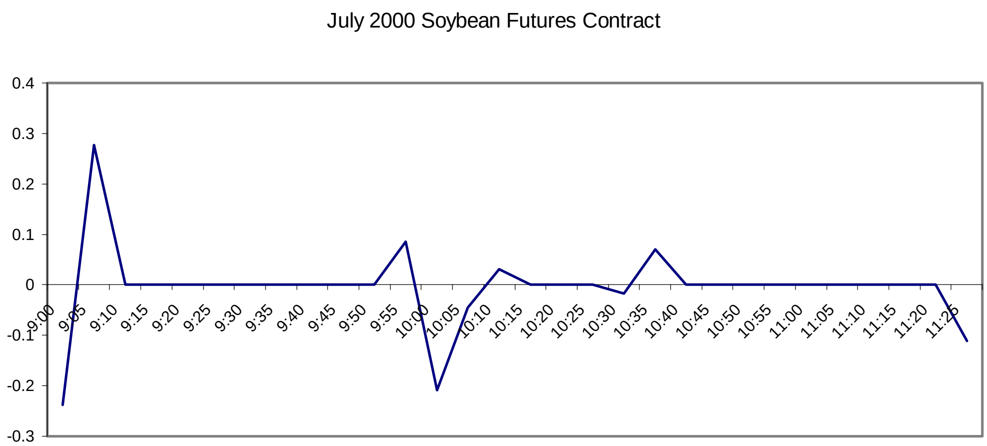


Figure 4. Estimates of the Time-of-the-Day Dummy Variables in Equation (8).