Are Market Makers Liquidity Suppliers?

Preliminary and Incomplete
Please Do Not Quote

Michel van der Wel[1]
VU University Amsterdam, Tinbergen Institute
De Boelelaan 1105, 1081 HV Amsterdam, Netherlands
wel@tinbergen.nl

Albert J. Menkveld
VU University Amsterdam, Tinbergen Institute
De Boelelaan 1105, 1081 HV Amsterdam, Netherlands
albertjmenkveld@gmail.com

Asani Sarkar
Federal Reserve Bank of New York
33 Liberty Street, NY 10045, New York
asani.sarkar@ny.frb.org

March 2008[2]

[1]Corresponding author.

[2]The views stated here are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of New York or the Federal Reserve System. We appreciate the comments of Riccardo Calcagno, Thierry Foucault, Borus Jungbacker, Andre Lucas, and participants at the Merton H. Miller doctoral seminar at the EFMA2007. We are grateful to the Netherlands Organization for Scientific Research (NWO) for a VENI grant and travel support. We are responsible for all errors.

Are Market Makers Liquidity Suppliers?

Preliminary and Incomplete
Please Do Not Quote

Abstract

We use a high-frequency dataset of the 30Y U.S. treasury futures with data for 1,958 traders to investigate the role of the market maker. Most theory assumes he is an uninformed liquidity supplier. We provide direct evidence of active position building by market makers. The extent to which they do so correlates positively with trading profits. The results suggest that some market makers are informed speculators and actively demand liquidity for a substantial part of the day. Additionally, we develop a new approach to sign trades in the absence of quotes. It is equally efficient as the Hasbrouck (2004) MCMC approach but it is 10 times faster.

Keywords: market makers, treasury futures, discount rate, macroeconomic announcements, dual trading

JEL: G14, E44

Market makers play an important role in financial markets. They stand ready to buy and sell in order to accommodate the asynchronous arrival of sellers and buyers. Classic inventory models assume that they are risk-averse and therefore need compensation for carrying suboptimal inventory through time. In the process they earn the bid-ask spread to compensate for bearing inventory risk.[1] Empirically, studies have measured inventory control through the rate of inventory mean reversion and results are relatively poor, i.e. half-life of inventory typically is too long relative to what one might expect.[2]

Two likely explanations for slow inventory mean-reversion are (i) institutional features of a market that affect market maker behavior and (ii) active position-taking by market makers to speculate on private information. Panayides (2007) provides an example of the first and shows that the New York Stock Exchange specialist is sometimes forced to take on positions due to the Price Continuity rule. Madhavan and Smidt (1993) illustrate that a second reason for slow mean-reversion is speculation. They develop a model where the market maker actively manages an inventory to make it return to an optimal long-run position, but, at the same time, they show that when he has access to private information he speculates by actively building a short-term position. This could explain the low level of mean-reversion if the econometrician ignores speculation.[3]

In this paper, we explore whether (unconstrained) market makers actively speculate in the sense of Madhavan and Smidt (1993). We examine a large cross-section of 1,958 market makers active on the 30Y U.S. treasury futures trading pit on the Chicago Board of Trade. We find evidence of inventory control as the end of day inventory distribution is concentrated around zero. In addition, we find that indeed market makers actively take positions in the course of the day, i.e. they initiate trades that increase their inventory position. When we relate the extent of active position taking to proprietary trading profits we find a significant and positive correlation. This profitable position taking is consistent with active speculation by the market maker.

The current literature provides at best indirect evidence that market makers at times

[1]The costs associated with the inventory risk is one of the three classic explanations for the bid-ask spread. The other two explanations are information asymmetry (see for example Kyle (1985) and Glosten and Milgrom (1985)) and order processing costs (such as in Roll (1984)). See O'Hara (1995) for an overview.

[2]For example, Hasbrouck and Sofianos (1993) show that it takes long to reduce an inventory position, sometimes up to two months. However, some of the inventory models' predictions are confirmed by data, most notably that market makers do manage inventory toward a target (see for example Manaster and Mann (1996) and Bjønnes and Rime (2005)).

[3]One outcome of their model is an equation that explicitly explains today's inventory as the sum of two components: (i) a fraction of yesterday's inventory consistent with inventory management and (ii) an active position on private information. We discuss the equation further in the literature session.

are speculators. Some studies find that the market maker initiates a significant share of his trades (Frino and Jarnecic (2000)) and interpret this as evidence of speculation. Initiation in itself, however, is not the same as speculation as market makers can initiate trades to actively manage their inventory position back to the long-term optimal level. A nice illustration of this phenomenon is the 'hot-potato' trading model of Lyons (1997). Locke and Sarajoti (2004) find market maker inventory can be split into a desired and undesired position (from a long-term rational expectations point of view), and that market makers are most aggressive to offset their undesired position. Manaster and Mann (1996) and Bjønnes and Rime (2005) document strong inventory control but, surprisingly, do not find the expected price effects of inventory.[4] They conclude that their results are consistent with active speculative position taking by floor traders. Anand and Subrahmanyam (2007) show that intermediaries, a subset of the market makers we study, have information orthogonal to their clients and account for greater price discovery. And, contrary to all these studies, Chakravary and Li (2003) study market making but do not find evidence in favor of speculation. We add to all of the aforementioned papers, as we are the first to provide direct evidence of active position taking by market makers. Moreover, when we relate this position taking to trading profits we find a positive and significant relation.

To study the liquidity demand and profitable position taking of the market maker further we disentangle our main result in two dimensions. Firstly, as we find that market makers can be informed speculators it is interesting to distinguish days with a high-information environment and days with a low-information environment. If market makers are able to trade on information we expect them to be more active in taking positions on days at which there is more information coming to the market, and that their trading profits from these positions are higher. To identify high- and low-information environments we use the days on which there are the scheduled releases of macroeconomic news. This is a contribution in itself: though many studies find that these scheduled releases of news significantly affect returns, volatility, volume and information asymmetry[5] the studies that look at liquidity supply[6] do not take these announcements into account.

[4]Demsetz (1968) and Stoll (1978) show that it could be optimal for market makers to not quote symmetrically around the efficient price, but deviate in order to create incentives for liquidity demanders to trade in the direction that brings the market maker inventory back to zero.

[5]See Ederington and Lee (1993, 1995), Fleming and Remolona (1997, 1999), Balduzzi, Elton, and Green (2001) and Andersen, Bollerslev, Diebold, and Vega (2003, 2007) for evidence on the effects of macroeconomic announcements on returns, volatility and trading volume. Green (2004), Pasquariello and Vega (2007) and Menkveld, Sarkar, and Van der Wel (2007) document higher information asymmetry after macroeconomic announcements.

[6]Such as Manaster and Mann (1996) and Chakravary and Li (2003) for the futures market, see Section 1 for a full overview.

We find empirically that the floor traders prefer a flat position before the announcement, and quickly build up a position after the news is released. In anticipation of the scheduled news release the inventory distribution is highly concentrated around zero. After the announcement market makers quickly build up their position, both through actively initiating trades and passively participating in trades that increase their inventory positions. The inventory positions on announcement days are larger than on nonannouncement days, confirming our expectation. If we relate the extent to which they participate (actively and passively) in trades that increase their inventory position to their profits from trading we find a significant positive correlation. This is consistent with the market makers demanding liquidity on days with high-information environment, and speculate right after the news announcement.

The second dimension with which we study the main result is the heterogeneity in information sets of the various market makers. Of the total group of 1,958 market makers on the average day there are 537 traders active, of which 169 traders trade both for own account and on behalf of customers. This last group of traders is commonly referred to as dual traders, or simply duals. Recent studies find that order flow coming from the customers of dual traders, the end-users in the economy, provides information orthogonal to that from the macroeconomic news (Menkveld, Sarkar, and Van der Wel (2007)), and may even predict macroeconomic variables (Evans and Lyons (2005a, 2005b)). Similar to looking at days with high- and low-information environment we expect the traders with the largest information set to be most active in building up positions, and that they obtain the highest profits from this position taking. Studying subgroups in the population of market makers is also consistent with the results of Manaster and Mann (1996, p.973), who point out that "market makers are not merely passive order fillers, ..., but are active profit-seeking individuals with heterogeneous levels of information and/or trading skill". We are the first to explicitly pick up heterogeneous subgroups in the context of liquidity supply and demand by comparing these dual traders with traders that only trade for their own account ('local' traders).[7]

We find that the market makers with the additional information of observing order flow from customers are more active in building up inventory positions after macroeconomic announcements. Moreover, for this subgroup of dual traders the relation between the amount of trades that increase their inventory position and trading profits is strongest. This is consistent with the dual traders using the information they obtain from bringing customer orders to the market and speculate.

[7] Others have compared profits of dual traders to profits of local traders (see a.o. Fishman and Longstaff (1992)), but not inventory management of these two groups of traders.

Our dataset of the 30Y U.S. treasury futures in 1995 has three advantages. Firstly, we can identify whether trades are proprietary or on behalf of customers. After signing the trades as buyer- or seller-initiated this allows us to study not only liquidity supply, but also liquidity demand of the market maker. Secondly, of the work that focuses solely on the liquidity supplying role of the market maker the majority looks at the New York Stock Exchange Specialist,[8] who, as was pointed out earlier, is not a pure market maker as he is sometimes restricted by his obligation to smooth transaction prices. Therefore it is more natural to study the market maker in settings where he does not have such an obligation, as in treasury futures markets. Thirdly, an advantage of our dataset over the existing treasury futures market liquidity supply studies is that the maturity we look at has the largest share of trading at one market. Manaster and Mann (1996) and Chakravary and Li (2003) study liquidity supply on the market for the less liquid 13 week bill, on which trading is split between the spot and futures market. When this is case one has to account for hedging across markets.[9]

Though in recent years on many markets other market participants supply liquidity through limit orders, the majority of markets still rely on a subset of traders that always stand ready to trade (of the 51 exchanges that Jain (2005) studies 27 have a dealer emphasis or hybrid system). The trend in financial markets is toward electronic trading platforms, but also here there are market makers and intermediaries active like the ones we study in this paper. For example, Hendershott, Jones, and Menkveld (2007) study algorithmic trading and emphasize the role of algorithmic traders as liquidity suppliers. In addition, recently markets are interested in the introduction of Designated Market Makers, who commit to providing a minimum level of liquidity.[10]

In the implementation we come across the challenge of signing transactions in the absence of quotes. Hasbrouck (2004) suggests implementing a signing method based on the Roll (1984) model that relies on a Bayesian inference technique, the Gibbs Sampler. As this is a simulation based method it might be computationally burdensome, and is too time-consuming for our dataset of over 10.7 million trades. The second main contribution of

[8]As in Madhavan and Smidt (1991), Hasbrouck and Sofianos (1993), Madhavan and Sofianos (1998) and Hendershott and Seasholes (2007), see Section 1 for a full overview.

[9]For the 13 week bill about 55% of volume trades on the futures market. For the 30 year bond almost all trading takes place on the futures market, about 95%. These calculations are based on Fleming and Sarkar (1999). For spot the on-the-run security is taken, for futures the nearby contract. The sample size of both studies illustrate the lower liquidity of the 13 week contract: Manaster and Mann (1996) look at 584 trader days, Chakravary and Li (2003) study only 6 traders for the treasury futures market (though both studies include more data, but from other futures contracts).

[10]See Menkveld (2006), Bessembinder, Hao, and Lemmon (2007), Venkataraman and Waisburd (2007) and Anand, Tanggaard, and Weaver (2008).

the paper is that we develop an innovative method for determining whether the buying or selling party initiated a trade. The method we propose follows from the same principles as Hasbrouck's (2004) method. However, as our model relies on methods of time-series models in state space form we greatly reduce the computational burden. Applying Hasbrouck's method to our dataset would require over 10 hours for one model variation to be estimated, whereas the method we suggest requires a little over 25 minutes.[11]

Overall our results imply that the market maker is not an uninformed liquidity supplier. He initiates a significant part of his trades, and sometimes actively builds up a speculative position. This is particularly true when looking at the high-information environment created by the scheduled releases of macroeconomic news and for traders with a large information set. The market making behavior is consistent with the Madhavan and Smidt (1993) model in which the market maker is both a dealer and a speculator. Our results emphasize the need for theoretical models that take the informativeness of the market maker into account, such as the model recently put forward by Boulatov and George (2007).

The rest of the paper is build up as follows. Section 1 discusses related literature. In Section 2 we discuss our dataset, provide some institutional background, and show summary statistics. Section 3 details the method we use to sign the trades in our dataset. In Section 4 we present our empirical findings. Section 5 concludes.

1 Related Literature

1.1 Market Making and Inventory

Our study of the market maker relates to several strands of literature. Firstly, it relates to the literature that assumes the market maker is an uninformed liquidity supplier. For example, in Stoll (1978) the market maker adjusts his quotes depending on his inventory position to get rewarded for the risk of holding a nonzero inventory position. In the adverse selection models of Kyle (1985) and Glosten and Milgrom (1985) the market maker sets

[11]The number of times each of the methods needs to run over all the observations causes the difference in required calculation time. Hasbrouck (2004) suggests 10,000 swoops over the data, while our likelihood-based method requires on average 10 maximum likelihood iterations to estimate the two parameters in which the likelihood is calculated about 6 times. See Section 3.2 for more details on the differences in estimation procedures and calculation times.

prices such that in expectation he has no profits and absorbs the net order flow. In both types of models the market maker is uninformed and a liquidity supplier.

Madhavan and Smidt (1993) are the first to provide an exception to the above setting. They introduce a model in which the market maker is both a dealer and an speculator. Equation (6) in their paper gives the optimal trade quantity of the market maker, and illustrates this dual nature:

$$I_{t+1} - I_t = \beta(I_t - I^d) - \frac{1+\beta}{2}x_t,$$

with I_t the market maker's inventory position at time t, $-1 < \beta < 0$ a parameter measuring the speed of inventory adjustment, I^d the long-term desired inventory position and x_t representing the short-horizon investment strategy. Thus in the Madhavan and Smidt (1993) model the optimal trade quantity of the market maker consists of two components: the deviation of his inventory from the long-run desired level and a short-run speculative strategy.

In Boulatov and George (2007) liquidity suppliers can also be informed. Specifically, informed traders may choose whether to act as liquidity demanders or suppliers. In case of fully anonymous liquidity provision the informed act exclusively as liquidity suppliers. If there is less than full anonymity some informed traders choose to provide liquidity while others demand liquidity. Hendershott, Jones, and Menkveld (2007) provide empirical results consistent with this model, as they find large informativeness of quotes. Our results offer empirical guidance on whether market makers can indeed be informed.

Secondly, we relate to empirical studies of liquidity supply and inventory management. The great majority of these papers look at the Specialist on the New York Stock Exchange (Hasbrouck (1988), Madhavan and Smidt (1991), Hasbrouck and Sofianos (1993), Madhavan and Sofianos (1998), Panayides (2007) and Hendershott and Seasholes (2007)). In addition researchers look at the U.S. treasury market (Manaster and Mann (1996) and Chakravary and Li (2003)), the exchange rate market (Lyons (1995), Bjønnes and Rime (2005) and Cao, Evans, and Lyons (2006)), the London Stock Exchange (Hansch, Naik, and Viswanathan (1998), Reiss and Werner (1998) and Naik and Yadav (2003)) and option data (Garleanu, Pedersen, and Poteshman (2005)).

We differ from these studies in a number of issues. Firstly, we do not take the liquidity supply role of the market maker as given, but also consider the liquidity demand role of the market maker and examine whether there indeed is a liquidity supply role. Secondly, we look at the treasury market in which there is a large cross-section of market makers active with large heterogeneity. These market makers are free of obligations, whereas the NYSE specialist is sometimes restricted by his other obligations such as smoothing transaction prices (Panayides (2007)). Compared to the current treasury market studies we distinguish ourselves also by looking at a maturity at which trading is concentrated on one exchange. In addition our market is more active, such that we have a larger sample of floor traders to examine (see Footnote 9 for more on these points).

Manaster and Mann (1996) and Bjønnes and Rime (2005) document strong evidence of inventory control by market makers. Surprisingly however, they do not find price effects of the inventory positions. They interpret this as being consistent with active position taking by floor traders. We add to this, and show direct evidence of active and passive position taking by market makers. Moreover, we find floor traders that are most active in building up a position earn higher profits from trading.

1.2 Signing Futures Market Trades

We also relate to the literature on classifying trades according to whether they are initiated by the buying or selling party (the so-called 'signing' of trades). For markets with explicit quotes a trade is qualified as being initiated by the buying party if it takes place closer to the ask than the bid (Hasbrouck (1988), Lee and Ready (1991) and Ellis, Michaely, and O'Hara (2000)).

For markets without quotes identifying whether the buying or selling party initiated the trade is more challenging as it is difficult to find a good 'reference' for the observed transaction prices. A tick test can be used, where a trade is labeled as being initiated by the buying party if it is an uptick (i.e. if the transaction price is larger than the previous price). However, this method has the disadvantage that a trade can be incorrectly labeled as buyer-initiated simply due to an orthogonal price innovation. Alternatively, Rosenberg and Traub (2007) suggest to use the quotes of a parallel market for the same asset as a reference: to sign futures market trades they use the quote from the forward market. Unfortunately, this is not applicable in general as there needs to be such a parallel market.

Hasbrouck (2004) suggests using a Bayesian methodology (the Gibbs sampler) to explicitly model the price innovation and trade sign. Unlike the aforementioned methods this grounds in economic theory: it is based on the Roll (1984) model. We follow his approach, but suggest a much quicker likelihood based algorithm to sign futures market trades. In addition we develop a method that deals with high-frequency datasets in which it can occur that there are multiple trades occurring at the same second at the same price.

2 Data and Institutional Background

To study the market maker we analyze trading in the 30Y U.S. treasury futures pit. This instrument trades on the Chicago Board of Trade (CBOT). On the trading floor (the 'pit') traders ('floor traders') gather between 8:20 a.m. and 3:00 p.m. Eastern Time. Trading takes place through the open outcry method: prices are negotiated by shouting out orders and indicating direction and quantity using hand signals.

We look at the 30Y maturity (instead of e.g. the 5Y) as this is the maturity where volume is most concentrated on one exchange. For the 30Y maturity about 95% takes place on the futures market and 5% on the spot, while for the 5Y bond this is 24% and 76% respectively (see Fleming and Sarkar (1999)). In addition, in our sample period of 1995 electronic trading is still limited. Thus, by looking at the 30Y treasury futures we have a setting where we observe almost all trading, and minimize the risk of missing offsetting trades in the other market or electronically.

At each moment in time multiple treasury bond futures contracts with different expiry months are traded. We focus on the most nearby as this is the most liquid of these (see Fleming and Sarkar (1999)) and makes it a very close substitute for the underlying spot instrument. As Ederington and Lee (1993, p.1164) point out, this makes our results generalizable to the spot market.

Our dataset records all trades taking place on the futures pit. For each trade are recorded: the time of the trade; a buy/sell indicator; trade quantity (in contracts); trade price; a floor trader identifier and a customer type indicator (CTI). Floor traders have to report their trades in 15 minute brackets. A timing algorithm (the Computerized Trade Reconstruction) is used to time the reported trades to their nearest second. Though this may be noisy we believe this timing is fairly accurate.[12] It is used by the Commodity Futures Trading Commission (CFTC) for regulation purposes, and is used in e.g. the studies of

[12]In addition, we apply several data filters. Firstly, we focus on 'regular' trades: we remove trades that are e.g. indicated to be spread trades. Secondly, we remove trades that show an unusual transaction pattern. Specifically, if a transaction return of more than 0.25% is followed by a return in the opposite direction also larger than 0.25% we expect these trades to suffer from serious timing error and eliminate it. In total we remove 1.44% of all trades with these two filters.

Fishman and Longstaff (1992) and Manaster and Mann (1996).

The CTI indicates for each trade whether it is a trade for the own account of the floor trader (a 'proprietary' trade), or on behalf of another party. In particular, we have the following four codes: CTI1: proprietary trade; CTI2: trade for clearing member's house account; CTI3: trade for another member present at the floor; CTI 4: a trade for (off-exchange) customers. Consistent with earlier futures market studies (such as Fishman and Longstaff (1992), Manaster and Mann (1996) and Chakravary and Li (2003)) we restrict attention to CTI1 and CTI4 trades as they represent most trading volume. Since both parties report a trade the trades are double counted. For example, a trade between two market makers each trading for own account appears twice in our dataset with both times the same quantity, price and CTI but different buy/sell indicator and floor trader identifier.

[insert Table 1]

Following the futures market literature (see for example Fishman and Longstaff (1992), Chang, Locke, and Mann (1994), Manaster and Mann (1996) and Chakravary and Li (2003)) we use the CTI codes to identify three groups of floor traders in our data. On a daily basis we identify traders that only trade on behalf of customers (we label these as 'brokers'), traders that only trade for own account ('locals', or local traders) and traders that do both ('duals', or dual traders).[13] Table 1 provides some summary statistics for these groups. Important to note is that of these three groups the locals and duals trade for own account, and are the market makers in this setting.

On an average day there are 537 traders active, each generating an average volume of 736 contracts for own account and 673 contracts on behalf of customers. This illustrates the enormous activity of this market: on an average day 339 thousand contracts are traded for own account, and 166 thousand contracts are traded on behalf of customers. Of the 537 traders active on an average day 292 are local traders, 169 dual traders and 77 brokers. Thus, on an average day in our sample 461 floor traders provide market making services.

We combine our above treasury futures dataset with a dataset on macroeconomic announcements from the International Money Market Services (MMS). We consider a broad set of 25 macro announcements such as the PPI, CPI and Nonfarm Payroll Employment figures (which have previously been studied by a.o. Green (2004), Pasquariello and Vega

[13] Following the literature we allow for a 2% error margin for this classification (see for example Fishman and Longstaff (1992) and Chang, Locke, and Mann (1994)). That is, if daily volume for a trader on a day consists of more than 98% (less than 2%) proprietary volume we label him a local (broker), otherwise a dual.

(2007) and Menkveld, Sarkar, and Van der Wel (2007)) that occur throughout the trading day at fixed times, such as at 8:30 a.m. ET and 10:00 a.m. ET. For each macro announcement an expectation of market participants is recorded, together with the first released (i.e., not revised) figure.

Consistent with the aforementioned studies, we focus on the 8:30 announcements as this is where the most significant announcements are. Using the announcement data we split our sample in two groups. We look at days at which there is one or more 8:30 announcement, and days at which there are no announcements at 8:30. To make sure the 8:30 announcement is driving the results we are careful to take out days with other announcements that take place in the morning (that is, at 9:15 and 10:00).

Table 1 also provides summary statistics for these announcement and nonannouncement days. Of the total 250 days in our sample we find there are 90 announcement days, and 91 nonannouncement days. We see a clear increase in trading activity both in average volume traded and number of traders on announcement days compared to nonannouncement days. For example, on average on announcement days there are 560 traders active, while on nonannouncement days there are 514 traders, 8.2% less.

[insert Figure 1]

For each trader we have a record of all his trades in the 30Y treasury futures, plus the direction of each of these trades. We use this to obtain the inventory for each trader. Consistent with the previous literature (see for example Manaster and Mann (1996)) we do this under the assumption that floor traders close out the day with zero inventory.[14] In Figure 1 we plot the end of day inventory that is obtained using this assumption. From the figure it is clear that end of day inventory is indeed centered around zero. The most common end of day inventory position is a flat position. Of the nonzero positions most are below 15 contracts in absolute terms, which is small compared to the average market maker's trade size of 736 contracts. This suggests that the assumption that is used to construct the inventory series is a reasonable one.

[14] There are some limitations to this way of calculating inventories. As we focus on CTI1 and CTI4 trades we miss possible CTI2 and CTI3 trades of market makers. In addition we only have a record of the trades in the 30Y treasury futures, and not in other markets. But similar to Manaster and Mann (1996), we believe the current method provides the most accurate estimate of inventories.

3 Signing Futures Market Trades

3.1 Methodology

To study the behavior of market makers it is necessary to identify whether the trades in which a market maker is involved are initiated by his counterparty or by himself. This amounts to determining for each trade whether it is initiated by the buying or selling party. For markets with explicit bid and ask quotes algorithms for this challenging task are available, an often employed technique that relates the transaction price to the average of the bid and ask quote (the 'midquote') was put forward by Lee and Ready (1991). For markets without quotes the identification is an even more challenging task. Whereas in the former case the observations consist of transaction prices and both bid and ask quotes, for the latter only the transaction prices are observed.

Hasbrouck (2004) proposes a new Bayesian methodology to deal with the challenge of estimating the unobserved sign of the trades from the observed transaction prices. The methodology is based on the Roll (1984) model of the bid-ask spread.[15] In this model the logarithm of the unobserved efficient price m_t evolves as a random walk:

$$m_t = m_{t-1} + u_t, \qquad u_t \sim N(0, \sigma_u^2). \tag{1}$$

The actually observed log transaction prices p_t are either above or below this unobserved efficient price, depending on whether the trade is initiated by the buyer or the seller of the transaction. If we let $q_t \in \{-1, +1\}$ denote the direction of a trade, with $+1$ a buyer-initiated trade and -1 a seller-initiated trade, and c the transaction costs we can write the observed log transaction price as:

$$p_t = \begin{cases} m_t + c, & \text{if } q_t = +1, \\ m_t - c, & \text{if } q_t = -1, \end{cases} \tag{2}$$

or simply $p_t = m_t + cq_t$.

Hasbrouck (2004) suggests a Markov Chain Monte Carlo (MCMC) methodology (the Gibbs Sampler), in which iteratively draws from the parameters c and σ_u^2 are obtained,

[15] In addition, Hasbrouck (2004) suggests several extensions to the Roll (1984) model that can be estimated in the Bayesian framework he proposes. As our main purpose is the signing of trades we choose a standard setting and therefore remain in the set-up of the Roll (1984) model. Note that in addition to this standard setting, in Footnote 19 we develop an alternative method to sign futures trades that allows for more flexibility.

together with draws for the unobserved time series of signs q_t, $t = 1, \ldots, n$. For a large number of draws the simulated distribution will be equal to the desired joint posterior distribution of the parameters and sign time series, conditional on the observed prices. An obvious disadvantage of these simulation based techniques is that they are computationally expensive and require a lot of simulations to obtain convergence. As we have over 10.7 million observations this MCMC technique requires long computation time.

Instead of the above Bayesian methodology we propose to estimate the Roll (1984) model parameters c and σ_u^2 and the series of trade initiating signs q_t in a State Space Framework (SSF). This class of time-series models builds on the idea that an observed series can be explained by several unobserved components.[16] If we write the Roll (1984) model in this framework we obtain:

$$\begin{aligned} p_t &= m_t + cq_t, & q_t &\in \{-1, +1\}, \\ m_t &= m_{t-1} + u_t, & u_t &\sim N(0, \sigma_u^2). \end{aligned} \tag{3}$$

As the q_t are not Gaussian but binary distributed (assumed to be initiated by the buying or selling party with equal probability[17]) this is not a standard linear Gaussian state space model. However, since q_t can only take on two values this model can be seen as a special case of state space models with regime switching. Kim and Nelson (1999) discuss the implementation of regime switching models in the state space framework, and show that it is a combination of the Kalman Filter for SSF models and the Hamilton (1989) filter for regime switching models. By implementing the recursions of this algorithm we obtain a likelihood value, which we can maximize using standard optimization techniques.

3.2 Simulation Study and Results

There are a few additional issues when applying our State Space Form Regime Switching (*SSFRegSw*) signing methodology to the data introduced in Section 2. As our dataset deals with a very actively traded instrument it occurs that there are multiple trades at the same

[16]See Durbin and Koopman (2001) for an introduction. Some recent financial market studies that use state space techniques are Driessen (2005) and Menkveld, Koopman, and Lucas (2007); Glosten and Harris (1988), Harris (1990) and Hasbrouck (1999) employ non-Gaussian state space methods.

[17]This is an assumption that can easily be relaxed in this framework, which we see as a major contribution of our methodology. Whereas the extensions that Hasbrouck (2004) proposes deal with the price impact of trades, trade clustering and price discreteness, we are also able to extend the model in terms of autocorrelation in sign.

second.[18] As in the Roll (1984) model the transaction cost and efficient price innovation and thus the sign does not depend on quantity we summarise the information of all trades in this second to one single observation. In addition, as was pointed out in Section 2, the time stamps of the trades are obtained using the Computerized Trade Reconciliation algorithm and are therefore noisy to some extent. Though this is not an issue addressed in the Hasbrouck (2004) methodology, for robustness we implement an alternative signing algorithm also based on the state space model, in which we aggregate all trades within each minute.[19] Our results remain unchanged.

[insert Table 2]

Panel A of Table 2 provides results from a simulation study of the accuracy and speed of the various signing algorithms. For a number of replications (100 in this set-up) we generate a fixed number of observations (chosen to be 50 here) with Roll (1984) as the Data Generating Process (DGP). For each of these replications we estimate the parameters of the Roll model and the sign (buyer- or seller-initiated) of each trade. We compare the following methods: the method of moments, the State Space Form Regime Switching (*SSFRegSw*) methodology from the previous section, the SSF Approximation (*SSFApprox*) method from Footnote 19, Hasbrouck's (2004) MCMC (*H-MCMC*) method and a tick test (in which a trade is considered to be buyer-initiated if it is an uptick).

We find that the method of moments, SSF Regime Switching and Hasbrouck's method all provide good estimates of the Roll model parameters. Moreover, the results for the SSF Regime Switching and Hasbrouck's method are very similar. For some parameter values and number of observations our SSFRegSw method performs slightly better,

[18]It can even occur that in the futures pit there are trades at different prices in the same second. On average this occurs 28 seconds per day (at about 1.1% of all seconds at which trading takes place). Though in the SSFRegSw signing framework this problem is ignored (i.e. in this case the trades are randomly sorted), we will address this in the robustness signing algorithm of Footnote 19.

[19]We approximate the Roll (1984) model of equation (3) with a linear Gaussian state space model:

$$\begin{aligned} p_t &= m_t + v_t, & v_t &\sim N(0, \sigma_v^2), \\ m_t &= m_{t-1} + u_t, & u_t &\sim N(0, \sigma_u^2), \end{aligned}$$

such that we have $\mathbb{E}[v_t] = \mathbb{E}[cq_t] = 0$ and $\mathbb{V}[v_t] = \mathbb{V}[cq_t] = 2c$. As we now do not need the additional calculations of the Hamilton (1989) filter we can straightforwardly implement a multivariate version of this model. This allows us to aggregate the trades within a certain interval (10 seconds for example, or 1 minute) by creating a multivariate price vector for each time. That this creates a variable number of observations is no problem for models in SSF, as this class of models is particularly well-suited for models with missings. In addition we can also use this approach to deal with the situation that in some seconds there are trades occurring at different prices.

for other parameter values and number of observations the H-MCMC method performs a bit better.[20] However, the SSF Approximating method performs very poor to estimate the model parameters.

In terms of estimating the sign of the trades we see both the SSF Regime Switching method and Hasbrouck's MCMC method perform very well, with an accuracy of over 95% and greatly outperforming the tick test. The MCMC and SSFRegSw methods provide the most accurate results, signing at least another extra 0.5% of trades correct compared to the competing methods. Interestingly, while the SSF Approximating method performs poor in obtaining the model parameters, it seems to work very well for signing trades.

In terms of time there is a clear difference between the SSF methods and the MCMC method. Hasbrouck's MCMC method is more than 10 times slower than the SSF Regime Switching method. As the MCMC method relies on simulation methods more loops over the data are needed. For example, taking 10,000 swoops (as Hasbrouck recommends) requires $10,000 * n$ calculations. The Maximum Likelihood (*ML*) calculations based on the SSF Regime Switching method require less. On average 10 iterations in the ML procedure are needed, in which on average 6 times the likelihood has to be calculated. Due to its smoothing nature the loop needs to be forward and backward, so must be multiplied by 2. Therefore on average the ML method requires about $10 * 6 * 2 * n = 120 * n$ calculations and is indeed a lot quicker. The SSF Approximation method provides the quickest results.[21]

Overall there is a case to be made for both of the SSF signing methods and the MCMC method. As our dataset contains many trades we prefer to take the quickest of these methods, and employ the SSF Regime Switching method. In addition we use the SSF Approximation method for robustness.

[insert Figure 2]

Figure 2 illustrates how we apply the SSF Regime Switching signing methodology to the data. In the top figure we plot the raw data: the observed transaction prices. Using these observations we obtain a smoothed efficient price series (also plotted in the top figure)

[20] From the results reported in the table it may seem that the Hasbrouck (2004) MCMC method is more biased and less efficient than the SSF Regime Switching method. However, this is due to the chosen number of swoops and burn-in of the MCMC method. With a greater burn-in results similar to the SSFRegSw can be obtained with the H-MCMC method, though this will add to the calculation time.

[21] This is however partially due to the underlying code. The Hasbrouck (2004) MCMC and State Space Form Regime Switching methods are straightforwardly implemented in Ox (see Doornik (1998)), while the SSF Approximation method uses the functions from the SsfPack (see Koopman, Shephard, and Doornik (1999)) which are programmed in (the quicker) programming language C.

and a smoothed probability of the trade begin initiated by the buying party. In general we see our signing methodology acts in the same way as the Lee and Ready (1991) methodology for signing trades when a bid-ask quote is available. In the latter case a trade is considered to be buyer-initiated if it is above the midquote, whereas we label a trade to be initiated by the buying party if it takes place above the smoothed efficient price. Thus in both cases an estimate of the underlying true price is obtained, the midquote and the smoothed efficient price, around which transactions take place.

Finally, in Panel B of Table 2 we provide some statistics of the results of the signing algorithm on a subset of our dataset. The sign we obtain with our SSF Regime Switching methodology agrees with Hasbrouck's method about 87% of all observations, and between 82% and 89% with the SSF Approximating method. Moreover, our concerns with calculation time seem to be justified: for an average day Hasbrouck's methodology requires more than 2 minutes, while our alternative SSF methods require less than 7 seconds.

We obtain a half-spread estimate of about 0.15. Following the calculations in Hasbrouck (2004) we transform this into a dollar figure by multiplying this estimate with the average transaction price. As the transaction price is very roughly about $110 in 1995, we get a spread estimate of 0.15*2*$110=$33. This is very close to the tick size on the market, which is $31.25 (see `www.cbot.com`). This adds further support to the reliability of the signing algorithm.

4 Empirical Results

4.1 Initiated Trades of the Market Makers

To study the liquidity supply role of market makers we first examine what portion of their trades they initiate. As described in Section 2, there are three groups of floor traders active on the 30Y treasury futures market. These are the local traders, who only trade for their own account, the dual traders, who trade for own account and on behalf of customers, and brokers, who only trade on behalf of customers. Of these the first two provide market making services, and these are the groups that we focus on in this study. The difference between these two is, besides possible trader heterogeneous effects, the information set: in addition to the publicly available information the dual traders observe the customer trades they bring to the market, from which they can also make inferences. Due to this we split our results for market makers to locals and duals.

In addition we split our results to those for days with macroeconomic announcements and compare these to days with no macroeconomic announcements. As on the former group of days it is known information will come to the market it is interesting to see if that extra information leads to difference in trade behavior.

[insert Figure 3]

Figure 3 shows the intraday pattern of the percentage of the market makers' trades that they initiate. On each day and in each 15 minute interval we calculate the total number of proprietary trades in which market makers are involved. Then we use the buyer- or seller-initiated indicator that we obtain from our State Space Form Regime Switching signing methodology from Section 3 and match it to the buy/sell indicator in our dataset. If these agree we label the trade as being initiated by a market maker. We then calculate the number of initiated market maker trades as a percentage of the total number of market maker trades. In Panel (A) we look at this variable for locals, in Panel (B) for duals.

For both locals and duals the percentage of initiated trades is high. On average market makers initiate more than 45% of their trades. As the trades are two-sided the maximum percentage for all market makers we could have here is 50%. That the percentage of initiated trades is close to this number indicates that market makers also demand liquidity for a significant part of the day.

That this percentage is high contradicts the assumption in classic market making models that the market maker is a passive liquidity supplier. However, it is not inconsistent with other economic theories. For example, in the 'hot-potato' trading model of Lyons (1997) in the first stage market makers trade with the general public and absorb their order flow. In the second stage in multiple rounds the market makers offset their inventory position by engaging in interdealer trading. Thus, one outside order brought to the market results in multiple trades on the interdealer market, consistent with a high percentage of initiated market maker trades.

The percentage of initiated trades is higher for local traders than for dual traders, 49% and 46% respectively. Interestingly, the difference in this percentage between days when information is coming to the market compared to nonannouncement days is only significant for the dual traders in the post-announcement interval.

These results are consistent either with the market makers being active in managing their inventory positions, or with them being active in building up speculative positions. In addition, the significant difference for dual traders in the half hour after macroeconomic announcements indicates they change their behavior shortly after there is information coming to the market. To study these issues further it will be interesting to look at the inventory positions that the market makers build up.

4.2 Market Maker Inventory and Macro News

[insert Figure 4]

In Figure 4 we show the inventory position, calculated as described in Section 2, of the market makers at four points in the day. We focus on the difference in the inventory between announcement and nonannouncement days. As the announcement days we consider are defined to have one or more macroeconomic announcement at 8:30 we show the inventory position around this time. We show the empirical distribution of trader inventories at 8:30, thus shortly *before* the news is released, the inventory position at 8:45, at 9:00 and at the end of the trading day.

From these figures it is clear the market makers prefer to enter the announcement with a zero inventory position, they like to 'go in flat'. The inventory distribution on nonannouncement days at 8:30 (the bold line) is much more dispersed than the distribution on announcement days. Immediately after the announcement the market makers quickly build up an inventory position: compared to nonannouncement days the empirical inventory distribution is more dispersed.

To illustrate how strong these results are we do not only show these for the set of all announcement days, but also refine them to the set of the three most influential announcement days (the nonfarm, CPI and PPI announcement, see a.o. Green (2004), Pasquariello and Vega (2007) and Menkveld, Sarkar, and Van der Wel (2007)) and only the most influential announcement (the nonfarm payroll employment figure). We find that on days when there is the strongest reaction to the news the distribution of inventory is widest. In addition we split the results to the inventory distribution of locals and duals (figures available from the authors upon request). The results for these market maker types show similar patterns, and are very similar to each other.

It remains a question however whether these positions are consistent with market maker liquidity supply behavior or speculative position taking. In the first situation the market makers accommodate the desire of the outside customers to trade after announcements by absorbing their trades and in the process thus accumulate an inventory position. In the second situation the inventory position is build up because the market maker has his own projection on the movement of the price, and wants to speculate on this.

4.3 Inventory Increasing Trades

To disentangle whether the results so far are consistent with liquidity supply or speculative position taking by market makers it is interesting to see what share of the large percentage of initiated trades that we find in Figure 3 increases the inventory position of the market makers. If the large percentage of initiated trades and the increased inventory position after macroeconomic announcements is consistent purely with their market maker liquidity supply role we expect them to only initiate trades that reduce their absolute inventory position. In other words, the market makers will only initiate trades that bring them closer to their preferred inventory position. On the other hand, if we find a high percentage of initiated trades that increase the market makers' absolute inventory position this is consistent with the market makers being informed and speculating on future price movements.

[insert Figure 5]

In Panels (A) and (B) of Figure 5 we split the percentage of initiated trades from Figure 3 to trades that are inventory increasing and those that are inventory decreasing. On each day and in each 15 minute interval we calculate the total number of proprietary trades in which market makers are involved. Then we use the buyer- or seller-initiated indicator that we obtain from our State Space Form Regime Switching signing methodology from Section 3 and match it to the buy/sell indicator in our dataset. If these agree we label the trade as being initiated by a market maker. Then, for each market maker we sum all their signed initiated trades in the interval and see whether it increases their inventory position. We then calculate the number of initiated inventory increasing market maker trades as a percentage of the total number of market maker trades.[22] In Panel (A) we look at this variable for locals, in Panel (B) for duals.

[22] The frequency with which we perform this analysis is low. It is very well possibly that within the 15 minute interval the initiated trades do not only respond to the inventory position at the begin of the interval, but also to uninitiated trades in the interval. We look at 15 minute intervals to ensure that possible errors due to the timing algorithm do not cause our results. In addition we also perform the analysis of this section in 1 minute intervals. This frequency is consistent with Manaster and Mann (1996), who look at inventory management for a similar futures market dataset. Though the percentages of inventory increasing trades are

We find a very high percentage of market maker trades that are initiated and increase individual inventory positions, over 25%. Unlike the total percentage of initiated trades, which is higher for local traders, the percentage of initiated inventory increasing trades is almost identical for local and dual traders. Interestingly, for both traders there is a significant different percentage of initiated inventory increasing trades in the 8:30-8:45 interval after announcements compared to nonannouncement days. This effect is strongest for the dual traders.

In addition we split the percentage of market maker trades that are uninitiated (the complement of the percentages shown in Figure 3) to the part that is inventory increasing (referred to as uninitiated inventory increasing trades) and the part that is inventory decreasing. We show these for the local traders in Panel (C) of Figure 5, and in Panel (D) for the dual traders. The results are similar to those for the initiated inventory increasing trades, though here the percentage is slightly higher for dual traders (29% compared to 27%). Most position taking takes place in the 8:30-8:45 announcement interval, and is strongest for the dual traders.

The results in Figure 5 are consistent with the market makers taking on a position after macroeconomic announcements. This is done both actively, through initiated trades, and passively, through uninitiated trades. Both local traders and dual traders do so, but in particular the traders with the additional information from bringing customer orders to the market build up a position after the announcement. The high percentage of initiated inventory increasing trades provides evidence against the market makers being uninformed liquidity suppliers, as pure market makers would only actively engage in trading to offset their inventory position. The high percentage of uninitiated inventory increasing trades indicates that the position taking is not only done through initiating trades, but also through passively participating in trades that steer the inventory position in a certain direction.

4.4 Inventory Increasing Trades and Trading Profits

If the market makers indeed take on speculative positions through both initiated and uninitiated trades then it is interesting to see if the traders that do so most derive positive profits from this. We examine this by looking in the cross-section of market makers, and relate the percentage of inventory increasing trades to profits from trading. We follow Fishman and

slightly lower we get qualitatively similar results (the corresponding figures are available from the authors upon request).

Longstaff (1992) and define profitability as:

$$\pi_{kt} = \frac{\left(\sum_{j=1}^{N_{kt}^s} q_{jkt}^s P_{jkt}^s - \sum_{j=1}^{N_{kt}^b} q_{jkt}^b P_{jkt}^b + (\sum_{j=1}^{N_{kt}^b} q_{jkt}^b - \sum_{j=1}^{N_{kt}^s} q_{jkt}^s) REFP_t\right)}{\max(\sum_{j=1}^{N_{kt}^b} q_{jkt}^b, \sum_{j=1}^{N_{kt}^s} q_{jkt}^s)}, \tag{4}$$

where π_{kt} is the profit per round-trip contract[23] for intermediary k on day t, N_{kt}^b (N_{kt}^s) is the total number of buys (sells), q_{jkt}^b (q_{jkt}^s) is the quantity of the jth transaction in terms of number of contracts, P_{jkt}^b (P_{jkt}^s) is the associated price, and $REFP_t$ is the reference price in day t. Similar to the calculation of inventory, the profit calculation assumes that the intermediary starts with zero inventory. The end of day position (if any) is liquidated at a reference price $REFP_t$, which for our full day results we take to be the daily settlement price.

[insert Table 3]

In Table 3 we split these profits from trading according to the percentage of inventory increasing trades. For each day we calculate the 25% quantile, median and the 75% quantile of the percentage of inventory increasing trades and based on this classify the traders and corresponding profits on a daily basis in four groups. In Panel A we split the trading profits based on the percentage of initiated inventory increasing trades. Looking at the median, we generally find for both the locals and duals on both announcement and nonannouncement days a positive relation between the percentage of initiated inventory increasing trades and trading profits.[24] Moreover, the results do not only seem to be in the median, also in the lower quantiles similar patterns can be found. Thus not only do market makers that have a large percentage of initiated inventory increasing trades earn higher profits from trading, they reduce the downside of their profits.

In Panel B of Table 3 we relate the percentage of uninitiated inventory increasing trades to profits from trading. There is evidence of similar patterns as documented above for initiated inventory increasing trades. However, for locals the relation seems to be a bit weaker, while for duals it is a bit stronger.

To study whether initiated or uninitiated inventory increasing trades has the strongest relation to the trading profits and see whether the above results also hold for the mean profits

[23] We use a per-contract profit measure to control for trade activity, as locals are more active than duals.

[24] For the dual traders the pattern is not always monotonous, which is in part caused by traders that are very inactive. For example, traders that only trade once on a day are automatically put in either the smallest or largest group, as either 0% or 100% of their trades are initiated inventory increasing.

we perform a regression. We regress the trading profits on both the percentage of initiated inventory increasing trades and the percentage of uninitiated inventory increasing trades and some control variables. The most natural candidates for control variables are volatility and market maker competition, as it is likely these influence trading profits of market makers. In particular, we estimate the following regression:

$$\begin{aligned} \pi_{j,t}^{d,f} &= \alpha^{d,f} + \beta_1^{d,f} IIIT_{j,t}^{d,f} + \beta_2^{d,f} UIIT_{j,t}^{d,f} \\ &\quad + \beta_3^{d,f} VOLA_t + \beta_4^{d,f} COMP_t + \textstyle\sum_k I_{k,t}\gamma_k^{d,f}|S_{k,t}| + \varepsilon_{j,t}^{d,f}, \end{aligned} \tag{5}$$

where $\pi_{j,t}^{d,f}$ is trader j's own-account profit per round trip on day t, $IIIT_{j,t}^{d,f}$ and $UIIT_{j,t}^{d,f}$ measure the percentage inventory increasing trades, $VOLA_t$ is the volatility, $COMP_t$ is a competition proxy and is defined as the number of active market makers, $I_{k,t}$ is a dummy that is one if there is an announcement of type k on day t and zero else, $S_{k,t}$ is the macro surprise, and $\varepsilon_{j,t}^{d,f}$ is the error term. We estimate the equation for two types of days d, announcement days ($d = ad$) and nonannouncement days ($d = nd$), and two floor trader types f, local traders ($f = lt$) and dual traders ($f = dt$). We have two variables that measure the percentage of inventory increasing trades: the percentage initiated inventory increasing trades ($IIIT_{j,t}^{d,f}$) and the percentage uninitiated inventory increasing trades ($UIIT_{j,t}^{d,f}$). For estimation, we use the Feasible Efficient GMM procedure with a Newey-West estimator (using three lags) for standard errors. The difference in results when comparing the median and mean in Table 3 indicate that there possibly are outliers in the profits series. To ensure these outliers do not cause the significance of estimates we set the 5% smallest and largest values at the 5% and 95% quantile respectively.

If the active inventory taking is indeed associated with speculative profits we expect a positive and significant estimate of $\beta_1^{d,f}$. If in addition profitable positions are achieved through selectively passively participating in trades we also expect $\beta_2^{d,f}$ to be positive and significant.

[insert Table 4]

Table 4 reports the estimates for the above regression. First, we estimate (5) without the control variables volatility, competition and the announcement surprises. We only find significance of the positive relation between inventory increasing trades and trading profits for the dual traders on announcement days. In a second set-up, with control variables, we get the same result.

In a third set-up we are careful to take any day specific effects into account by including a dummy for every day.[25] In this set-up the strong results for the dual traders on announcement days are confirmed, and we find similar effects for the local traders.[26]

We therefore conclude that for locals and duals on announcements days there indeed is a positive and significant relation between inventory increasing trades and profits from trading, with the strongest relation for the dual traders. These results are consistent with the market makers building up a position after the announcement, and earning a profit from this. The market makers that have the highest percentage of inventory increasing trades earn the highest profits. Moreover, this relation is strongest for the group of market makers with the additional information set of observing what orders customers bring to the market.

4.5 Bid-Ask Spread of Market Makers

Our results so far show that the market makers with the largest information set, the dual traders, are most active in the interval after announcements to build up an inventory position compared to nonannouncement days. Moreover, we find that these traders earn the highest profits from trading, and that this is positively related to the percentage of inventory increasing trades.

[insert Figure 6]

If these dual traders have more information and the other market participants have a signal on which market makers are dual traders, then these other participants should charge these dual traders a higher spread to protect themselves against this information. In Figure 6 we examine this thesis, by comparing the bid-ask spread of dual traders to that of local traders. To calculate the bid-ask spread we first use our State Space Form Regime Switching methodology to obtain a buyer- and seller-initiated indicator. We then follow the Manaster and Mann (1996) methodology to calculate spread in futures markets: we calculate the difference between the average (volume-weighted) buy price and the average sell price.

[25] Note that in this case the control variables can not be included anymore, as they span the same space as the day dummies.

[26] That for the local traders the percentage inventory increasing trade variables are not significant in the first two model variations but only in the third (with day-dummies) is possibly caused by omitted variable problems. The difference between the regression set-up with controls and day-dummies is 88 variables. Moreover, the estimates themselves do not change over the different variations used, the difference only comes in through the standard errors.

On both announcement and nonannouncement days duals get charged a higher spread than local traders, \$31 compared to \$29. However, consistent with the duals having a significantly larger percentage of inventory increasing trades and higher profits in the post announcement interval, the bid-ask spread they pay is significantly higher than the spread on nonannouncement days and than the local traders on announcement days.[27]

These results are consistent with the market participants having a signal on who the dual traders are, and charging them a higher spread as they are the most informed market makers. The signal is not perfect however, as we find the dual traders still earn positive profits. Overall our results provide evidence against the market maker being an uninformed passive liquidity supplier.

5 Conclusion

We examine the 30Y U.S. treasury futures market to study the market maker. Classic models assume he is an uninformed liquidity supplier who actively manages his inventory. So far, the empirical support is poor. We examine a large cross-section of 1,958 intermediaries who to greater or lesser extent provide market making services and study whether position taking by market makers explains the difference between theory and empirics.

We find that market makers initiate a significant amount of trades that increase their inventory positions. When we look at the cross-section of market makers and relate the extent to which their trades are inventory increasing to their profits from trading we find a significant and positive relation. These results are strongest when looking at the high-information environment created by the scheduled releases of macroeconomic news and for market makers that have the largest information set.

Overall our results provide evidence against the market maker being an uninformed liquidity supplier. We document market making behavior consistent with the Madhavan

[27]The spread we derive here is higher than that calculated from customer trades as in Menkveld, Sarkar, and Van der Wel (2007). This finding relates to Dunne, Hau, and Moore (2007), who find higher spread for interdealer trades compared to the customer segment for European bond markets. Also note that the spread we find adds further support to our State Space Form Regime Switching signing algorithm. In the extreme case of the algorithm generating random signs the Manaster and Mann (1996) procedure to calculate spreads would result in a spread of zero dollars. The spread we obtain is significant, and has intraday patterns that agree with those derived from the (already signed) customer trades. Moreover, its average of a little under \$30 agrees with the tick size in the market and the estimates of the half spread which are reported in Section 3.2.

and Smidt (1993) model, in which the market maker is both a dealer and a speculator. Our results stress the need for the development of theoretical models in which the market maker is informed, such as the recent Boulatov and George (2007) model.

References

Anand, A., and A. Subrahmanyam. 2007. "Information and the intermediary: Are market intermediaries informed traders in electronic markets?" *Journal of Financial and Quantitative Analysis (forthcoming).*

Anand, A., C. Tanggaard, and D.G. Weaver. 2008. "Paying for Market Quality." Working Paper, WFA 2007 paper.

Andersen, T.G., T. Bollerslev, F.X. Diebold, and C. Vega. 2003. "Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange." *American Economic Review* 93:p38–62.

———. 2007. "Real-Time Price Discovery in Stock, Bond and Foreign Exchange Markets." *Journal of International Economics* 73:p251–277.

Balduzzi, P., E.J. Elton, and T.C. Green. 2001. "Economic News and Bond Prices: Evidence From the U.S. Treasury Market." *Journal of Financial and Quantitative Analysis* 36:p523–543.

Bessembinder, H., J. Hao, and M. Lemmon. 2007. "Why Designate Market Makers? Affirmative Obligations and Market Quality." Working Paper.

Bjønnes, G.H., and D. Rime. 2005. "Dealer Behavior and Trading Systems in Foreign Exchange Markets." *Journal of Financial Economics* 75:p571–605.

Boulatov, A., and T.J. George. 2007. "Securities Trading when Liquidity Providers are Informed." Working Paper, AFA 2008 paper.

Cao, H.H., M.D. Evans, and R.K. Lyons. 2006. "Inventory Information." *Journal of Business* 79:p325–363.

Chakravary, S., and K. Li. 2003. "An Examination of Own Account Trading by Dual Traders in Futures Markets." *Journal of Financial Economics* 69:p375–397.

Chang, E.C., P.R. Locke, and S.C. Mann. 1994. "The Effect of CME Rule 552 on Dual Traders." *Journal of Futures Markets* 14:p493–510.

Demsetz, H. 1968. “The Cost of Transacting.” *Quarterly Journal of Economics* 82:p33–53.

Doornik, J. A. 1998. *Object-oriented Matrix Programming Using Ox 2.0.* Timberlake Consultants Ltd.

Driessen, J. 2005. “Is Default Risk Priced in Corporate Bonds?” *Review of Financial Studies* 18:p165–195.

Dunne, P., H. Hau, and M. Moore. 2007. “A Tale of Two Platforms: Inter-Dealer and Retail Quotes in the European Bond Markets.” Working Paper.

Durbin, J., and S. J. Koopman. 2001. *Time Series Analysis by State Space Methods.* Oxford Statistical Science Series.

Ederington, L., and J. Lee. 1993. “How Markets Process Information: News Releases and Volatility.” *Journal of Finance* 45:p1161–1191.

———. 1995. “The Short-Run Dynamics of the Price Adjustment to New Information.” *Journal of Financial and Quantitative Analysis* 30:p117–134.

Ellis, K., R. Michaely, and M. O’Hara. 2000. “The Accuracy of Trade Classification Rules: Evidence from Nasdaq.” *Journal of Financial and Quantitative Analysis* 35:p529–552.

Evans, M.D.D., and R.K. Lyons. 2005a. “Exchange Rate Fundamentals and Order Flow.” Working Paper.

———. 2005b. “Meese-Rogoff Redux: Micro-Based Exchange Rate Forecasting.” *American Economic Review* 95:p405–414.

Fishman, J.F., and F.A. Longstaff. 1992. “Dual Trading in Futures Markets.” *Journal of Finance* 47:p643–671.

Fleming, M.J., and E.M. Remolona. 1997. “What Moves the Bond Market?” *Economic Policy Review* 97-Dec:p31–50.

———. 1999. “Price Formation and Liquidity in the U.S. Treasury Market: The Response to Public Information.” *Journal of Finance* 54:p1901–1915.

Fleming, M.J., and A. Sarkar. 1999. “Liquidity in U.S. Treasury Spot and Futures Markets.” *Market Liquidity Research Findings and Selected Policy Implications.*

Frino, A., and E. Jarnecic. 2000. “An empirical analysis of the supply of liquidity by locals in futures markets.” *Pacific-Basin Finance Journal* 8:p443–456.

Garleanu, N., L.H. Pedersen, and A.M. Poteshman. 2005. “Demand-Based Option Pricing.” NBER Working Paper.

Glosten, L.R., and L.E. Harris. 1988. "Estimating the Components of the Bid-Ask Spread." *Journal of Financial Economics* 21:p123–142.

Glosten, L.R., and P.R. Milgrom. 1985. "Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders." *Journal of Financial Economics* 14:p71–100.

Green, T.C. 2004. "Economic News and the Impact of Trading on Bond Prices." *Journal of Finance* 59:p1201–1233.

Hamilton, J. 1989. "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle." *Econometrica* 57:357–84.

Hansch, O., N.Y. Naik, and S. Viswanathan. 1998. "Do Inventories Matter in Dealership Markets? Evidence from the London Stock Exchange." *Journal of Finance* 53:p1623–1656.

Harris, L.E. 1990. "Statistical Properties of the Roll Serial Covariance Bid-Ask Spread Estimator." *Journal of Finance* 45:p579–590.

Hasbrouck, J. 1988. "Trades, Quotes, Inventories, and Information." *Journal of Financial Economics* 22:p229–252.

———. 1999. "The Dynamics of Discrete Bid and Ask Quotes." *Journal of Finance* 54:p2109–2142.

———. 2004. "Liquidity in the Futures Pit: Inferring Market Dynamics from Incomplete Data." *Journal of Financial and Quantitative Analysis* 39:p305–326.

Hasbrouck, J., and G. Sofianos. 1993. "The Trades of Market Makers: An Empirical Examination of NYSE Specialists." *Journal of Finance* 48:p1565–1593.

Hendershott, T., C.M. Jones, and A.J. Menkveld. 2007. "Does Algorithmic Trading Improve Liquidity?" Working Paper.

Hendershott, T., and M. Seasholes. 2007. "Market Maker Inventories and Stock Prices." *American Economic Review* 97:p210–214.

Jain, P. 2005. "Institutional Design and Liquidity on Stock Exchanges around the World." Working Paper.

Kim, C. J., and C. R. Nelson. 1999. *State Space Models with Regime Switching*. Cambridge, Massachusetts: MIT Press.

Koopman, S. J., N. Shephard, and J. A. Doornik. 1999. "Statistical algorithms for models in state space using SsfPack 2.2." *Econometrics Journal* 2:p113–166.

Kyle, A.S. 1985. "Continuous Auctions and Insider Trading." *Econometrica* 53:p1315–1336.

Lee, C.M., and M.J. Ready. 1991. "Inferring the Trade Direction from Intraday Data." *Journal of Finance* 46:p733–746.

Locke, P.R., and P. Sarajoti. 2004. "Aggresive dealer pricing." *The Quarterly Review of Economics and Finance* 44:p559–573.

Lyons, R. 1995. "Tests of Microstructural Hypotheses in the Foreign Exchange Market." *Journal of Financial Economics* 39:p321–351.

———. 1997. "A Simultaneous Trade Model of the Foreign Exchange Hot Potato." *Journal of International Economics* 42:p275–298.

Madhavan, A., and S. Smidt. 1991. "A Bayesian Model of Intraday Specialist Pricing." *Journal of Financial Economics* 30:p99–134.

———. 1993. "An Analysis of Changes in Specialist Inventories and Quotations." *Journal of Finance* 48:p1595–1628.

Madhavan, A., and G. Sofianos. 1998. "An Empirical Analysis of NYSE Specialist Trading." *Journal of Financial Economics* 48:p189–210.

Manaster, S., and S.C. Mann. 1996. "Life in the Pits: Competitive Market Making and Inventory Control." *Review of Financial Studies* 9:p953–975.

Menkveld, A.J. 2006. "Designated Market Makers for Small-Cap Stocks: Is One Enough?" Technical Report, VU University Amsterdam, AFA 2008 paper.

Menkveld, A.J., S.J. Koopman, and A. Lucas. 2007. "Modelling Round-the-Clock Price Discovery for Cross-Listed Stocks using State Space Methods." *Journal of Business and Economic Statistics* 25:p213–225.

Menkveld, A.J., A. Sarkar, and M. Van der Wel. 2007. "Discovering the Equilibrium Riskfree Rate." Tinbergen Institute Discussion Paper, EFA 2007 paper.

Naik, N.Y., and P.K. Yadav. 2003. "Risk Management with Derivatives by Dealers and Market Quality in Government Bond Markets." *Journal of Finance* 58:p1873–1904.

O'Hara, M. 1995. *Market Microstructure Theory*. Blackwell Publishers.

Panayides, M. A. 2007. "Affirmative obligations and market making with inventory." *Journal of Financial Economics* 86:p513–542.

Pasquariello, P., and C. Vega. 2007. "Informed and Strategic Order Flow in the Bond Market." *Review of Financial Studies* 20:p1975–2019.

Reiss, P.C., and I. Werner. 1998. "Does Risk Sharing Motivate Interdealer Trading?" *Journal of Finance* 53:p1657–1703.

Roll, R. 1984. "A Simple Implicit Measure of the Effective Bid-ask Spread in an Efficient Market." *Journal of Finance* 39:p1127–1139.

Rosenberg, J.V., and L.G. Traub. 2007. "Price Discovery in the Foreign Currency Futures and Spot Market." Federal Reserve Bank of New York Staff Reports, no. 262.

Stoll, H.R. 1978. "The Supply of Dealer Services in Securities Markets." *Journal of Finance* 33:p1131–1151.

Venkataraman, K., and A.C. Waisburd. 2007. "The Value of a Designated Market Maker." *Journal of Financial and Quantitative Analysis* 42:p735–758.

Table 1: Summary Statistics

This table shows the trading activity for locals, duals and brokers on the market for the 30Y treasury futures in 1995. We classify traders at the daily basis, and label a trader to be a local (broker) if more than 98% (less than 2%) of his trades are for own account, otherwise he is a dual. For these three groups we show the average number of days a trader is active, the average number of traders active on a day, the total number of trading days and the average daily volume per trader. In addition we show these for the three groups of traders combined (*All Traders*). The column *Sample* shows the total number of days and number of traders observed in our sample.

Summary Statistics - Trader Activity					
	Sample	All Traders	Locals	Duals	Brokers
Avg #days a trader is active					
all days	250	69	72	78	13
ann days	90	26	27	29	5
nonann days	91	24	25	27	4
Avg #traders active per day					
all days	1,958	537	292	169	77
ann days		560	304	175	82
nonann days		514	279	163	71
Total number of trading days					
all days		134,301	72,951	42,189	19,161
ann days		50,417	27,340	15,736	7,341
nonann days		46,734	25,419	14,812	6,503
Average daily volume per trader					
For own account					
all days		736	988	300	
ann days		851	1,147	336	
nonann days		599	797	260	
For customers					
all days		673		765	472
ann days		776		897	517
nonann days		550		616	402

Table 2: Signing Futures Market Trades - Simulation Study and Results

This table shows the results for signing the futures market trades on the market for the 30Y treasury futures in 1995. We compare the output from the State Space Form Regime Switching (*SSFRegSw*) signing algorithm we propose to the State Space Form approximation method (*SSFApprox*), Hasbrouck's (2004) MCMC (*H-MCMC*) method and a tick test (in which a trade is labeled as being initiated by the buying party if it is an uptick). In Panel A we show the output from a simulation study of these signing methods. The parameters we use for our data generation process (DGP) are chosen such that they are close to values actually observed in the data. For the five signing methods we report the mean and standard deviation (*St.Dev.*) of the half-spread c and the efficient price variance (*Eff Price Var*), the percentage of trades that are signed correctly, the root mean squared error (*RMSE*, x1,000,000) of the smoothed efficient price versus the true value and the time needed to run the algorithm (in seconds). For the simulation 50 observations and 100 replications are used. In Panel B we report results from running various algorithms on the first 10 days of our dataset. We look at the SSFRegSw method, SSFApprox with aggregation of both 10 and 60 seconds (see Footnote 19) and the H-MCMC method. We show the mean and standard deviation (*St.Dev.*) of the half-spread c and the efficient price variance (*Eff Price Var*), the percentage of trades that are labeled the same as the SSFRegSw method and the average time needed to obtain these results for one day (in seconds).

Panel A: Signing Futures Market Trades - Simulation Study

	Half-Spread (c; x1,000)		Eff Price Var (σ_u^2; x1,000,000)		% Sign	RMSE	Calc
	Mean	St.Dev.	Mean	St.Dev.	Correct	of m_t	Time
Parameters DGP	0.200		0.010				
Method of Moments	0.199	0.034	0.009	0.019			0.0
SSF Regime Switching	0.199	0.011	0.010	0.002	95.7	0.290	0.4
SSF Approximation	0.089	0.036	0.041	0.007	95.1	0.550	0.0
Hasbrouck MCMC	0.153	0.046	0.036	0.019	95.6	0.422	3.9
Tick Test					73.6		0.0

Panel B: Signing Futures Market Trades - Results for 10 Days

	Half-Spread (c; x1,000)		Eff Price Var (σ_u^2; x1,000,000)		% Sign Same as	Calc
	Mean	St.Dev.	Mean	St.Dev.	RegSw	Time
SSF Regime Switching	0.158	0.002	0.017	0.004		6.7
SSF Approx (10s)	0.091	0.030	0.042	0.005	89.1	1.4
SSF Approx (60s)	0.192	0.071	0.089	0.035	81.9	0.3
Hasbrouck MCMC	0.157	0.003	0.019	0.005	86.7	143.3

Table 3: Own-Account Trading Profits and Inventory Increasing Trades
This table reports summary statistics on the cross-sectional distribution of proprietary trading profits split to percentage of trades that increase trader inventory for both locals and duals. We classify traders at the daily basis, and label a trader to be a local (broker) if more than 98% (less than 2%) of his trades are for own account, otherwise he is a dual. To obtain the profits per contract traded round trip for each trader we subtract the value of purchases from the value of sales and add the value of end-of-period inventory (assuming zero inventory at the start). We divide this by the total number of contracts traded to arrive at a profit per contract traded round trip. We split these profits according to percentage of inventory increasing trades. That is, for each day we calculate the 25% quantile (*Q(25%)*), the median and the 75% quantile (*Q(75%)*) of the percentage of inventory increasing trades and based on this classify daily the traders and corresponding profits in four groups. In Panel A we split the trading profits based on the %initiated inventory increasing trades (*%iiit*), in Panel B this is done according to the %uninitiated inventory increasing trades (*%uiit*). We show the mean, standard deviation (*St Dev*) and the three quartiles (*25% Quant*, *Median* and *75% Quant*) of the cross-sectional distribution (across intermediaries) of own-account trading profits (with the number of trader days in each group in the column *#Trader Days*).

Panel A: Trading Profits split to %Initiated Inventory Increasing Trades						
	#Trader Days	Mean	St Dev	25% Quant	Median	75% Quant
Local Traders						
announcement days						
%iiit < Q(25%)	6,826	5.8	162.1	-10.0	4.7	20.5
Q(25%) ≤ %iiit < Median	6,804	3.9	73.7	-3.6	5.0	14.4
Median ≤ %iiit < Q(75%)	6,799	6.0	90.0	-1.2	6.3	14.9
%iiit ≥ Q(75%)	6,911	4.0	159.9	-2.2	6.8	18.5
nonannouncement days						
%iiit < Q(25%)	6,313	6.5	140.1	-11.3	3.8	20.2
Q(25%) ≤ %iiit < Median	6,332	4.3	72.0	-4.2	5.0	14.8
Median ≤ %iiit < Q(75%)	6,339	7.0	70.2	-1.9	5.7	14.4
%iiit ≥ Q(75%)	6,435	7.7	151.8	-4.7	5.9	18.8
Dual Traders						
announcement days						
%iiit < Q(25%)	3,899	6.3	71.4	-7.8	7.8	23.3
Q(25%) ≤ %iiit < Median	3,908	8.1	50.3	-2.6	8.9	19.7
Median ≤ %iiit < Q(75%)	3,920	7.9	46.4	-0.5	8.8	18.2
%iiit ≥ Q(75%)	4,009	7.2	74.3	0.0	8.7	18.0
nonannouncement days						
%iiit < Q(25%)	3,658	5.9	69.9	-8.1	7.6	22.6
Q(25%) ≤ %iiit < Median	3,672	6.9	48.4	-3.8	7.8	18.8
Median ≤ %iiit < Q(75%)	3,677	7.5	39.6	-0.9	8.5	18.3
%iiit ≥ Q(75%)	3,805	8.5	62.8	0.0	7.3	17.2

(continued on next page)

(continued from previous page)

Table 3, Panel B: Trading Profits split to %Uninitiated Inventory Increasing Trades						
	#Trader Days	Mean	St Dev	25% Quant	Median	75% Quant
Local Traders						
announcement days						
%uiit < Q(25%)	6,838	4.4	141.6	-6.9	5.6	21.3
Q(25%) ≤ %uiit < Median	6,794	4.4	70.0	-3.9	4.8	13.9
Median ≤ %uiit < Q(75%)	6,805	2.8	85.9	-2.7	5.1	13.2
%uiit ≥ Q(75%)	6,903	8.1	181.5	-1.7	7.8	21.0
nonannouncement days						
%uiit < Q(25%)	6,330	9.0	140.9	-7.9	5.3	22.0
Q(25%) ≤ %uiit < Median	6,323	5.4	66.1	-4.8	4.4	14.3
Median ≤ %uiit < Q(75%)	6,348	4.3	66.3	-3.8	4.7	12.9
%uiit ≥ Q(75%)	6,418	6.8	155.4	-3.7	6.7	19.7
Dual Traders						
announcement days						
%uiit < Q(25%)	3,912	8.0	80.3	-6.8	8.3	23.9
Q(25%) ≤ %uiit < Median	3,875	5.8	47.4	-4.3	7.0	17.9
Median ≤ %uiit < Q(75%)	3,933	6.6	46.9	-0.8	8.4	18.1
%uiit ≥ Q(75%)	4,016	9.1	66.4	0.1	10.4	19.7
nonannouncement days						
%uiit < Q(25%)	3,676	7.4	67.5	-7.3	7.3	22.8
Q(25%) ≤ %uiit < Median	3,654	7.8	48.7	-4.0	7.6	19.0
Median ≤ %uiit < Q(75%)	3,681	5.0	45.1	-2.5	7.2	16.6
%uiit ≥ Q(75%)	3,801	8.6	61.4	0.0	8.9	18.7

Table 4: Determinants of Own-Account Trading Profits

This table reports the estimation results of the following regression:

$$\pi_{j,t}^{d,f} = \alpha^{d,f} + \beta_1^{d,f} IIIT_{j,t}^{d,f} + \beta_2^{d,f} UIIT_{j,t}^{d,f} + \beta_3^{d,f} VOLA_t + \beta_4^{d,f} COMP_t + \sum_k I_{k,t}\gamma_k^{d,f}|S_{k,t}| + \varepsilon_{j,t}^{d,f}$$

where $\pi_{j,t}^{d,f}$ is trader j's own-account profit per round trip on day t, $IIIT_{j,t}^{d,f}$ and $UIIT_{j,t}^{d,f}$ measure the percentage inventory increasing trades, $VOLA_t$ is the volatility, $COMP_t$ is a competition proxy and is defined as the number of active market makers, $I_{k,t}$ is a dummy that is one if there is an announcement of type k on day t and zero else, $S_{k,t}$ is the macro surprise, and $\varepsilon_{j,t}^{d,f}$ is the error term. We estimate the equation for two types of days d, announcement days ($d = ad$) and nonannouncement days ($d = nd$), and two floor trader types f, local traders ($f = lt$) and dual traders ($f = dt$). We have two variables that measure the percentage of inventory increasing trades: the %initiated inventory increasing trades ($IIIT_{j,t}^{d,f}$) and the %uninitiated inventory increasing trades ($UIIT_{j,t}^{d,f}$). For estimation, we use the Feasible Efficient GMM procedure with a Newey-West estimator (using three lags) for standard errors.

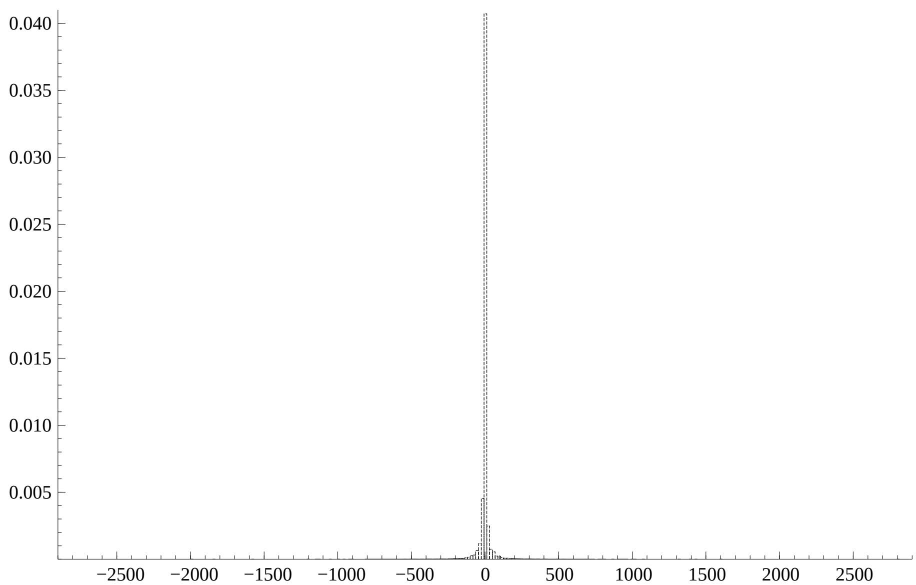
Dependent Variable: Trading Profit per Contract Traded Round Trip			
	(1)	(2)	(3)
%Init inv incr trades			
locals			
ann days	0.0164	0.017	0.0148**
	0.608	0.629	2.68
nonann days	0.0133	0.0129	0.0145
	0.546	0.53	1.4
duals			
ann days	0.0446*	0.0446*	0.0398**
	2.23	2.23	3.75
nonann days	0.0258	0.0259	0.0271
	1.34	1.34	1.57
%Uninit inv incr trades			
locals			
ann days	0.0676	0.0673	0.0674**
	0.608	0.629	2.68
nonann days	0.0305	0.0302	0.0323
	0.546	0.53	1.4
duals			
ann days	0.0646*	0.0645*	0.068**
	2.23	2.23	3.75
nonann days	0.0251	0.0254	0.0274
	1.34	1.34	1.57
Controls		yes	
Day dummies			yes

/ indicates significance at the 5%/1% level.*

Figure 1: End of Day Inventory

Panel (A) shows the end of day inventory for floor traders active in the 30Y treasury futures in 1995. For each day the end of day inventory position is calculated only for traders that were active on that day, assuming a zero inventory position at the beginning of the day. The figure shows the histogram of the end of day inventories, with an estimated empirical distribution. Panel (B) repeats panel (A), but zooms in on the part of the distribution around zero.

(A) End of Day Inventory, Empirical Distribution



(B) Repeats (A), Zoomed in at part of Distribution around Zero

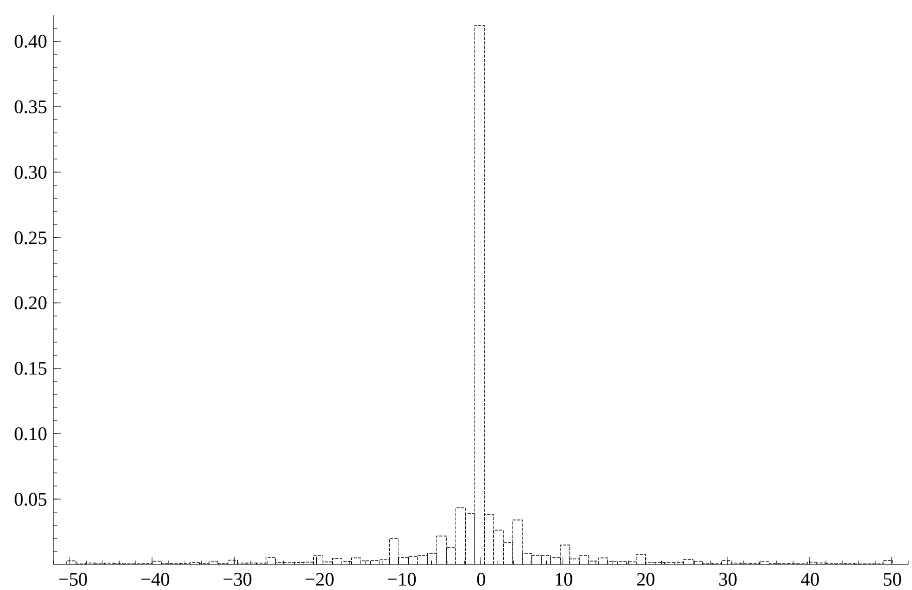


Figure 2: Signing Futures Market Trades - Example for 1995/01/03

This figure illustrates how the State Space Form Regime Switching (*SSFRegSw*) signing algorithm is applied to the data. The observations consist of the sequence of the prices reported on January 3, 1995. If multiple trades are observed in the same second at the same price we consider this to be one observation. In the top plot the first 100 reported prices are indicated with crosses. The smoothed efficient price series obtained using the SSFRegSw methodology is given by the solid line. The bottom plot gives the smoothed probability that the trade is initiated by the buying party for the first 100 observations. We label a trade as 'buyer-initiated' if this probability is greater than 0.5.

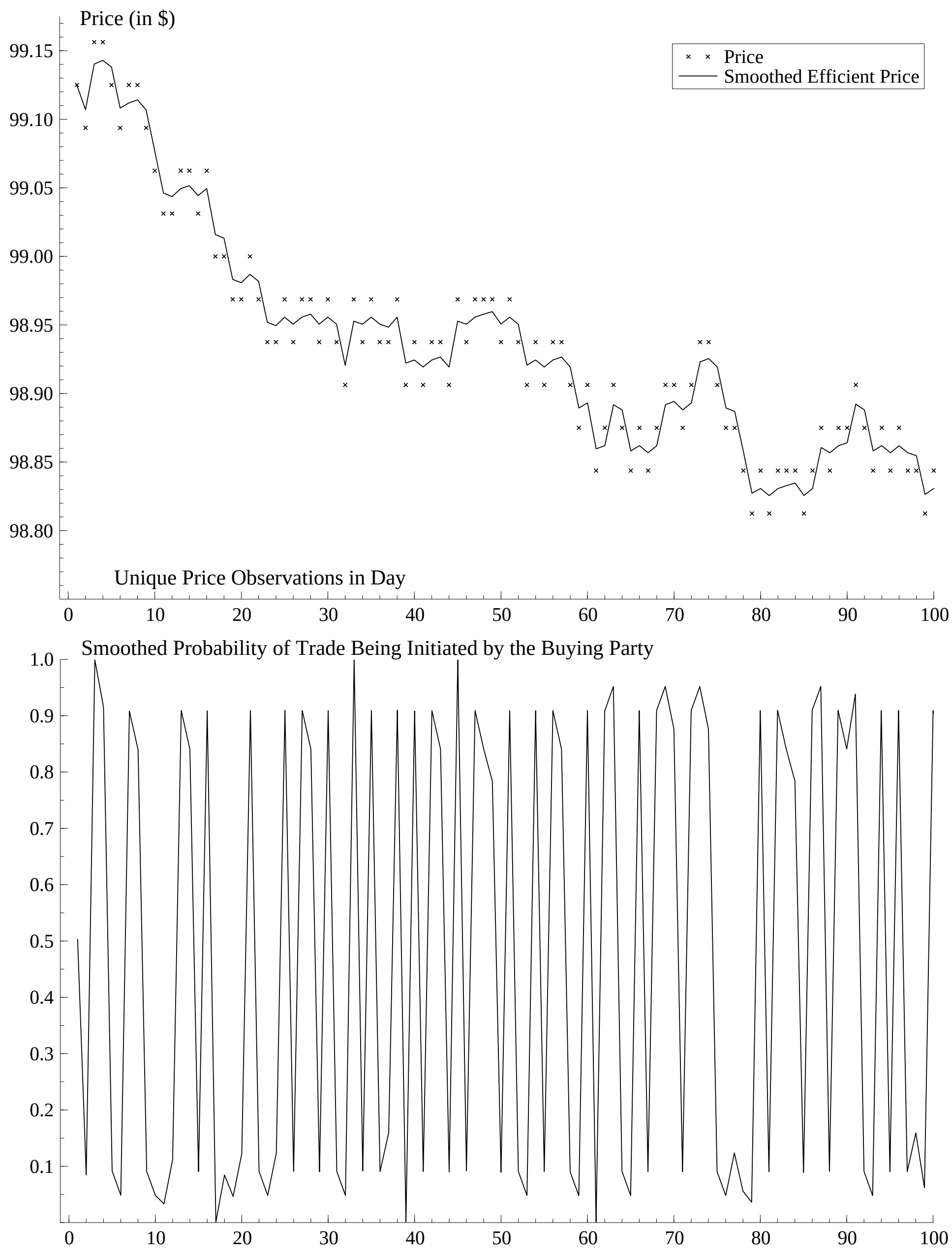
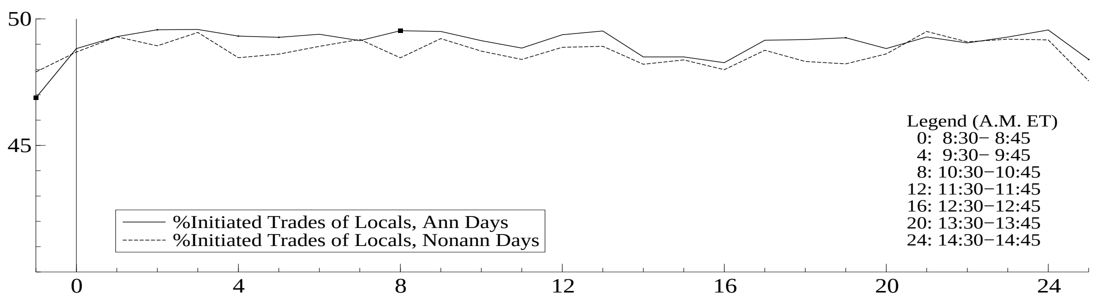


Figure 3: Percentage of Trades Initiated by Market Makers

These figures show the intraday pattern of the percentage of proprietary trades of locals (A) and duals (B) that they initiate. We classify traders at the daily basis, and label a trader to be a local (broker) if more than 98% (less than 2%) of his trades are for own account, otherwise he is a dual. We sign data according to our State Space Form Regime Switching methodology and match the obtained buyer- and seller-initiated indicator with the buy and sell indicator from our dataset. If they agree we classify the trade as being initiated by the market maker. For each day and trader group we calculate the percentage of total proprietary trades that they initiate, we label this as *%initiated trades*. The solid (dashed) lines show the intraday pattern for announcement (nonannouncement) days, the solid vertical lines represent the 8:30-8:45 announcement interval. A circle indicates a significant difference between announcement and nonannouncement days at the 1% level.

(A) %Initiated Trades of Locals



(B) %Initiated Trades of Duals

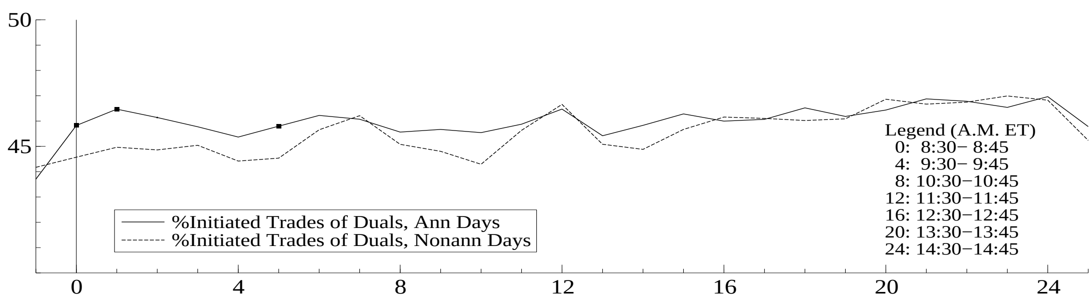


Figure 4: Inventory Positions over Day, Three Types of Announcements
The figure reports the distribution of inventory positions for different times in the day on three type of announcement days and on nonannouncement days for floor traders active in the 30Y treasury futures in 1995. For each time point the inventory position is calculated only for traders that were active before that time, assuming a zero inventory position at the beginning of the day. On announcement days, the distribution of inventory is calculated separately for three groups of announcements: all announcements (indicated by *All Announcement Days*), Nonfarm payroll employment, CPI and PPI announcements (indicated by *Nonfarm, CPI, PPI Ann Days*) and Nonfarm payroll announcements only (indicated by *Nonfarm Payroll Emp Ann Days*). The distribution is shown for four time points in the day: 8:30, 8:45, 9:00 and the end of the trading day (*EoD*).

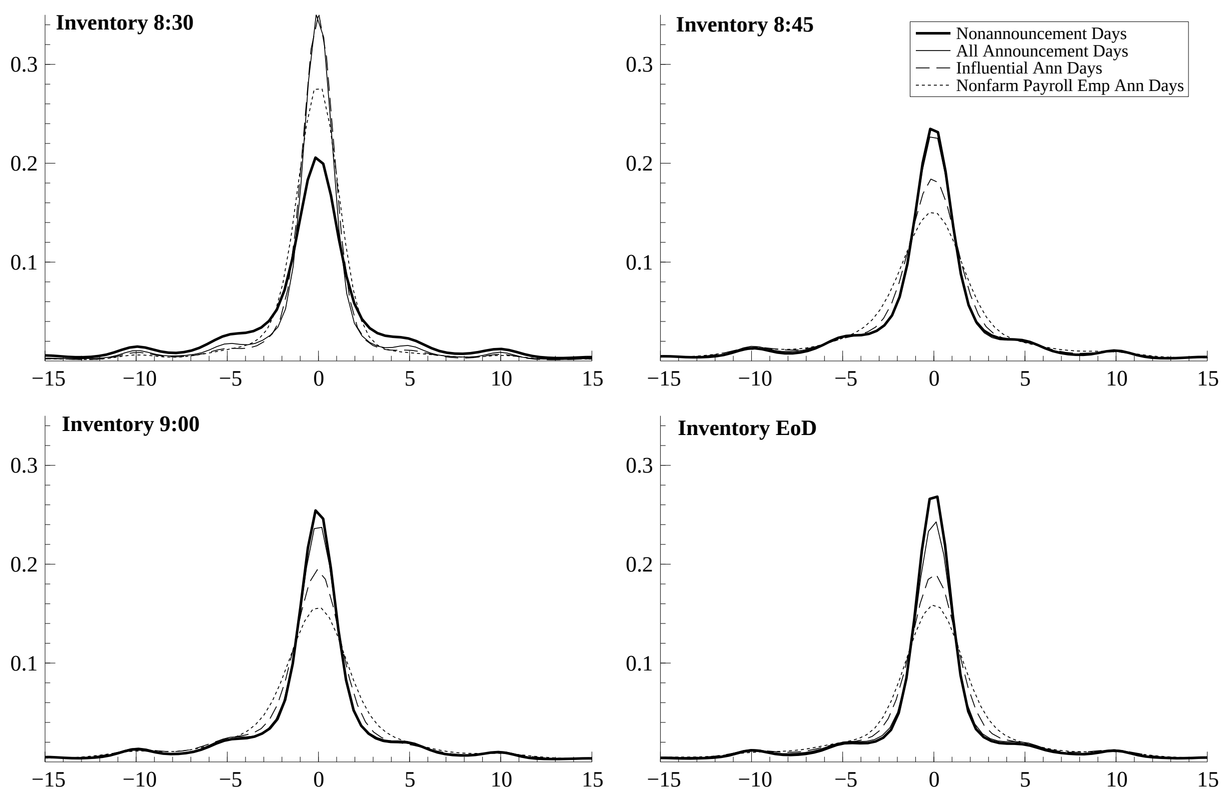
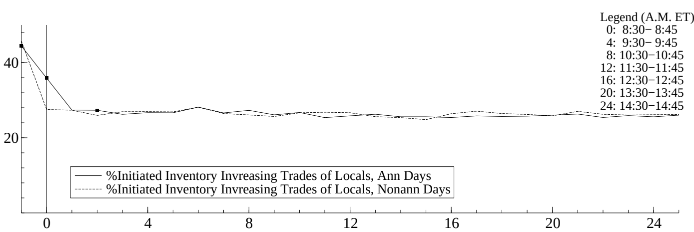


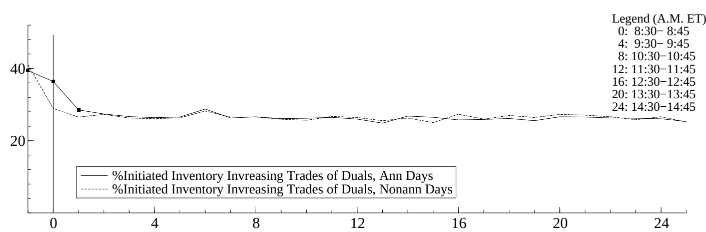
Figure 5: Percentage of Inventory Increasing Trades by Market Makers

These figures show the intraday pattern of the percentage proprietary trades of locals (A, C) and duals (B, D) which increase individual traders' inventory positions. We classify traders at the daily basis, and label a trader to be a local (broker) if more than 98% (less than 2%) of his trades are for own account, otherwise he is a dual. We sign data according to our State Space Form Regime Switching methodology and match the obtained buyer- and seller-initiated indicator with the buy and sell indicator from our dataset. If they agree we classify the trade as being initiated by the market maker, if they do not agree we classify the trade as being an uninitiated market maker trade. For each day and trader group we then calculate the percentage of total proprietary trades that they initiate and which increase individual traders inventory (labelled as *%initiated inventory increasing trades*), and do the same for uniniated trades (*%uninitiated inventory increasing trades*). Panels (A) and (B) show the percentage of trades initiated by the local and dual trader that increase inventory, panels (C) and (D) the percentage of trades not initiated by the local and dual that increase inventory. The solid (dashed) lines show the intraday pattern for announcement (nonannouncement) days, the solid vertical lines represent the 8:30-8:45 announcement interval. A circle indicates a significant difference between announcement and nonannouncement days at the 1% level.

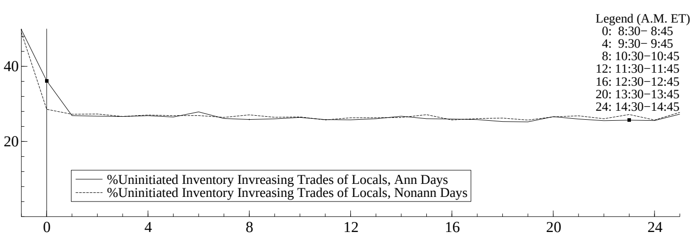
(A) %Initiated Inventory Increasing Trades of Locals



(B) %Initiated Inventory Increasing Trades of Duals



(C) %Uninitiated Inventory Increasing Trades of Locals



(D) %Uninitiated Inventory Increasing Trades of Duals

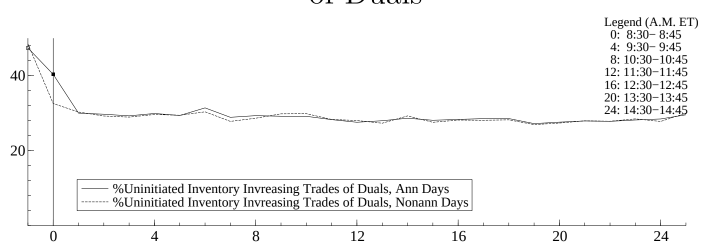
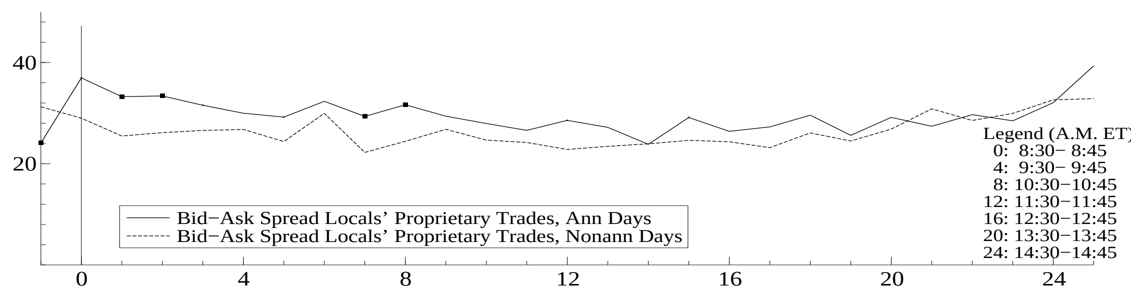


Figure 6: Bid-Ask Spread of Proprietary Order Flow of Locals and Duals

These figures show the intraday pattern of the Bid-Ask spread calculated from proprietary trades of locals (A) and duals (B) in the 30Y treasury futures market. We classify traders at the daily basis, and label a trader to be a local (broker) if more than 98% (less than 2%) of his trades are for own account, otherwise he is a dual. We sign proprietary trades according to our State Space Form Regime Switching methodology and thus obtain a buyer- and seller-initiated indicator. We then follow the Manaster and Mann (1996) methodology to calculate spread: we calculate the difference between the average (volume-weighted) buy price and the average sell price. The solid (dashed) lines show the intraday pattern for announcement (nonannouncement) days, the solid vertical lines represent the 8:30-8:45 announcement interval. A circle indicates a significant difference between announcement and nonannouncement days at the 1% level.

(A) Bid-Ask Spread (in $) calculated from Trades of Locals



(B) Bid-Ask Spread (in $) calculated from Trades of Duals