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Was There Front Running During the LTCM Crisis?

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Abstract: This paper uses a unique dataset of audit trail transactions to examine the trading behavior of market makers in the Treasury bond futures market when Long-Term Capital Management (LTCM) faced binding margin constraints in 1998. Although identities are concealed in the dataset, I find strong evidence that during the crisis market makers in the aggregate engaged in front running against customer orders from a particular clearing firm (coded "PI7") that closely match various features of LTCM's trades through Bear Stearns. That is, market makers traded on their own accounts in the same direction as PI7 customers did, but *one or two minutes* beforehand. Furthermore, a significant percentage of market makers made abnormal profits on most of the trading days during the crisis. Their aggregate abnormal profits, however, were more than offset by abnormal losses realized after the private sector recapitalization of LTCM. Moreover, I show that before the rescue, a market maker's cumulative abnormal profit was positively correlated both to her tie as contra party with PI7 and to the intensity of her front running, but these relationships turned negative after the rescue. The overall evidence suggests that the recapitalization plan effectively relaxed LTCM's binding constraints and therefore reversed the profitability of front running.

Keywords: front running, strategic trading, market microstructure, trading behavior, margin constraints, financial crisis

* Staff economist of the Division of International Finance of the Federal Reserve Board. This paper is based on one part of my doctoral dissertation at the University of Michigan Business School. An earlier draft was circulated under the title "Does the Market Conspire Against the Weak? An Empirical Study of Front Running Behavior During the LTCM Crisis". I am grateful to my committee members Douglas Skinner, Ennio Stacchetti and Lu Zheng, and especially to Gautam Kaul (Chair) and Tyler Shumway, for their numerous insightful discussions and encouragement. I have also greatly benefited from comments of an anonymous referee, Sugato Bhattacharyya, Markus Brunnermeier, Mark Carey, Joshua Coval, Raymond Fishe, Richard Green, Dale Henderson, Harrison Hong, Marcin Kacperczyk, Lutz Kilian, Pete Kyle, Vikram Nanda, David Smith, Anjan Thakor, Leonard Zaban and seminar participants at the CFTC, Federal Reserve Board, Freddie Mac, George Mason University, Moody's KMV, University of Illinois at Chicago, University of Miami, University of Michigan, the 2002 Global Finance Association annual meeting, and the 2002 Western Finance Association annual meeting. I thank Joshua Coval and Tyler Shumway for providing the data used for this study. The views in this paper are solely the responsibility of the author and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or any other person associated with the Federal Reserve System.

"*Markets can remain irrational longer than you remain solvent*."

— JOHN MAYNARD KEYNES

One of the most astounding financial events in 1998 was the near collapse of Long-Term Capital Management (LTCM), a fabled hedge fund staffed with famous traders and renowned financial economists. After dramatic successes in the first four years since it opened in 1994, LTCM began to suffer heavy losses from global financial turmoil triggered by a Russian debt default in mid-August of 1998. Amid fears that LTCM's fall might lead to costly disruptions in world financial markets, the Federal Reserve Bank of New York hosted a meeting of fourteen financial institutions on Sept. 23 that led to a $3.625 billion private sector recapitalization of LTCM on Sept. 28, 1998. The aftermath continued until October.

During the crisis, there were many press reports about how market participants exploited LTCM's weakness by "front running", but very little compelling evidence has been available to date. This paper uses a detailed audit trail transactions dataset to investigate whether market makers in the CBOT Treasury bond futures market, who may have had superior knowledge of customer order flow, exploited such informational advantage in their trading and profited from LTCM's weakness when it faced binding margin constraints.

The term "front running" refers to a situation in which a trader, knowing that an order is about to come in, trades in the same direction before the anticipated order is executed. The front runner plans to unwind her position afterwards and hopes to profit through the price impact of the expected order. In microstructure models (e.g., Admati and Pfleiderer (1991), Fishman and Longstaff (1992), Pagano and Roell (1992), Danthine and Moresi (1998)), a front runner is usually a dual trader who trades on her own account in the same direction prior to executing her customer's order. In this paper, front running is defined in a broader sense and refers to trading in the same direction by a market maker ahead of *any* observed customer's order. While front running by a trader against *her own* customers violates CFTC and exchange rules, front running based on signals observable in the trading pit about *other* incoming customer orders is legal.[1]

The case of LTCM raises some very interesting and broad issues about trading behavior and market mechanisms in the microstructure framework. Canonical models in the microstructure literature (e.g., Glosten and Milgrom (1985), Kyle (1985), Easley and O'Hara (1987)) assume that market makers are uninformed and behave competitively. In recent years, several empirical studies have documented that market makers do have some market power or informational advantages in trading. For example, Christie and Schultz (1994) observe that NASDAQ dealers may have implicitly colluded to set spreads wider than those justified by perfect competition. Manaster and Mann (1996, 1999) find that market makers have better information regarding short-term price movements, which gives them a timing advantage relative to other participants in the futures market. Madhavan and Sofianos (1998) document that NYSE market makers selectively time the size and direction of their trades.[2]

The availability of transaction-by-transaction data during the LTCM crisis period offers a unique opportunity to examine whether market makers exploited their informational advantage about customer order flow when LTCM was financially

[1] For a more detailed analysis of legal vs. illegal front running, see *Ch*. 11 of Harris (2002).
[2] The idea of informed market makers has also received some attention in some theoretical models, e.g., Brown and Zhang (1997), Seppi (1997), Cao and Lyons (1998), Ready (1999).

distressed. Although the data do not reveal the true identities of clearing firms and traders, I find one large clearing firm (coded "PI7") with large customer orders during the crisis period which closely match various features of LTCM's trades executed through Bear Stearns, including trade size, pattern and timing. By examining the market making behavior and patterns of PI7 customer order flow (as a proxy for LTCM orders) during the crisis, I test the following null hypotheses: (1) market makers did not engage in front running against the presumed LTCM orders when LTCM was financially distressed; (2) market makers made zero abnormal profits during the crisis; and (3) there were no changes in market liquidity, trading behavior and profitability after the recapitalization.

This paper is the first empirical study to uncover strong evidence of front running behavior by market makers, based on their informational advantages about customer order flow and the trading environment. By examining how the binding margin constraints faced by one large market participant alter other traders' trading behavior, this study also contributes to the existing literature on the impact of margin constraints on asset prices and trading strategies.[3]

I find that trades by PI7 customers as well as other customers had an unusually large price impact during the crisis. More importantly, I find that market makers (also called "locals" in the futures pit), in the aggregate, traded on their own accounts in the same direction just one or two minutes before PI7 customer orders were executed. Moreover, the extent of locals' front running against PI7 customer trades during the crisis was much larger than that against all other off-exchange customers during the same period, as well as that against PI7 customers during the first half of the year. It is also

[3] For example, Grossman and Vila (1992) show that when a leverage constraint is imposed, an investor alters her optimal trading strategy even if the leverage constraint is not binding. Pulvino (1998) shows that financial constraints cause firms to liquidate assets at deep discounts in "fire sales".

interesting to notice that front running was even stronger after the consortium's rescue, which could be explained by herding and overreaction by locals who expected LTCM to continue unwinding its positions. Furthermore, market makers who traded with PI7 as contra parties engaged in significant front running, but there is no evidence of front running for market makers who executed orders for PI7 customers.

Having established the evidence of front running, I then examine whether market makers made abnormal profits during the crisis. I calculate the daily profits/losses during the crisis period for each of the 437 active market makers. I find that a significant percentage of market makers made abnormal profits on most of the days during the crisis. Their aggregate abnormal profits before the rescue, however, were more than offset by the abnormal losses after the rescue. Moreover, before the rescue, a market maker's cumulative abnormal profit was positively correlated to both her relative trading frequency as contra party with PI7 and to the intensity of her front running, but these relationships turned negative after the rescue. Front running against PI7 customers did not appear profitable to market makers as a whole group over the entire crisis period.

The overall evidence presented in this study shows that non-fundamental speculators, who possess no private information on fundamental asset values but have superior knowledge of the market environment, tend to chase trends and lose money after market "overreactions" are corrected, consistent with Madrigal (1996). It also suggests that the recapitalization by the LTCM's creditors effectively helped LTCM avoid "fire sale" trading by restoring its margin, and therefore reversed the profitability of speculative trading by market makers.

The rest of the paper proceeds as follows. In Section I, I discuss the setting of the LTCM crisis in more detail and describe the trading mechanism in the CBOT Treasury bond futures pit. Section II outlines the dataset used in this study and discusses the procedure followed to discern possible LTCM's trades in the data. In Section III, I examine the market liquidity during the crisis and the price impact of PI7 customers' trades. Section IV establishes the main results regarding the occurrence of front running behavior. Section V investigates the aggregate profitability of market makers during the crisis and also presents cross-sectional tests of the relation between front running and profitability. Section VI concludes the paper.

I. The LTCM Case and the Treasury Bond Futures Market

A. The LTCM Case

In the late summer of 1998, as prices on equity and corporate bond markets plummeted, U.S. Treasury bond prices soared in a flight of capital to quality, pushing the yield to as low as 4.71% on Oct. 5, the lowest level for any comparable long-term Treasury bond since 1967. Simultaneously, yield differences between U.S. Treasury bonds and riskier bonds widened, just the opposite of what LTCM had bet on. On Sept. 2, 1998, LTCM founder John Meriwether sent a letter to investors saying that LTCM had lost 44% in August alone. Though the letter was confidential, the news was immediately leaked to the public and reported by the *Wall Street Journal*. According to sources after the fact, LTCM received at least two margin calls, on Sept. 10 and 21, from Bear Stearns, the investment bank that cleared trades for LTCM at CBOT.[4] As LTCM's crisis rattled the world financial markets, the Federal Reserve Bank of New York hosted a meeting of

[4] For more details, see Lowenstein (2000), *p*. 169 and *Risk* (Oct., 1998), *p*. 36 respectively.

fourteen financial institutions on Sept. 23 that led to a $3.625 billion private sector recapitalization of LTCM on Sept. 28. The FOMC cut the federal funds rate by 25 basis points on Sept. 29, and again on Oct. 15 in a rare inter-meeting move. By mid-October, as T-bond yields finally started to back up, LTCM's portfolio value began to rebound.

During the crisis, LTCM was widely known to be short Treasury bonds and had to buy a large amount of Treasury bond futures contracts to unwind its positions. As an article in *Wall Street Journal* (Oct. 5, 1998) noted, "... a lot of the recent rally has been because of Long-Term Capital…The market believes that Long-Term Capital is long risky positions and short Treasurys (*sic*), and the threat of them buying back Treasurys (*sic*) has helped the Treasury market at the expense of riskier markets." With correct anticipation of the direction of LTCM's trades and the advantage of being able to observe customer order flow, market makers had strong incentives to engage in front running to profit from LTCM's weakness. In later interviews, LTCM partners often blamed some of their losses on front running by other market players. For example, John Meriwether stated, "…the few things we had on that the market didn't know about came back quickly. It was the trades that the market knew we had on that caused us trouble."[5]

B. Trading Mechanics of the Treasury-Bond Futures Market

The T-bond futures market at CBOT is an open outcry exchange. In the futures pit, traders use open outcry and elaborate physical gestures to attract attention to their bid and offering prices.

[5] See "How the Eggheads Cracked?", *New York Times*, Jan. 24, 1999.

Floor traders who trade on their own accounts (also called "locals") play the role of market makers and provide liquidity to the market.[6] In the pit, market makers do not quote explicit bid-ask spreads. Instead, price almost always moves by just one tick, most of which can be considered the effective bid-ask spread. Besides locals, there are also many floor brokers acting on behalf of off-exchange customers or brokerage firms.

Locals' trades and customers' trades are the two major types of trades. As soon as a local opens a new position (either long or short), she will attempt to close out the position at a favorable price and make a profit. At the conclusion of the trading day, she hopes to be without any open position, i.e., to be "flat". On the other hand, off-exchange customers are often hedgers who trade futures to reduce some pre-existing risk exposure. They usually trade through brokerage firms. Besides, brokerage firms and some other exchange members may also trade for hedging purposes.

To trade in the futures market, a trader must establish an account with a clearing firm. Subsequent to posting an initial margin, she must also maintain a maintenance margin to ensure her performance against the obligations of the futures contract. At the end of each trading day, a trader's daily profits (losses) are credited (debited) to her account by marking-to-market. If her account balance falls below the maintenance margin, she will be asked to deposit enough funds to bring the account back up to the initial margin level. Because margins represent a very small portion of a trader's total market exposure, T-bond futures positions are highly leveraged transactions.[7]

[6] Unlike specialists on NYSE, market makers on NASDAQ, or dealers on other exchanges, futures floor traders are not obliged to provide quotes or even be present.

[7] For example, the minimum initial margin required by CBOT for a T-bond futures contract (worth $100,000) may be just $2,160 and the minimum maintenance margin may be as little as $1,600. A clearing firm may require margins in excess of the minimum amounts specified by the exchange.

II. Data and Methodology

The data used in this study consist of audit trail transaction records from the CBOT Treasury bond futures pit during 1998.[8] The data include identifiers for the buying trader and the selling trader, the clearing firms they are affiliated with, and the time and price for each transaction. They also include a customer type indicator (CTI) indicating whether each trade is performed for a market maker's (or local's) personal account (CTI 1), for the account of the trader's clearing firm (CTI 2), for any other exchange member (CTI 3), or on behalf of an outside customer (CTI 4). For example, if a commercial clearing member's floor trader executes a trade for that firm, it will be denoted as a CTI 2 trade, while trades for other exchange members' accounts will be categorized as CTI 3 trades. Following Manaster and Mann (1999), these four types of trades may be simply called "local trades", "commercial trades", "hedger trades" and "customer trades" respectively.

The data include over five million futures transaction records, more than 97% of which involve front-month contracts.[9] Therefore, only transactions in front-month contracts are examined in this paper. I define Sept. 2 through Oct. 15, 1998 as the crisis period. Besides the audit trail data, I also use the publicly available Time and Sales data that record all price changes (second-by-second) for the T-bond futures contracts in 1998.

Table I provides some summary statistics for the audit trail data. Panel A breaks down the total contract volume by trader type combinations, while Panel B provides the percentage of contract volume by trader type combinations. The most frequent combination is a customer order (CTI 4) filled by a local (CTI 1), which accounts for

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[8] The data were obtained from the CFTC via a Freedom of Information Act Filing.
[9] The front-month contract is the most active contract 1 to 4 months to delivery.

more than 50% of the total volume of trades. Panel C shows the participation rate in volume for each CTI type. More than 90% of the total volume involves locals as at least one side of the trade and more than 57% of the total volume involves customers. Therefore, I mainly focus on the trading behavior of the locals, especially as they traded against customers (CTI 1 paired with CTI 4). Panel D and Panel E report the average trade size by contra party combinations and the average trade size by trader types, respectively. Local trades are characterized by relatively small sizes, especially as they trade with each other (only 7.74 contracts per trade on average). Hedger trades are usually small too. On the other hand, customer and commercial trades are larger, on average about 25.52 contracts and 35.32 contracts respectively.

There are 1,082 different locals in the data. Similar to Coval and Shumway (2001b), I identify 437 active local traders who executed at least 1,500 trades each on their own accounts during the whole year and had trading activities during the crisis period. I track each of these active locals' trades on their own accounts and the associated profits throughout each trading session during the crisis.

Although identifiers for the traders and the clearing firms are provided in the audit trail data, they are encrypted to conceal the true identities of individual market participants. This complication creates difficulties in discerning possible LTCM's trades through Bear Stearns.

I attempt to infer which firm is Bear Stearns by examining the major clearing firms' trades for their customers, and trying to match the trading patterns with the evidence documented by numerous news reports and book excerpts about what happened to LTCM and the market responses at that time. In particular, I first sort out about ten clearing firms with the largest cumulative net purchases in September on behalf of their customers in the front-month T-bond futures contracts (i.e. the December 1998 contracts). Next I look at the net purchases of these firms around Sept. 10 and Sept. 21 (the dates when the two margin calls were made). Although a few firms had large cumulative net purchases for customers during September, I find only one firm (coded "PI7" in the data) with huge net purchases for customers around the margin call days, especially around Sept. 10. As a final check, I compare the price movements of Treasury bond futures in September and October with the cumulative net purchases of these candidate firms. Only "PI7" had customer cumulative net purchases of T-bond futures contracts that match almost perfectly with the price movements during this period and imply huge losses from these trades. Consequently, PI7 customers' trades provide the closest match to various features of LTCM's trades cleared by Bear Stearns.

Figure 1 depicts hourly price changes of T-bond futures and the cumulative net order flow of PI7 customers over September and October of 1998. Although LTCM was not the only customer of Bear Stearns, it was probably Bear Stearns' largest customer at that time. Since the data do not provide more detailed identifiers for individual customers executing their trades through one clearing firm, I use PI7's total net order flow from all customers (CTI 4) as a proxy for the presumed net order flow from LTCM. This treatment adds some noise to the data and may impart a downward bias to the strength of the empirical evidence in this paper.[10]

[10] The big net selling on Sept. 11 and 14 in Figure 1 was more likely from LTCM after meeting margin calls than from other customers of Bear Stearns. Anecdotal evidence suggests that, when trades diverged, LTCM's philosophy was to simply hang on and wait until the spread converged back again. Only under binding margin constraints as a result of widened yield difference was LTCM forced to unwind its short position in T-bond futures. Once the margin requirement was met and the price dropped, LTCM was likely to go short again to resume its trading strategy.

III. PI7 Customers' Trades and Market Depth

Since a front runner usually plans to unwind her position after the expected customer order is executed and hopes to profit through the price impact of the customer order, I first examine market depth and the price impact of PI7 customers' trades during the crisis, in a way similar to Manaster and Mann (1996).[11]

To analyze the price impact of PI7 customers' net order flow during the crisis, I perform a conditional depth regression by controlling for all other customers' aggregate net order flow. In particular, I calculate price changes Δp_t in every minute *t* as the last price record in *t* minus the last price record in minute *t*-1. I calculate net order flow (buy volume less sell volume) for PI7 customers ($LTNOF_t$) as well as for all other customers in each minute *t* ($OCNOF_t$) during the whole year. To capture the abnormal price impact of PI7 customers as well as all other customers' trades during the crisis, I also add two interaction terms $D*LTNOF_t$ and $D*OCNOF_t$, each of which equals a dummy multiplied by the corresponding net order flow in minute *t*, where the dummy term *D* equals 1 if date $\in$ [9/2/1998, 10/15/1998], and 0 otherwise. The depth regression is as follows:

$$\begin{aligned}\Delta p_t = \alpha + \beta_1(LTNOF_t/1000) + \beta_2(OCNOF_t/1000) + \\ \gamma_1 D*(LTNOF_t/1000) + \gamma_2 D*(OCNOF_t/1000) + \varepsilon_t\end{aligned} \qquad (1)$$

where the error terms are corrected for second order autocorrelation. The regression result is reported in the second column of Table II. The coefficients of ($LTNOF_t$/1000) and ($OCNOF_t$/1000) are both significantly positive, but the magnitude of PI7 customers' price impact is smaller than that of all other customers during the rest of the year and the

[11] While bid-ask spread is another measure of liquidity widely examined by numerous studies (e.g., Bessembinder (1994), Christie and Schultz (1994, 1999), Huang and Stoll (1996), etc.), O'Hara (1995) points out that price revisions may provide a more accurate reflection of the "costs" of trading (or illiquidity). Kyle (1985) shows that market depth, or the inverse of the price response to customer order flow, is inversely proportional to the information asymmetry between market makers and customers.

difference is statistically significant (based on an *F*-test). In economic terms, an increase of one thousand contracts in PI7 customers' net order flow would normally cause the contract price to increase by about $6.1 in the same minute (because T-bond futures price is quoted for a bond with face value of $100 and each contract has a face value of $100,000), while an increase of one thousand contracts in all other customers' net order flow would normally cause the contract price to increase by about $10.6. This might suggest that, before the crisis, PI7 customers had better trading skills than other customers so that their price impact was about 40 percent lower.

Moreover, the coefficients of $D^*(LTNOF_t/1000)$ and $D^*(OCNOF_t/1000)$, which capture respectively the abnormal price impact of PI7 customers and all other customers during the crisis period, are also positive and significant. This evidence shows that both PI7 customers and all other customers had an abnormally large price impact during the crisis. Since market depth is just the inverse of the price impact coefficients, it also means that the market depth was reduced and the market liquidity was unusually low during the crisis. More interestingly, one should note that during the crisis period, PI7 customers actually had a larger abnormal price impact than all other customers, the difference between the two coefficients is significant at 10% level. Specifically, when PI7 customers increased their net order flow by one thousand contracts in any minute during the crisis period, the contract price would rise $11.5 more than usual, higher than the abnormal price impact of $7.8 caused by an increase of one thousand contracts in other customers' net order flow. Since PI7 customers' trades during the crisis were not likely to be perceived as containing superior information, the evidence suggests that they were unable to execute trades in a way to avoid excess price impact at that time.

I repeat the regression in (1) for the two sub-periods of the crisis: before rescue (Sept. 2 – Sept. 28) and after rescue (Sept. 29 – Oct. 15) by redefining the dummy variable correspondingly. The results are shown in the third and fourth column of Table II. In the third column, the difference between the coefficients of the two interaction terms is very significant, showing that PI7 customers had an abnormal price impact almost five times larger than that of all other customers in September before the rescue. On the other hand, in the fourth column, although the two interaction terms' coefficients are both larger than those in the third column, the difference between them is very small.

The overall evidence shows that PI7 customers as well as all other customers had an abnormally large price impact during the crisis and the market was illiquid. The finding of low liquidity for the distressed trader is consistent with both Brunnermeier and Pedersen (2003) and Pritsker (2003). Before the rescue, trades by PI7 customers had an abnormal price impact almost five times larger than that of all other customers. Moreover, after the rescue, PI7 customers and other customers had an even greater price impact than before the rescue, yet the difference between PI7 customers and other customers in price impact is not statistically significant. The increased magnitude of the abnormal price impact by PI7 customers and other customers suggests that market liquidity was further reduced after the rescue, which may result from increased speculative activities by locals against PI7 customers.

IV. Occurrence of Front Running Behavior

The main focus of this paper is to examine how market makers traded against presumed LTCM orders in the T-bond future market during its crisis. More specifically, I examine whether market makers exploited their superior information about the customer order flow by timing their own trades ahead of PI7 customers, or in other words, front running. Any market maker who knows that an order is "overhanging the market" can exploit this information in the short run, even if she has no superior information about the fundamental value of the security.

As market makers expected LTCM to be a large net buyer of T-bond futures contracts due to increasingly binding margin constraints and thus to push the futures price higher, they clearly had an incentive to cumulate net long positions before the LTCM's orders were placed. Therefore, it may be possible to observe the net order flow of these market participants preceding the net order flow of PI7 customers. Market makers who are well informed about the customer order flow and highly proximate to the price setting process are more likely to time their trades than other types of traders to exploit the opportunity, thus I mainly focus on the trades by market makers during the crisis.

Since the market makers' advantage is in observing highly short-lived signals, front running, if it exists, would also occur over a very short time horizon, for example, within a few minutes before the customer orders are executed. Table III reports the regression results of several front running models. Model 1 is a simple model in which aggregate locals' net order flow (CTI 1) in each minute t ($lNOF_t$) during September and the first half of October, 1998 is regressed on PI7 customers' net order flow in minute t+i ($LTNOF_{t+i}$, where i = 1, 2, 3, 4). Specifically, Model 1 is specified as follows:

$$lNOF_t = \alpha + \sum_{i=1}^{4} \beta_i LTNOF_{t+i} + \varepsilon_t \qquad (2)$$

where the error terms are corrected for fourth order autocorrelation. The result is shown in Table III. The significantly positive coefficients on lead terms t+1 and t+2 suggest that locals' net order flow preceded PI7 customers' net order flow by about two minutes. Every increase of one contract in net purchase by PI7 customers in minute t+1 would cause an increase of 0.1004 contract in locals' net order flow in minute t during the crisis.

Since both net order flow from the locals and net order flow from PI7 customers are time series that are usually autocorrelated, the autocorrelations might cause misleading regression results. Simple diagnoses from ARIMA procedures suggest that the autocorrelations in net order flow could be captured by an AR(20) model. Therefore, in Model 2, 3, 4, and 5, I first "prewhiten" all time series by fitting an AR(20) model to the dependent and independent variables respectively, and then use the residual series filtered from the AR(20) procedure in the front running regressions. In Model 4 and 5, prewhitened net order flow for all other customers around minute t is also included for comparison purpose. Model 2, 3, 4, 5 are specified as follows:

$$lNOF_t^* = \alpha + \sum_{i=1}^{4} \beta_i LTNOF_{t+i}^* + \varepsilon_t \tag{3}$$

$$lNOF_t^* = \alpha + \sum_{i=1}^{4} \beta_{-i} LTNOF_{t-i}^* + \sum_{i=1}^{4} \beta_i LTNOF_{t+i}^* + \varepsilon_t \tag{4}$$

$$lNOF_t^* = \alpha + \sum_{i=1}^{4} \beta_i LTNOF_{t+i}^* + \sum_{i=1}^{4} \gamma_i OCNOF_{t+i}^* + \varepsilon_t \tag{5}$$

$$\begin{aligned} lNOF_t^* = \alpha &+ \sum_{i=1}^{4} \beta_{-i} LTNOF_{t-i}^* + \sum_{i=1}^{4} \beta_i LTNOF_{t+i}^* + \\ &\sum_{i=1}^{4} \gamma_{-i} OCNOF_{t-i}^* + \sum_{i=1}^{4} \gamma_i OCNOF_{t+i}^* + \varepsilon_t \end{aligned} \tag{6}$$

where $lNOF_t^*$ is the prewhitened net order flow of all locals in minute t, $LTNOF_{t-i}^*$ and $LTNOF_{t+i}^*$ are the prewhitened net order flow of PI7 customers around minute t, and $OCNOF_{t-i}^*$ and $OCNOF_{t+i}^*$ are the prewhitened net order flow of all other off-exchange customers around minute t.[12] After "prewhitening" the time series, the results from Model 2 are even stronger than those from Model 1. The coefficients of $LTNOF^*_{t+1}$ and $LTNOF^*_{t+2}$ are both positive and significant at 1% confidence level. The results in Table III indicate an increase of 0.1376 and 0.0738 respectively in the net order flow by locals in minute t for every increase in net purchase by PI7 customers in minute t+1 and t+2. The coefficient of $LTNOF^*_{t+3}$ becomes small and insignificant, and the negative coefficient of $LTNOF^*_{t+4}$ shows that locals unwind their positions in a matter of just a few minutes. Front running by locals mainly occurred within two minutes before PI7 customers' trades were executed.

To find out whether the locals' trades in minute t were also closely related to the PI7 customers' trades observed in the preceding minutes, I include four lagged terms $LTNOF^*_{t-i}$ (i = 1, 2, 3, 4) as well as four lead terms in Model 3. The coefficients on the lagged terms are mostly negative and insignificant, while the coefficients on the first two lead terms remain positive and significant. This suggests that locals' trades preceded PI7 customers' orders by no more than three minutes, and they did not mimic PI7 customers' trades after observing their orders.

The evidence so far has indicated that locals engaged in front running against PI7 customers during the crisis. However, it is not clear yet whether the locals also front ran all other off-exchange customers' orders. Therefore, I next include all other customers' net order flow (CTI 4) into the regressions. Model 4 includes the lead terms for both PI7

[12] The contemporaneous net order flow terms are excluded from the right hand side of the regressions to avoid tautological misspecifications, because net order flow by locals in minute t is almost equal to the negative of the sum of net order flow by customers.

customers' net order flow ($LTNOF^*_{t+i}$, i = 1, 2, 3, 4) and all other customers' net order flow ($OCNOF^*_{t+i}$, i = 1, 2, 3, 4). The positive and significant coefficients of $OCNOF^*_{t+i}$ (i = 1, 2, 3, 4) show that the front running by locals occurred with respect to all other customers as well. However, by comparing the magnitude of the coefficients of $OCNOF^*_{t+1}$, $OCNOF^*_{t+2}$ with those of $LTNOF^*_{t+1}$, $LTNOF^*_{t+2}$ respectively, I find that locals' front running against PI7 customers was far more severe than against all other customers. The differences between the two sets of coefficients are both significant (the F-test results are not reported here). While an increase of one contract in the net order flow of all other customers in minute t+1 and t+2 would cause the locals' net order flow in minute t to rise by 0.0349 and 0.0287 contract respectively, an increase in PI7 customers' net order flow in minute t+1 and t+2 would cause the locals to increase their net order flow by 0.1543 and 0.0906 contract respectively. In other words, the extent of front running against PI7 customers was more than four times as large as that against all other customers. Model 5 includes the lagged and the lead terms for PI7 customers as well as all other customers. The results are similar: locals did not chase customers' order flow. On the contrary, their trades preceded customers' orders. During the crisis, front running occurred to all customers, but it was much more severe for PI7 customers than for all others.[13]

To find out whether front running prevailed in other periods besides the crisis period, I repeat these regressions for the first six months of 1998. This period was relatively calm and is used as a comparison period. The results are quite different for the

[13] I repeat the front running regressions using buy orders only and find similar results, although with lower significance. Since anecdotal evidence suggests that LTCM could also have engaged in enormous selling during the crisis when it expected the worst might be over, looking at buy orders only rather than net order flow could cause some distortion in the analyses and also cannot conclusively identify LTCM.

comparison period (see Table IV). The signs and magnitude of the coefficients suggest that front running still occurred to all other customers within a few minutes prior to their order execution, but it was not the same case for PI7 customers. In fact, coefficients of $LTNOF^*_{t+1}$ are negative in all models. On the other hand, coefficients of $LTNOF^*_{t-1}$ are positive and significant, which actually suggests that locals mimicked PI7 customers' trades during the first half of the year.

I also repeat the front running regressions for two sub-periods of the crisis period: before rescue (Sept. 2 – Sept. 28) and after rescue (Sept. 29 – Oct. 15). The results are reported in Table V. For simplicity, only results using Model 2 and 4 are reported. I find the extent of front running to be even greater after the rescue than before the rescue. One possible explanation is that more locals joined the herd in front running after the rescue, as they expected LTCM to continue unwinding its positions.

So far I have examined the front running behavior by the locals trading on their own accounts at the aggregate level. However, these locals may be heterogeneous in terms of the amount of private information they had about LTCM as well as about the general market conditions. Therefore, I sort out those locals who executed PI7 customers' orders and those locals who traded against PI7 customers' orders as contra parties at least once during September and October of 1998. These two subsets of locals might possess more accurate information about the incoming LTCM orders and thus might time their own trades more precisely than others.

There are 29 locals who executed orders for PI7 customers and also traded on their own accounts during the two crisis months. It seems that PI7 customer orders were placed by a small group of locals who maintained a stable relationship with the firm. On the other hand, there are 301 locals who acted as the contra parties of PI7 customers' trades, accounting for more than 60% of the locals frequently trading in the market. Table VI reports the front running regression results by replacing $lNOF_t^*$ in Model 2 (equation (3)) and Model 4 (equation (5)) with net order flow from locals who traded for PI7 customers ($tlNOF_t^*$) and net order flow from locals who filled these orders as contra parties ($clNOF_t^*$), respectively.

Interestingly, for the locals who executed PI7 customers' trades, no pattern of front running or mimicking is detected since almost all the coefficients are insignificant. This result is consistent with the finding of Chakravarty and Li (2002) that dual traders do not seem to front run their own customers. Although these locals are most likely to possess private information about PI7 customers' orders, they did not exploit such advantage, most likely to avoid the violation of CFTC rules and/or to maintain the long-term relationship with PI7. In contrast, there are strong patterns of front running for locals who traded against PI7 customers' orders as contra parties. The coefficients on $LTNOF_{t+1}^*$ and $LTNOF_{t+2}^*$ are both larger than those reported in the corresponding regressions in Table III. By closely observing locals who executed customer orders for PI7, locals who traded as contra parties could have inferred whether they themselves were trading against LTCM orders and therefore acted accordingly.

Finally, I also examine commercial trades (CTI 2), hedger trades (CTI 3) and other customers' trades (CTI 4) relative to PI7 customers' trades. I find no evidence of front running by any of these three other types of traders as a whole (results not reported here). This finding is not surprising since other types of traders were unlikely to have the informational advantage of observing short term order flow as locals did, and therefore were not able to time their trades as precisely as locals. Besides, CTI 2 and CTI 3 trades are usually executed for hedging or rebalancing reasons, and therefore may not be motivated by front running. CTI 4 trades by all other customers in minute *t* actually appeared to be negatively related to PI7 customers' trades in the subsequent few minutes, which means that all other customers were selling before PI7 customers bought. Off-exchange customers in general are uninformed about short-term price movements in the pit, and on average take the other side of locals' front running trades.

Local's precise timing ability arises from their superior information about customer order flow as well as the open outcry environment itself. The evidence supports the findings of Coval and Shumway (2001a) that the sound level in an open outcry exchange conveys information regarding the emotion of market participants. During the crisis, market makers were very likely to be able to infer LTCM-specific order flow information from the sound level in the pit, from traders' identities, and from traders' facial expressions and other body languages. Such informational advantages allowed them to time their own trades right ahead of PI7 customers' trades.

V. Profitability Analyses

A. Aggregate Profitability for All Active Locals

Since there is strong evidence of front running by the locals against presumed LTCM trades, a natural question arises: did the locals make abnormal profits by front running? In this section, I focus on those active locals and track the profits/losses of the trades on their personal accounts during the crisis period. Since much anecdotal evidence suggests that market makers close out their positions by the end of each day and do not carry significant inventory overnight (e.g., Kuserk and Locke (1993), Manaster and Mann (1996), Coval and Shumway (2001a, 2001b)), I assume zero inventory for each local at the beginning of each trading day and evaluate her performance on a daily basis.

I calculate daily profits/losses for each local as in Coval and Shumway (2001b). Specifically, I multiply the difference between purchase and sales prices by quantities to get a profit figure for each local at each point in time, and add the market value of any inventory, calculated as the current price times the number of contracts outstanding, to each local's running profit figure to generate a total profit variable for any time of the day. The end-of-the-day profit is therefore the daily profit after marking to market.

To arrive at an abnormal daily profit figure for each active local, I adopt several alternative benchmarks as "normal" daily profit. The first benchmark is each local's mean daily profit during the whole year. I subtract this figure from her daily profit during the crisis period to get an estimate of her abnormal daily profit. The second benchmark is each local's median daily profit during the year, which would be more appropriate if a local's daily profit distribution is skewed. Moreover, since locals' daily profit may be closely related to the total trading volume in the pit on the particular day, I also compute a volume-adjusted benchmark profit for each local. Specifically, I regress each local's daily profit series on the daily pit trading volume series, and the fitted values are expected daily profit series for each local trader, adjusting for pit volume. This volume-adjusted expected daily profit series is used as the third benchmark.

I examine the distribution of abnormal profits among all active locals during the crisis using these three alternative benchmarks. If a local's profit (loss) on a particular day is at least two standard deviations away from the benchmark used, the abnormal profit (loss) is considered significant. To see whether a majority of the active locals made abnormal profits during the crisis, I record the number of locals who experienced abnormal profits (losses) and significant abnormal profits (losses) on each day as percentages of total number of active locals in the pit. I also calculate the dollar amount of the total abnormal profits (losses) in the pit for each day during that period.

Table VII reports these results. For simplicity, only results using the second benchmark, median daily profit, are shown.[14] Out of 30 trading days during the crisis period, there are 24 days on which more than 50% of active locals made higher profits than their individual median daily profits. The difference between percentages of locals with abnormal profit and percentages of locals with abnormal loss is statistically significant at 1% level in both the paired t-test and the nonparametric sign test. The difference between percentages of locals with *significant* abnormal profit and percentages of locals with *significant* abnormal loss, however, is not significant. Moreover, these two series fluctuate together from day to day, largely depending on the magnitude of price changes during the day. For example, on days when there were large price movements such as Sept. 10 (margin call day), 11, 21 (margin call day), Oct. 5, 7, 8, and 9, both percentages of locals with significant abnormal profits and percentages of locals with significant abnormal losses are larger than on other days. The last three columns report total abnormal profits, total abnormal losses, and net abnormal profits (the sum of total

[14] The results using mean daily profit or volume-adjusted expected profit as benchmark are very similar to those using median daily profit as benchmark, and therefore are not reported.

abnormal profits and total abnormal losses) for all active locals in thousands of dollars. It is interesting to note that there were big downward price movements around Oct. 7 – 9, 1998 and locals suffered enormous losses during these days. Such dramatic changes about ten days after the rescue of LTCM indicate that the market finally started to realize its overreaction by that time and market beliefs also shifted as a result. This price pattern is consistent with Brunneremeier and Pedersen (2003) that predatory trading against a distressed trader leads to price overshooting.

In Figures 2, 3 and 4, I plot the cumulative abnormal profits for all active locals, using mean daily profit, median daily profit and volume-adjusted expected profit as benchmark respectively. Figures 2 and 3 show that the cumulative abnormal profit for market makers as a whole group was modestly positive in September but turned sharply down into the negative territory later in October. In Figure 4, the cumulative abnormal profit appears to be smaller than in Figures 2 and 3.

The overall evidence suggests that market makers did seem to profit from LTCM's weakness during the early period of the crisis. However, after the recapitalization of LTCM, especially by the time when the market realized it overreaction and started to correct itself, locals' speculative trading turned unprofitable and the abnormal losses more than offset their initial gains. Such a pattern may result from herding and "overshooting" by locals when they continued to front run LTCM after the rescue. Since locals' speculative trades were based on their superior knowledge of the market environment rather than about the asset fundamentals, this evidence on profitability is consistent with Madrigal (1996) model in which non-fundamental speculators appear to chase trends and lose money after market overreactions.

B. *Cross-sectional Relationship Between Front Running and Abnormal Profits*

The previous analyses show that locals in the aggregate engaged in front running, and that their cumulative abnormal profits were positive before the rescue but dropped sharply to negative after the rescue. To shed some light on the relation between front running and profitability, I further examine the cross-sectional front running behavior and its relation to profitability variation. For each of the 437 active locals *j*, I first calculate a "front running measure" $frm_j = \beta_{j1} + \beta_{j2} + \beta_{j3}$, where β_{j1}, β_{j2} and β_{j3} are obtained from a volume-adjusted front running regression in the following form:

$$\frac{lNOF_{jt}^*}{\overline{vol}_j} = \alpha_j + \sum_{i=1}^{4} \beta_{ji} LTNOF_{t+i}^* + \varepsilon_{jt} \tag{7}$$

where $lNOF_{jt}^*$ is the prewhitened net order flow for local *j* in minute *t*, $LTNOF_{t+i}^*$ is the prewhitened net order flow for PI7 customers in minute *t+i*, and $\overline{vol}_j$ is the average trading volume for local *j* in any minute throughout the year. To control for the possible effect on the beta coefficients of different trading volume across the locals, I standardize the net order flow for local *j* by her average volume in a minute in (7). The sum of the first three coefficients from the regression (frm_j) is used as a proxy for the degree of front running by local *j*. The fourth coefficient is excluded because the results from Section IV suggest that front running occurred one to three minutes before PI7 customers' trading.

I then perform a cross-sectional regression of locals' cumulative abnormal profits (*cap*) during the crisis period on their front running measures (*frm*). Here abnormal profit is defined as a local's daily profit minus her median daily profit during the year.[15] I also perform the regression for two sub-periods: Sept. 2 – Sept. 28 and Sept. 28 – Oct. 15.

[15] Again, results using the other two benchmarks are very similar and therefore omitted here.

The results are reported in Panel A of Table VIII. For the entire crisis period, the front running measure is positively associated with the cumulative abnormal profit, however the relation is not significant. Moreover, the relationship between front running and profitability was positive before the rescue but turned negative after the rescue, although both coefficients are insignificant. In economic terms, if a local increased her degree of front running in any minute by one standard deviation, her cumulative abnormal profit before the rescue would be increased by about 4.5% standard deviation. On the other hand, in the after-rescue period, a local's cumulative abnormal profit would be reduced by about 5.8% standard deviation if she increased her degree of front running by one standard deviation.

Besides front running, one may suspect that a local's tie with PI7 as contra party could also affect her abnormal profits during the crisis. One proxy for the tie with PI7 is a local's trading frequency with PI7 as contra party. For example, a local who traded with PI7 80% of the time during the crisis was probably better informed about LTCM's trades than a local who traded with PI7 only 5% of the time. Therefore, I add another explanatory variable *freq*, defined as the number of CTI 1 trades with PI7 divided by the total number of CTI 1 trades by a local. The results are shown in Panel B of Table VIII. For the whole crisis period, there is a negative and insignificant relation between *freq* and a local's cumulative abnormal profit. In the first sub-period, the coefficients of *freq* and *frm* are both positive, which indicates that a local profited from front running and from a close tie with PI7 before the rescue. Interestingly, although the coefficient of *frm* is not significant, the coefficient of *freq* is highly significant, which suggests locals with closer relationships with PI7 might have had more accurate information about LTCM's trades than other locals, and therefore extracted higher abnormal profits. However, in the second sub-period, both coefficients turned negative, especially the coefficient of *freq*, which shows that both front running and high trading frequency with PI7 actually hurt the profitability after the rescue. The evidence that locals with close relationships with PI7 suffered greater losses afterwards suggests that their trading strategies were driven by trend chasing rather than by knowledge of the asset fundamentals, and therefore did not respond in a timely way to the dramatic changes in market conditions after the rescue.

To further investigate the possible impact of change in front running behavior on profitability, I also track the profitability for four different types of locals, based on their front running behavior before and after the rescue. In particular, for the two sub-periods, I sort all active locals into two groups respectively, those with front running measures during the corresponding sub-period above the median (denoted by 1) and those with front running measures below the median (denoted by 2). I then take the four different combinations: type (1,1), type (1,2), type (2,1) and type (2,2), where type (1,1) consists of locals who were aggressive in front running in both sub-periods, type (1,2) consists of locals who were aggressive front runners before the rescue, but not so after the rescue, and so on. The results are shown in Figure 5.

Figure 5 indicates that front running was profitable in the first sub-period. Type (1,1) had the highest abnormal profits before the rescue, while type (2,2) had the worst performance. However, such pattern was reversed in the second sub-period, when type (2,2) turned out to outperform all other types, especially type (1,1). Type (1,2) and type (2,1) fell between the two extreme types. During the entire period, locals who were aggressive front runners did not seem to be able to make abnormal profits persistently.

Finally, I also track the performances of four front running groups. Specifically, I construct four quartiles based on locals' front running measures in the two sub-periods respectively. Four front running groups are formed so that Group 1 contains the most aggressive front runners and Group 4 contains the least aggressive locals in both sub-periods. A local may fall into different groups in the two sub-periods if she changed her intensity of front running after the rescue. The results are reported in Figure 6.

Figure 6 again shows that the relationship between front running and profitability turned from positive to negative after the rescue. Group 4 had the best performance with their cumulative abnormal profits close to zero throughout the period, while Group 1 suffered the biggest abnormal losses after their initial gains.

The results in Table VIII and Figures 5-6 provide an explanation for the aggregate patterns in Figures 2, 3, and 4. They suggest that locals' speculative trading was modestly profitable in the early period of the crisis, but turned unprofitable after the market started to correct its overreactions. The recapitalization by LTCM's creditors successfully helped LTCM avoid a "fire sale' liquidation of its assets, and therefore reversed the profitability of speculative trading by market makers.

C. Caveats

One limitation of the profitability analyses so far is that locals' daily profitability is marked to market based on an important assumption: each local starts with zero inventory at the beginning of each day. While this may be true in practice under most circumstances, one might challenge its validity for the crisis period. In the LTCM case, the T-bond futures price was widely expected to move up, so it was possible that at least some aggressive locals became willing to carry some inventory overnight. If this was true, then the profitability analyses may be biased. For example, on day *t*, if a local was assumed to start with zero inventory but she actually was long 50 contracts, then her profit figure for day *t* was inaccurate, with a bias equal to the change in closing price from day *t*-1 to day *t*, times 50 contracts carried over from day *t*-1. Moreover, such bias would exist until the true end-of-day inventory goes back to zero.

Since the data record all transactions with identifiers for each trading party, an alternative measure is considered. Specifically, I assume zero position at the beginning of the front month period and track each local's end-of-day inventory on each day and calculate daily profits with the inventory rolled over.[16] However, this alternative measure has its own biases too, mainly because locals often execute trades for each other and one cannot tell such trades from the data. For example, if local A asked local B on day *t* to buy 50 contracts on her behalf, the trade would be recorded as a trade by local B on behalf of another exchange member (CTI 3) rather than a CTI 1 trade by local A. Therefore, local A might appear to be short 50 contracts under this measure when she actually had closed out her positions. Again, the daily profit calculated this way would differ from the true profit figure by the change in closing prices times the inventory bias. To make things worse, the bias would be rolled over to all the subsequent days.

For reasons discussed above, it is not surprising that the profitability figures under different assumptions can be somehow different. However, the main findings using the alternative measure remain basically unchanged: the aggregate profitability took a dive to

[16] The front month period is the period during which a certain contract remains the front month contract. During the crisis, the front month contract was the December 1998 contract, with its front month period from Aug. 31, 1998 to Nov. 30, 1998.

the negative territory after the rescue, and a local's tie with PI7 was positively associated with her profitability before the rescue, but no so afterwards.[17]

This paper focuses on the results under the zero inventory assumption, for the following reasons. First, although the zero inventory assumption has some limitations, the potential biases caused by the alternative measure may be greater due to the persistent nature of inventory rollover. To see this, I check the mean of the absolute values of inventory across locals during the front month period under the alternative measure. The mean series gradually increases up to the last day of the front month period, which seems unrealistic because locals are unlikely to keep large inventory (either long or short) when a contract is soon to expire. Second, the risk of holding overnight inventory is influenced by margin funding costs. Even though some locals appear to carry some inventory overnight, the magnitude of inventory is still small relative to their daily trading volumes during the crisis. Finally, since the zero inventory assumption is widely adopted in the literature, using the same assumption in this paper makes the profitability results more comparable to those in other studies.

VI. Conclusion

In the existing literature, there is relatively little empirical evidence on market makers' trading behavior, largely due to lack of detailed transactions data. This paper uses an audit trail transactions dataset to examine the occurrence of front running behavior in the T-bond futures market during the LTCM crisis. The availability of transactions data for the crisis period provides a unique opportunity to investigate

[17] Results of the profitability analyses using the alternative measure are available upon request.

whether market makers exploited their informational advantage about customer order flow in trading for their own accounts when LTCM was financially distressed.

Although traders' true identities are concealed in the dataset, I find strong evidence that market makers in the aggregate engaged in front running against customer orders from a particular clearing firm "PI7", which closely match various characteristics of LTCM trades through Bear Stearns during the crisis. Specifically, market makers traded ahead of PI7 customer orders in the same direction by just one or two minutes. During the crisis period, PI7 customer orders had an unusually high price impact and the market liquidity was low. In the aggregate, locals made modest abnormal profits from their speculative trades before the rescue. However, as they continued front running, their initial abnormal profits were more than offset by abnormal losses realized after the rescue. This evidence suggests that the recapitalization effectively relaxed the margin constraints for LTCM and wiped out the profitability of front running.

Although this paper is a case study of front running behavior, the empirical evidence presented here has broad implications regarding the role of market makers and the impact of margin constraints on trading behavior. The findings that market makers attempted to exploit their superior information about customer order flow by front running calls into question the conventional assumption of uninformed and competitive market makers in most microstructure models. The evidence also sheds some light on the probable effect of central bank involvement if conditions like the LTCM crisis were to recur. If front running is common, it could significantly affect the asset pricing process, and could also make margin constraints more costly to the affected traders. Further research effort might explore the extent to which this is the case.

Table I. Summary Statistics

This table reports contract volume, percentage of volume and average trade size by trader type and contra party trader type for front-month T-bond futures in 1998. The transactions data include a customer type indicator (CTI) indicating whether each trade is performed as a local trade (for a market maker's own account with CTI 1), or as a commercial trade (for the account of the trader's clearing member with CTI 2), or as a hedger trade (for any other exchange member with CTI 3), or as a customer trade (for an outside customer with CTI 4).

Panel A. Contract volume by contra party combination

Trader type	**Contra party trader type**			
	Local	Commercial	Hedger	Customer
Local	19,514,184	11,395,315	7,706,501	46,198,148
Commercial		165,955	230,279	1,577,878
Hedger			112,547	1,218,658
Customer				3,808,045
Total contract volume: 91,927,510				

Panel B. Percentage of volume by contra party combination

Trader type	**Contra party trader type**			
	Local	Commercial	Hedger	Customer
Local	21.23%	12.40%	8.38%	50.25%
Commercial		0.18%	0.25%	1.72%
Hedger			0.12%	1.33%
Customer				4.14%
Total: 100%				

Panel C. Percentage of volume with given trader type on at least one side of trade

Trader type	Local	Commercial	Hedger	Customer
Percentage	92.26%	14.54%	10.08%	57.44%

Panel D. Average trade size by contra party combination

Trader type	**Contra party trader type**			
	Local	Commercial	Hedger	Customer
Local	7.74	34.34	12.47	24.22
Commercial		40.60	28.26	45.80
Hedger			12.51	27.52
Customer				46.17

Panel E. Average trade size with given trader type on at least one side of trade

Trader type	Local	Commercial	Hedger	Customer
Avg. trade size	15.77	35.32	13.64	25.52

Table II. Market Depth Regression

This table reports the results of market depth regressions. The depth regression is as follows: $\Delta p_t = \alpha + \beta_1(LTNOF_t/1000) + \beta_2(OCNOF_t/1000) + \gamma_1 D^*(LTNOF_t/1000) + \gamma_2 D^*(OCNOF_t/1000) + \varepsilon_t$, where Δp_t is the price change in every minute t defined as the last price quote in t minus the last price quote in minute t-1 throughout the whole year of 1998, $LTNOF_t$ and $OCNOF_t$ are the net order flow of PI7 customers and all other customers in minute t, $D^*(LTNOF_t/1000)$ and $D^*(OCNOF_t/1000)$ are two interaction terms of the two net order flow series with a dummy variable D. In the second column, D equals to 1 for date $\in$ [9/2/1998, 10/15/1998] and 0 otherwise; in the third column, D equals to 1 for date $\in$ [9/2/1998, 9/28/1998] and 0 otherwise; in the fourth column, D equals to 1 for date $\in$ [9/29/1998, 10/15/1998] and 0 otherwise. The error terms are corrected for 2nd order autocorrelation. t-statistics are reported in brackets, and ***, **, * indicate significance at 1%, 5%, and 10% confidence level respectively.

Dependent variable: price change in minute *t*: Δp_t

	***D* = 1 for (9/2/98 – 10/15/98)**	***D* = 1 for (9/2/98 – 9/28/98)**	***D* = 1 for (9/29/98 – 10/15/98)**
Intercept	0.0001	0.0001	0.0001
	[0.67]	[0.68]	[0.69]
$LTNOF_t/1000$	0.0061	0.0065	0.0074
(β_1)	[7.19]***	[7.86]***	[9.36]***
$OCNOF_t/1000$	0.0106	0.0115	0.0108
(β_2)	[36.94]***	[40.98]***	[39.07]***
$D^*LTNOF_t/1000$	0.0115	0.0095	0.0103
(γ_1)	[5.47]***	[4.10]***	[2.38]**
$D^*OCNOF_t/1000$	0.0078	0.0017	0.0147
(γ_2)	[9.51]***	[1.60]	[12.22]***
Test: $\beta_1 - \beta_2 = 0$			
F-statistics	27.25	33.29	18.10
p-value	(0.00)***	(0.00)***	(0.00)***
Test: $\gamma_1 - \gamma_2 = 0$			
F-statistics	2.98	10.93	0.99
p-value	(0.08)*	(0.00)***	(0.32)

Table III. Front Running Regressions for the Crisis Period

This table reports the results of a number of different regressions relating PI7 customers' net order flow (*LTNOF*) and other customers' net order flow (*OCNOF*) around minute *t* to the locals' net order flow (*lNOF*) in minute *t* for the crisis period (9/2/1998 – 10/15/1998). The models are specified by columns. Model 1 is a simple regression corrected for 4th order autocorrelation in the error terms. In Model 2, 3, 4 and 5, all the time series are prewhitened by the AR(20) model, and then the filtered series (denoted by *lNOF**, *LTNOF** and *OCNOF**) are used in the corresponding regressions. *t*-statistics are reported in brackets, and ***, **, * indicate significance at 1%, 5%, and 10% confidence level respectively.

Dependent variable: locals' net order flow in minute *t* ($lNOF_t$ in Model 1, $lNOF_t^*$ in Model 2 - 5)

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-2.5824	0.1981	0.8311	0.1418	0.8804
	[-0.69]	[0.05]	[0.22]	[0.04]	[0.24]
$LTNOF^*_{t-4}$			0.0599		0.0687
			[2.41]**		[2.75]***
$LTNOF^*_{t-3}$			-0.0106		0.0000
			[-0.43]		[-0.00]
$LTNOF^*_{t-2}$			-0.0125		0.0027
			[-0.51]		[0.11]
$LTNOF^*_{t-1}$			-0.0027		0.0099
			[-0.11]		[0.40]
$LTNOF^*_{t+1}$	**0.1004**	**0.1376**	**0.1400**	**0.1543**	**0.1583**
(w/o * in Model 1)	[4.21]***	[5.70]***	[5.84]***	[6.35]***	[6.56]***
$LTNOF^*_{t+2}$	**0.0401**	**0.0738**	**0.0788**	**0.0906**	**0.0957**
(w/o * in Model 1)	[1.67]*	[3.06]***	[3.29]***	[3.73]***	[3.97]***
$LTNOF^*_{t+3}$	**-0.0046**	**0.0122**	**0.0125**	**0.0320**	**0.0325**
(w/o * in Model 1)	[-0.19]	[0.51]	[0.52]	[1.32]	[1.35]
$LTNOF^*_{t+4}$	**-0.0696**	**-0.0497**	**-0.0408**	**-0.0309**	**-0.0224**
(w/o * in Model 1)	[-2.92]***	[-2.07]**	[-1.70]*	[-1.27]	[-0.93]
$OCNOF^*_{t-4}$					-0.0025
					[-0.26]
$OCNOF^*_{t-3}$					-0.0037
					[-0.38]
$OCNOF^*_{t-2}$					0.0157
					[1.62]
$OCNOF^*_{t-1}$					0.0056
					[0.58]
$OCNOF^*_{t+1}$				**0.0349**	**0.0376**
				[3.62]***	[3.85]***
$OCNOF^*_{t+2}$				**0.0287**	**0.0310**
				[2.96]***	[3.16]***
$OCNOF^*_{t+3}$				**0.0405**	**0.0421**
				[4.18]***	[4.31]***
$OCNOF^*_{t+4}$				**0.0354**	**0.0348**
				[3.64]***	[3.57]***

Table IV. Front Running Regressions for the Comparison Period

This table reports the results of a number of different regressions relating PI7 customers' net order flow (*LTNOF*) and other customers' net order flow (*OCNOF*) around minute *t* to the locals' net order flow (*lNOF*) in minute *t* for the comparison period (1/1/1998 – 6/30/1998). The models are specified by columns. Model 1 is a simple regression corrected for 4th order autocorrelation in the error terms. In Model 2, 3, 4 and 5, all the time series are prewhitened by the AR(20) model, and then the filtered series (denoted by *lNOF**, *LTNOF** and *OCNOF**) are used in the corresponding regressions. *t*-statistics are reported in brackets, and ***, **, * indicate significance at 1%, 5%, and 10% confidence level respectively.

Dependent variable: locals' net order flow in minute *t* ($lNOF_t$ in Model 1, $lNOF_t^*$ in Model 2–5)

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-0.7178	-0.3310	0.0302	-0.3090	0.0416
	[-0.39]	[-0.17]	[0.02]	[-0.16]	[0.02]
$LTNOF_{t-4}^*$			-0.0411		-0.0405
			[-2.69]***		[-2.65]***
$LTNOF_{t-3}^*$			-0.0616		-0.0596
			[-4.04]***		[-3.91]***
$LTNOF_{t-2}^*$			-0.0294		-0.0335
			[-1.62]		[-1.85]*
$LTNOF_{t-1}^*$			0.0669		0.0630
			[3.68]***		[3.47]***
$LTNOF_{t+1}^*$	**-0.0260**	**-0.0095**	**-0.0275**	**-0.0058**	**-0.0260**
(w/o * in Model 1)	[-1.79]*	[-0.64]	[-1.55]	[-0.39]	[-1.46]
$LTNOF_{t+2}^*$	**0.0014**	**0.0073**	**-0.0142**	**0.0120**	**-0.0094**
(w/o * in Model 1)	[0.10]	[0.42]	[-0.80]	[0.69]	[-0.53]
$LTNOF_{t+3}^*$	**0.0016**	**0.0015**	**0.0020**	**0.0034**	**0.0051**
(w/o * in Model 1)	[0.11]	[0.09]	[0.11]	[0.19]	[0.28]
$LTNOF_{t+4}^*$	**-0.0660**	**-0.0641**	**-0.0596**	**-0.0629**	**-0.0580**
(w/o * in Model 1)	[-4.52]***	[-3.66]***	[-3.34]***	[-3.60]***	[-3.25]***
$OCNOF_{t-4}^*$					-0.0002
					[-0.04]
$OCNOF_{t-3}^*$					0.0092
					[1.79]*
$OCNOF_{t-2}^*$					-0.0074
					[-1.44]
$OCNOF_{t-1}^*$					-0.0109
					[-2.12]**
$OCNOF_{t+1}^*$				**0.0136**	**0.0119**
				[2.70]***	[2.31]**
$OCNOF_{t+2}^*$				**0.0215**	**0.0183**
				[4.25]***	[3.55]***
$OCNOF_{t+3}^*$				**0.0098**	**0.0102**
				[1.94]**	[1.98]**
$OCNOF_{t+4}^*$				**0.0066**	**0.0066**

Table V. Front Running Regressions for Two Sub-periods of the Crisis

This table reports the results of a number of different regressions relating PI7 customers' net order flow (*LTNOF*) and all other customers' net order flow (*OCNOF*) around minute *t* to the locals' net order flow (*lNOF*) in minute *t* for two sub-periods of the crisis: before the rescue (9/2/1998 – 9/28/1998) and after the rescue (9/29/1998 – 10/15/1998). The models are specified by columns. Only Model 2 and Model 4 are used here. All the time series are prewhitened by the AR(20) model, and then the filtered series (denoted by *lNOF**, *LTNOF** and *OCNOF**) are used in the corresponding regressions. *t*-statistics are reported in brackets, and ***, **, * indicate significance at 1%, 5%, and 10% confidence level respectively.

Dependent variable: locals' net order flow in minute *t* ($lNOF_t^*$)

	Before Rescue (9/2/98 – 9/28/98)		After Rescue (9/29/98 – 10/15/98)	
	Model 2	**Model 4**	**Model 2**	**Model 4**
Intercept	0.1090 [0.02]	0.1397 [0.03]	0.3846 [0.07]	0.1983 [0.03]
$LTNOF_{t+1}^*$	**0.1323** [4.96]***	**0.1504** [5.57]***	**0.1712** [2.81]***	**0.1843** [3.03]***
$LTNOF_{t+2}^*$	**0.0637** [2.39]**	**0.0841** [3.12]***	**0.1303** [2.14]**	**0.1397** [2.29]**
$LTNOF_{t+3}^*$	**-0.0042** [-0.16]	**0.0187** [0.69]	**0.0843** [1.39]	**0.0976** [1.61]
$LTNOF_{t+4}^*$	**-0.0601** [-2.26]**	**-0.0406** [-1.51]	**0.0159** [0.26]	**0.0335** [0.55]
$OCNOF_{t+1}^*$		0.0367 [2.92]***		0.0327 [2.17]**
$OCNOF_{t+2}^*$		0.0362 [2.87]***		0.0169 [1.11]
$OCNOF_{t+3}^*$		0.0445 [3.53]***		0.0328 [2.16]**
$OCNOF_{t+4}^*$		0.0349 [2.75]***		0.0369 [2.45]**

Table VI. Front Running Regressions for the Participating Locals in PI7 Customers' Trades During the Crisis Period

The net order flow (CTI 1) from two subsets of locals is examined here: 29 locals who executed PI7 customer orders and 301 locals who traded with LTCM as contra parties during the crisis period. This table reports the results of a number of different regressions relating PI7 customers' net order flow (*LTNOF*) and all other customers' net order flow (*OCNOF*) around minute *t* to these two subsets of locals' net order flow (*tlNOF* and *clNOF*) respectively in minute *t* for the crisis period (9/2/1998 – 10/15/1998). The models are specified by columns. Only Model 2 and Model 4 are used here. All the time series are prewhitened by the AR(20) model, and then the filtered series (denoted by $tlNOF_t$, $clNOF_t$, $LTNOF^*$ and $OCNOF^*$) are used in the corresponding regressions. *t*-statistics are reported in brackets, and ***, **, * indicate significance at 1%, 5%, and 10% confidence level respectively.

	Dependent Variable: tlNOF$_t^*$		**Dependent Variable: clNOF$_t^*$**	
	Model 2	**Model 4**	**Model 2**	**Model 4**
Intercept	-0.2264 [-0.52]	-0.0071 [-0.04]	0.2498 [0.09]	0.0664 [0.02]
$LTNOF^*_{t+1}$	**0.0020** [0.95]	**0.0001** [0.04]	**0.1433** [3.52]***	**0.1572** [3.90]***
$LTNOF^*_{t+2}$	**0.0020** [0.95]	**0.0017** [1.30]	**0.1033** [2.55]***	**0.1129** [2.81]***
$LTNOF^*_{t+3}$	**0.0020** [0.94]	**0.0006** [0.47]	**0.0124** [0.31]	**0.0242** [0.60]
$LTNOF^*_{t+4}$	**-0.0028** [-1.32]	**-0.0016** [-1.20]	**0.0099** [0.25]	**0.0198** [0.50]
$OCNOF^*_{t+1}$		-0.0011 [-2.19]**		0.0184 [1.77]*
$OCNOF^*_{t+2}$		0.0009 [1.76]*		0.0037 [0.35]
$OCNOF^*_{t+3}$		0.0003 [0.66]		0.0233 [2.23]**
$OCNOF^*_{t+4}$		-0.0004 [-0.71]		0.0311 [2.97]***

Table VII. Daily Profit Distribution During the Crisis Period

This table reports percentages distribution of locals who experienced abnormal profits/losses during the crisis period (9/2/1998 – 10/15/1998). Daily profits are calculated by marking to market under zero inventory assumption. Each local's median daily profit during the whole year is used as benchmark to calculate abnormal profit. Abnormal profit (loss) is defined as each local's daily profit minus her median profit (loss), and significant abnormal profit (loss) denotes the case in which a local's profit (loss) on a particular day is at least two standard deviations away from the benchmark.

Date	Total # of active locals	% of locals with significant abnormal profit (1)	% of locals with significant abnormal loss (2)	% of locals with abnormal profit (3)	% of locals with abnormal loss (4)	Total abnormal profits (in $1,000s)	Total abnormal losses (in $1,000s)	Net abnormal profit (in $1,000s)
9/2	411	0.73%	0.24%	54.74%	45.26%	1,060.77	-1,770.41	-709.64
9/3	413	0.00%	0.00%	52.78%	47.22%	1,520.16	-669.89	850.27
9/4	414	0.97%	1.45%	54.59%	45.41%	4,002.28	-3,305.20	697.08
9/8	392	0.00%	1.53%	52.04%	47.96%	1,612.38	-1,590.70	21.67
9/9	410	1.46%	2.93%	60.98%	39.02%	3,870.92	-3,352.02	518.91
9/10	406	10.59%	9.85%	52.96%	47.04%	8,071.86	-9,329.69	-1,257.83
9/11	411	10.46%	8.76%	53.04%	46.96%	8,043.41	-6,343.16	1,700.25
9/14	394	0.51%	3.30%	46.70%	53.30%	860.88	-2,413.19	-1,552.31
9/15	400	4.50%	3.75%	57.25%	42.75%	3,925.11	-2,233.72	1,691.39
9/16	410	3.66%	5.12%	48.78%	51.22%	2,336.22	-3,271.70	-935.48
9/17	405	0.74%	2.22%	56.54%	43.46%	1,555.53	-1,263.34	292.19
9/18	375	0.53%	1.60%	46.67%	53.33%	1,428.50	-1,525.06	-96.56
9/21	320	6.25%	3.13%	65.31%	34.69%	2,486.72	-1,286.45	1,200.27
9/22	373	1.34%	2.41%	52.28%	47.72%	779.34	-1,769.72	-990.38
9/23	385	3.38%	3.64%	57.92%	42.08%	2,522.53	-1,721.23	801.30
9/24	390	1.54%	1.03%	48.97%	51.03%	1,504.08	-1,218.55	285.53
9/25	381	0.79%	3.15%	55.64%	44.36%	1,157.17	-1,291.95	-134.78
9/28	362	0.28%	0.55%	38.67%	61.33%	624.55	-1,015.73	-391.19
9/29	384	2.34%	4.69%	44.53%	55.47%	1,200.08	-2,925.42	-1,725.34
9/30	332	6.93%	7.83%	51.81%	48.19%	2,520.48	-3,672.39	-1,151.91
10/1	396	5.81%	5.30%	54.04%	45.96%	3,261.16	-3,398.98	-137.83
10/2	403	3.23%	2.23%	61.54%	38.46%	2,549.16	-1,487.13	1,062.03
10/5	364	6.04%	12.64%	57.14%	42.86%	2,238.42	-5,764.53	-3,526.11
10/6	381	3.15%	2.36%	59.58%	40.42%	2,607.69	-1,968.69	639.00
10/7	388	9.54%	7.47%	60.82%	39.18%	4,475.67	-7,628.08	-3,152.41
10/8	389	17.22%	16.45%	58.35%	41.65%	6,250.36	-15,228.92	-8,978.56
10/9	358	12.01%	9.22%	57.82%	42.18%	4,464.00	-6,478.52	-2,014.52
10/13	385	3.38%	3.38%	51.95%	48.05%	4,355.67	-3,185.86	1,169.81
10/14	386	4.15%	5.70%	50.52%	49.48%	2,048.80	-4,990.28	-2,941.48
10/15	391	2.56%	4.86%	53.96%	46.04%	3,853.52	-3,712.98	140.53

Test: (2) – (1) = 0
***p*-value (paired *t*-test):** 0.23
***p*-value (sign test):** 0.57

Test: (4) – (3) = 0
***p*-value (paired *t*-test):** 0.00
***p*-value (sign test):** 0.00

Table VIII. Cross-sectional Relationship Between Front Running and Cumulative Abnormal Profits

Panel A. of this table reports the results of cross-sectional regression of cumulative abnormal profits (*cap*) on front running measure (*frm*) for the crisis period (9/2/1998 – 10/15/1998) as well as the two sub-periods (9/2/1998 – 9/28/1998) and (9/29/1998 – 10/15/1998), where *cap* denotes cumulative abnormal profit (using each local's median daily profit as benchmark) and *frm* is the sum of the first three regression coefficients in (7). Panel B. shows the results of cross-sectional regression of cumulative abnormal profits (*cap*) on front running measure (*frm*) and relative trading frequency with PI7 (*freq*), where *freq* is defined as number of trades with PI7 by each local divided by her total number of trades during the relevant period. *t*-statistics are reported in brackets, and ***, **, * indicate significance at 1%, 5%, and 10% confidence level respectively.

Panel A. Regression of Cumulative Abnormal Profits on Front Running Measure:

	Whole Period (9/2/98 – 10/15/98)	**Before Rescue (9/2/98 – 9/28/98)**	**After Rescue (9/29/98 – 10/15/98)**
Intercept	-38.98 [-2.35]**	3.80 [0.31]	-40.23 [-2.65]***
frm	3,085.16 [0.18]	13,385.00 [0.99]	-8,475.59 [-1.26]

Panel B. Regression of Cumulative Abnormal Profits on Front Running Measure and Relative Trading Frequency with PI7:

	Whole Period (9/2/98 – 10/15/98)	**Before Rescue (9/2/98 – 9/28/98)**	**After Rescue (9/29/98 – 10/15/98)**
Intercept	-38.36 [-2.15]**	-17.27 [-1.34]	-32.36 [-2.08]**
frm	3,319.51 [0.19]	8,668.13 [0.65]	-7,287.05 [-1.09]
freq	-79.96 [-0.09]	2,381.29 [4.54]***	-1,160.03 [-2.14]**

Figure 1. T-bond Futures Price vs. PI7 Customers' Cumulative Net Buys (9/1/1998 - 10/30/1998)

This figure shows cumulative net buys from customers of clearing firm "PI7" (on left scale) and T-bond futures price (on right scale) during September and October of 1998. Date labels are points in time, e.g. the space between 9/1 and 9/2 represents events on 9/1, and so on. Holidays and weekends are excluded.

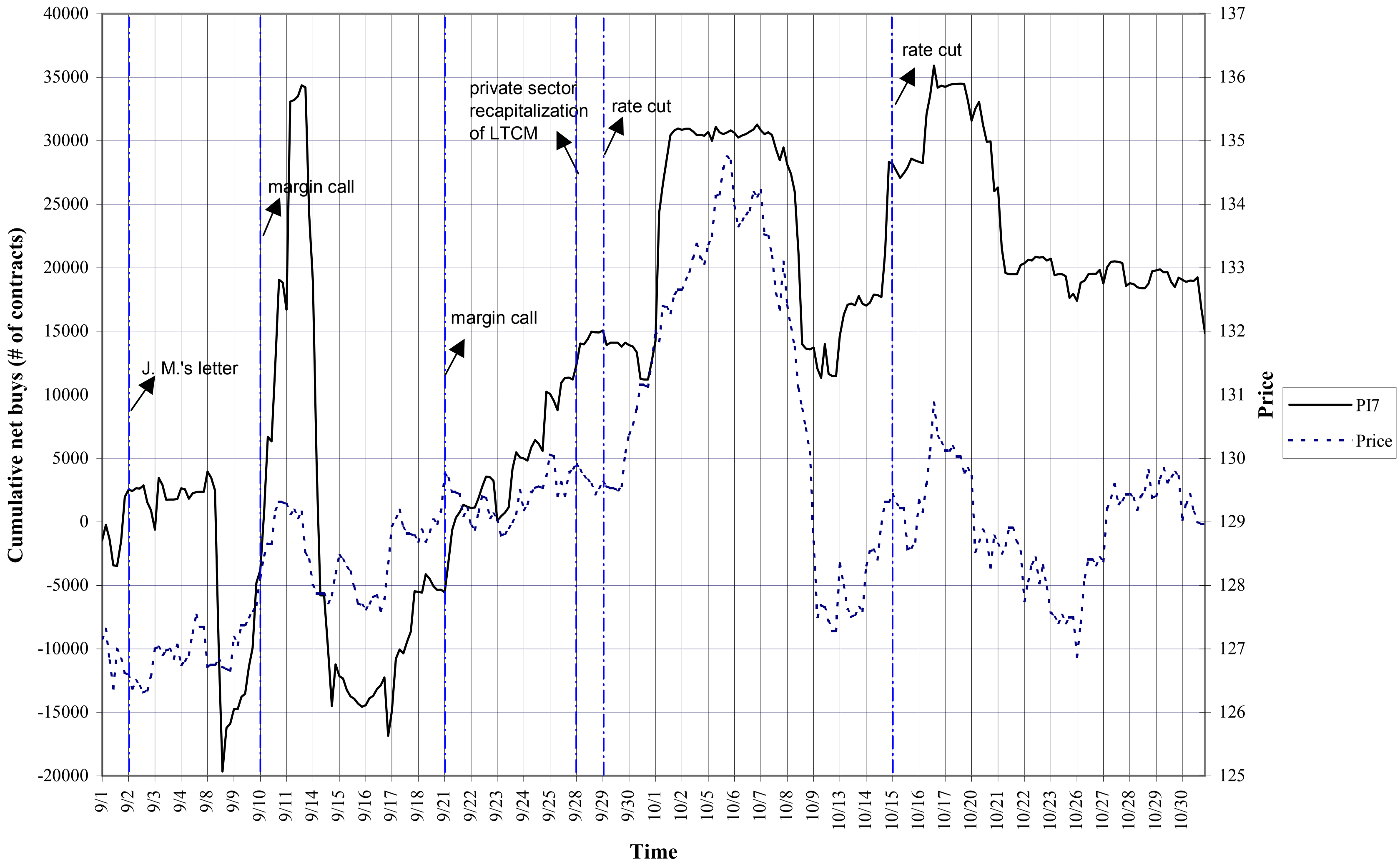


Figure 2. Cumulative Abnormal Profits for All Active Locals (9/2/1998 - 10/15/1998) (mean profit as benchmark)

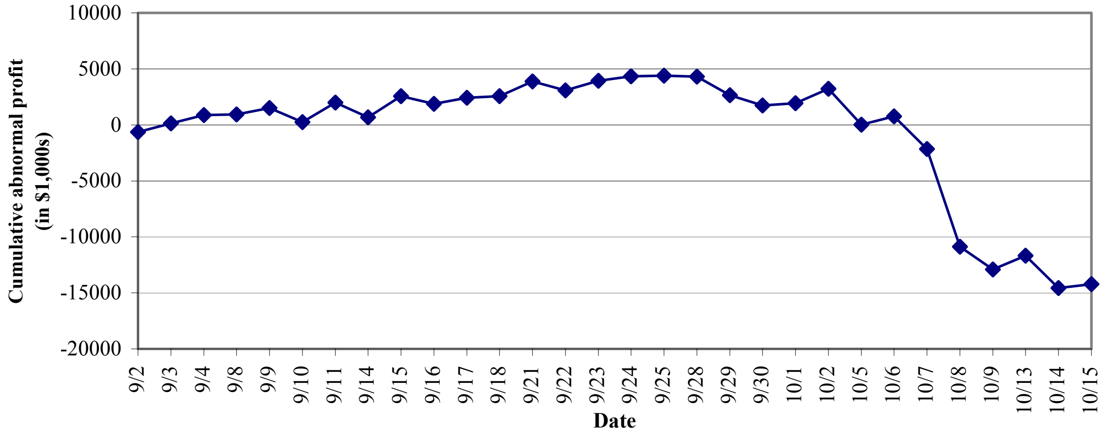


Figure 3. Cumulative Abnormal Profits for All Active Locals (9/2/1998 - 10/15/1998) (median profit as benchmark)

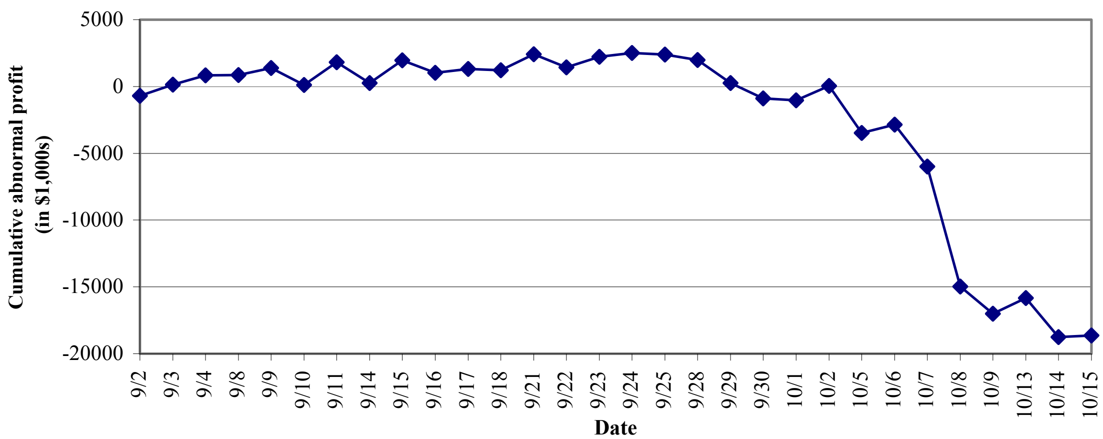


Figure 4. Cumulative Abnormal Profits for All Active Locals (9/2/1998 - 10/15/1998) (volume-adjusted expected profit as benchmark)

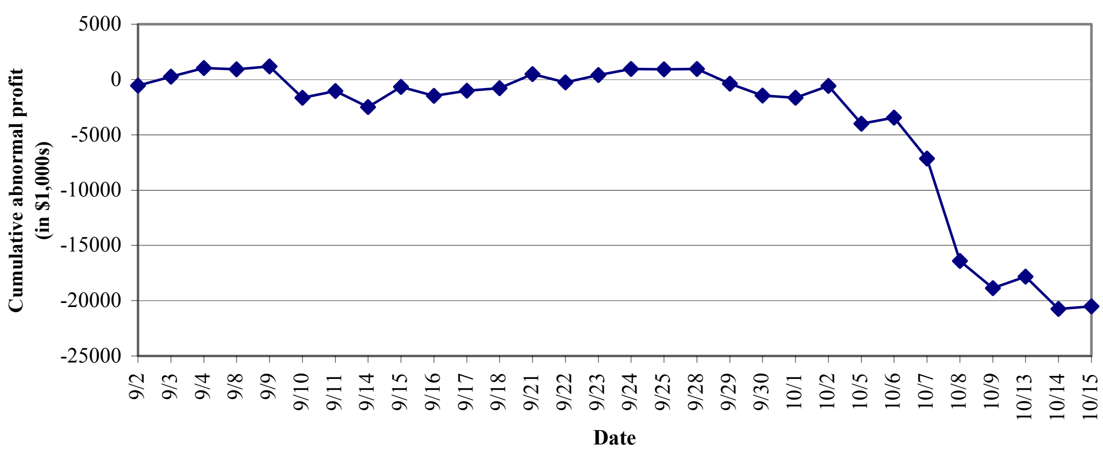


Figure 5. Cumulative Abnormal Profits for 4 Types of Front Running Locals (sorted by front running measures in two sub-periods)

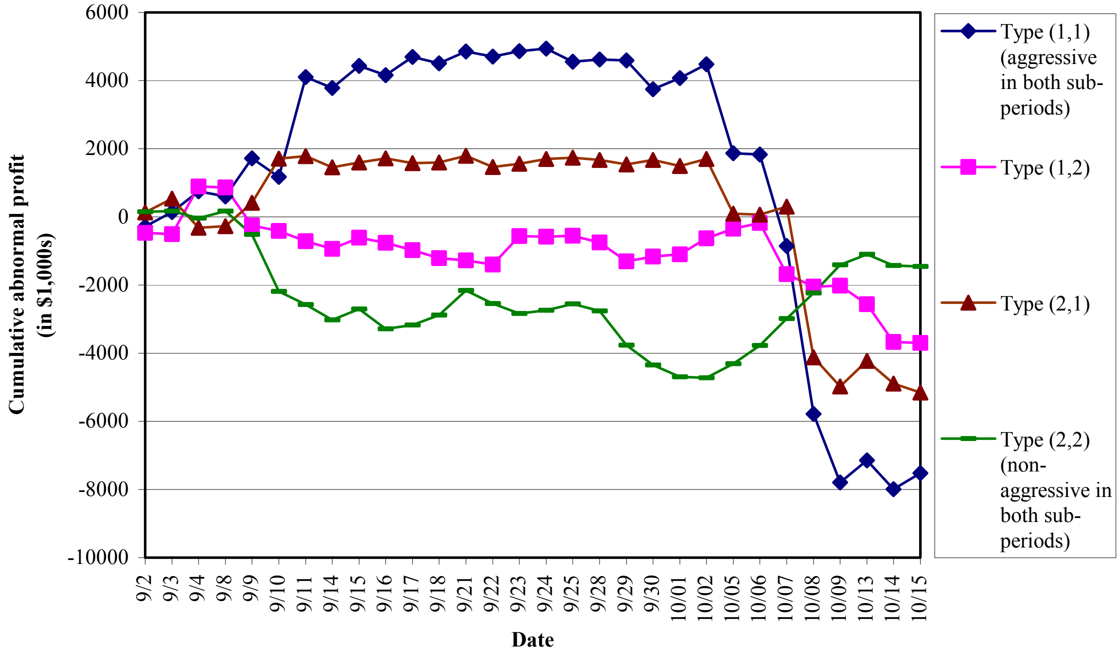
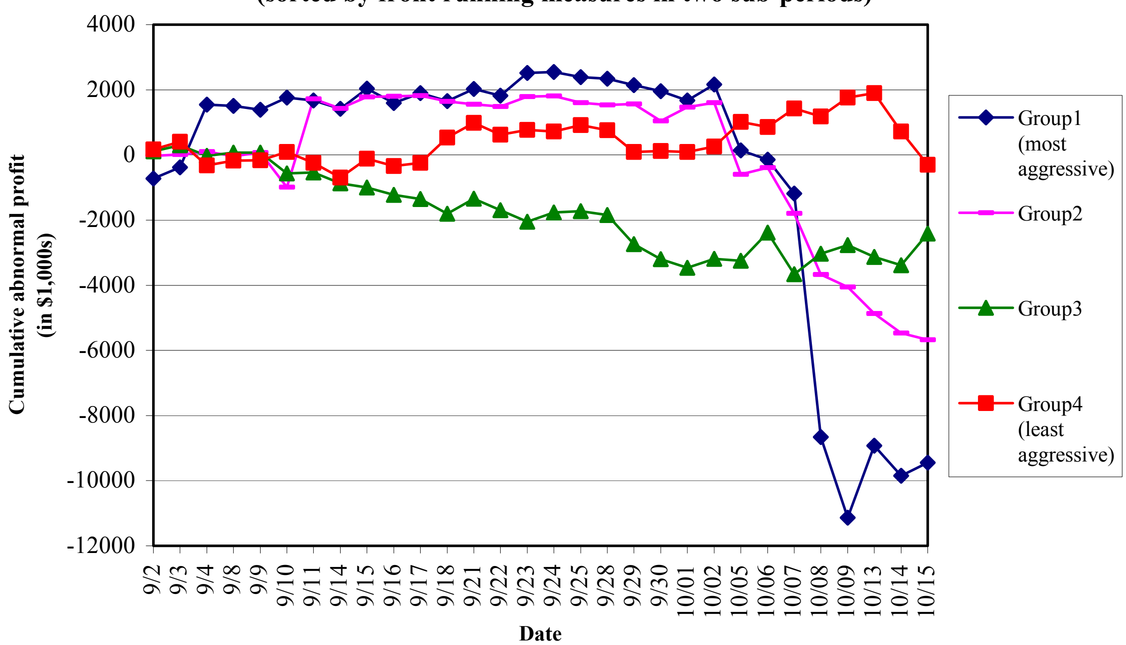


Figure 6. Cumulative Abnormal Profits for 4 Front Running Groups (sorted by front running measures in two sub-periods)



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