# Anatomy of a Market Crash: A Market Microstructure Analysis of the Turkish Overnight Liquidity Crisis*

Jón Daníelsson
London School of Economics

Burak Saltoğlu
Marmara University

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**Abstract**

An order flow model, where the coded identity of the counterparties of every trade is known, (providing institutional order flow) is applied to both stable and crisis periods in a large and liquid overnight repo market in an emerging market economy. Institutional level order flow is much more informative than cross sectionally aggregated order flow. The informativeness of order flow increases with financial instability. Traders place greater emphasis on measuring the trading activities of their competitors when markets are more volatile, enabling them to identity potential targets for squeezing, especially during the crisis when several banks are vulnerable.

JEL: F3, G1, D8. Keywords: order flow model, financial crisis, institution identity, Turkey

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# 1 Introduction

When a crisis originates in the financial markets, market microstructure can be better suited as a research methodology to capture the salient features of the crisis than traditional macroeconomic and institutional explanations. Market microstructure emphasizes decision making at the most detailed level, providing a play–by–play level analysis of how a crisis progresses. Individual trading strategies can have considerable crisis potential, as financial institutions squeeze their competitors, potentially causing prices to spiral up. To capture such behavior it is essential to study market activity at the highest frequencies. Our objective is the application of empirical market microstructure methods to the study of financial crisis, where our particular example is the November 2000 Turkish liquidity crisis, when annual interest rates exceeded 2000% overnight, ultimately sparking a major economic crisis. We use an order flow model for interest rate determination, where our data set includes detailed information about each transaction in the Turkish overnight repo market for most of the year 2000. A unique feature of the data is that coded intuitional identities are known, enabling us to explicitly document the impact of individual trading strategies on interest rates.

At the beginning of the year 2000, Turkey was emerging from a long period of high inflation, and with IMF support embarked on an initially successful stabilization program.[1] Throughout most of the year, overnight rates were relatively low (see Figure 1), but then exploded on December 1$^{st}$, supposedly, taking most observers by a complete surprise. In the postmortem it emerged that some institutions had been financing themselves partly on the overnight market, for example to meet margin calls, and were highly leveraged.

A major cause of financial crises is the combination of lax banking supervision associated with weak macroeconomic factors, as suggested by e.g. Mishkin (2000); Corsetti et al. (1999); Goldstein et al. (2000); Beim and Calomiris (2001). Recently Freixas et al. (2000); Caballero and Krishnamurthy (2001, 2002a,b) relate domestic liquidity and financial crisis, either generally, or in emerging markets, and argue that the money market may have negative impacts on an emerging market crises. This suggests that empirical market microstructure analysis of money markets in emerging markets may provide valuable insight into the causes of financial crisis.

Our main investigative tool is an order flow[2] model, where interest rate

[1]See e.g. www.nber.org/crisis/turkey_agenda.html for more information on the Turkish financial crisis.

[2]Borrow (buy) order flow is the total transaction volume for trades from market borrow in a given time period. Lend (sell) order flow is defined analogously. In defining order

changes are regressed on their own lags, and contemporaneous and lagged order flow. We include both borrow and lend order flow in our regressions and use the term *aggregate order flow* to distinguish this from institutional level order flow. Order flow models with aggregate order flow have had considerable success in explaining price changes.[3] While most applications only use order flow aggregated across all market participants[4] Fan and Lyons (2000) decompose forex order flow model into three main categories of institutional order flow, and Furfine (2002) uses data on US interbank payment flows, where he knows the exposure of each bank to every other bank.

Order flow models have, however, not seen many applications to either overnight repos or to emerging markets. Overnight repo contracts do have one important characteristic different from most other types of assets, i.e. the overnight repo is a contract for the provision of 24-hour liquidity, like a perishable good which expires worthless if not lent each day, either overnight or at longer maturities. Trading in such assets may generate different, and perhaps even stronger, microstructure patterns than trading in securities with a longer shelf–life. For example, a financial institution borrowing such liquidity may at times have a very inelastic demand function, especially in times of crisis, and be a prime candidate for squeezing. In this case order flow would be an important information channel, where we expect it to become increasingly informative with the onset of crisis. A similar suggestion is made by Lee (1998) who argues that hidden information may trigger a crisis. In emerging market countries with substantial overnight repo markets, and perhaps lax supervision, such overnight money markets may be the primary outlet for financial crisis. This hypothesis has not been verified since very few market microstructure level studies on financial crisis have been made with emerging markets data. One reason is a lack of data, since in most cases

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flow one must distinguish between borrower and lender initiated transactions. While every trade consummated in a market has both a lender and a borrower, the important member of this pair is the aggressive trader, the individual actively wishing to transact at another agent's prices.

[3]Initially with equities (see e.g. Hasbrouck, 1991), and subsequently in forex markets (see e.g. Evans and Lyons, 2002). Several recent studies consider fixed income markets, primarily U.S. Treasuries, e.g., Fleming (2001) who finds that when estimating an order flow model for the two–year note that $R^2$ exceeds 30%, while Cohen and Shin (2002) find that in the U.S. Treasury market order flow has a strong negative impact on interest rates.

[4]Other applications use datasets with indicative quotes, e.g the Olsen HFDF93 dataset, where the identity of quoting institutions is available, which is studied by e.g. Peiers (1997) and de Jong et al. (2001) who study the leadership hypothesis of Goodhart (1988). Using a different approach, Lyons (1995) studies one week of trading by a spot foreign exchange dealer. Furthermore, several authors have studied market manipulation in Treasury auctions, (see e.g. Jegadeesh, 1993).

high frequency data in emerging markets is either not collected or otherwise not available for academic research. Indeed, microstructure level studies of financial crisis tend to focus on developed markets, e.g., Blume et al. (1989) who consider the relationship between order imbalances and stock prices in the 1987 crash. Repos have played an important role in several institutional failures, e.g. Orange County (see e.g. Jorion, 1995), and the LTCM crisis in 1998 (see e.g. Jorion, 1999). More generally, repos are studied by e.g. Duffie (1996) and Jordan and Jordan (1997) who focus on the special repo rate. Hartmann et al. (2001) study the microstructure of the overnight euro money market.

In this study we use data from the Turkish overnight repo market, spanning most of the year 2000, excluding the December holiday period when trading was very sparse. It includes detailed information about each transaction in the overnight repo market, i.e., annual interest rate, quantity, whether each trade was a market borrow or market lend,[5] and the coded identity of the counterparties. The overnight repos are traded on the Istanbul stock exchange (ISE) on an electronic closed limit order system. (For details on the market structure see the Appendix.) In contrast to many other overnight money markets, the government does not intervene in the market as a condition of its IMF mandate.[6] Finally, the data set includes an extreme crisis episode on December 1st.

For each transaction we observe the coded identity of the borrowing and lending institution, and whether it was a market borrow or market lend. Over time, we therefore have four key variables measuring each institution's order flow activity: borrowing volume split into the institution's limit borrow and market borrow, ditto for lending volume. We term this *institutional order flow*. While the sample contains 136 different financial institutions, resulting in 544 institutional order flow variables, most of them have either values of zero, or are very small. By excluding the smallest institutional order flows, we avoid estimation difficulties caused by the matrix of explanatory variables not having full rank due to colinearity. This implies that the measured explanatory power will be lower than it potentially could be. We use the 5

[5] The convention in the order flow literature is to use the terms buy and sell, while for repos the terminology is e.g. borrowing/lending, take/give, long/short. In this paper we use the repo terminology, and use borrow/lend instead of buy/sell.

[6] The reason for the IMF mandate is probably a desire to stabilize the exchange rate, higher interest rates would lead to capital inflow, supporting the exchange rate. With the stabilization program agreed with IMF, the government controls the exchange rate by supplying foreign reserves to financial institutions but not the domestic interest rate. This is archived by fixing the "Net Domestic Assets" at each time. Because of this mandate, the Central Bank did not intervene in the money market.

most important lenders and borrowers, where only one institution is both a significant lender and borrower.

We estimate this model with two levels of temporal aggregation, daily and five–minute. The reason for estimating the model at the daily frequency is to obtain a birds eye view of the market, especially prior to the crisis. We observe a structural break at about ten days prior, on day 225 (Nov 20), suggesting that it is necessary to estimate the model separately for each of the two periods. We, therefore, consider the stable period as days 1–225 (Jan 4 to Nov 20), and designate the rest (days 226–240) as the crisis period. Since the crisis took place mostly on one particular day, the daily model is too aggregated to provide an accurate picture. Hence we use data disaggregated to 5 minutes, where we estimate the model separately in the stable and crisis periods. We consider four different model specifications, interest rate changes regressed on own lags, the inclusion of either aggregate or institutional order flow, and the inclusion of both types of order flow. These models are estimated in both the crisis and stable periods at the five-minute aggregation level. Unfortunately, we do not have sufficient degrees of freedom to estimate the model at the daily frequency over the crisis period.

Potentially, it might be interesting to consider the post crisis time period also, however, in practice we chose not to. There are two reasons why. First, this would include the Christmas holidays, when trading was very sparse. Second, subsequent to the crisis, several important financial institutions were taken over by the authorities, including the biggest purchaser of repos. At the same time the government was actively attempting to stabilize the market. Hence this would not be a realistic control case.

In the *stable period* we note that adding aggregate order flow to the basic interest rate model, has practically no impact on the explanatory power at the daily frequency, (the change in $R^2$ is 2%) while at the five minute frequency $R^2$ increases by 10%. Adding institutional order flow to the model alters the picture considerably, at the daily frequency, $R^2$ increases by 44% and 9% at the five-minute frequency. Finally, the result from excluding aggregate order flow, whilst including the institutional order flow, indicate that the institutional order flow is by a considerable margin the most important determinant of interest rate changes.

In the *crisis period*, where we are limited to results from the five-minute aggregation level, we find that the results are somewhat different. Overall, the explanatory power increases, for example, for the basic interest rate equation $R^2$ is 23%, increasing to 27% with aggregate order flow, and 83% when institutional order flow is also included.

We obtain the following main results:

- Result A Order flow is a strong determinant of overnight interest rates
- Result B Institutional level order flow has much more explanatory power than aggregate order flow
- Result C The informativeness of institutional order flow decreases with temporal aggregation
- Result D Trading volume is lower during the financial crisis, but not by a large amount
- Result E The order flow model has more explanatory power during the crisis period than when markets are more stable
- Result F Institutional order flow is much more informative during the crisis than when markets are more stable

In aggregate, we find those results consistent with extant results from empirical microstructure, and theories of informed trading. Aggregate order flow is a significant determinant of rate changes, more so at higher temporal aggregation levels and especially during the crisis. The results from the crisis period suggest that the informativeness of order flow increases with financial instability.

The results from the institutional level order flow are in our view the most interesting. In stable times, institutional order flow is not very important for rate determination at the highest frequencies. However at the daily frequency this changes considerably, and during the crisis, the institutional order flow model explains more than 80% of price changes. The fact that institutional order flow is significant does not surprise us, in a market with a small number of large players, each institution's trading can be expected to have a significant impact, and as a result institutional order flow should be significant. For trading institutions it matters whether the counterparties are informed or noise traders, and by observing the trading activity of other institutions, traders learn. In this case, traders can estimate what their competitors are up to by looking at their own counterparties, as well as other forms of news (indicative Reuters quotes, informal news, broker info, market gossip, etc.). Our results suggest that the informativeness of order flow changes with market conditions, where banks may allocate more resources to information gathering in crisis periods than when the markets are relatively quiet. Banks may find it easier to learn about aggregate order flow simply by monitoring book activity, while they learn about institutional order flow over time, with a significant component learned after trading ceases at 2 pm. Furthermore, institutional order flow depends on the positions held by a bank and its institutional customers and on trends in the personal and corporate lending books. It can be expected to be very heavily serially correlated. An institution with a big funding requirement today is likely to have a big funding requirement tomorrow.

In the crisis period the situation changes. In particular, with volatility and interest rates increasing, we might expect noise traders to exit the market, and institutions with less immediate needs for overnight liquidity to do the same. In contrast, the increase in interest rates may attract new supply. The decrease in volume corresponds to an increase in interest rates, which might be at first considered counterintuitive. However, the borrowing and lending order flow behave differently, as can be seen in Figure 2. Lend order flow is decreasing throughout, while borrow order flow first increases and then starts to drop few days before the crisis. We would expect this e.g. if good credits are able to lock into longer–term funding, suggesting this is a well–informed market. If noise traders have by then exited the market, the informativeness of order flow should increase. The institutional order flow is most relevant during the crisis, when the financial institutions seem to have a much clearer picture of who is actively trading, and react strongly to that information. For example, the observation that a particular financial institution is seen to be a large demander of repos, in spite of the ever–increasing rates, could be seen as weakness. Squeezing such institutions may lead to even larger rate increases, where the perceived threat of (formal or informal) rationing will cause the institutions with the funding requirements to bid the rate up. In that case, institutions demanding repos might prefer to act quickly, while those selling repos might want to delay trading. Therefore, in our specific case, since the Central Bank was prevented by the IMF from supplying liquidity, the crisis may be, at least in part, caused by market squeezes.

Caballero and Krishnamurthy (2001, 2002a,b) find that there may be a linkage between the structure of domestic money markets and crisis in emerging markets, where the domestic money market structure may have negative impact on financial structure. Our results have implications on understanding crisis in emerging markets and support some theoretical predictions of Caballero and Krishnamurthy (2001, 2002a,b). In particular, we find that the institutional order flows is a significant determinant of the rate of interest in domestic money market during crisis. This suggests that in implementing implementing policy prescriptions during financial crisis, monetary authorities in emerging markets and supranational bodies such as the IMF should acknowledge that the market microstructure in domestic money markets may be different than that in developed economies. In our case, the particular market microstructure allow for squeezing of vulnerable institutions causing a severe and perhaps unnecessary destabilization of the financial system.

# 2 Market Structure, Crisis, and Data

## 2.1 Crisis

Our data consists mostly of data on the overnight repo market in Turkey before and throughout a major financial crisis. The sample covers the year 2000, when Turkey experienced one major crisis episode when overnight interest rates reached 2000% (observed transaction rates) on December 1$^{st}$. The year started better, with the government announcing a major stability program aided by the IMF. This program was perceived as a success, and so when the actual crisis hit, it was seen as a total surprise, with no external shocks appearing to have been the trigger. Indeed, as can be seen in Figure 5, the Turkish lira/U.S. dollar exchange rate does not seem to have been affected by the crisis[7] , and the stock market, which had been declining prior to the crisis, was not much affected either. The short end of the money market reflects the crisis in its purest form because it is in the money market that liquidity is best reflected. As a result, overnight repurchase rates (repo) which are the price of overnight liquidity, well reflect the crisis. Furthermore, since overnight repos are a perishable good, the difficulties facing liquidity constrained financial institutions become most visible in the repo market. For details on the crises see the Appendix.

## 2.2 Market Structure

The Turkish repo market is based on a closed electronic limit order system, established on the Istanbul Stock Exchange (ISE). Traders do not know the identity of counterparties prior to trading, and other traders do not know that the trade took place, except by observing that a particular limit order has vanished. Counterparty credit risk is considered minimal in this market, since ISE guarantees that trades clear, indeed traders at ISE consider counterparty risk to be irrelevant. In addition to the organized market, an informal market based on Reuters quotes exists. Since the institutional identities of indicative

[7]The Central Bank bought USD 6bn worth of lira to support the exchange rate

Reuters quotes is known, it serves as an important source of information. However, as in many other markets indicative Reuters quotes tend to be a form of advertising with the actual quotes containing little information (see e.g. Daníelsson and Payne, 2002). Finally, some trading takes place at the Central Bank. While the exact volume in these two latter markets is unknown (it does not appear to be recorded), it is assumed by market participants to be much smaller than the organized market. Trading takes place between 10 am and 2 pm with a one hour lunch break. In special circumstances there might be some trading before 10 am and after 2 pm. See Figure 6. The ISE opens earlier and closes later, but trading in the large repos only takes place between 10 and 2. For details see the Appendix or the ISE factbook at website `www.ise.gov.tr`.

## 2.3 Data

Our data set is all transactions on the overnight repo market spanning 240 days from beginning of year 2000 (Jan 4) to Dec 11. In this period, 256,141 transactions were recorded. For each transaction we know the interest rate, volume, and whether it was borrowing or selling initiated hence providing signed order flow. Furthermore, we know the coded identity of each institution enabling us to identify the order flow from each institution.

While the main crisis happens on day 234 (Dec 1), in estimating the daily model, we observe a structural break about ten days prior, on day 225 (Nov 20). Some reasons for the structural break can be obtained by considering Figures 3 and 4 which show aggregate daily volume and realized volatility[8] over the entire data sample in Panel (a), and days 200–240 in Panel (b). There is a clear break around day 225, with volatility increasing, and aggregate volume decreasing. This suggests that it is necessary to estimate the model separately for each of the two periods. As a result, we split the data up into two main subsamples: days 1 to 225 referred to as the *stable period*, and days 226 to 240 referred to as the *crisis period*.

Our sample contains 136 different financial institutions, and we therefore have potentially 544 institutional order flow variables to include in the regressions. Further counting lagged observations, the number of dependent variables would be very large, causing estimation problems where the matrix of explanatory variables might not have full rank. It is, however, not necessary to include all institutional order flows. First, in most cases institutions

[8]i.e. the standard error of interest rates every 10 minutes throughout the day, see Andersen et al. (2002) for some background discussion

are either lenders or borrowers not both, leaving almost half of the institutional order flow variables with zero values. Second, most institutions are very small, (see Figure 7), trading is dominated by a small set of institutions, and the sample of independent variables can be reduced considerably by excluding the smallest institutions. This of course directly affects the results, in particular, the explanatory power of $R^2$ will be lower when some institutions are excluded from the regression. In other words, the results will be weaker than they potentially could be, representing the worst case scenario. We use the 5 most important lenders and borrowers in the regressions, see Table 2. Of the larger institutions, most are either lenders or borrowers, only one is both. See Table 2. The institutions we chose were, on the borrowing side have codes 2,4,12,22,24, and on the lending side codes 24,27,29,30,48. Of these, only 24 shows up in both cases.

## 2.4 Notation

We employ three types of variables in our analysis, interest rates, aggregate order flow, and institutional order flow.

The interest rate variable, $r_t$, records the last observation in each time interval. For the daily data it is the closing interest rate, and for the five–minute aggregated data it is the last observation in each interval. In general, we use interest rate changes, i.e., $\Delta r_t \equiv r_t - r_{t-1}$.

The counterparties either lend or borrow on the interbank market, and order flow is hence segmented into borrow and lend order flow. Borrow order flow, $b_t$, is defined as the sum of transaction volume from market borrow orders over the time interval. If $\upsilon_\tau$ is the transacted volume of trade at time $\tau$, and $\iota_\tau$ is an indicator variable that takes the value one if the trade at time $\tau$ was a market borrow, and zero otherwise, then

$$b_t \equiv \sum\nolimits_\tau \upsilon_\tau \iota_\tau, \quad t \leq \tau < t+1.$$

The definition of lending order flow, $l_t$, is equivalent.

The data sample contains observations on 136 different financial institutions, where each institution is known by a random identity code, i.e., a number between 0 and 135. The transacted volume of each institution over the time interval can therefore be calculated. For each transaction, we know the identity code of both counterparties. We also know whether each transaction was lender or borrower initiated, i.e., if the market order was a lend or borrow. As a result we record four separate variables for each institution, i.e., the volume of the institution's borrowing and lending, and whether this volume came from market orders or limit orders. For each institution $i$ in the time interval $t$ to $t+1$:

- An institution's borrowing volume, segmented into volume where the market order is:

  $b_t^b(i)$ borrow

  $l_t^b(i)$ lend

- An institution's lend volume, segmented into volume where the market order is:

  $b_t^l(i)$ borrow

  $l_t^l(i)$ lend

There are therefore two differences between the institutional order flow notation and the aggregate order flow notation, i.e., the $^b$ and $^l$ signaling that the institution was the lender and the borrower, respectively. The second difference is the $(i)$ identifying the order flow by institution.

We define the the entire vector of institutional order flow as:

$$\widetilde{\boldsymbol{W}}_t \equiv \begin{pmatrix} b_t^b(0) & l_t^b(0) & b_t^l(0) & l_t^l(0) \\ \vdots & \vdots & \vdots & \vdots \\ b_t^b(135) & l_t^b(135) & b_t^l(135) & l_t^l(135) \end{pmatrix}$$

Since we only use a subset of the institutional order flow, we denote $\boldsymbol{W}$ as the matrix of the institutional order flows that are used in the estimation.

### 2.5 Summary Statistics

The data at the daily aggregation level is summarized in Table 1, for both of the main subsamples used here. Most variables are not normally distributed, they have high autocorrelation, and are in most cases stationary. The interest rates are plotted in Figure 1, with order flow in Figure 2, trading volume in Figure 3, and realized volatility in Figure 4.

## 3 Model Specifications

We consider four different model specifications, a basic interest rate model, a model where either aggregate or institutional order flow is included, and finally the interest rate model with both aggregate and institutional order flow. We estimate the models at both the daily and the five-minute frequency.

## 3.1 Models

### 3.1.1 Interest Rate Model

Our interest rate model is a regression of interest rate changes on its own lags:

$$\Delta r_t = c + \alpha_N(L)\Delta r_{t-1} + \epsilon_t \tag{1}$$

where $_N(L)$ is the lag operator with $N$ lags, and $\epsilon_t$ is noise.

### 3.1.2 Aggregate Order Flow Model

The standard order flow model is where rate changes are regressed on net order flow, $(b - l)$, see e.g. Hasbrouck (1991) and Evans and Lyons (2002). This is a reasonable assumption when buy and sell order flow are equally informative, as in the foreign exchange markets. Several authors studying equity markets, e.g. Harris and Hasbrouck (1996) and Lo et al. (2002) suggest that the informativeness of buy and sell order flow might not be equal. In our case not only are the statistical properties of borrowing and lending order flow significantly different, see Table 1 and 2, in most cases the financial institutions are either lenders or borrowers, not both. There is only one sizable exception to this, institution 24. As a result, our order flow model contains borrowing and lending order flow separately, i.e.:

$$\Delta r_t = c + \alpha_N(L)\Delta r_{t-1} + \beta_N(L)b_t + \delta_N(L)l_t + \epsilon_t. \tag{2}$$

### 3.1.3 Institutional Order Flow

Institutional order flow is included in a similar manner as aggregate order flow, and with the same lag structure:

$$\Delta r_t = c + \alpha_N(L)\Delta r_{t-1} + \mathbf{\Gamma}_N(L)\boldsymbol{W}_t + \epsilon_t \tag{3}$$

where $\boldsymbol{W}_t$ is the matrix containing the order flow from the selected institutions, see Section 2.3.

### 3.1.4 Institutional and Aggregate Order Flow

In our final specification we include both aggregate and institutional order flow:

$$\Delta r_t = c + \alpha_N(L)\Delta r_{t-1} + \beta_N(L)b_t + \delta_N(L)l_t + \mathbf{\Gamma}_N(L)\boldsymbol{W}_t + \epsilon_t \tag{4}$$

## 3.2 Temporal Aggregation Levels

We have several choices in selecting temporal aggregation levels. The higher the temporal aggregation, the more representative the model is of long run phenomena, while a lower level of temporal aggregation enables us to measure high frequency strategic behavior. However, we are limited by our data sample, and application. We consider two levels of temporal aggregation, daily and five-minute. The daily frequency is chosen to give a birds eye view of the market, in particular to be able to measure the effects of learning throughout the day. Unfortunately, the crisis period only contains 15 days implying that it is not feasible to estimate the model at the daily frequency in that period. The five-minute data does not have that restriction with the first sample having 5818 observations, or 25 per day on average, and the second 366 observations or 24 per day on average.[9]

A key problem arises due to overnight interest rate changes (close to open), since they have a standard error of 50.2 while the five-minute intraday interest rate changes have a standard error of 2.03. Since our objective is to understand the relationship between order flow and interest rate changes, and since the overnight change is affected by other factors, we have chosen to disregard the overnight interest rate change. Given the long lag structures at the five-minute aggregation levels (12 observations) this specification will likely bias the contribution of order flow to interest rate changes downwards.

## 3.3 Criteria

We have a choice of several methodologies for evaluating and comparing the different models. In general, $R^2$ provides a direct measure of the explanatory power of each model, and given the relatively high number of observations, we do not suffer from the small sample properties of $R^2$.

[9] The reason for the discrepancy is that trading does not always start at 10 am, but usually sometime after, see Figure 6. Indeed, there are 36 five-minute intervals in the trading day.

# 4 Results

We consider the results from the estimation for the two subperiods separately.

## 4.1 Stable Period

First, consider a model at the daily aggregation level and a regression of interest changes on four of its own lags without any order flow. This results in $R^2$ =18%. By including order flow (borrowing ($b$) and lending ($l$) separately) in the equation, $R^2$ only increases to 20.3%. However, by including institutional order flow also, $R^2$ increases to 64.2%. This clearly suggests that the primary transmission mechanism of information is not aggregate order flow but instead institutional order flow.

At the five-minute aggregation level, we can see in Table 4 that $R^2$ for the basic interest rate model (1) is only 2.0%, while by including aggregate order flow $R^2$ increases to 11.5%, and when the institutional order flow is added, $R^2$ increases to 20.4%. Interestingly, if aggregate order flow is excluded from this model, the $R^2$ remains at 17.9%. Just as in the daily model, institutional order flow is the dominating factor.

## 4.2 Crisis Period

A different picture emerges in the second subsample, where $R^2$ for the basic interest rate equation is 6.4% and with order flow 33.0%. As discussed in section 3.2, the small number of degrees of freedom implies that is not possible to include institutional order flow, and that comparison based on $R^2$ is not very reliable.

At the five-minute aggregation level, $R^2$ from the basic interest rate model is 23.2% which increases to 77% when institutional order flow is included which also dominates aggregate order flow.

# 5 Analysis

We obtain the following main results:

Result A Order flow is a strong determinant of overnight interest rates

Result B Institutional level order flow has much more explanatory power than aggregate order flow

Result C The informativeness of institutional order flow decreases with temporal aggregation

Result D Trading volume is lower during the financial crisis, but not by a large amount

Result E The order flow model has more explanatory power during the crisis period than when markets are more stable

Result F Institutional order flow is much more informative during the crisis than when markets are more stable

## 5.1 Result A: Basic Order Flow Model

Aggregate order flow is found to be a significant determinant of interest rate changes, confirming results from other markets. Furthermore, since these results are obtained from an overnight money market in an emerging market economy, they reinforce the generality of the order flow model since the order flow model has not before been estimated in such cases. The explanatory power of order flow in our case is in line with results for other markets.

## 5.2 Result B: Institutional Order Flow Model

Institutional level order flow is found to be a much stronger determinant of rate changes than aggregate order flow, i.e., the sum of institutional order flows. In our view, this reinforces the view that the market considers some institutions to be more informative than others, i.e., the conventional split between informed and noise traders. Aggregating order flow information across institutions therefore not only increases the noise of the measured information by including noise traders, conflicting, but relevant, information may cancel out.

This problem only faces an academic researcher since market participants are able to indirectly measure identities, and policy makers do have direct access to that information. The results suggest that the market efficiently records institutional level information when necessary, in spite of the fact that other than own institution level order flow is not directly observable by market participants. Indeed, financial institutions are able to combine the various sources of information into an accurate measurement of their competitors' activities. They may not be able to do so in real time, but can, with time, estimate this. Within this particular market, we identify three main sources of information. First, institutions know the identity of their own counterparties, and therefore observe whether the trading patterns of their counterparties are unusual. In our case, of course, since most institutions do not trade on both sides of the market, this can only provide a partial picture. Indeed, it is surprising that not more institutions trade on both sides of the market, if only to get more information. The second information source is Reuters indicative quotes, where the identity of quoting institutions is known. While the accuracy of the indicative quotes, especially the spread, is likely to decrease during the crisis, it may still be a valuable source of information, at lease by providing identities of quoting institutions. Finally, indirect information channels, (traders gossip, news, etc.) is likely to be invaluable.

One reason why institutional level order flow is important is that it may provide information about firms' elasticity of demand/supply. For example, we may expect firms that are more desperate to prefer to trade early in the trading day, signaling high elasticity. This might also explain the intraday seasonality, see Figure 6 where firms are reluctant to trade early for this reason. It follows that high frequency order flow should become more informative during the crisis.

## 5.3 Result C: The Importance Of Temporal Aggregation

We are only able to compare the importance of temporal aggregation in the stable period. The informativeness of most models increases with temporal aggregation, confirming results from studies of other markets. We suspect that one reason is that at the higher frequency information is more diffuse than at lower frequency levels, both because processing information is costly, and also because information is only revealed over time. In particular, we expect the market to learn about institutional level trading only over time, when an important part of the learning process takes place after trading hours.

Another reason may have to do with the special nature of repos. In contrast to most other types of financial assets to which order flow models have been applied, repos are a perishable good. For example, for an institution with excess liquidity, if it fails to sell it by the end of the business day, it is worthless. And the same for an institution needing liquidity, it has to obtain it by the end of business. This suggests that financial institutions are playing a game, for example where an institution desperately in need of liquidity might prefer to trade early, providing information to those willing to learn by trading small amounts early.

In such an environment, we might expect that, in some cases, institutional order flow at the daily frequency is more significant than at the five–minute frequency, because the relative order flow across the day is only known after trading ceases.

## 5.4 Result D: Trading Volume And Crisis

In our case, trading volume does not decrease much during the crisis, even on the main crisis day volume is only 22% below average. This is in contrast to other crisis episodes, e.g., the 1987 crash and the 1998 Russia/LTCM crisis. For example in equity market crisis we may observe "fire sales" which are not relevant in the overnight money markets. The Turkish repo market is a relatively closed domestic market required for the ongoing functioning of the banking system. Furthermore, the crisis primarily plays out in the overnight market, with the impact on the equity prices and yields on longer maturities much lower. All these instruments trade on the same exchange as the overnight repos. Another reason why trading volume did not drop very much is due to the perishable nature of overnight repos, institutions holding liquidity gain nothing from not trading since such liquidity is worthless unless traded. This may ensure a continuous supply of liquidity to the market even during the worst of crisis. This is of course conditional on the fact that it was generally assumed that institutions would not default on their obligations. Indeed, even though a number of institutions went bankrupt as a consequence of the crisis, none of them defaulted on their transactions in the repo market. One puzzle remains, i.e. why did the supply of liquidity not increase in spite of the stratospheric interest rates. It is not possible to answer this question without knowing the names of trading institutions and augment the data sample with public information about each institution.

## 5.5 Result E: Order Flow Model During Crisis

The explanatory power of aggregate order flow, increases ($R^2$ rises from 23% to 28%) when the market is in a crisis. We suspect the main reason is that the informativeness of order flow increases both because noise traders may exit the market, and that order flow may provide information about which (borrowing) institutions are suffering difficulties, rendering such information more valuable and worthwhile to collect.

### 5.6 Result F: Institutional Order Flow Model During Crisis

The institutional order flow model becomes especially strong during the crisis. While aggregate order flow only increases $R^2$ by 5%, institutional order flow increases $R^2$ by 55% (to 77%). Including both institutional and aggregate order flow takes $R^2$ to 83%. This is in contrast to the non crisis period when institutional order flow makes only a small difference at the five-minute aggregation level. There are several possible explanations for this. First, institutions are less willing or able to hide. Second, since the market is more volatile, monitoring trading activity and gathering information is much more important. Third, since institutions continue to borrow overnight liquidity even while the rates continue increasing to stratospheric levels, might be perceived as desperate, inducing squeezing.

## 6 Conclusion

Taken together, the results presented in this paper are consistent with the order flow model and highlight the role of information in the formulation of interest rates. Aggregate order flow is shown to be an important contributor to interest rates, across sampling frequencies, with the significance increasing during the financial crisis. It is, however, institutional level order flow that is most interesting. When the market is relatively quiet, institutional level order flow is not very important at high sampling frequencies, it is only at the daily frequency where it becomes a significant determinant of interest rates. In contrast, institution level order flow becomes a very strong determinant of interest rates with the onset of financial crisis, even at the highest sampling frequencies. The reason is that financial institutions that are desperate for liquidity are increasingly being harmed by ever rising interest rates, implying that they become prime targets for squeezing. Institutional level order flow may therefore provide valuable information at times of crisis, while being less informative when markets are more stable.

From a policy point of view, the probability of crisis seems to increase with the informativeness of the order flow. This suggests that supervisory authorities ignore the market microstructure at their peril. Indeed, most supervisors in developed markets pay close attention to high frequency trading patterns. Since financial crises are more prevalent in emerging markets, their national supervisory authorities, as well as supranational bodies such as the IMF, may want to lavish the same attention on financial markets in emerging economies.

# A Details

## A.1 Microstructure

The majority of Turkish repos are traded on the stock exchange where the market structure is an electronic limit order market. Market participants have a choice of either limit quotes or market orders, with the minimum quote size of $5\times10^{11}$ TL. The limit orders are one–sided, i.e., traders either enter lend or borrow quotes where these quotes are firm in the sense that the quoting institution is committed to lend until it either withdraws the quote or another institution hits the limit order with a market order. Each trader sees the five best bid/ask limits but does not know the identity of the quoting institution. Trading usually takes place between 10 and 12am, and 1–2 pm. However, there are recorded transactions after 2 pm especially on days with very high volume. Furthermore, the occasional transaction is recorded before 10 am. Limit orders are recorded from 9 am. There are few days, usually before public holidays with very light trading. The traders know the identity of the counterparty only after the deal, and only the two traders know that this particular deal took place. The actual deal finalizes at 4:30 pm, i.e. the daily deals settle just at the end of same day at 4:30 pm. Transaction costs for overnight repos are 0.00075%. The Stock Exchange clears transactions via Clearing House which is a joint affiliated with the Stock Exchange. The stock exchange strives to guarantee that counterparties will not default. For more details see the ISE factbook at website `www.ise.gov.tr`.

## A.2 Crisis

The Turkish government following reforms aimed at maintaining low inflation, adopted a crawling peg exchange rate system where interest rates were to be market determined (in 1999). This system was initially successful, however uncertainty remained increasing throughout 2000. Furthermore, widespread use of carry trades further led to instability. Finally an extremely levered institution, had problems borrowing on Monday, November 20, 2000, and overnight interest rates started to increase, with many foreign creditors withdrawing their credit lines. This led to a rapid capital outflow, starting Wednesday, November 22. The Central Bank started to provide liquidity to the market (though not to the overnight repo market), inadvertently promoting additional demand for foreign currency. Therefore, the Central Bank stopped providing liquidity after six business days, on Thursday, November 30, 2000. Immediately, the overnight interest rate reached its peak at (simple annual) 2000 percent on Friday, December 1, 2000. Total capital outflow during this period reached an estimated USD 6 billion, eroding approximately 25 percent of the foreign exchange reserves of the Central Bank. This led to an IMF emergency loan announced on Tuesday, December 5. This briefly stabilized the economy, however uncertainty remained and financial bankruptcies continued.

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## Table 1: Sample Statistics, Daily Aggregation

$p(JB)$ is the significance level of of the Jarque–Bera test normality, ar1 is the first order autocorrelation coefficients, $p(Q(5))$ is the significance level of the 5th order autocorrelation, $p(ADF)$ , unit root Augmented Dickey-Fuller

| days | variable | mean | s.e. | skewness | kurtosis | $p(JB)$ | ar1 | $p(Q(5))$ | $p(ADF)$ |
|---|---|---|---|---|---|---|---|---|---|
| 1-225 | $r$ | 40.8 | 17.4 | 2.3 | 8.74 | 0.00 | 0.48 | 0 | |
| | $s$ | 0.992 | 0.306 | 0.23 | 0.44 | 0.15 | 0.86 | 0 | |
| | $b$ | 0.945 | 0.178 | -1.3 | 5.03 | 0.00 | 0.53 | 0 | $< 5\%$ |
| | $b^b(2)$ | 0.223 | 0.087 | 0.23 | 0.92 | 0.01 | 0.63 | 0 | |
| | $l^b(2)$ | 0.208 | 0.117 | 0.73 | 0.06 | 0.00 | 0.83 | 0 | |
| | $b^b(4)$ | 0.293 | 0.185 | 0.20 | -0.85 | 0.02 | 0.82 | 0 | |
| | $l^b(4)$ | 0.254 | 0.206 | 1.07 | 0.34 | 0.00 | 0.89 | 0 | |
| | $b^b(12)$ | 0.064 | 0.031 | 0.43 | 0.17 | 0.03 | 0.58 | 0 | $< 1\%$ |
| | $l^b(12)$ | 0.077 | 0.034 | 0.14 | -0.20 | 0.59 | 0.70 | 0 | |
| | $b^b(22)$ | 0.039 | 0.033 | 0.95 | 0.82 | 0.00 | 0.67 | 0 | $< 1\%$ |
| | $l^b(22)$ | 0.048 | 0.036 | 0.71 | 0.23 | 0.00 | 0.74 | 0 | |
| | $b^b(24)$ | 0.049 | 0.041 | 1.07 | 0.82 | 0.00 | 0.75 | 0 | |
| | $l^b(24)$ | 0.047 | 0.039 | 1.07 | 0.90 | 0.00 | 0.73 | 0 | |
| | $b^l(24)$ | 0.126 | 0.040 | -0.02 | -0.15 | 0.90 | 0.56 | 0 | |
| | $l^l(24)$ | 0.154 | 0.057 | 0.49 | 0.35 | 0.01 | 0.70 | 0 | |
| | $b^l(30)$ | 0.125 | 0.038 | 0.10 | 1.19 | 0.00 | 0.56 | 0 | |
| | $l^l(30)$ | 0.135 | 0.063 | 0.41 | -0.43 | 0.02 | 0.84 | 0 | |
| | $b^l(27)$ | 0.065 | 0.020 | -0.28 | 0.21 | 0.18 | 0.27 | 0 | $< 1\%$ |
| | $l^l(27)$ | 0.102 | 0.031 | -0.16 | 0.61 | 0.11 | 0.67 | 0 | |
| | $b^l(48)$ | 0.047 | 0.019 | 0.13 | 0.01 | 0.72 | 0.53 | 0 | |
| | $l^l(48)$ | 0.035 | 0.017 | 0.49 | 0.21 | 0.01 | 0.56 | 0 | |
| | $b^l(29)$ | 0.032 | 0.013 | 0.32 | 0.20 | 0.12 | 0.52 | 0 | $< 1\%$ |
| | $l^l(29)$ | 0.020 | 0.012 | 0.69 | 0.18 | 0.00 | 0.29 | 0 | $< 1\%$ |
| 226-240 | $r$ | 225.3 | 166.7 | 1.26 | 0.33 | 0.13 | 0.6 | 0.01 | |
| | $s$ | 1.235 | 0.311 | 0.13 | -1.01 | 0.71 | 0.53 | 0.01 | |
| | $b$ | 0.815 | 0.237 | 1.08 | 0.27 | 0.23 | 0.44 | 0.13 | |
| | $b^b(2)$ | 0.089 | 0.083 | 0.95 | 0.05 | 0.32 | 0.73 | 0.00 | |
| | $l^b(2)$ | 0.166 | 0.150 | 0.78 | -0.32 | 0.45 | 0.87 | 0.00 | |
| | $b^b(4)$ | 0.271 | 0.149 | 1.31 | 1.84 | 0.04 | 0.27 | 0.89 | |
| | $l^b(4)$ | 0.423 | 0.222 | 0.25 | -1.35 | 0.52 | 0.42 | 0.16 | |
| | $b^b(12)$ | 0.077 | 0.044 | 0.37 | -0.89 | 0.66 | 0.42 | 0.54 | |
| | $l^b(12)$ | 0.080 | 0.030 | 0.39 | -0.86 | 0.66 | 0.19 | 0.87 | |
| | $b^b(22)$ | 0.067 | 0.035 | 0.80 | 0.24 | 0.44 | 0.12 | 0.14 | |
| | $l^b(22)$ | 0.149 | 0.039 | 1.53 | 5.77 | 0.00 | 0.05 | 0.99 | |
| | $b^b(24)$ | 0.006 | 0.012 | 2.13 | 3.47 | 0.00 | 0.66 | 0.05 | |
| | $l^b(24)$ | 0.010 | 0.016 | 1.70 | 1.50 | 0.01 | 0.83 | 0.00 | |
| | $b^l(24)$ | 0.044 | 0.022 | 0.57 | 0.05 | 0.67 | 0.28 | 0.41 | |
| | $l^l(24)$ | 0.083 | 0.033 | 0.78 | -0.68 | 0.40 | 0.46 | 0.01 | |
| | $b^l(30)$ | 0.111 | 0.059 | 1.01 | 0.23 | 0.27 | 0.63 | 0.04 | |
| | $l^l(30)$ | 0.198 | 0.074 | 0.33 | -0.38 | 0.83 | 0.38 | 0.06 | |
| | $b^l(27)$ | 0.063 | 0.027 | 0.05 | -0.72 | 0.85 | 0.01 | 0.82 | |
| | $l^l(27)$ | 0.151 | 0.029 | -0.13 | -0.57 | 0.88 | 0.03 | 0.71 | |
| | $b^l(48)$ | 0.035 | 0.021 | -0.04 | -0.67 | 0.87 | 0.33 | 0.22 | |
| | $l^l(48)$ | 0.039 | 0.026 | 0.43 | -0.11 | 0.79 | 0.47 | 0.44 | |
| | $b^l(29)$ | 0.044 | 0.019 | -0.27 | -1.30 | 0.54 | 0.24 | 0.28 | |
| | $l^l(29)$ | 0.060 | 0.020 | 0.49 | -0.75 | 0.62 | -0.04 | 0.26 | |

Table 2: Institution trading volume relative to total volume

The table shows the relative trading volume of the seven largest institutions in the whole sample, two subsamples (the staple and unstable periods), and the crisis day. The institutions in bold font are those used in daily and five-minute aggregation regressions.

| Days | Rank | Lending Institutions | | Borrowing Institutions | |
|---|---|---|---|---|---|
| | | ID | % | ID | % |
| 1 to 240 | 1 | **24** | **13.9** | **4** | **28.6** |
| | 2 | **30** | **13.5** | **2** | **21.6** |
| | 3 | **27** | **8.8** | **12** | **7.3** |
| | 4 | **48** | **4.2** | 8 | 5.9 |
| | 5 | 106 | 3.9 | 7 | 5.1 |
| | 6 | 42 | 3.5 | **22** | **4.9** |
| | 7 | **29** | **2.9** | **24** | **4.7** |
| 1 to 225 | 1 | **24** | **14.4** | **4** | **28.3** |
| | 2 | **30** | **13.4** | **2** | **22.2** |
| | 3 | **27** | **8.6** | **12** | **7.3** |
| | 4 | **48** | **4.2** | 8 | 5.8 |
| | 5 | 106 | 3.9 | 7 | 5.1 |
| | 6 | 42 | 3.4 | **24** | **5** |
| | 7 | **29** | **2.7** | **22** | **4.5** |
| 226 to 240 | 1 | **30** | **15.1** | **4** | **33.8** |
| | 2 | **27** | **10.5** | **2** | **12.4** |
| | 3 | **24** | **6.2** | **22** | **10.5** |
| | 4 | **29** | **5.1** | **12** | **7.7** |
| | 5 | 42 | 5.1 | 8 | 6.2 |
| | 6 | **48** | **3.6** | 7 | 6.1 |
| | 7 | 36 | 3.4 | 95 | 3.9 |
| 234 to 234 | 1 | **27** | **13.5** | **22** | **20.1** |
| | 2 | **30** | **7.4** | **12** | **18.6** |
| | 3 | **29** | **7.1** | **4** | **14.5** |
| | 4 | **24** | **6.1** | 8 | 11.2 |
| | 5 | **48** | **5.8** | 7 | 7.9 |
| | 6 | 26 | 4.7 | 10 | 7.4 |
| | 7 | 56 | 4.3 | 46 | 4.7 |

Table 3: $R^2$ for the daily interest rate equation with three model specifications

The table shows for an equation with interest rate changes ($\Delta r$) as the dependent variable, regressed on lagged $\Delta r$, and possibly lagged order flow ($b$ and $l$) and some institutional order flow ($\boldsymbol{W}$). The number of lags is 4 in the first subsample and two in the second subsample. $\boldsymbol{W}$ is not included in the second subsample due to lack of degrees for freedom

| Days | independent variables | $R^2$ |
|---|---|---|
| 1 to 225 | | |
| | $\Delta r$ | 18.0% |
| | $\Delta r$, $l$, $b$ | 20.3% |
| | $\Delta r$, $l$, $b$, $\boldsymbol{W}$ | 64.2% |

Table 4: $R^2$ from various model specifications 5 minute, 12 lags

interest rates changes and 4 model specifications, five-minute aggregation, 12 lags in VAR

| Days | dep var | $R^2$ |
|---|---|---|
| 1 to 225 | | |
| | $\Delta r$ | 2.0% |
| | $\Delta r$ , $l$ , $b$ | 11.5% |
| | $\Delta r$ , $\boldsymbol{W}$ | 17.9% |
| | $\Delta r$ , $l$ , $b$ $\boldsymbol{W}$ | 20.4% |
| 226 to 240 | | |
| | $\Delta r$ | 23.2 |
| | $\Delta r$ , $l$ , $b$ | 27.8% |
| | $\Delta r$ , $\boldsymbol{W}$ | 77.0% |
| | $\Delta r$ , $l$ , $b$ $\boldsymbol{W}$ | 82.8% |

Figure 1: Interest Rates

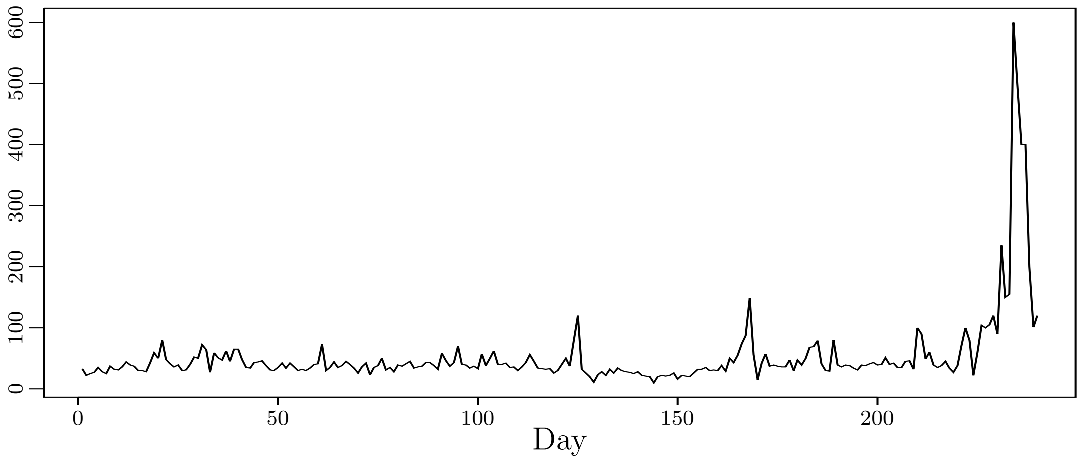



Figure 2: Lend and Borrow Order Flow, $b, l$,

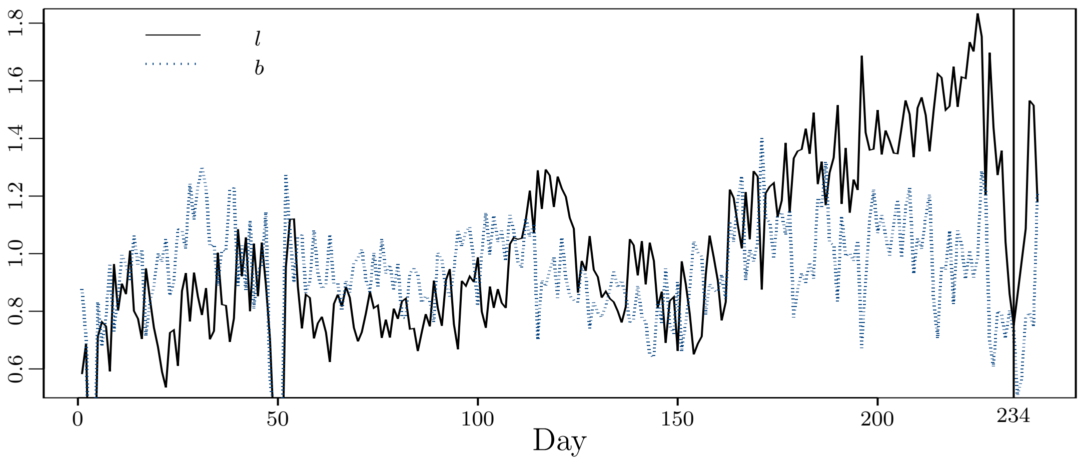
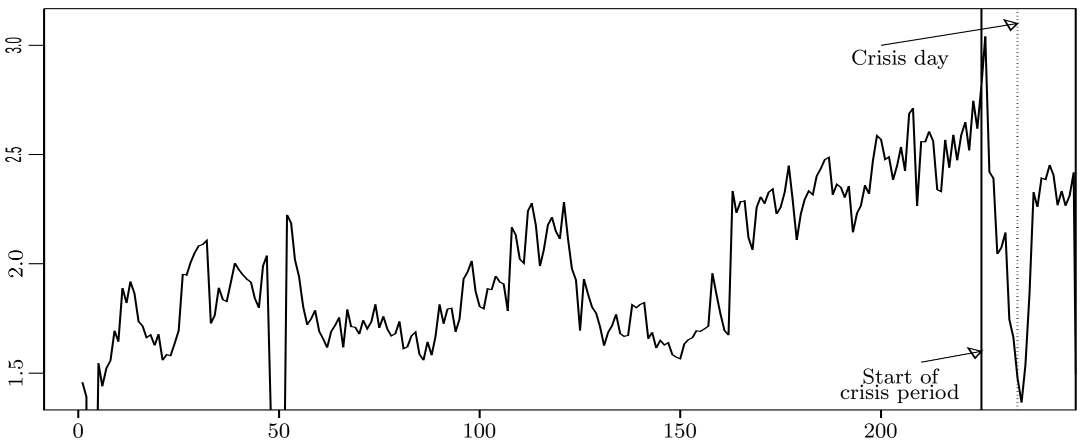
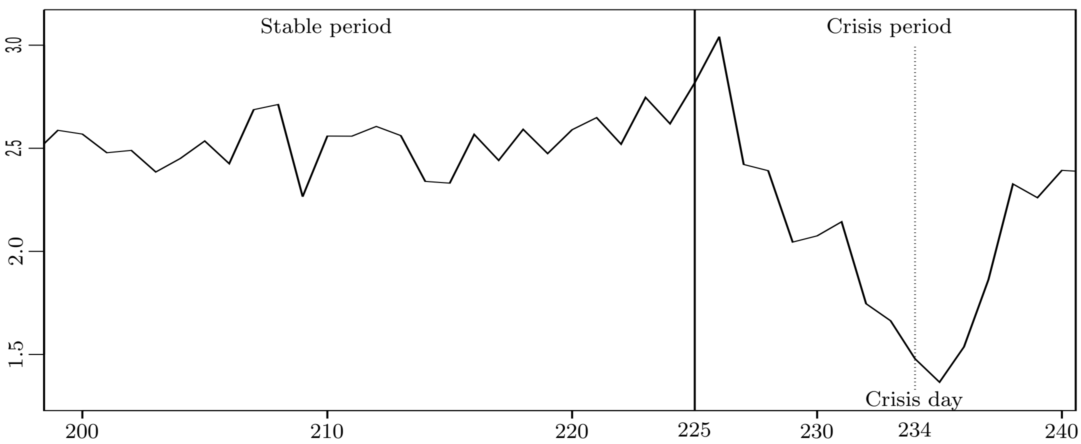


Figure 3: Daily Trading Volume in qn. TL.

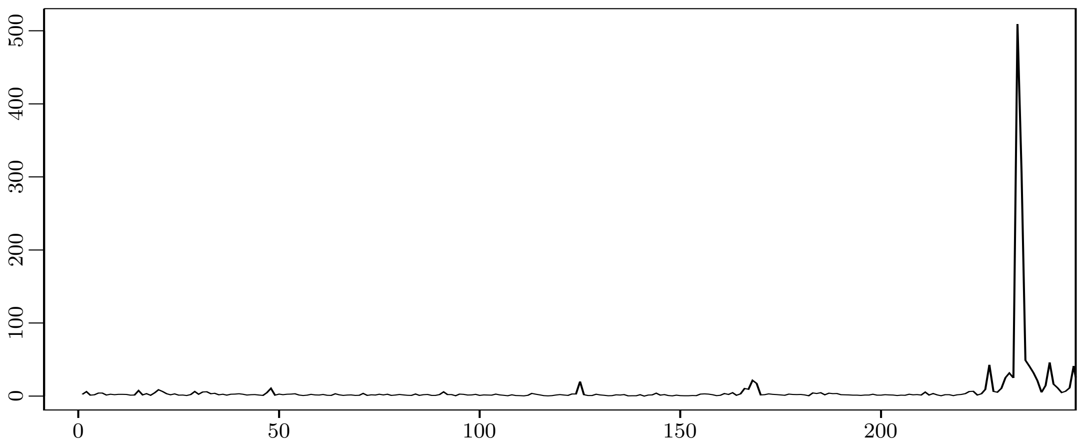



(a) The Whole Sampling Period

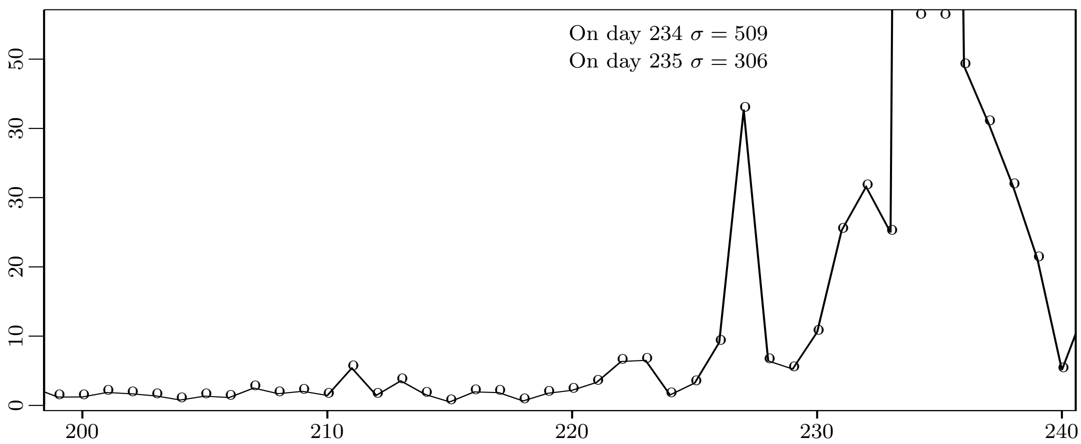



(b) Days 200–240

Figure 4: Realized Volatility, $\sigma$




(a) The Whole Sampling Period




(b) Days 200–240, truncated

Figure 5: Stock Market And Exchange Rates

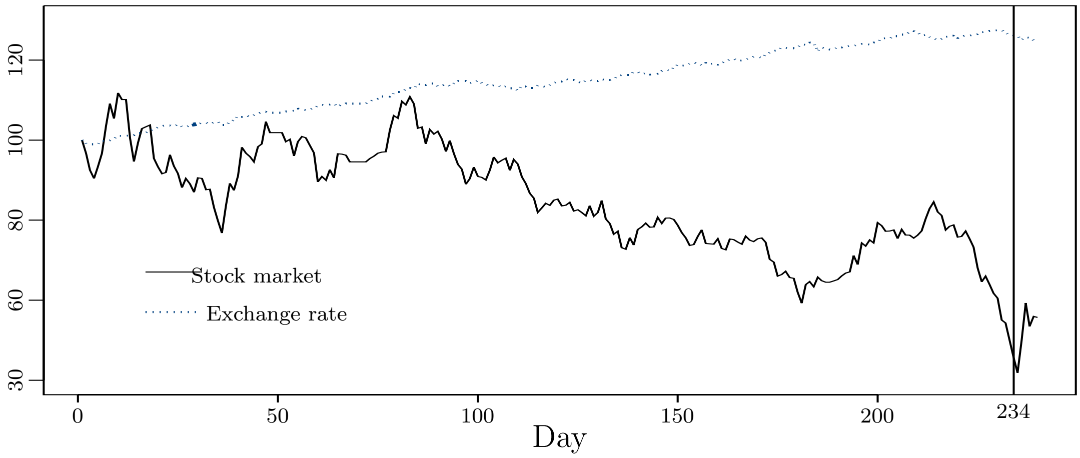



Figure 6: Intra Day Seasonality

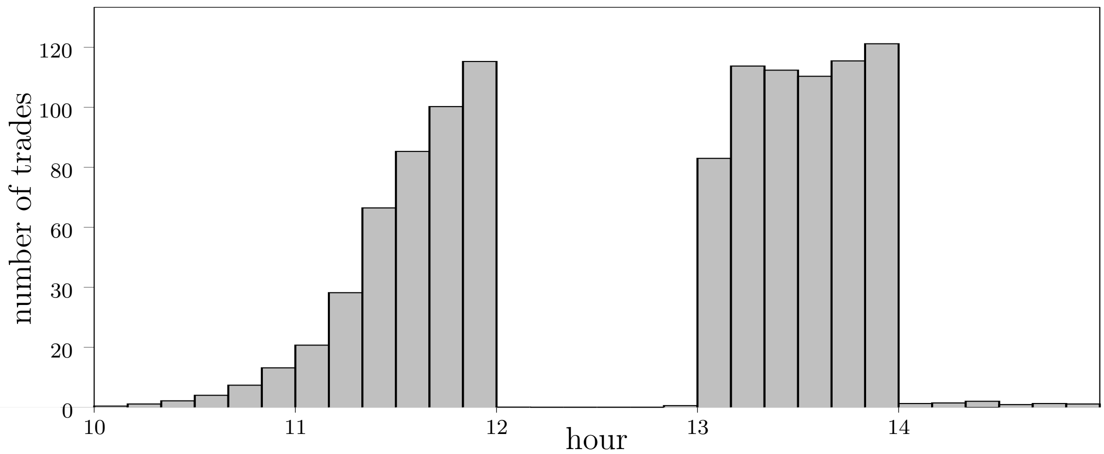
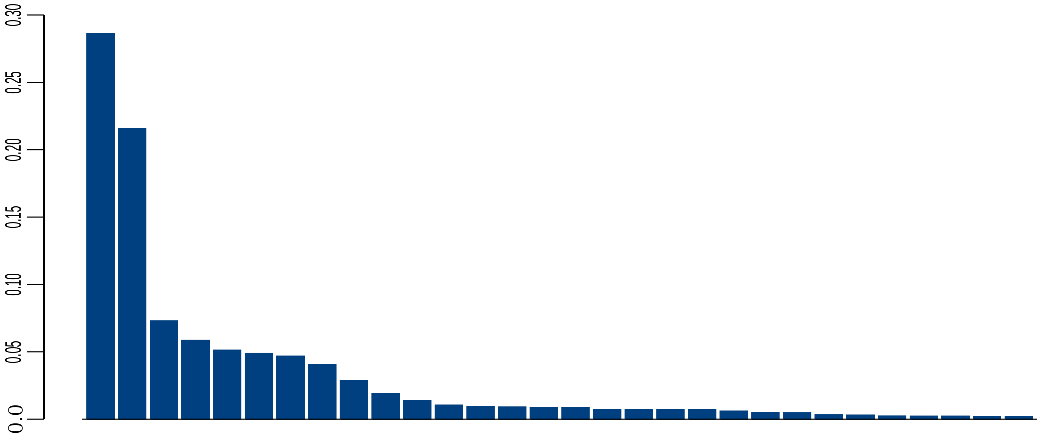
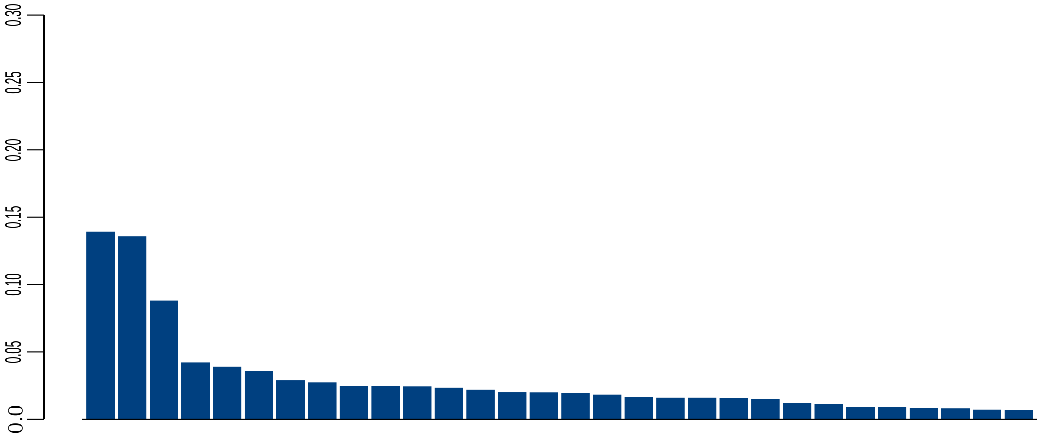


Figure 7: The Relative Trading Volume Of The 30 Largest Institutions




(a) Buyers




(b) Sellers