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

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Abstract

An order flow model, where the coded identity of the counterparties of every trade is known, hence providing institution level order flow, is applied to both stable and crisis periods in a large and liquid overnight repo market in an emerging market economy. Institution level order flow is much more informative than cross sectionally aggregated order flow. The informativeness of institution level order flow increases with financial instability, with considerable heterogeneity in the yield impact across institutions.

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

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1 Introduction

A liquidity crisis hit Turkey in November 2000. At its peak, annual interest rates reached 2000% overnight. The crisis was short lived, but had far reaching implications for the Turkish financial system. Our objective is to analyze the crisis episode with empirical market microstructure methods, making use of an unique dataset containing details of each transaction in the overnight repo market, including *coded institutional identities*. This enables us to explicitly document the impact of individual trading strategies on the crisis.

Traditional methods for analyzing financial crisis focus on macroeconomic explanations, making use of low frequency macro variables, thus mostly ignoring factors such as institutional structures and the trading of financial assets. In contrast, empirical market microstructure provides an efficient framework for analyzing price formation and informational linkages in financial markets. Applied to financial crises, market microstructure methods emphasize decision making at the most detailed level, providing a play–by–play level analysis of how a crisis progresses. Our main investigative tool is an order flow[1] model, enabling us to explore the impact of individual trading strategies on yields. Order flow models have had considerable success in explaining price changes in developed markets,[2] but we are not aware of any applications of order flow models to emerging markets crisis.

Most applications of order flow models focus on price determination with *aggregate order flow*, i.e. the sum total flow from market borrow and lend orders, separately. An exception is Fan and Lyons (2000) who study the price impact of individual flows from several different categories of institutions and

[1]Borrow (buy) order flow is the total transaction volume in a given time period for trades when a market borrow order was used. Lend (sell) order flow is defined analogously. In defining order 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. The convention in the order flow literature is to use the terms buy and sell, while for repos the terminology is e.g. borrow/lend, take/give, long/short. In this paper we use the repo terminology, and use borrow/lend instead of buy/sell.

[2]Initially with equities (see e.g. Hasbrouck, 1991), and foreign exchange (see e.g. Evans and Lyons, 2002). Recently several market microstructure studies focus on fixed income markets, primarily U.S. Treasuries, e.g. Fleming (2001), Cohen and Shin (2002), and Brandt and Kavajecz (2002), while Hartmann et al. (2001) study the microstructure of the overnight Euro money market. A few empirical market microstructure studies of US financial crises are available, e.g., Blume et al. (1989) who consider the relationship between order imbalances and stock prices in the 1987 crash.

Furfine (2002) who analyzes US interbank payment flows, knowing the exposure of each bank to every other bank. Several authors make use of data sets containing limited information about institutional identities, e.g. the Olsen HFDF93 indicative quote dataset containing the identity of quoting institutions in FX markets. Peiers (1997) and de Jong et al. (2001) use the HFDF93 data to study the leadership hypothesis of Goodhart (1988), while Covrig and Melvin (2002) examine with similar data whether Japanese or foreign banks are more informed when trading USD/YEN, and Hasbrouck (1995) analyzes the price discovery process on related financial equity markets. Most of these models are based on the notion of efficient martingale prices, where a risk neutral institution observes a noisy signal of the "true" price process. This is rooted in asset price theories where the noisy signal represents information. This modelling approach is not directly applicable to the study of overnight liquidity; the yields are not martingales, the institutions are not necessarily risk neutral, and the order flow not only represents information about fundamentals and portfolio shifts, but also the individual demand and supply functions for liquidity.

Our data derives from the Turkish overnight repo market, spanning most of the year 2000. The overnight repos are traded on the Istanbul stock exchange (ISE), an electronic closed limit order system, where credit risk is minimal. The data set contains detailed information on each transaction in the sample period, i.e. whether the transaction was a market borrow or market lend, the annual interest rate, quantity, and most importantly the coded identity of the counterparties. We therefore identify four key variables measuring each financial institution's trading activity: borrowing volume split into volume from market orders and transacted limit orders, ditto for the lending volume. We term this *institution level order flow*, in contrast to cross sectionally aggregate order flow.

We estimate our model at two levels of temporal aggregation, daily and five–minute. We observe a structural break about ten days prior to the main crisis day, on day 225 (Nov 20), and therefore split the sample into two subsamples: the *stable period* on days 1–224 (Jan 4 to Nov 17), and the *crisis period* spanning days 225–240. It might be of interest to also consider the post crisis time period, however that would not be a realistic control case: The post crisis period includes the Christmas holidays, when trading was very sparse. Furthermore, subsequent to the crisis, several important financial institutions were taken over by the authorities, including the biggest purchaser of repos, while at the same time the government was actively attempting to stabilize the market.

The model is estimated over the full sample at the daily frequency, while the five–minute frequency model is estimated separately for each subsample. We employ three different model specifications: interest rate changes regressed on own lags, aggregate order flow, or institution level order flow.

We obtain the following main results:

Result A Aggregate order flow is a significant but small determinant of overnight interest rates, with less explanatory power during the crisis than when markets are more stable

Result B Transacted limit order flow has a significant impact on interest rate changes. Its yield impact is generally different than the yield impact of market order flow

Result C Institution level order flow has much higher explanatory power than aggregate order flow, its coefficients are generally of the expected sign, and demonstrate considerable heterogeneity

Result D Institution level order flow is much more informative during the crisis than when markets are more stable

The aggregate order flow results are generally consistent with conclusions from empirical microstructure studies and theories of informed trading (see e.g. O'Hara, 1994; Lyons, 2001). There are however important differences between the overnight liquidity markets and the better studied equity and foreign exchange markets, suggesting that most standard theories of market maker and limit order markets do not fully reflect the market structure in our case. These differences relate to the type of asset, and how it is traded. In our case the asset is generally only traded once, and then consumed, where the individual supply/demand functions for liquidity play an important role in determining trading strategies. Both our statistical analysis and local news accounts suggest that some borrowers were desperate for liquidity, especially during the crisis, when not being able to borrow may have resulted in bankruptcy. In contrast, the lenders had more elastic supply functions, implying that they had the market power, especially if they colluded in the runup to the crisis, as was claimed by the local press.

Aggregate order flow is a small but significant determinant of interest rate changes, more so at higher temporal aggregation levels but less during the crisis, suggesting that the informativeness of aggregate order flow decreases with financial instability and higher sampling frequencies. We find that institution level order flow is a much stronger determinant of interest rates than aggregate order flow, regardless of time aggregation and the degree of financial stability. Furthermore, while the informativeness of aggregate order flow decreases in the crisis period, the informativeness of institution level order flow increases during the crisis, when it explains 52% of interest rate changes. In most cases, the institution level regression coefficients have the expected signs and are significant. There is considerable heterogeneity in the yield impact of institution level order flow, both between different institutions and market and limit orders. Some institutions are yield takers, i.e. their trading does not affect the interest rates much, whilst others have a significant impact on yield. In some cases there is a considerable difference in the yield impact of an institution's limit and market orders. The order flow of some institutions is highly predictable, while for others the predictability is lower. In general, order flow predictability decreases during the crisis but its yield impact increases.

Lend order flow is decreasing throughout the latter part of the sample, while borrow order flow first increases and then starts to drop few days prior to the crisis. We would expect this e.g. if good credits are able to lock into longer–term funding. Since the order book is closed, and banks only learn of the identity of their counterparties after a trade, the high informativeness of institution level order flow suggests this is a well informed market. Institution level order flow depends on the positions held by a bank and its institutional customers and trends in the personal and corporate lending books. It can be expected to be heavily serially correlated, with highly persistent demand/supply schedules. An institution with a big funding requirement today is likely to have a big funding requirement tomorrow. By aggregating order flow information across institutions, we loose an essential part of the picture by disregarding the asymmetry in the informativeness of different institutions, especially because of the heterogeneity in the elasticities of supply/demand. There is considerable heterogeneity in the trading strategies and degree of price leadership across the various institutions, and limit orders have a significant but different degree of informativeness from market orders. This is especially prevalent during the crisis, when other factors, such as fundamentals and portfolio shifts, became relatively less relevant for price determination, causing lower informativeness of aggregate order flow during the crisis.

These results also underscore the relevance of market microstructure in the analysis of financial crisis. Macroeconomic analysis, focussing on low frequency variables such trade balances, GDP, inflation, and central bank reserves, is likely to miss the salient features of the crisis. On a macroeconomic timescale the crisis happens in a blink of an eye. The 2000 Turkish crisis played out in the financial markets. Arguably, individual trading strategies, and not macroeconomic fundamentals were the main direct cause of the crisis. Market microstructure analysis provides here the missing pieces of the puzzle, providing guidelines to national supervisors and supranational organizations in the design of robust financial architectures.

2 Crisis, Market Structure, Data, and Information

The main visible impact of the 2000 Turkish financial crisis was in the overnight money market. The effect on other markets, longer maturity interest rates, foreign exchange, and equities was relatively minor in relation. Essentially, the crisis was about supply and demand of overnight liquidity.

2.1 Crisis

Turkey has a long history of financial instability.[3] Inflation was high throughout the 1990s, close to 100%. Turkey signed its 16th standby agreement with the IMF at the end of 1999, stipulating the maintenance of price levels, with exchange rates to be determined by a crawling peg, leaving interest rates floating. The government could not intervene in the overnight money market as a condition of its IMF mandate.

As a part of the restructuring program the short foreign currency positions of Turkish banks were to be limited to 20% of their total assets. Many banks, however, exceeded this ceiling by using "off–balance sheet" transactions and various derivative instruments, often using local bonds or Eurobonds as collateral. If the value of the collateral drops, as when domestic yields increased in the latter part of 2000, banks face margin calls. When some of the off–balance sheet deals went against the banks, they often used the overnight market as a source of funds to cover the resulting margin calls, leading to increasing yields, particularly at the shortest end of the yield curve. This in turn, caused difficulties for banks speculating on the yield curve, and a drop in the value of the collateral, further fuelling demand for overnight liquidity. Effectively, a vicious feedback loop between short yield increases, margin calls, and short liquidity demand was formed.

Several large financial institutions started running into serious difficulties in the second half of 2000, partly as a result of a yield curve inversion. Some of

[3] See e.g. (see e.g. Eichengreen, 2001) and `www.nber.org/crisis/turkey_agenda.html`.

these banks were effectively starving off bankruptcy by borrowing overnight including the largest borrower in the overnight market, Demirbank. This was a key factor in fuelling rapid increases in liquidity demand, especially late in 2000, and is the main reason for why the demand for liquidity was very inelastic for many institutions. Neither the supervisors, the IMF, nor the rating agencies seem to have taken much notice of these events, indeed, the resulting crisis apparently took most interested parties by complete surprise.

Banks experiencing difficulties started to dump assets, contributing to a sharp stock market drop, including Demirbank who tried unsuccessfully to sell its 3 and 9 month Tbills in November. The government tried to "talk down" the crisis and the IMF signalled its support. This was not successful. Rumors started to spread in the local financial community in late November claiming some banks were close to fail. At the same time solvent local banks started to limit their exposure to banks rumored to be in trouble. Towards the end of November, many foreign creditors withdrew their credit lines, and along with solvent domestic investors, sold the domestic currency, leading to a rapid capital outflow, starting November 22. The Central Bank (CB) provided some liquidity to the market, (but it did not intervene in the overnight repo market), inadvertently promoting additional demand for foreign currency. Subsequently, the CB stopped providing liquidity on Nov 30, 2000. The ever increasing demand for overnight money, fuelled rapidly increasing yields, culminated on December 1 when the overnight interest rate reached its peak at (simple annual) 2000%. That day local newspapers claimed the liquidity shortage triggering the crisis was caused by large banks deliberately withholding liquidity from the market in order to squeeze Demirbank.

Total capital outflow during this period reached an estimated USD 6 billion, eroding approximately 25% of the foreign exchange reserves of the Central Bank. This led to an IMF emergency loan announced on Dec 5. This briefly stabilized the economy, however uncertainty remained and financial bankruptcies continued. (See the Chronicle of the Crisis in the Appendix for an overview of crisis events, and the role played by the largest borrower of overnight money, Demirbank)

2.2 Market Structure

The Bonds and Bills Market which works under the Istanbul Stock Exchange (ISE) is the only organized, semi–automated market for both outright purchases and sales and repo/reverse repo transactions in Turkey. The average daily volume of overnight repo transactions exceeded 3 Billion USD in the sample period. Financial institutions communicate their orders via telephone to ISE staff who act as blind brokers. The repo market operates on a multiple price–continuous trading system. All orders are continuously entered into the computer system and the orders[4] automatically matched. Members are subsequently informed about the executed transaction.[5] In order to trade on the ISE, member institutions need to provide collateral in the form of Tbills. If this collateral is eroded institutions can no longer trade. Historically, practically no institution has defaulted on ISE trading obligations, and traders in ISE consider counterparty credit risk to be negligible.

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 from the screen. Market participants have a choice of either limit quotes or market orders, with a minimum quote size of 5×10^{11} Turkish Liras (TRL). 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/borrow 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. 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%. Trading takes place between 10 am and 2 pm with a one hour lunch break. (See Figure 5 for a plot of the intra day seasonality pattern). For details see the ISE factbook at website `www.ise.gov.tr`.

In addition to the organized market, an informal market based on Reuters quotes exists. Since the institution level identities of indicative 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

[4]Bid orders are matched with equal or lower priced ask orders and ask orders are matched with equal or higher priced bid orders

[5]Various tasks such as daily marking-to-market of securities (government bonds, treasury bills) during the validity period of the repo transaction, computing margin excess deficit automatically and making margin calls if necessary, and ensuring securities and cash transfers at the close of the transaction are performed by the ISE Bonds and Bill Market and Settlement and Custody Bank Inc. (Takasbank). However, clearing and settlement operations are handled by the ISE Settlement and Custody Bank Inc., which is the institution inaugurated by the ISE and its members and institution safekeeps the underlying securities.

be much smaller than the organized market.

2.3 Data

The dataset contains details of all transactions in the overnight repo market for 240 days from the beginning of year 2000 (Jan 4) to Dec 11. During this period, 256,141 transactions are recorded. For each transaction we know the interest rate, volume, and whether the trade was borrow or lend initiated, providing signed order flow. Furthermore, we know the coded institutional identity of the counterparties in each trade, enabling us to identify the *institution level order flow*, see Section 3.1. The sample contains 136 different financial institutions.

The main crisis occurs on day 234 (Dec 1). Statistical analysis of the data and newspaper accounts of the crisis indicate that the buildup to the crisis starts a few days earlier. Effectively, we observe a structural break about ten days prior, around day 225 (Nov 20) suggesting 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 224 referred to as the *stable period*, and days 225 to 240 referred to as the *crisis period*.

2.4 Information Available to Market Participants

Information is at the heart of market microstructure analysis, see e.g. Easley and O'Hara (1987), O'Hara (1994), and Lyons (2001). In the Turkish market, several channels of information are open to market participants.

First, large local banks have extensive dealings with big foreign banks, implying that the local actions of foreign banks can be inferred by their local counterparties. Second, institutions know the identity of their own counterparties after executing trades, and therefore observe whether the trading patterns of their counterparties are unusual. The third 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 least by providing the identities of quoting institutions. Fourth, indirect information channels, (traders gossip, news, etc.) are very active in the Turkish market. Finally, observing interest rate movements, both in the overnight market as well as on longer maturities provides valuable insights to traders. For example, a large yield drop for long maturity bonds, coupled with a large yield increase in the overnight market may suggest that institutions speculating on the yield curve are experiencing difficulties. By combining these information sources it is possible for market participants to get a fairly accurate picture of market activity. Hence, the information content of institution level order flow has the potential to be considerable.

3 Model Specifications

Order flow affects asset prices because it conveys information, (see e.g. O'Hara, 1994; Lyons, 2001, for an overview). In their preference for limit or market orders, traders reveal their private information. In such models, sell market orders reflect selling pressure, and buy market orders buying pressure. Typically, the underlying asset is assumed to follow a martingale process, where order flow helps in explaining contemporaneous price movements, but does not forecast asset price movements. Most order flow models focus on market orders, since in the absence of other information, limit order flow is simply the reverse of market order flow.

Order flow models have been successfully applied to equity markets (see e.g. Hasbrouck, 1991), foreign exchange markets (see e.g. Evans and Lyons, 2002), and fixed income markets (see e.g. Brandt and Kavajecz, 2002). They are typically found to have considerable explanatory power when measured by R^2, often in the range of 40% to 60% as in the Evans and Lyons (2002) study of daily exchange rates. However, Brandt and Kavajecz (2002) find much lower R^2 for order flow models when applied to the lowest maturity US government bonds.

In constructing our model we need to take into account several unique features of the overnight repo market and the Turkish economic situation.

1. Turkey is an emerging markets economy, with a small number of large market players and light supervision.

2. Overnight repos represent liquidity which is needed for the regular running of the banking system. It can be very costly for individual institutions not to obtain this liquidity. Most financial institutions in this market trade for liquidity reasons and not for speculative reasons.

3. The overnight repo has a lifetime of one trading day. Throughout the trading day market participants are trading an asset that only exchanges hands after trading ceases. Since a one day repo today is not the same asset as a one day repo tomorrow, the observed prices over time are prices of the same units of different assets. Most market

participants trade only on one side of the market, i.e they either borrow or lend, but not both.

4. We can not assume the repos follow a martingale process, e.g. because of the short life time of the asset. For most other types of assets, the underlying price process is a martingale whereby the asset price reflects fundamentals or the intrinsic value of the asset, with market efficiency ensuring random walk. Here, after first being traded, the asset is generally not traded again, but consumed. The yields therefore reflect the price of a diminishing quantity of supply, with the agents supply and demand functions determining the price. As a consequence, order flow reflects the short term demand and supply for liquidity, above and beyond the impact of portfolio shifts and fundamentals.

These features of the overnight repo markets and the specific situation in Turkey imply that the theoretic environment of the one day repo market differs from better known equity and foreign exchange markets, and longer maturity fixed–income markets. While market efficiency dictates that such market prices cannot be forecasted with either own lags or lagged order flow, this is not the case for one day repos. The trading volume of individual institutions is predictable due to persistence in demand/supply needs, implying that both order flow and interest rates can be forecasted to some extent.

It is beyond the scope of this paper to develop and test theories about trading in overnight liquidity markets. Instead, we focus on establishing empirical stylized facts. To this end we consider three different model specifications, where interest rate changes are regressed on own lags, aggregate order flow, or institution level order flow. The models are estimated at both daily and five–minute frequencies where the daily model covers the entire data sample whilst the five–minute model is estimated for the crisis and stable periods separately, i.e. days 1–224 and 225–240. We use two main diagnostic tools. First, the explanatory power of the models is measured by centered R^2. Second, we gauge the importance of institution level order flow by recording parameter values, signs, and significance.

3.1 Notation

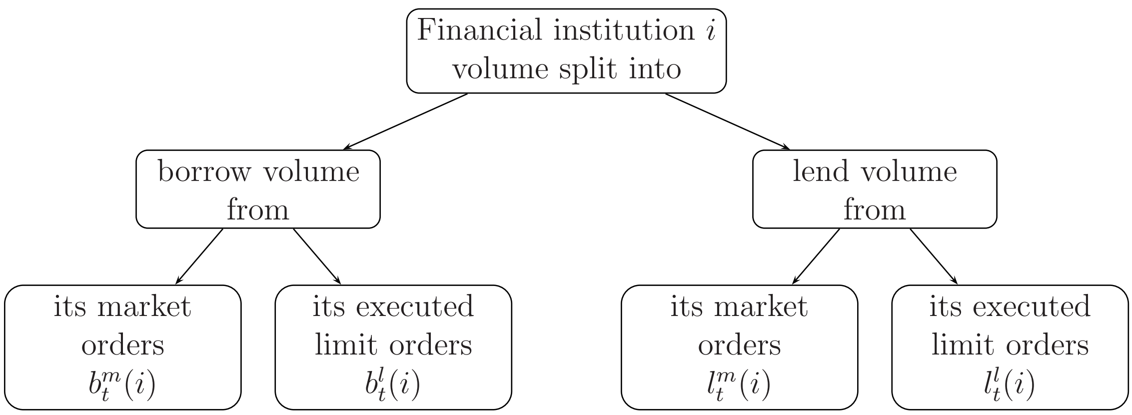
We use three types of variables in our analysis, interest rates, aggregate order flow, and institution level order flow. Most empirical order flow models use changes in asset prices as the dependent variable, implying a linear relationship between order flow and prices. In our case, this is not a reasonable assumption because of the extreme differences between price changes in the stable and crisis periods. Hence, we use log interest rate differences, where order flow affects relative and not absolute rate changes. 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. Hence, the dependent variable is $\Delta r_t \equiv \log R_t - \log R_{t-1}$.

Borrow order flow, b_t, is defined as the sum of transaction volume from market borrow orders over the time interval. If v_τ is the transacted volume of trade at time τ, and ι_τ is an indicator variable that takes the value one if the trade at time τ was a market borrow, and zero otherwise, then

$$b_t \equiv \sum\nolimits_\tau v_\tau \iota_\tau, \quad t-1 \leq \tau < t.$$

The definition of lend 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. For each transaction, we know the identity code of both counterparties and whether each transaction was lender or borrower initiated, i.e., if the market order was a lend or borrow. For each institution we know its borrow volume and sell volume and whether the volume results from the institutions market orders or *executed* limit orders. Note that this is not the limit order flow, only limit orders resulting in a transaction in the time interval. As a result we record four separate variables for each institution i in the time interval $t-1$ to t:



Hence, the $b()$ and $l()$ signals the institutions borrowing and lending, while

^{m} indicates the institution flow from market orders, and ^{l} is the flow from its executed limit orders. (i) identifies the institution.

We define the entire vector of institution level order flow as:

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

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

3.2 Models

3.2.1 Interest Rate Model

The baseline interest rate model is a regression of interest rate changes on own lags.

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

where R_t is the repo rate, c is a constant, $_N(L)$ is the lag operator with N lags, and ϵ_t is a white noise innovation term.

3.2.2 Aggregate Order Flow Model

In the standard order flow model price changes are regressed on net order flow, i.e. buy minus sell flow, see e.g. Hasbrouck (1991) and Evans and Lyons (2002). This is a reasonable assumption when buy and sell order flow are assumed to be 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 borrow and lend order flow significantly different, see Tables 1 and 2, in most cases the financial institutions are either lenders or borrowers, not both.

Given the relationship between order flow and interest rate changes, including lagged order flow also captures some of the information in lagged rate changes, without increasing the number of parameters to be estimated. We hence exclude lagged interest rate changes from the model.

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

where b is borrow order flow and l lend order flow.

3.2.3 Institution Level Order Flow

We are not aware of any published empirical market microstructure studies where the institutional identities of the counterparties of every transaction are known. However, several authors have analyzed price formation when some information about the identity of individual institutions is available, typically indicative quotes in foreign exchange markets. Many such studies use the Olsen HFDF93 dataset, e.g. Peiers (1997) and de Jong et al. (2001), while Covrig and Melvin (2002) consider whether Japanese or foreign banks are more informed while trading YEN/USD, and Wei and Kim (1997) use data on the foreign currency positions of large market participants. Alternatively, Hasbrouck (1995) analyzes the price discovery process on related financial markets. Most of these studies are based on the idea that prices follow a single unobserved efficient martingale process from which the price quotes of banks are derived. The quotes then equal the efficient price times an idiosyncratic component that can be either noise or reflect the strategic behavior of a bank. Hasbrouck (1995) specifies a multivariate time series model of the vector of prices, while de Jong et al. (2001) use quotes in a similar manner. Their model allows for measurement of lead and lag relations between the quote revisions of individual banks, identifying price leaders in the market, where the quotes of different banks are cointegrated.

Unfortunately, this theoretic approach can not be used in our context. As discussed above, not only are our yields not martingales, the institutions are not necessarily risk neutral. In addition, the order flow only partially derives from information in the traditional sense (fundamentals and portfolio shifts), since liquidity supply and demand considerations also play a significant part in the yield impact of order flow. Perhaps the best methodology would relate to global games models of the type used by Dasgupta et al. (2001), unfortunately, the derivation of reduced form equations of such models is somewhat challenging. As a result, we extend the aggregate order for model in a manner similar to Fan and Lyons (2000), by including order flow from key institutions separately in the model.

The sample contains 136 different financial institutions, implying 544 institution level order flow variables $\left(b^m(i), b^l(i), l^l(i), l^m(i)\right)$. Counting lagged observations, the number of dependent variables is potentially very large, causing estimation problems where the matrix of explanatory variables might not have full rank. It is, however, not necessary to include all institution level order flows since most institutions are either lenders or borrowers not both, and most institutions have a very small market share (see Figure 6). Hence, in the empirical analysis we only use order flow from the 4 largest lenders and borrowers, representing 63% of total borrow volume and 40% of total lend volume. We aggregate the rest of the institutions into one variable called *residual order flow*, b^r and l^r, on the borrow and lend side, respectively. This means that the explanatory power of R^2 will be lower than it would be if all institution level order flow variables were used. The institution level order flow model is:

$$\Delta r_t = c + \beta_N^r(L)l_t^r + \delta_N^r(L)b_t^r + \mathbf{\Gamma}_N(L)\boldsymbol{W}_t + \epsilon_t \qquad (3)$$

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

3.3 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 lower levels of temporal aggregation enable us to measure high frequency strategic behavior. We use two temporal aggregation levels, daily and five–minute. The daily frequency is chosen to give a birds eye view of the market, in particular the effects of learning throughout the day. The daily models are estimated over the entire sample. The five–minute data sample has 5546 observations in the stable period, or 25 per day on average, and 378 observations in the crisis period, or 24 per day on average.[6]

A key problem arises due to overnight interest rate changes (close to open), since they have a standard error of about 25 times the five–minute intraday interest rate changes. 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 disregard the overnight interest rate changes. Given the long lag structures at the five–minute aggregation levels this specification will likely bias the contribution of order flow to interest rate changes somewhat downwards.

[6]The reason for the discrepancy is that trading does not always start at 10 am, but usually sometime after, see Figure 5. Indeed, there are 36 five–minute intervals in the trading day.

3.4 Diagnostics

We have a choice of several methodologies for evaluating and comparing the different models, but we follow standard practice and use centered R^2 to provide a direct measure of the explanatory power of each model. Given the high number of observations, we do not suffer from the small sample properties of R^2. We assess the importance of both aggregate order flow and institution level order flow with the estimated coefficient values, signs, and significance. After estimating (2) and (3) we test for causality by excluding each order flow variable from the model, one at a time. We report the $p-$value of the test.

4 Results

4.1 Overview

Trading volume in the Turkish repo market during our sample, see Figure 3, fluctuated from about 1.5 quadrillion, (qn. or 10^{15}) Turkish liras (TRL) to 3qn., (the exchange rate was about 500,000 TRL to 1 USD, see Figure 4). Trading volume peaked few days before the crisis at 3.0 qn. and dropped to 1.5 qn. on the main crisis day, when volume was 22% below average. Interestingly, as shown in Figure 2, early in the sample borrow order flow is generally higher than lend order flow, but from day 130 this reverses and lend order flow becomes much higher. Superficially, this might be interpreted as signalling dropping yields, but this is not the case, as can be seen in the order flow regressions discussed in Section 4.3 below.

The relative trading volume of the largest borrowing and lending institutions is shown in Figure 6. On the borrowing side we note that one institution has almost 30% of trading volume and the second–largest more than 20%. The market share distribution of institutions on the lend side is much more even. The intra day seasonality is shown in Figure 5, trading volume picks up slowly in the morning trading session, but is more constant in the afternoon. There are a few trades after 2 PM, these happen after very heavy trading days when the trading system needs to “catch up”.

We present the sample statistics in Table 1. The log interest rate changes, Δr, are not normally distributed, with a negative 1^{st} order autoregressive coefficient (AR1) signifying mean reversal, and significant 5^{th} order autoregressive coefficients. Most other variables are not normally distributed, and exhibit significant positive autocorrelation. By focusing on the crisis period, a less precise picture emerges because only 16 observations are available, and hence it is difficult to obtain any statistical significance.

We observe a large difference between the AR1 coefficients of the various order flow variables. For aggregate order flow, the borrow order flow AR1 coefficient is 0.86, and 0.53 on the lending side. In general, the largest borrowing institutions have the highest AR1 coefficients implying higher predictability of the borrowing institutions order flow. The value of the AR1 coefficients is lower during the crisis period, suggesting lower order flow predictability at that time.

4.2 The Explanatory Power of Order Flow

Table 3 shows the explanatory power of order flow at the daily frequency while Table 6 shows the five–minute results. The order flow is in units of trillion (tn. or 10^{12}) TRL. At the daily frequency, regressing Δr only on own lags results in about 16% explanation of interest rate changes, measured by centered R^2. By using aggregate order flow instead, the explanatory power drops to 6%. In contrast, the institution level order flow regressions have 52% explanatory power.

At the five–minute frequency a different picture merges. Here, lagged interest rate changes have practically no explanatory power. In the stable period aggregate order flow explains 12% of interest rate changes, while in the crisis period it only explains 6%. By comparison, the explanatory power of institution level order flow increases from 23% in the stable period to 55% in the crisis period.

4.3 The Impact of Institutions

4.3.1 Daily Aggregation

We show the impact of individual institutions at the daily frequency in Tables 4 and 5. Column 3 shows the contemporaneous impact of order flow on interest rate changes, with the significance value in column 2 ($p-$exclude). Column 5 shows the sum of coefficients for lags 1 to 3. Table 4 shows the results from the aggregate order flow regression. Contemporaneously, only lend order flow is significant, but both coefficients have the expected sign, positive for borrowing and negative for lending. This results reverses for the lags, for reasons discussed below. The results for the institution level order flow are presented in Table 5. At the top of the table we show the residual order flow, followed by the borrowing institutions, with the lending institutions at the bottom. Most of the contemporaneous coefficients have the right sign, but not significantly. The same asymmetry between contemporaneous and lagged coefficients is present in the institution level results.

There is a big difference between market order flow and traded limit order flow for the two largest borrowing institutions where the price impact of limit orders is more than double that of market orders. This result is reversed for institution 12, which order flow furthermore has the highest price impact of any institution. On the lending side the dominant institution is 24, with an equal yield impact of market and executed limit order flow.

4.3.2 5–Minute Aggregation

In focussing on the five–minute frequency in Tables 7 and 8 we do not observe, nor do we expect, any asymmetry between contemporaneous and lagged coefficients, and hence we simply report the coefficient sum and the significance level. For the aggregate order flow in Table 7, all coefficients have the expected sign, and all but one are significant. A similar result obtains from the institution level order flow in Table 8 where all coefficients have the right sign. In the stable period all coefficients are significant, while in the crisis period that is not the case. There are several reasons for this, the degrees of freedom in the crisis period are much lower, and a top four institution in the entire sample may have a low trading volume during the crisis.

The same asymmetry between market and traded limit orders for the top two borrowers at the daily frequency is present here. The price impact of limit orders is much higher than for market orders. In most cases, the coefficient values in the crisis period are significantly higher than in the stable period.

5 Analysis

Order flow has considerable explanatory power for interest rate changes, especially institution level order flow. This confirms results from other markets and asset types. The institution level variables have the expected signs, with considerable heterogeneity between institutions. The market efficiently observes institution level information when necessary, and considers some institutions to be more informative than others, reflecting the split between informed and noise traders. By aggregating order flow information across institutions, we loose an essential part of the picture by disregarding the asymmetry in the informativeness of different institutions. We obtain the following main results:

Result A Aggregate order flow is a significant but small determinant of overnight interest rates, with less explanatory power during the crisis than when markets are more stable

Result B Transacted limit order flow has a significant impact on interest rate changes. Its yield impact is generally different than the yield impact of market order flow

Result C Institution level order flow has much higher explanatory power than aggregate order flow, its coefficients are generally of the expected sign, and demonstrate considerable heterogeneity

Result D Institution level order flow is much more informative during the crisis than when markets are more stable

5.1 Result A: Aggregate Order Flow

Aggregate order flow is a significant determinant of yield at the five–minute sampling frequency during the stable period, but less so at the daily frequency and in the crisis period. These results broadly correspond to Brandt and Kavajecz (2002) who find low explanatory power of order flow for low maturity U.S. Treasury bonds. The coefficients on contemporaneous aggregate order flow have the expected signs, but the sign reverses for the lagged coefficients at the daily frequency. We suspect the reason is that banks are not able to fully respond to changes in aggressive borrowing and lending (market orders) immediately. Instead, the banks adjust their order flow over time, where e.g. aggressive lending today, bringing with it lower yields, attracts more aggressive borrowers tomorrow, raising yields.

5.2 Result B: Impact of Limit Orders

Most theoretical and empirical research on order flow models focusses on market orders. The main reason is probably lack of data since in most cases limit orders are simply the inverse of market orders. By studying institution level order flow, we can explicitly measure the impact of market orders and transacted limit orders, i.e. those limits executed in a given time interval. For the largest 2 borrowers, and the largest 3 lenders, market order flow is higher than limit orders, a result which reverses for most smaller institutions. In accordance with theories of informed trading, we expect the largest institutions to be best informed, and hence to favor market orders.

The limit order flow flow of the largest borrowers, has a much stronger yield impact than market order flow. This may be because these borrowers are seen as having highly inelastic demand for liquidity, with the preference for order type providing information about the degree of demand elasticity to the market.

5.3 Result C: Institution Level Order Flow

An extensive literature exists on the impact of individual institutions on price formation, e.g., Peiers (1997), de Jong et al. (2001), Covrig and Melvin (2002), Fan and Lyons (2000), Wei and Kim (1997), and Hasbrouck (1995). Of these studies, perhaps Fan and Lyons (2000) is closest to our methodology. As noted in Section 3.2.3, important institutional structural differences exist between foreign exchange and equity markets on one hand and overnight liquidity on the other.

Generally, we find institution level order flow to be a much stronger determinant of yield changes than aggregate order flow. At the daily frequency, the explanatory power of the aggregate order flow model is 5% measured by R^2, and 52% for the institution level order flow model. Similar results are obtained at the 5 minute frequency. Clearly, much information is lost by aggregating institution level order flow into aggregate order flow. The reason for this becomes clear when we focus on individual institutions, and integrate the statistical analysis with news of actual events in Turkey.

In the sample statistics, the order flow of most borrowing institutions has higher AR1 coefficients than that of lenders. The higher predictability of borrower order flow, implies that relative market power is in the hands of the lenders. The impact of not transacting for a lender are lower than for a borrower. The borrower may need the money to sustain other trading strategies, e.g. to meet margin calls, whilst the lender simply forgoes some earnings. Hence we suspect that the elasticity of demand is lower than the elasticity of supply. In general, there is considerable heterogeneity in the elasticities of demand/supply among institutions, implying that the yield impact of the various institution order flows is far from uniform. In turn, this causes much information to be lost when institution level order flow is summed up into aggregate order flow.

5.4 Result D: Institution Level Order Flow During Crisis

The predictability of institution level order flow drops in the crisis period, but the yield impact is higher. By looking at the AR1 coefficients from the sample statistics, they are about 0.2 lower in magnitude in the crisis period, on average. The lower persistence in behavior may signal that banks are more engaged in strategic trading in the crisis period, than in the stable period, resulting in lower predictability. This effect is especially strong for the lenders. Such behavior is in accordance with events before and during the crisis, see Sections 2.1 and A. The large borrowers were rumored to be in serious difficulties, and subject to liquidity squeezes from the lenders. The post crisis examination of financial institutions that defaulted, which includes the largest borrowers, suggests they were financing margin calls on the overnight market, rolling loans over in the forlorn hope that the market might move in the right direction.

We only have results from the order flow regressions at the 5 minute frequency. The institution level order flow model becomes especially strong during the crisis, with R^2 increasing by 32% (to 55%). This is in contrast to the aggregate order flow model where the R^2 actually drops in the crisis. The individual regression coefficients increase in magnitude in the crisis period, with the lenders coefficients increasing by 190% and the borrowers by 150%, on average.

The importance of individual institutions becomes clear during the crisis. Consider the bank with ID=24 who by supplying limit orders exerts a considerable downward pressure on yields. The same effect is observable for 2 other lenders, ID=27 and ID=30, the three largest lenders. Since the supply of limits is more readily observable by other banks than market orders, perhaps this signals some form of collusion by the lenders. After all, rumors of collusion in yield manipulation were strong during and after the crisis.

The stronger impact of institution level order flow during the crisis indicates that banks became more informed in the crisis period. There are several reasons for this. First institutions are less willing to or able to hide their trading strategies. Second, since the market is more volatile, monitoring trading activity and gathering information is more important. Third, institutions continuing to borrow overnight liquidity even with rates increasing to stratospheric levels, might be perceived as desperate demanders of liquidity, thus becoming a target for their more fortunate competitors. This would be in accordance with the news accounts of the crisis.

6 Conclusion

Aggregate order flow in the Turkish overnight repo market is an important contributor to interest rates, but still plays a secondary role to institution level order flow. In the sample period there was considerable heterogeneity in the trading behavior of individual institutions, where most institutions traded for liquidity reasons, and borrowers were often desperate to obtain funds. Some banks, especially suppliers of liquidity, were more speculative and manipulative in their trading behavior. In aggregate, many of these differences disappear. The results from the crisis period are especially interesting. While aggregate order flow dropped in importance, the yield impact of institution level order flow increased, highlighting the role of institutions and individual trading strategies in the understanding of financial crisis.

Taken together, our results are consistent with established results from order flow analysis in other markets, highlighting the role of information in the formulation of interest rates. At the same time, the unique structure of the overnight repo markets and the special situation in Turkey gives rise to empirical results that may require extending existing theoretical frameworks.

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 pay more attention to actual trading patterns in financial markets in emerging economies, instead of macroeconomic variables, or daily market summary variables. Our results accentuate the importance of the financial markets in emerging markets. While the IMF and the government focussed their attention on macroeconomic factors in Turkey, the crisis potential of the market for liquidity was left unchecked. This suggests that the supervisory authorities ignore the microstructure of liquidity markets at their peril. Indeed, most supervisors in developed markets pay close attention to high frequency trading patterns, especially in the very important overnight liquidity market. Our results suggest that emerging markets supervisors and supra-national organizations may want to do the same.

A Chronicle of the Crisis

20 Nov. Start of crisis. Rumors about instability, with some banks supposedly being in trouble. Two banks cut their credit lines.

21 Nov. Demirbank, tries unsuccessfully to sell its treasury bonds with Feb 2001 and a Aug 2001 maturities. Bond yields at their highest rate of the year to date.

22 Nov. Fire sales of equities and fixed income assets. Bond prices collapse. The Prime Minister warns banks and the public not pay much attention to "Rumors and Gossips". The Treasury Exchequer claims the central bank (CB) is trying to provide some liquidity to the market. This is the first indication that the liquidity crisis is taken seriously by the authorities.

23. Nov "Black Wednesday". Banks buy large amounts of USD, while the CB finally provides liquidity.

24. Nov Major commercial banks increase credit and deposit interest rates. CB's funds are helpful in relaxing the market sentiment but many banks continue to buy USD.

25 Nov Minister of Economics announces that "we will make the banks pay for the cost of the crisis created by gossip mongering".

27 Nov Purchases of TBills with maturities in July and August 2001.

28. Nov The CB and the Treasury appear together, along with market maker banks in the Tbill market, but without Demirbank. This is the first sign that Demirbank may be taken over by the Turkish Financial Service Authority.

29. Nov Johannes Linn, vice president of the World Bank, declares there will be some financial assistance to Turkey. But markets do not take this seriously, and repo rates go up.

30. Nov Economic officials issued various communiques in an attempt to calm the market. But the CB announced that it was back to its *Net Domestic Assets* target, refusing to provide additional funds to the domestic market, causing repo rates to go up again.

1. Dec The CB stopped providing liquidity, large capital outflows ensued. Local newspapers said a squeezed bank (Demirbank) was creating a lot of problems.

2. Dec CB firmly states it is not providing liquidity to the market.

4. Dec The IMF managing director, Horst Köhler, declares the IMF is to help Turkey. IMF executives to investigate the repo transactions among banks, and explore their impact on the CB's money lending. Repo rates still high.

6. Dec. Demirbank stops all banking functions. Demirbank said to have done 4,926 billion TRL worth of transactions in ISE repo market between 20 – 24 Nov, and, 3.271 billion between 24 Nov - 1 Dec.

A.0.1 Demirbank: Role of an institution

Demirbank was established in 1953, and was the 9$^{\text{th}}$ biggest bank in Turkey. It is known to be the largest borrower of overnight money before the crisis with a large portfolio of government bonds financed by foreign borrowing and overnight repos. Demirbank owned a 5.5 bn. (in USD terms) government bond portfolio, constituting up to 15% of the whole Tbill stocks of Turkey, while only having 300 million USD in capital. At the end of November, rumor has it that Demirbank got squeezed by two competitors. It gets margin calls from Deutsche Bank (who supposedly loses large amounts in the bankruptcy of Demirbank).

In the postmortem analysis Demirbank was found to have been highly leveraged and executing very risky trading strategies, but this was not obvious to the outside financial community. For example, on July 14, 2000 Demirbank received $110 mn. syndicated loan at Libor plus 75 basis points coordinated by ABN AMRO and Dai Ichi Kangyo. Standard & Poors upgraded its ratings of Demirbank on Nov 22, assigning it B+ long-term and B short–term ratings ("Positive Outlook"), meanwhile the crisis was underway, and Demirbank was becoming shunned by local banks. Demirbank gets taken over by government on December 6, and was eventually sold to HSBC.

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Table 1: Sample Statistics, Daily Aggregation

The order flow of the 4 largest institutions. $p(JB)$ is the significance level of the Jarque–Bera test normality, AR1 is the first order autocorrelation coefficient, $p(Q(5))$ is the significance level of the 5$^{\text{th}}$ order autocorrelation. Order flow is in units of 10^{15}, (qn.) Turkish Liras (TRL).

days	variable	mean	s.e.	skewness	kurtosis	$p(JB)$	AR1	$p(Q(5))$
Stable period	r	40.8	17.4	2.30	8.74	0.00	0.48	0.00
	Δr	0.267	35.6	-0.36	2.63	0.00	-0.27	0.00
	l	0.992	0.306	0.23	0.44	0.15	0.86	0.00
	b	0.945	0.178	-1.30	5.03	0.00	0.53	0.00
	$b^m(2)$	0.223	0.087	0.23	0.92	0.01	0.63	0.00
	$b^l(2)$	0.208	0.117	0.73	0.06	0.00	0.83	0.00
	$b^m(4)$	0.293	0.185	0.20	-0.85	0.02	0.82	0.00
	$b^l(4)$	0.254	0.206	1.07	0.34	0.00	0.89	0.00
	$b^m(8)$	0.052	0.035	0.80	0.58	0.00	0.73	0.00
	$b^l(8)$	0.061	0.038	0.31	-0.65	0.02	0.75	0.00
	$b^m(12)$	0.064	0.031	0.43	0.17	0.03	0.58	0.00
	$b^l(12)$	0.077	0.034	0.14	-0.20	0.59	0.70	0.00
	$l^l(24)$	0.126	0.040	-0.02	-0.15	0.90	0.56	0.00
	$l^m(24)$	0.154	0.057	0.49	0.35	0.01	0.70	0.00
	$l^l(27)$	0.065	0.020	-0.28	0.21	0.18	0.27	0.00
	$l^m(27)$	0.102	0.031	-0.16	0.61	0.11	0.67	0.00
	$l^l(30)$	0.125	0.038	0.10	1.19	0.00	0.56	0.00
	$l^m(30)$	0.135	0.063	0.41	-0.43	0.02	0.84	0.00
	$l^l(48)$	0.047	0.019	0.13	0.01	0.72	0.53	0.00
	$l^m(48)$	0.035	0.017	0.49	0.21	0.01	0.56	0.00
Crisis period	r	225	167	1.26	0.33	0.13	0.60	0.01
	Δr	4.62	56.0	1.01	1.08	0.20	-0.14	0.12
	l	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
	$b^m(2)$	0.089	0.083	0.95	0.05	0.32	0.73	0.00
	$b^l(2)$	0.166	0.150	0.78	-0.32	0.45	0.87	0.00
	$b^m(4)$	0.271	0.149	1.31	1.84	0.04	0.27	0.89
	$b^l(4)$	0.423	0.222	0.25	-1.35	0.52	0.42	0.16
	$b^m(8)$	0.073	0.036	-0.60	-1.25	0.39	0.84	0.00
	$b^l(8)$	0.054	0.026	-0.36	-1.45	0.44	0.78	0.00
	$b^m(12)$	0.077	0.044	0.37	-0.89	0.66	0.42	0.54
	$b^l(12)$	0.080	0.030	0.39	-0.86	0.66	0.19	0.87
	$l^l(24)$	0.044	0.022	0.57	0.05	0.67	0.28	0.41
	$l^m(24)$	0.083	0.033	0.78	-0.68	0.40	0.46	0.01
	$l^l(27)$	0.063	0.027	0.05	-0.72	0.85	0.01	0.82
	$l^m(27)$	0.151	0.029	-0.13	-0.57	0.88	0.03	0.71
	$l^l(30)$	0.111	0.059	1.01	0.23	0.27	0.63	0.04
	$l^m(30)$	0.198	0.074	0.33	-0.38	0.83	0.38	0.06
	$l^l(48)$	0.035	0.021	-0.04	-0.67	0.87	0.33	0.22
	$l^m(48)$	0.039	0.026	0.43	-0.11	0.79	0.47	0.44

Table 2: The Relative Trading Volume of the Largest 4 Institutions

ID is the institutional code.

Rank	Lending Institutions		Borrowing Institutions	
	ID	%	ID	%
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

Table 3: R^2 for the Daily Log Interest Rate Equation for the Three Model Specifications. Full sample

Results for an equation with log annualized interest rate changes (Δr) regressed on either lagged Δr, contemporary and lagged order flow (b, l), or contemporary and lagged residual order flow (l^r, b^r) and institution level order flow, ($\boldsymbol{W}$). The number of lags is 3. DW is the Durbin-Watson statistic.

Right hand side variables	R^2	DW
lags of Δr	0.157	
l, b	0.053	2.44
l^r,b^r, $\boldsymbol{W}$	0.522	2.54

Table 4: Significance of the Aggregate Order Flow at the Daily Frequency. Full Sample

Daily log annualized interest rate changes (Δr) regressed on contemporary and lagged aggregate order flow (l, b). The number of lags is 3. The order flow variables are in units of TRL tn. (10^{12}). The sum of regression coefficients are reported, separately for contemporaneous and lagged order flow. p–exclude is the significance level of whether the coefficients are different than zero, lower values rejection of that hypothesis.

Variable	Contemporaneous		Lags 1–3	
	p–exclude	coefficient	p–exclude	coefficient sum
b	0.03	3.84	0.36	-3.19
l	0.24	-1.94	0.07	2.13

Table 5: Significance of the Institution Level Order Flow at the Daily Frequency. Full Sample

Daily log annualized interest rate changes (Δr) regressed on contemporary and lagged residual order flow (l^r, b^r) and institution level order flows. The number of lags is 3. The order flow variables are in units of TRL tn. (10^{12}). The sum of regression coefficients are reported, separately for contemporaneous and lagged order flow. p–exclude is the significance level of whether the coefficients are different than zero, lower values rejection of that hypothesis.

Variable	Contemporaneous		Lags 1–3	
	p–exclude	coefficient	p–exclude	coefficient sum
b^r	0.34	3.96	0.32	-9.0
l^r	0.79	-1.15	0.11	14.3
$b^m(2)$	0.26	5.47	0.72	-7.5
$b^l(2)$	0.08	12.69	0.02	-25.3
$b^m(4)$	0.14	5.34	0.31	-7.6
$b^l(4)$	0.11	10.59	0.18	-17.1
$b^m(8)$	0.50	8.00	0.59	-11.3
$b^l(8)$	0.78	-3.57	0.93	-10.2
$b^m(12)$	0.00	42.48	0.03	-18.7
$b^l(12)$	0.18	16.78	0.01	-30.7
$l^l(24)$	0.02	-28.45	0.01	49.4
$l^m(24)$	0.00	-28.57	0.00	34.8
$l^l(27)$	0.97	1.22	0.17	28.9
$l^m(27)$	0.94	-1.82	0.05	-48.7
$l^l(30)$	0.22	-14.09	0.23	32.1
$l^m(30)$	0.35	-8.08	0.02	12.1
$l^l(48)$	0.50	14.59	0.27	-26.8
$l^m(48)$	0.83	-5.08	0.33	-15.0

Table 6: R^2 for the 5 Minute Log Interest Rate Equation for the Three Model Specifications.

Results for an equation with log annualized interest rate changes (Δr) regressed on either lagged Δr, contemporary and lagged order flow (b, l), or contemporary and lagged residual order flow (l^r, b^r) and institution level order flow, ($\boldsymbol{W}$). DW is the Durbin-Watson statistic. The number of lags is 11.

	Right hand side variables	R^2	DW
Stable period			
	Δr	0.01	
	l, b	0.12	2.05
	l^r,b^r, $\boldsymbol{W}$	0.23	2.09
Crisis period			
	Δr	0.04	2.00
	l, b	0.06	1.96
	l^r,b^r, $\boldsymbol{W}$	0.55	2.14

Table 7: Significance of the Aggregate Order Flow at the 5 minute Frequency. Full Sample

5 minute log annualized interest rate changes (Δr) regressed on contemporary and lagged aggregate order flow (l, b) and institution level order flows. The number of lags is 3. The order flow variables are in units of TRL tn. (10^{12}). The sum of regression coefficients are reported, separately for contemporaneous and lagged order flow. p–exclude is the significance level of whether the coefficients are different than zero, lower values rejection of that hypothesis.

	Stable period		Crisis period	
Variable	p–exclude	Coefficient sum	p–exclude	Coefficient sum
b	0.00	0.44	0.00	0.98
l	0.00	-0.09	0.41	-0.15

Table 8: Significance of the Institution Level Order Flow at the 5 minute Frequency. Full Sample

5 minute log annualized interest rate changes (Δr) regressed on contemporary and lagged residual order flow and institution level order flows. The number of lags is 3. The order flow variables are in units of TRL tn. (10^{12}). The sum of regression coefficients are reported, separately for contemporaneous and lagged order flow. p–exclude is the significance level of whether the coefficients are different than zero, lower values rejection of that hypothesis.

	Stable period		Crisis period	
Variable	p–exclude	Coefficient sum	p–exclude	Coefficient sum
b^r	0.00	0.83	0.00	2.87
l^r	0.00	-1.03	0.06	-1.65
$b^m(2)$	0.00	0.57	0.09	2.54
$b^l(2)$	0.00	1.73	0.00	5.05
$b^m(4)$	0.00	0.59	0.01	2.55
$b^l(4)$	0.00	1.84	0.00	4.31
$b^m(8)$	0.00	0.66	0.18	3.24
$b^l(8)$	0.00	2.37	0.15	4.63
$b^m(12)$	0.00	1.28	0.74	0.60
$b^l(12)$	0.00	1.28	0.27	3.10
$l^l(24)$	0.00	-1.55	0.00	-17.43
$l^m(24)$	0.00	-1.29	0.83	-0.54
$l^l(27)$	0.00	-2.45	0.03	-5.37
$l^m(27)$	0.00	-0.32	0.88	-0.26
$l^l(30)$	0.00	-1.74	0.08	-3.47
$l^m(30)$	0.00	-0.65	0.66	-0.58
$l^l(48)$	0.05	-1.41	0.95	-0.30
$l^m(48)$	0.04	-1.44	0.29	-3.60

Figure 1: Interest Rates

Note: Annualized daily yields. The last transaction of day.

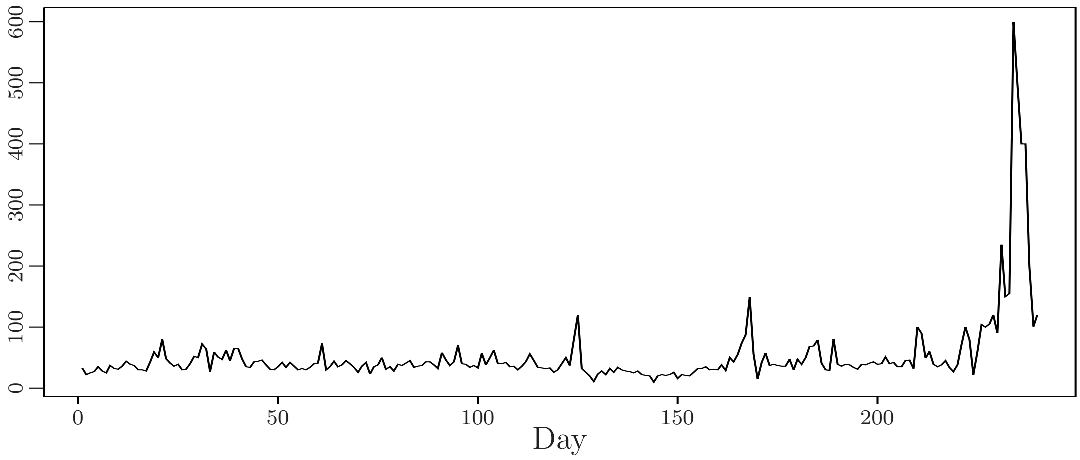


Figure 2: Daily Lend and Borrow Order Flow, b, l,

Note: In units of quadrillion, (qn.or 10^{15}) Turkish liras (TRL).

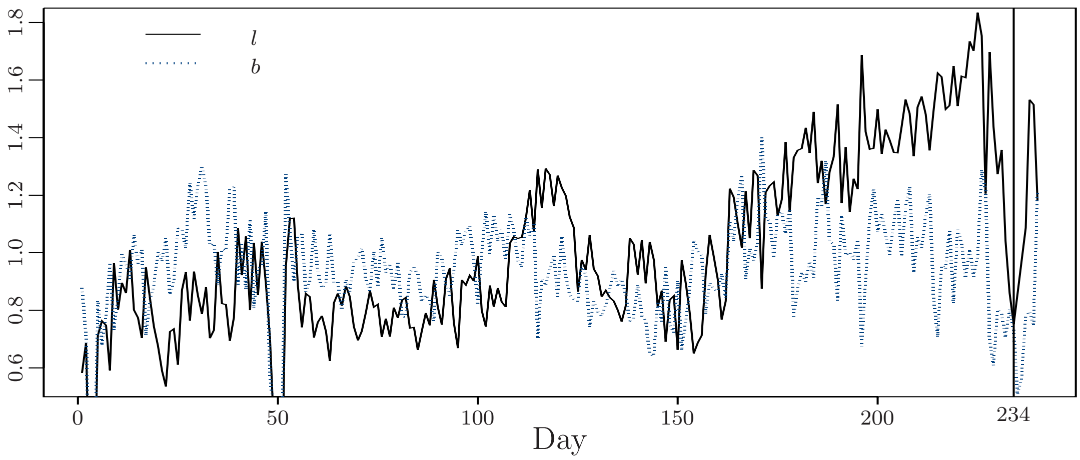
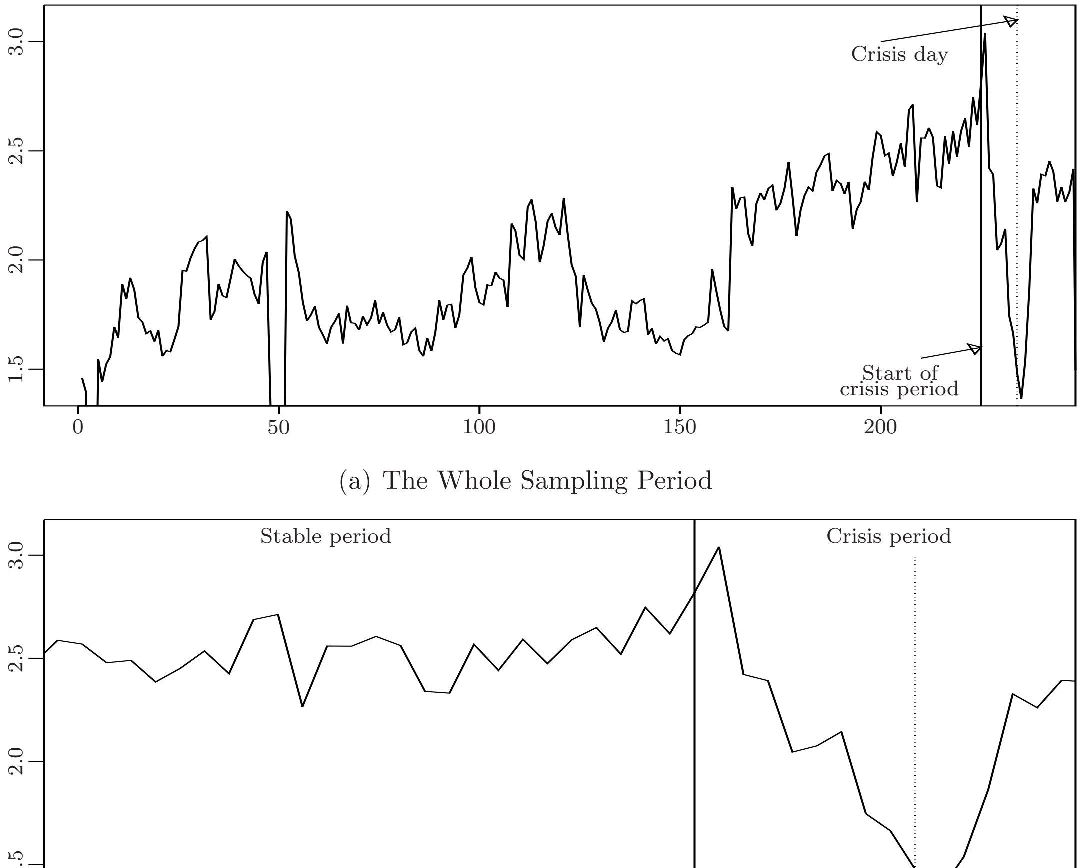


Figure 3: Daily Trading Volume in qn. TRL.

Note: In units of quadrillion, (qn.or 10^{15}) Turkish liras (TRL).



(a) The Whole Sampling Period

(b) Days 200–240

Figure 4: USD Exchange Rates and the Stock Market

Note: ISE (Istanbul Stock Exchange) is the main stock market index. USD is the exchange rate of TRL/USD

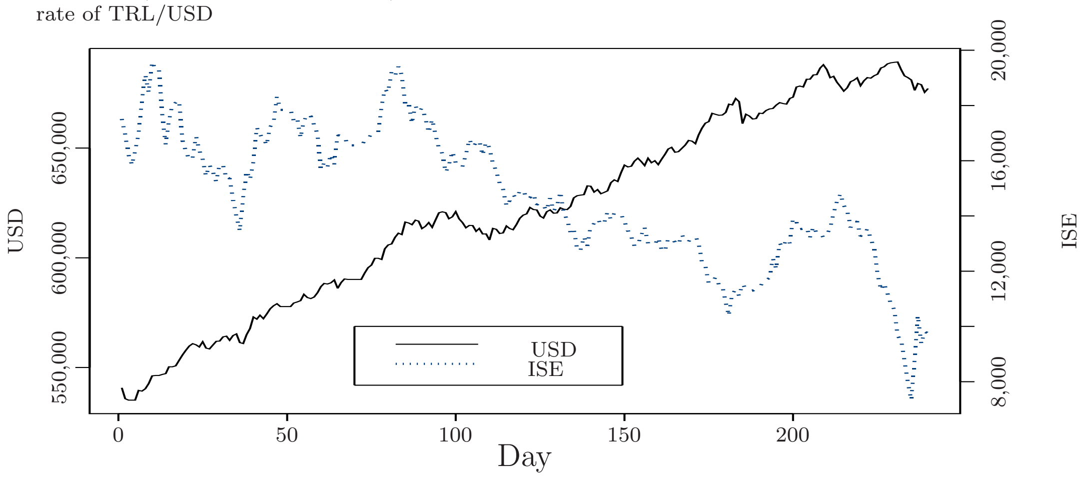


Figure 5: Intra Day Seasonality

Note: Average number of trades in each 10 minute interval.

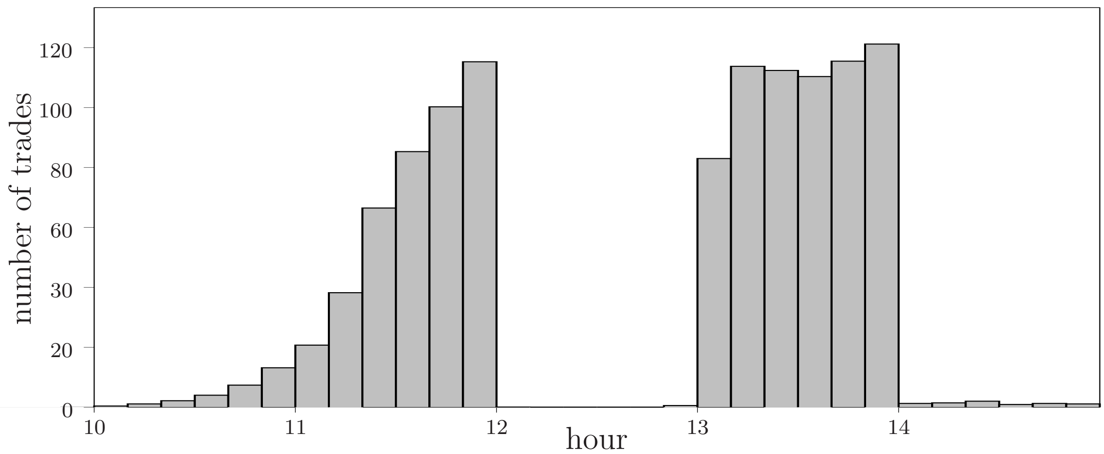
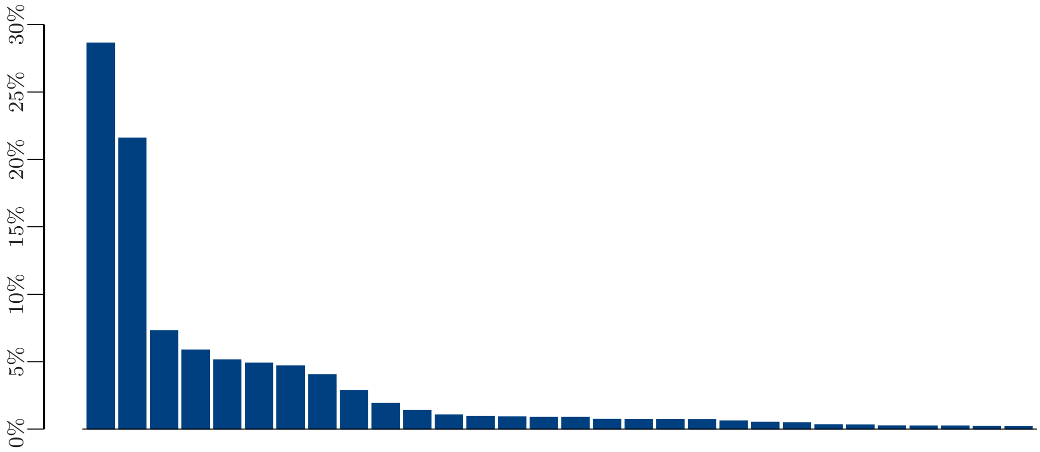
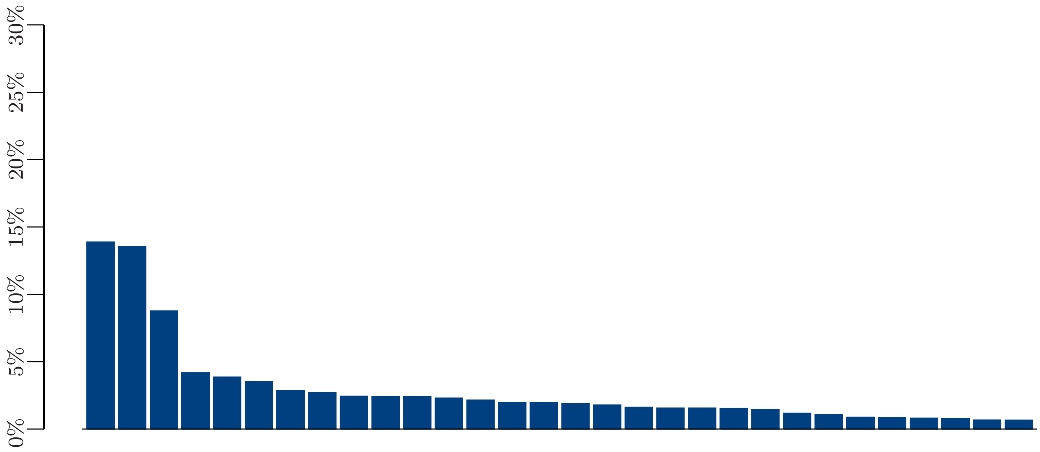


Figure 6: The Relative Trading Volume Of The 30 Largest Institutions

Note: In some cases the same institution might appear both as a borrowing and lending institution.



(a) Borrowers



(b) Lenders