The Venezuelan Overnight Fund Market: Understanding a Credit Constraint Limit Order Market

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Abstract

The Venezuelan overnight market trades funds electronically similarly to limit order markets, but allows the imposition of credit lines, which inflict binding credit restrictions to some participants and introduce a peculiar bid-ask spread dynamic. The objective of this paper is to determine whether the trading costs exhibited in this market can be explained by credit constraints, and other particular market features such as, the degree of collateralized trades and the flow of government payments into the financial system. Econometrically, we test this hypothesis using a definition of effective spread that takes into account the special microstructure of the market, and measuring credit constraints throughout two different observable expressions. We carry out the empirical study estimating single equation GARCH models on the effective spread and on other two broader measures of market performance extracted from the application of principal component analysis. Results indicate that distortions associated to credit constraints are important, and there is room for policy prescriptions that promote the elimination of credit lines.

Keywords: Money Market Microstructure; Limit Order Markets; Credit Constraints; Trading Costs; Monetary Policy

JEL Classification: G14; D49; C81; E59

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* Opinions expressed on this paper are personal and do not compromise those of the Banco Central de Venezuela.

I.- Introduction

The overnight fund market can be defined as the starting point of the transmission mechanism of monetary policy, since the behavior of the fund rate not only contains information on bank responses to monetary actions, but also modifies the structure of commercial interest rates, which eventually affect aggregate demand in the economy[1]. In this sense, it is important that this short run rate contains more signals related to the state of the fundamentals of the money market and less noise coming from existing distortions that increase trading costs.

Operations in the Venezuelan overnight fund market are traded electronically through a system of submissions and information similar to limit order markets functioning in important international bourses. However, the system allows its participants to assign credit lines to their potential trading partners, and/or request up to a 100% of collateral for potential transactions. This implies that the amount of potential trades in the market (market depth) is presumably reduced, since the exchange of funds only occurs when the interest rate, credit line and collateral solicited by suppliers of funds are met with the corresponding characteristics in buy orders.

However, a more crucial consequence to the existence of credit lines refers to the process of market segmentation that indirectly promotes. Initially, credit lines were conceived as a price-neutral mechanism to protect banks against the potential risk of default of some of their partners, but actually they have translated in significantly high interest rates charged to some banks. This recurring practice indicates that credit lines work as a form of market discrimination, in which credit restrictions applied to some participants are not lifted until a high enough premium interest rate is paid. This market segmentation that stems from the application of discretionary credit lines grounds distortions in the levels of the short run interest rate and misleads any traditional market performance evaluation.

The objective of this paper is to determine whether the trading costs exhibited in the Venezuelan fund market can be explained by market peculiarities such as: credit constraints, collateral requests and the flow of government payments into the financial system. To do so, we adapt a standard definition of trading costs used in the literature (the effective market spread) to the special microstructure of the Venezuelan market. The working definition of effective spread refers to the difference between the interest rate paid by agents with potential binding credit constraints and the interest rate paid by agents trading freely in the market. Econometrically, we evaluate the impact of market credit restrictions and government payments on the effective spread through the estimation of a single equation GARCH model.

To assess credit restrictions, we compute two variables that proxy the magnitude of the distortions caused in the market: the difficulty of buy orders to find a match, although being competitive in price, and the relative quantity of trades that have to make price concessions to lift credit constraints. Results show that the greater the distortions associated to the existence of credit constraints, the bigger the trading costs in the form of higher effective spreads. This finding has two immediate consequences: the first one is that credit constraints distort the observed levels

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[1] See Pagliacci and Ruda (2004) for a discussion on how monetary policy actions affect the overnight market rate in Venezuela, and its relationship with commercial banks interest rates.

of interest rate in the market, which introduces noise to the price signal extraction undertaken by market participants. The second consequence is that there are bigger rents appropriated by those market participants that are able to intermediate funds between the constrained segment of the market and the unconstrained one. These rents not only affect market depth by triggering extra-higher rates for increasing transaction volumes, but probably have an impact on efficiency, as long as these rents also react to private market information arriving to the market.

From the positive association estimated between collaterals and the effective spread, we infer that collaterals are perceived as an extension of the credit line discrimination mechanism, instead of being considered as insurance for coverage against the risk of loan default. Among other results, we find out that that government erratic fund transfers into the financial system affect both the mean and volatility of the spread, especially when hitting credit constraint buyers of funds.

Given the lack of applicability of other standard measures of trading costs to the microstructure of the Venezuelan trading system[2], we study alternative notions of frictions to provide a more comprehensive description of the market. Starting from the general definition of friction provided in Stoll (2000), i.e. the difficulty to trade a financial asset, a friction can be measured not only as the price concession paid for immediacy (the half spread), but also as the time needed for an asset to be traded. Alternatively, one could argue that frictions in a market are inversely related to the possibility faced by a financial asset of finding a match, since the greater the friction, the larger the risk of not being picked off for a trade. Following this reasoning, we study the waiting time and probability of execution met by orders as complementary market expressions of frictions. Using principal component analysis, we combine information of the effective spread and these variables into two new synthetic measures denominated *friction* and *activity* levels respectively. Likewise, we relate the behavior of these synthetic variables to market peculiarities through the estimation of single equation GARCH models.

In terms of policy prescriptions, the distortions associated to observing non-traded competitive buy orders are more detrimental to market performance than the distortions expressed as more expensive or collateralized trades. This is the case because, although all these distortions increase effective spreads and therefore trading costs for credit constraint participants, the second ones reduce other forms of market frictions, i.e. the probability of not finding a match or the waiting time for execution. This interpretation of the results suggests that improving market performance necessarily involves the elimination of credit lines and the introduction of an alternative mechanism for reducing the exposure to the risk of a loan default.

The paper outline is the following. First, we describe market protocols in the Venezuelan Overnight Fund Market in order to understand its particular dynamic. Next, we describe the data set available and some of the statistics used in this paper and adapted to the presence of credit constraints. In particular, we classify orders according to their function in the market, and introduce the concepts of effective spread, probability of execution of orders, and the average waiting time for execution of orders. All these statistics are employed to describe the intraday patterns of the data, and to infer possible working hypotheses regarding agents' interactions and the effects of credit constraints. In the econometric section, we perform Maximum Likelihood

[2] Typically trading costs can be expressed in terms of effective, traded or quoted spreads, depending on the context in which they are defined. See Stoll (2000) for a full discussion on the topic.

Estimation of GARCH single equation models on three variables: the effective spread and two synthetic variables derived from the application of principal component analysis, i.e. the friction and activity levels. We interpret the results focusing on the effect of credit constraints, collaterals and government payments into the financial system. Finally, based upon our findings, we provide some recommendations to improve general market performance.

II.- Description of Market Protocols

The Venezuelan Overnight Fund Market operates through a computerized system called SET (*Sistema Electrónico de Transferencias* or Electronic Transfer System), which started carrying out transactions in October 2000, and it has been progressively growing up to currently include more than 95% of overnight bank loans.

This market, like some major financial bourses in the world, is based in a system of limit order submissions to buy or sell overnight funds at any interest rate[3]. After a market participant submits a limit order, a trade occurs only if two conditions are met: there is a limit order on the opposite side of the market that matches the quoted interest rate; and the lender of funds has extended a credit line to the potential borrower. Credit lines are pre-established by each market participant at the beginning of the day and the system automatically checks for their compliance. These credit lines are also dynamic, in the sense that can be modified by market operators at any time during the trading day. If there is more than one order that matches an entering order, they are executed according to their time priority.

Differently from other electronic markets, market orders are not allowed[4]. To obtain the best bid of funds in the market, a matching price limit order needs to be submitted, and it is immediately executed if credit constraints are not binding. Any excess quantity of the limit order that cannot be instantaneously satisfied by the market, it will remain in the system waiting for execution or cancellation.

In order to provide more flexibility to the matching process between limit orders, when no credit constraints exist, a buy limit order could be executed at a lower price than the posted one, if and only if the system does not find an exact price matching sell limit order. For example, if there are two posted sell orders, Bs. 100 MM at 2% and Bs.100 MM at 1,5%, and there is an entering buy limit order for Bs.150 MM at 2%, then the system will assign to the borrower Bs. 100 MM at 2% and the remaining Bs. 50 MM at 1,5%. This second order search ensures that lenders of funds will always get the exact interest rate of their sell orders, but borrowers might obtain a smaller interest rate than the one posted in their buy orders. This particular mechanism is called *sweeping*.

[3] A limit order in the overnight fund market is defined as a buy or sell order that specifies the interest rate and the maximum quantity of domestic funds that a bank wants to buy or sell. Rates can take any continuous value and are not forced to conform to a specific pricing grid.

[4] A buy (sell) market order specifies the quantity of an asset that a trader wants to buy (sell), without indicating the execution price.

Since all traders submit limit orders, in this market it is no longer true that *limit orders supply liquidity* exclusively[5]. However, ex-post the initial system search, we could classify orders in *standing* and *fast execution* orders. In particular, a *standing* order is a limit order that, when entering the system, does not have a matching order in the opposite side of the market, and therefore it remains in the system supplying liquidity to *fast execution* orders or waiting to be cancelled. Conversely, a *fast execution* order is one that enters into the system to hit a *standing* order, that is, to pact a transaction[6]. By definition, standing orders add up liquidity to the order book, while fast execution orders consume it.

This classification of orders (*standing* versus *fast execution*) will afterward allow simplifying market characterization. It is interesting to note that, while many studies in the literature have devoted to explain why investors can choose to either post limit orders or submit market orders[7], analogously in the Venezuelan fund market a trader might decide to submit either a standing order or a fast execution order. However, the theoretical reasons might not be as clear: patient traders might prefer standing orders, but also traders facing binding credit constraints or simply by mistake might end up providing these orders.

Besides credit lines, market participants can ask before hand for the provision of collateral to their transactions, which typically consist of government bonds under custody of the Venezuelan Central Bank, which is the system administrator. When a limit order is submitted by a bank, neither its name, credit status or collateral information is displayed in the screen to others market participants, but it is accessible to the Central Bank. However, at the end of the trading day, each bank receives a report of the undertaken transactions, which indicates the time, price and quantity of funds exchanged, collateral and liquidation conditions, and the name of the counterpart financial institution. This disclosure of information, coupled with the fact that there is a relative small number of banks interacting repeatedly, allows each bank to imperfectly learn which are its trading partners and the most common strategies employed.

According to the above description, it is clear that this market exhibits particular features that are not present in most limit order markets, such as: the assignment of credit lines, the request of collateral and the imperfect anonymity of market participants. These elements not only introduce several difficulties to analyze market performance and microstructure, but also allow for market discriminating practices that cause a strong segmentation of prices and provide important rents for those participants intermediating funds between the unconstrained traders and the constrained ones. In the following sections we will try to characterize the Venezuelan fund market, taking into account its peculiarities.

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[5] The expression *to supply liquidity* is used as in the literature of limit order markets, meaning to supply immediacy to other traders.

[6] Notice that in this paper, execution is used as synonymous of trading.

[7] Among others: Foucault (1999) and Foucault et al. (2004).

III.- The Data Set and Statistics

Data corresponds to total market activity for the period April 2005 and November 2005, which corresponds to 164 trading days. Data is received in two separate files. One file contains information regarding all limit orders (to buy and sell funds) and cancellations submitted during the trading day, with their identification number and time of registration into the system. In the case of cancellations, information about the counterpart order is also available (that is, the amount and identification of the standing order that is being cancelled). Order data contains both, fast execution and standing orders. Cancellations are considered different than orders, but erase from the system an amount of previously submitted standing orders. The second file has available information about trades, describing the time of the transaction (execution), the matching conditions (interest rate, amount of funds exchanged and collateral) and the identification of orders and market participants involved.

A trading day typically starts at 8:00 a.m. and formally finishes at 2:30 p.m.. Between 2:30 p.m. and 3:00 p.m., it operates the "leveling market", which is basically an extra time given to institutions to level up their cash flow in case funds obtained during the morning period were not enough. However, during the "leveling period" most of financial institutions do not participate for reputational reasons, and generally after 1:00 p.m., transactions are seldom. We use the data available until 1:00 p.m. since afterwards most of the statistics cannot be computed (due to the lack of observations) and transaction are not too informative of the market conditions prevailing during the first part of the day.

In this paper data is organized in three different ways to analyze diverse aspects of the market activity. At daily level, we compute average or sum statistics with the complete information of the trading day (up to 1:00 p.m.). We obtain 164 observations that are employed to describe the general characteristics of the market, such as: number and amount of limit orders and cancellations, number and amount of trades, average size of orders and trades, and the average interest rate and collateral of transactions.

To study intraday patterns of the data we divide the trading day in ten half-hour intervals. Since a certain number of trades and orders occur during each interval, we calculate half-hour statistics such as, the relative frequency with which standing orders are filled (traded), and the average time that takes to a standing order to be traded or cancelled. These statistics are extremely valuable, since they convey information about the degree of friction in the market, when friction is defined as the "difficulty" to trade an asset[8]. For each half-hour statistic at each time interval, we construct a probability distribution of 164 observations (days) that allows computing and observing the evolution of distribution quartiles over the day. This organization of the data provides us with the heuristic about the intraday interaction that might occur between volumes of orders, volumes of trades, and interest rate of trades.

Third, we organize the information of the half-hour statistics in a time series format and obtain a sample of 1,640 observations that allows analyzing the dynamic relationship between variables.

[8] For a discussion about the notion of friction and its possible measures, see Stoll (1993).

Next, we describe the construction and variations of some of the statistics used in this paper, as an effort to convene the specific characteristics of this market.

Effective spread of trades

According to Stoll (2000) a market friction can be defined as the price concession needed for an immediate transaction, and spreads are the direct measure of frictions. Stoll (2000) also presents three alternatives measures of spreads (quoted, effective and traded spread), arguing that each measure might entail different types of frictions.

In the Venezuelan overnight market, binding credit constraints impose a different order book dynamic than the observed in equity financial markets, and therefore precludes the straightforward application of any of the spread measures suggested by Stoll. In particular, when a limit order is submitted, the system searches for its match in terms of interest rate (the price of funds), collateral and credit conditions. Therefore, it might be the case that for an incoming buy order that has an interest rate identical to some of the sell orders standing in the system, there is no feasible match because of the collateral or credit conditions imposed. Moreover, these constraints explain that at a given point in time the best ask quote in the market might be smaller than the best bid quote, forcing a meaningless definition of quoted spread[9]. Likewise, the calculation of a traded spread might be pointless because the condition that transactions at the ask have a greater average price than transactions at the bid is not necessarily satisfied in this market[10].

The above discussion leads to think that the only feasible measure of spread in this market is the effective half-spread, which measures the distance between the price of a trade and the best estimation of the fundamental value of the asset (typically the midpoint between the ask and the bid quotes)[11]. The difficulty that arises is to find a suitable estimation of the efficient price of the asset, considering that binding credit constraints introduce an additional premium in the price of funds paid by credit constrained market participants and that simple quoted spreads are misbehaved. Next, we discuss how we handle the effect of credit constraints for the estimation of an alternative midpoint and effective spread.

Alternative midpoint estimation under market discriminating practices

One way to rationalize credit lines is assuming that they divide the market in at least two segments or groups (constrained and unconstrained market participants), each of which exchange funds around two different levels of prices, i.e. low prices for unconstrained participants and high prices for the rest. This is equivalent to say that credit constraints lead to observe two types of

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[9] Another way to think about this anomaly is to picture an order book in which the ask schedule intersects with the bid schedule.

[10] See Stoll (2000) for a discussion on the differences between the measures of spread provided.

[11] Stoll (2000) refers to the effective half-spread as the distance between the price of a trade and the quoted midpoint prevailing in the market. We are directly assuming that the mid-quote stands for a simple estimation of the efficient value of the asset.

prices because there are two different segments of the market functioning simultaneously[12]. It follows that among unconstrained financial institutions trades should be executed around the *fundamental value of funds* that satisfies the standard conditions of financial markets. Among constrained participants, the price of funds includes a premium that is equivalent to the value paid to the sellers of funds to lift the credit constraint imposed.

The above hypothesis points to think that, if credit lines are relatively stable in time, the average price of funds exchanged among the group of unconstrained banks should reflect an approximate fundamental value of funds. This *midpoint of unconstrained trades* would impose that in average, bid-gains and ask-losses among unconstrained banks be balanced. On the other hand, the difference between the interest rate paid by the rest of banks and this unconstrained midpoint, not only would contain the usual trading costs components, but also the premium associated to binding credit constraints. Banks that practice intermediation, typically buying funds in the unconstrained segment of the market and selling funds in the constrained one, are the banks that would tend to cash these premiums at the expenses of the credit constrained banks.

Operationally the difficulty resides in pinning down the group of banks that trade among them with mutual broad credit lines (not binding), and in most of the cases lean to pact without any collaterals. To identify this set of banks, we make use some of the credit lines reports generated by the Venezuelan Central Bank for market analysis purposes. Once identified a tentative pull of candidates, information is validated with market analysts at the Central Bank.

To compute the weighted effective spread of trades, initially we use two measures of the midpoint[13]. One in which the midpoint is simply the average interest rate of all trades for the corresponding half-hour interval, and a second one in which the midpoint is the average interest rate of trades executed among the set of unconstrained banks. The first spread resembles more closely a measure of volatility of traded prices, while the second one intends to capture a more realistic measure of trading costs, given the existence of credit constraints.

Rate of execution of standing orders

According to the definition provided, once entered into the system, standing orders do not find an immediate match and therefore remain waiting until cancelled or matched with a fast execution order. At each half hour interval, we can compute the ratio of traded funds during that particular interval respect to the amount of standing orders available. This ratio is exactly what we define as the rate of execution of standing orders, which intends to measure the degree of difficulty (the chances) that an incoming unit of funds (1 Bs.) has to be executed (sold or bought) in a given interval. This concept resembles the definitions of *fill rate* in Foucault (1999), and of probability of execution in Hollifield et al. (2002), but translated within the context of this particular market.

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[12] This conceptualization of the market would also imply that there are banks that having access to both segments of the market practice intermediation, typically buying funds in the unconstrained segment and selling funds in the constrained one. We will refer again to this issue later in the discussion.

[13] A weighted effective spread is defined as $ES = \frac{\sum_{\forall i} 2|r_i - m| v_i}{\sum_{\forall i} v_i}$, where r_i is the interest rate of the i[th] trade and v_i its volume; m is the relevant midpoint for the time interval at which such trade occurs.

Operationally, to obtain the amount of standing orders available at a particular interval (the denominator of the execution rate), we first compute the *stock* of standing orders *at the end* of each interval[14]. Then, the denominator of the execution rate is the sum of the stock of standing orders coming from the preceding interval, plus the amount of incoming limit orders, less the amount of cancellations and fast execution orders submitted during that interval.

Time of execution of standing orders

Since trades always involve a match between a standing order and a fast execution order, for each trade there is a standing order that had been waiting to be hit by the fast execution order. This waiting time or time spent between the arrival and the partial or total filling of a standing order is what we call the execution time. This concept is analogous to the one analyzed by Lo et al. (2002), but it does not discriminate between orders that have been partially filled and those that have been completely filled. For a given half hour interval, this statistics represents the average time length (in minutes) a traded standing order had been sitting in the system[15].

Time of cancellation of standing orders

Similarly to the former definition, we can think of a cancellation as an operation that always involves a cancellation submission and a standing order (the order that is being cancelled). Therefore, for a given half hour interval, this statistic measures the average time length (in minutes) a single standing order had been sitting in the system until cancelled in that interval[16].

IV.- Market Characterization

Daily aggregated statistics

A total of 48 commercial banks and financial institutions participate in the overnight fund market to balance the domestic currency cash flows involved in daily operations. Traded funds in this market represent, on average, a 25% of non-required reserves kept by commercial banks in the vaults of the Venezuelan Central Bank, and less than 4% of the average money base in 2005.

For a representative trading day, submitted limit orders can correspond to a 77% of non-required reserves, while for days of extreme activity (the top quartile of the distribution) orders can represent more than 95% of non-required reserves. However, of the total buy and sell orders submitted to the electronic system, cancellations at the end of the day might correspond to a 30% of orders[17]. The average size of a typical limit order is of Bs. 4.7 billions, while the average size

[14] The stock of standing order at the end of each time interval is a proxy for the depth of the order book at all existing quotes.

[15] Notice that while the probability of execution refers to the chances of matching of a unit of funds, the execution time refers to the waiting time of an individual order, independently of its size.

[16] In Lo et al. (2002) the analysis of times of execution is performed using individual data. In this paper, time of execution and cancellation of standing orders refer to averages computed for half-hour intervals.

[17] Recall that total orders refer to the sum of fast execution and standing orders. Cancellations erase from the system an amount of previously submitted standing orders.

of a trade is only of Bs. 2.6 billions, implying that generally it takes around 2 transactions to fill an order completely. Average cancellations are of Bs. 4.1 billions, indicating that an important number of cancellations eliminate orders that were not even partially traded. Of the total amount of traded funds, an average of 38% is backed by collaterals. However, collaterals can represent up to a 54% of traded funds for days of strong trading activity. See tables 1 and 2 for details about these statistics.

Table 1. Summary Daily Statistics for Submission of Orders and Cancellations

Percentiles	Number of Total Orders	Number of Cancellations	Amount of Total Orders (Billions Bs)	Amount of Cancellations (Billions Bs)	Average Order Size (Billions Bs)	Average Cancellation Size (Billions Bs)
Mean	**276**	**98**	**1,267**	**381**	**4.7**	**4.1**
P-0.05	97	27	587	128	3.7	3.0
P-0.25	204	62	976	244	4.1	3.5
P-0.50	277	95	1,215	357	4.6	4.0
P-0.75	330	123	1,558	492	5.2	4.5
P-0.95	440	184	2,076	699	6.4	6.0

Total Orders: Fast Execution plus Standing Orders

Table 2. Summary Daily Statistics for Trades

Percentiles	Number of Trades	Amount of Trades (Billions Bs)	Average TradeSize (Billions Bs)	Ratio of Collateralization of Trades
Mean	**155**	**411**	**2.6**	**0.38**
P-0.05	63	142	2.0	0.26
P-0.25	126	309	2.3	0.32
P-0.50	154	408	2.5	0.38
P-0.75	186	491	3.0	0.43
P-0.95	241	677	3.6	0.54

The average interest rate at which transactions occur is 2.76%. However, looking at the entire distribution of interest rates, there is almost a difference of 9.8 percentage points (p.p.) between the lower and the upper fifth-percentiles, which denotes a particularly high dispersion of rates (see table 3). Taking the average interest rate for all trades as a coarse estimation of the fundamental value of funds, the resulting average effective spread is of 1.18 p.p., which is on average equivalent to a 43% of the referential mid-interest rates. Dispersion of effective spreads is also high and ranges between a 13% and 81% of their midpoints. Both distributions, of interest rates and spreads, present a long right tail, indicating that few trades are contracted at particularly high interest rates.

Because probably, the average price of trades is a noisy estimation of the fundamental value of funds (due to the credit constraints), in table 4 we report the distribution of average interest rates for trades occurring only between the set of unconstrained banks[18]. Since the distribution of unconstrained interest rates is placed to the left of the distribution of total interest rates, effective

[18] Eight banks, out of forty-eight, are classified as unconstrained banks. Although the average price of trades between unconstrained banks is still a very coarse estimation of the fundamental value of funds, it intends to partially control for the premium paid by constrained banks.

spreads are generally higher, but especially for the upper quartile of the distribution. For this case, relative effective spreads range between a 15% and a 267% of their midpoints, which are very striking figures for a standard financial market.

All the above suggests that when specific daily events or conditions affect the market, the level and volatility of fund prices increases, but the resulting rise in trading costs is probably exacerbated by the lack of liquidity (depth) of the market, which is importantly explained by the presence of binding credit constraints.

Table 3. Summary Daily Statistics for Total Prices and Spreads

Percentiles	Average Interest Rate of Total Trades (p.p.)	Effective Spread w.r.t. Total Interest Rate (p.p.)	Relative Effective Spread w.r.t. Total Interest Rate
Mean	**2.76**	**1.18**	**43%**
P-0.05	0.37	0.06	13%
P-0.25	0.64	0.24	26%
P-0.50	1.27	0.66	40%
P-0.75	3.38	1.76	53%
P-0.95	10.16	3.88	81%

Table 4. Summary Daily Statistics for Unconstrained Interest Rate and Spreads

Percentiles	Average Interest Rate of Unconstrained Trades (p.p.)	Effective Spread w.r.t. Unconstrained Interest Rate (p.p.)	Relative Effective Spread w.r.t. Unconstrained Interest Rate
Mean	**2.16**	**1.66**	**110%**
P-0.05	0.30	0.07	15%
P-0.25	0.50	0.33	42%
P-0.50	0.96	0.96	79%
P-0.75	2.58	2.41	136%
P-0.95	8.82	5.42	267%

Intraday patterns

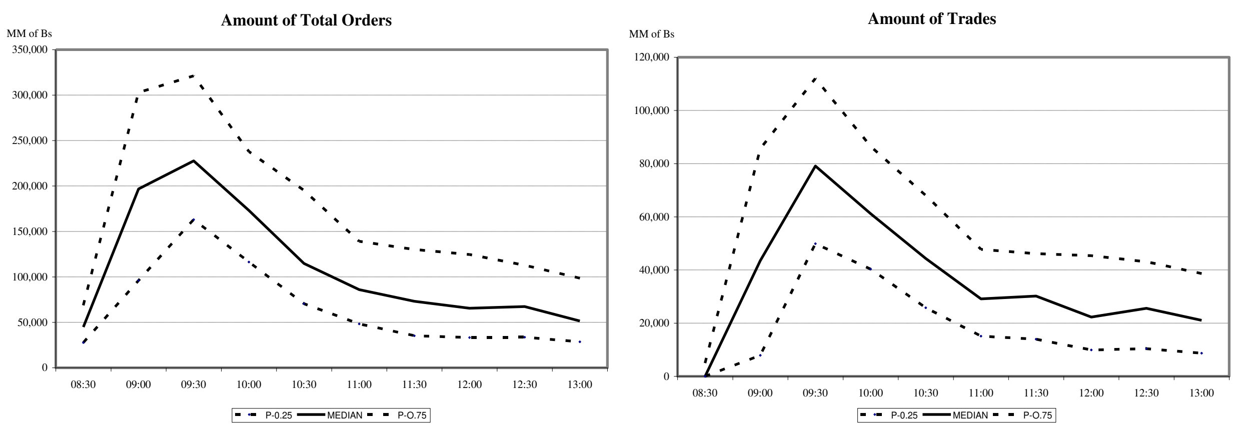
Intraday patterns of the data are typically studied to look for insightful information that could shed light about the dynamic relationship among variables throughout the trading day. In particular, the literature focuses on analyzing the intraday behavior of spreads, which convey the sum of all trading costs faced by market participants.

According to Lee et al. (1993) and most of the empirical evidence, the analysis of intraday patterns of spreads, trade volumes and depths indicates that spreads and trade volumes increase at the beginning and at the end of the trading day, while liquidity (market depth) falls during these periods. That is, spreads and trade volumes follow a U-shape along the day, while depth follows a reversed U-shape. As pointed out by Madhavan et al. (1997), some theoretical models suggests that spreads should steadily decrease over the day, as market participants learn the fundamental value of the asset from the trading process. Madhavan et al. (1997) reconcile the empirical evidence with the estimation of a structural model and suggest that the U-shape is the result of the interaction between two different types of trading costs. On one hand, the portion of the spread associated to the flow of information, which decreases over the day as the informational content of orders augments, and on the other hand, dealer costs, which increase over the day probably reflecting costs associated to inventory management.

In this section of the paper we analyze intraday patterns of variables by graphing the evolution of the different statistics along the ten half-hour intervals of the trading day. We plot the median, and bottom and top quartile of the probability distribution of each statistic for the sample of 164 trading days (see figures 1 to 6).

Differently from standard empirical evidence, volumes of total orders and trades have a maximum at the interval between 9:00 a.m. and 9:30 a.m., indicating that most of the trading activity does not occur at the opening of the market but later in the morning and drops importantly afterwards. After 11:00 a.m. activity in the market seems to decline more steadily (see figure 1).

Figure 1. Intraday Patterns of Volumes



According to the empirical evidence in standard financial markets, the depth of the order book at the best quotes tends to fall during hours of stronger trading activities (Lee et al., 1993). Although the stock of standing order is a relatively different measure, e.g. orders that are available for matching or cancellation at the end of each interval, one would expect this measure also to decline for periods of more trading[19]. Curiously, the stock of standing orders follows the same patters of orders and trades, that is, mostly accumulates during the first part of the morning, reaches a peak during at the 9:00 - 9:30 a.m. interval, and starts gradually falling afterwards (see figure 2). This behavior of standing orders indicates that the submission of orders exceeds by far the trades executed during hours of stronger activity, but does this mean that *market liquidity* is also increasing? It is important to stress that because of credit lines and collateral requests, the accumulation of standing orders could conform to the significant number of buying and selling orders that do not get to be traded exactly because of their lack of match with credit lines or collateral requests. If this were the case, the stock of standing orders would be a lousy measure of market liquidity.

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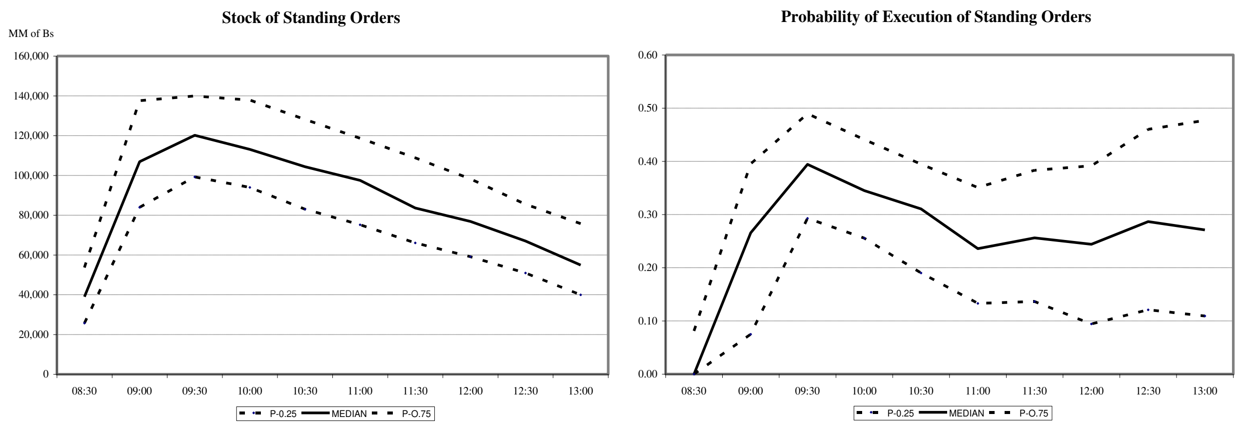
[19] Implicitly we interpret the stock of standing orders as the depth of the order book at all quotes. We base our prior on the assumption that the depth *at all quotes* should behave similarly to the depth *at the best quotes*. For a related discussion regarding the depth of an order book at different quotes, see Biais et al. (1995).

Figure 2. Intraday Patterns of the Stock and Rate of Execution of Standing Orders



The ratio of execution of standing orders also increases for the 9:00 - 9:30 a.m. interval, suggesting that during this interval (in the margin), the amount of traded funds increases more than the available standing orders (see figure 2). Relating this observation with the above discussion we could characterize, that during peak activity hours an incoming (marginal) unit of funds has more chances to be traded, but because of the important amount of standing orders submitted, an overall accumulation of such orders occurs. It is interesting to note that by the end of the trading day the ratio of execution slightly rises simultaneously with its dispersion.

The intraday pattern of the average execution time is particularly appealing since its behavior depends on the type of standing order considered (see figure 3). Average execution time of standing sell orders increases along the day, denoting that *buyer initiated trades* occurring late in the day pick sell orders that have entered in the system earlier in the morning. On the contrary, average execution time of standing buy orders decreases by the end of the day, indicating that *seller initiated trades* pick buy orders that have entered into the system more recently. These facts can be characterized as a more active participation of buyers in the second part of the morning[20].

The patterns of the execution time of bids along with the slight rising of the execution rate at the end of the day could be consistent with a peculiar strategic interaction of banks that has been reported by market analysts at the Central Bank. They describe that because of reputational considerations, some of the credit constrained banks do not like to have standing orders in the system for long time and tend to place buy orders by the end of the day, once they have learned market conditions[21]. On the other hand, knowing the practice of constrained banks and their willingness to pay a higher premium for funds towards the end of the day, some banks suppliers of funds wait to lend funds until high enough bids have been placed or the premiums implicit in their posted asks are accepted.

[20] Average cancellation times follow a similar pattern to average execution times.

[21] It seems that these credit constrained banks tend to think that long standing buy orders signal desperation for the acquisition of funds and explicitly reveal to the market the negative risk assessments made by some market participants.

Another element that could significantly affect banks behavior and activity of buy orders during the second part of the morning is government interventions[22]. The data of funds cashed in and out of the financial system shows that median withdraws (debits) mainly take place between 10:30 and 11:00 a.m., while deposits (credits) primarily occur between 12:00 and 12:30 p.m. (see figure 4 for a graphical representation of this behavior). That is, the major distribution of resources by the government is expected to occur mostly after 10:30 a.m., but sometimes it is delayed until the very end of the trading day. This implies that, when unexpected withdraws take place or expected credits do not occur early enough in the morning, buyers try to compensate the unanticipated lack of funds during the second part of the morning. According to market analysts, since the government payment schedule during this analytical period has been difficult to predict, a late demand of funds by banks with short cash positions could be perceived as a relatively regular practice[23].

Figure 3. Intraday Patterns of Execution Time of Standing Orders

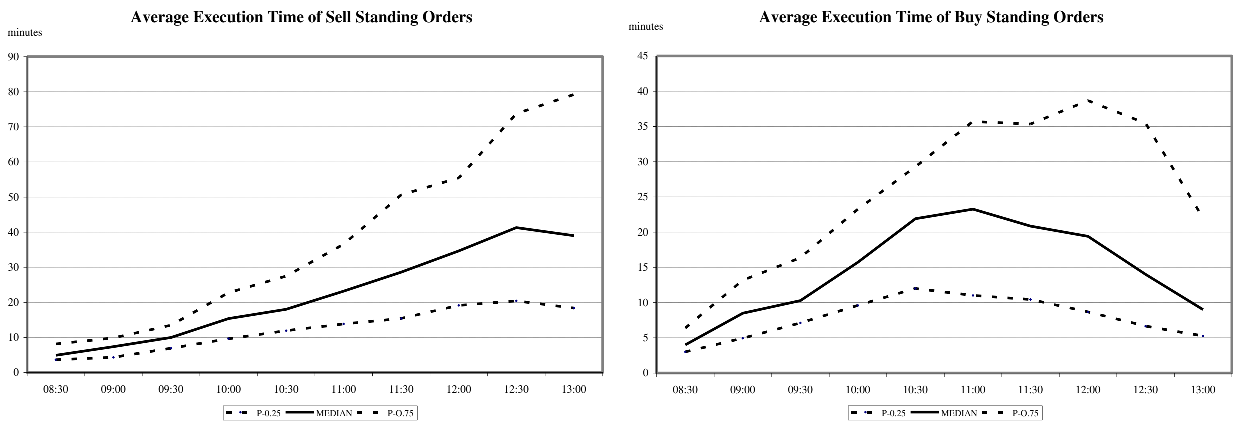
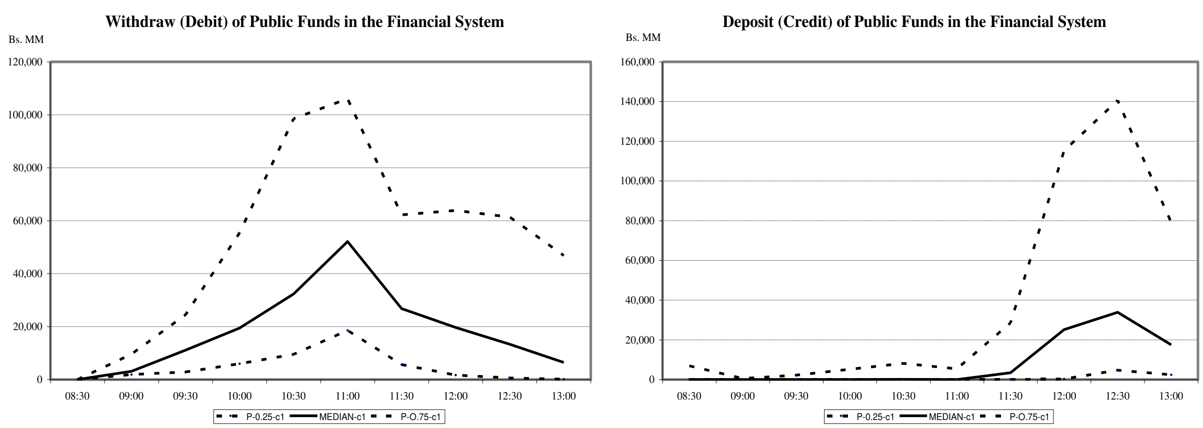


Figure 4. Intraday Patterns of Withdraws and Deposits of Public Funds in the Financial System



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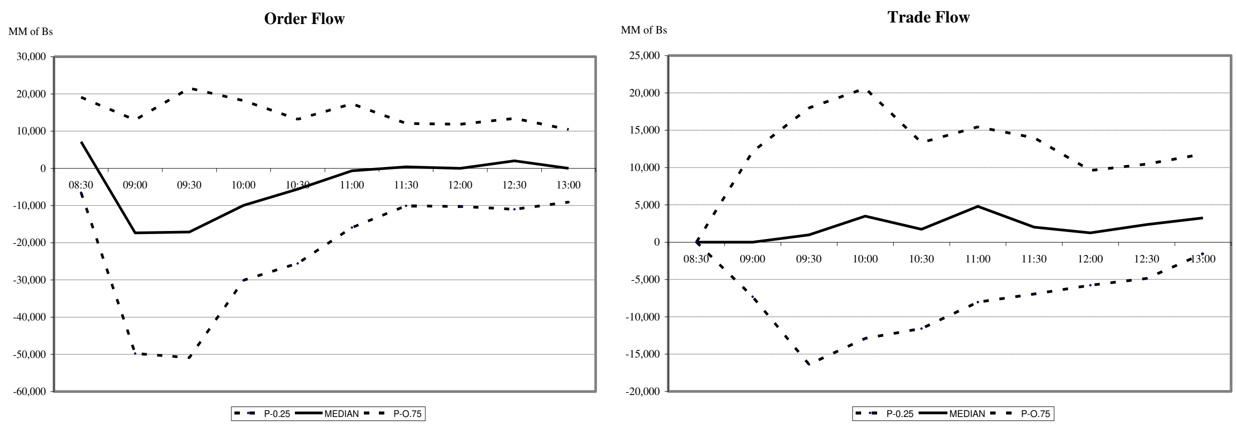
[22] We define government interventions as the amount of funds that are deposited in (credited) or withdrawn from (debited) the financial system by the National Treasury Office (ONT from the Minister of Finance), the state oil company (PDVSA) and BANDES (a second floor public development bank). Net deposits (deposits minus withdraws) capture the amount of domestic currency supplied to the financial system that is redistributed among banks through overnight operations. From a macroeconomic point of view, net deposits are a proxy for the money supply created by public sector.

[23] More on this discussion will be addressed in the description of the effective spread.

In general, order and trade flows are not studied from the point of view of intraday patterns since there are not specific conjectures regarding the way they should behave along the day[24]. Nonetheless, the peculiarities of this market might shed some light regarding the patterns of these variables. As observed in figure 5, during the first part of the morning participants tend to submit mostly sell orders, and after 9:30 a.m. this patterns starts slowly reversing throughout the rest of the trading day. During the interval between 12:00 a.m. and 12:30 a.m. a slight increase of buy orders is registered. This implies that suppliers of funds tend to reveal information about the expected price of funds earlier than demanders. However, after the peak of trading activities, more than 50% of trades are initiated by buyers of funds, indicating that fund seeking participants tend to be more active in the market by the second part of the morning, and in particular by the end of the trading day.

Figure 5. Intraday Patterns of Order and Trade Flows



The median of average interest rates of trades between unconstrained banks tend to fall along the trading day after achieving its peak at the 9:00-9:30 a.m. (see figure 6). This pattern is consistent with the prior that prices (and typically trading costs) increase during periods of stronger activity and reduce afterwards. However, the behavior of the right tail of the distribution indicates that the volatility of prices tend to rise between 10:30 a.m. and 12:30 p.m.. Contrary to the expected, the effective spread does not have a clear intraday pattern, but on average seems to slightly rise over the second part of the morning. It is noticeable that the dispersion of spreads is also higher between 10:00 a.m. and 12:30 p.m. (as in the case of average unconstrained rates).

The increasing spread during the second part of the morning could be consistent with any of the two proposed working hypotheses, the one regarding the strategic behavior of constrained banks and the other regarding the effects of government net deposits in the market. Moreover, the latter hypothesis finds indirect theoretical grounds in a paper of Naranjo and Nimalendran (2000) that claims that unexpected government interventions increase exchange rate spreads because market participants try to protect themselves against the adverse selection costs associated to the superior (asymmetric) information of the government.

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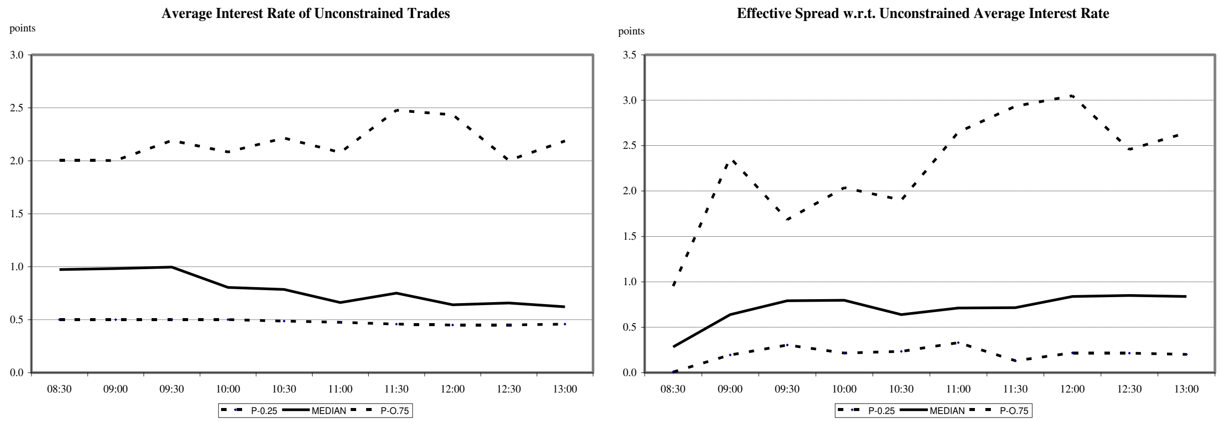
[24] An order flow is defined as the signed amount of total orders submitted at a given interval. Similarly, a trade flow refers to the signed amount of trades undertaken at a given interval. Buy (sell) orders are signed positively (negatively). Buyer initiated trades (seller initiated trades) are signed positively (negatively).

Figure 6. Intraday Patterns of Unconstrained Interest Rate and Effective Spread



However, the distribution of spreads shows an elongated right tail, especially between 10:30 a.m. and 12:30 p.m., which deserves an additional explanation. These particularly high observations for the effective spread correspond to days of strong volatility, i.e. days with a sudden and significant increase of spreads in the second part of the morning. One could argue that such volatility occurs when fiscal uncertainty hits precisely credit constrained banks, or when unfavorable market events affect these banks. If this were the case, it would be feasible to generalize that negative liquidity shocks in this market tend to translate in an overshooting of spreads because of the lack of market depth, which is partially originated by the existence of binding credit constraints.

V.- Econometric Analysis

The analysis of intraday patterns in the data allowed forming working hypotheses regarding the potential relationships among variables and the effect of credit constraints on market behavior. In this section, using a sample a 1,640 observations (intervals) we will contrast such hypotheses through the estimation of a single equation GARCH model for the effective spread. Using principal component analysis, we combine information on the effective spread, the probability of execution and execution time of standing orders, and construct two new variables of synthesized market dimensions: the market friction and activity level. The behavior of these synthetic variables is also explained by single equation GARCH models and then used in cluster analysis to characterize time intervals.

<u>Effective Spread Behavior</u>

In the literature there are numerous works that analyze the different components of spreads, or estimate the effect of trading volumes and market order flows[25]. However, the Venezuelan overnight market presents several peculiarities that are worthwhile testing, especially those related to the existence of binding credit constraints, the effect of the government's interventions

[25] See for example Glosten and Harris (1987), Lee et al. (1993), Madhavan et al. (1997) and Stoll (2000) among others.

into the financial system and the request of trading collaterals. In this sense, the focus of the estimation model presented in this section is to capture whether these particular conditions influence the effective spread of transactions. The traditional variables used to explain spread behavior, such as the order flow and trade volumes, are simply used as control variables. The relevant measure of effective spread is the one that uses the rate of unconstrained trades as midpoint, capturing among other things, the average interest rate magnitude in which constrained and unconstrained trades differ.

To assess credit restrictions, we compute two variables that proxy the magnitude of the distortions caused in the market: the difficulty of buy orders to find a match, although being competitive in price, and the relative quantity of trades that have to make price concessions to lift credit constraints. The first variable (CC1) is calculated as the proportion of buy orders, entering in a given time interval, that are willing to pay interest rates above the observed unconstrained interest rate of trades, but remain standing in the system. The second variable (CC2) indicates the proportion of constrained trades occurred in a given time interval, that end up paying interest rates above the unconstrained interest rate.

The GARCH regression for the effective spread models the mean as an autoregressive process that is also influenced by the behavior of other endogenous variables such as: the amount of trades, the order flow, and the average interest rate of unconstrained trades. This last variable is included because under the hypothesis that the market identifies the occurrence of segmented trades, there is a potential process of signaling of the fundamental value of funds from unconstrained trades to constrained ones that might affect transaction costs and premiums. We also control for the existence of deterministic intraday patterns, the change of the structure of interest rates and terms of open market operations by the Central Bank, and the sale of U.S. dollar treasury bonds to the financial system by the Minister of Finance[26].

The working hypotheses regarding the impact of the market specific characteristics on the spread are the following:

1) Credit constraints raise the mean and the variance of the effective spread since they are used as a market discrimination mechanism and the effective spread is a direct measure of trading costs.
2) Collaterals affect the effective spread, but their impact depends on the way agents use collaterals. That is to say, if collaterals are perceived as a mean to reduce the exposure to the risk of default, then their use should reduce spreads. On the contrary, if collaterals are perceived as an extension of the credit line discrimination mechanism, their use should increase spreads.
3) Unexpected government interventions increase both, the mean and variance of the effective spread. These unexpected interventions are measured either as the amount of unexpected withdraws or deposits of funds, or as the variance of the unexpected withdraws or deposits, as done in Naranjo and Nimalendran (2000).

[26] The estimation strategy consisted in obtaining a reduced model (only with significant coefficients), starting from the specification of a general autoregressive model of order 10 (the number of time intervals in a trading day). Autocorrelation of residuals and squared residuals was tested using the correlograms computed by E-views.

4) Greater levels of activity for buy orders, measured as the reduction of execution time of buy orders, might increase the volatility of the effective spread, especially when such activity is coupled with unexpected net withdraws of funds by the public sector[27].
5) Greater volatility of the rate of unconstrained trades increases effective spreads since it proxies the volatility of the fundamental value of funds in the market. This hypothesis comes from an adaptation of Foucault (1999) testable hypothesis that, a greater volatility in asset values increases spreads because agents try to protect themselves against the potential higher losses associated to the higher risk of being "picked off".

Results from the regression analysis (see table 5) show that both measures of credit constraints are significant and positively related to the effective spread. However, only the variable that measures the proportion of constrained trades (CC2) affects the variance of the spread negatively, indicating that when this type of distortion occurs, the spread is less volatile around a higher level.

An increase in the proportion of collateralized trades, specifically trades that are buyer initiated, tend to increase the level of the spread. This might reflect that, when trades are initiated by buyers of funds that are credit constrained, buyers have to both, raise the interest rate they are willing to pay and increase the amount of available collateral in order to lift the credit constraint. In this sense, a higher proportion of collateralized trades is a mere reflection of greater credit restrictions.

Unexpected deposits (unexpected withdraws) of funds by the public sector are computed as the difference between the actual amount of deposits (withdraws) and its estimated value. Estimations of the expected values are carried out using regression ARMA models and controlling for deterministic intraday patterns. The effective spread regression shows that, while deposits above their expected values cause a reduction in the spread, withdraws above their expected values explain an increase of the spread. The volatility of unexpected withdraws (and deposits) is computed on a daily basis, meaning that for a given day such volatility is constant and depends on the intraday behavior of unexpected funds. A greater volatility of both, deposits and withdraws, increases the size of the spread, but only a higher volatility of withdraws affects variance of the spread.

A net government deposit is computed as the amount of deposits minus the amount of withdraws. We cannot reject that, a larger than expected withdraw (or a smaller than expected deposit) coupled with a smaller time of execution of buy orders, augments the variance of the spread. This evidence and the above results on unexpected behavior of funds point out that government erratic behavior in the market affects positively both the mean and volatility of the spread, especially when hitting credit constraint buyers of funds.

Finally, we do find that an increase in the daily volatility of unconstrained interest rates is positively related to the mean and volatility of the spread, as predicted by the theory. Unexpected shocks to the effective spread cause an increase in its variance, independently if the shock affecting the market is positive or negative. A model to incorporate asymmetric shock effects on the spread was rejected by the data.

[27] This hypothesis is directly derived from the observation of intraday patterns of variables exposed earlier.

Table 5. Results for the GARCH Estimation of the Effective Spread

Dependent Variable: Effective Spread (in percentage points)			
Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)			
	Coefficient	**Std. Error**	**Prob.**
Mean Equation			
C	-0.40	0.022	0.000
DUM_12:00-12:30	-0.08	0.016	0.000
DUM_$ Treasury Bonds	12.82	0.718	0.000
DUM_CB Intervention day -2	1.97	0.126	0.000
DUM_CB Intervention day -1	3.46	0.285	0.000
DUM_CB Intervention day 0	5.31	1.056	0.000
DUM_CB Intervention day 1	1.56	0.251	0.000
Daily Effect of the Lagged Effective Spread	0.53*		
Daily Effect of the Volume of Trades per 1000 Billions of Bs	2.20*		
Daily Effect of the Order Flow per 1000 Billions of Bs	1.21*		
Daily Effect of the Rate of Unconstrained Trades (in percentage points)	0.12*		
Ratio of Non-Traded Competitive Buy Orders (CC1)	0.50	0.039	0.000
Ratio of Expensive Constrained Trades (CC2)	0.33	0.017	0.000
Ratio of Collateralized Buyer Initiaded Trades	0.16	0.022	0.005
Unexpected Withdraws of Public Funds (in 1000 Billions of Bs)	0.55	0.000	0.000
Unexpected Deposits of Public Funds (in 1000 Billions of Bs)	-0.23	0.000	0.000
Daily Volatility of Unexpected Withdraws (in 1000 Billions of Bs)	2.24	0.000	0.000
Daily Volatility of Unexpected Deposits (in 1000 Billions of Bs)	0.81	0.000	0.000
Daily Volatility of the Rate of Unconstrained Trades (in percentage points)	0.14	0.015	0.000
Conditional Variance Equation			
C	1.71	0.351	0.000
Squared Effective Spread Error (-1)	0.82	0.283	0.004
Ratio of Expensive Constrained Trades (CC2)	-1.10	0.223	0.000
Unexpected Net Government Deposits/Execution Time of Buy Orders(-1)	-5.68	0.001	0.000
Daily Volatility of Unexpected Withdraws (in 1000 Billions of Bs)	-6.90	0.003	0.015
Daily Volatility of the Rate of Unconstrained Trades (in percentage points)	1.73	0.403	0.000
GED PARAMETER	0.547	0.02954	0.000
R-squared	0.629		
Adjusted R-squared	0.616		
S.E. of regression	1.626		
Mean dependent var	1.814		
S.D. dependent var	2.626		
Durbin-Watson stat	1.926		

* The value corresponds to the sum of the significant coefficients for the lagged variable (from 1 up to 10 lags)

Principal Component Analysis

According to Stoll (2000), a friction can be defined as the difficulty with which a financial asset is traded. Frictions can be indirectly measured as the price concession paid for immediacy (the half spread) or as the time needed for an asset to be traded. Alternatively, one could argue that frictions in a market are inversely related to the possibility faced by a financial asset of finding a match, since the greater the friction, the larger the risk of not being picked off. This leads to think that, a broader measure of friction should take into account the price concession paid to be traded, the time waited until traded, and the probability of execution faced, since they convey different market expressions of the same phenomenon.

Bearing the above idea in mind, the principal component analysis is the natural framework to combine these three variables in a synthetic one that can be interpreted as a general measure of friction. In this section, after applying principal component analysis, we undertake GARCH regression analysis for two of the components obtained and test their response to credit constraints, collaterals and volatility of government interventions and unconstrained rates.

Results for the principal component analysis are shown in table 6. The third component, although it only explains 28% of the joint variation of variables, has the appropriate signs to be interpreted as a measure of *market friction*. In particular, for values of the effective spread above the sample average, and probabilities of execution below de sample average, this synthetic variable is positive, indicating that an incoming unit of funds has a relatively elevated trading difficulty, either in terms of the high concessions in interest rates or in terms of a low likelihood of execution[28].

Table 6. Principal Component Analysis

Variables:			
Execution Time of Standing Orders (ET)			
Probability of Execution of an Incoming Fund (PE)			
Effective Spread (ES)			
	Comp 1	**Comp 2**	**Comp 3**
Eigenvalue	1.310	0.86	0.83
Variance Proportion	0.437	0.29	0.28
Cumulative Proportion	0.437	0.72	1.00
Eigenvectors:			
Variable	**Vector 1**	**Vector 2**	**Vector 3**
ET	-0.563	0.826	0.005
PE	0.584	0.402	-0.705
ES	0.585	0.394	0.709

The first component can be also of interest from the theoretical point of view. Notice that this synthetic variable might take a positive value when in a given interval, the effective spread and the probability of execution are above their sample average, while the waiting time of orders is below its mean. This characterization of an interval corresponds to a market with high levels of

[28] The fact that the execution time of standing order does not have a significant weight in this component implies that the execution time of orders contains similar information to the one provided by the probability of execution of funds.

activity in which, the significant submission of orders and the realization of large amounts of trades presumably derive in an elevated turnover rate of standing orders, but at the expense of a significant effective spread. GARCH estimations of these variables, i.e. the market friction and activity, are presented in tables 7 and 8. The general strategy estimation is identical to the one applied to the effective spread[29].

Tabla 7. Results for the GARCH Estimation of the Measure of Market Friction

Dependent Variable: Market Friction (standarized units) Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)			
	Coefficient	**Std. Error**	**Prob.**
Mean Equation			
C	0.00	0.045	0.924
DUM_8:00-8:30	0.52	0.057	0.000
DUM_8:30-9:00	-0.12	0.060	0.043
DUM_9:00-9:30	-0.21	0.057	0.000
DUM_9:30-10:00	-0.14	0.056	0.010
DUM_11:00-11:30	0.10	0.054	0.054
DUM_11:30-12:00	0.14	0.050	0.005
DUM_12:00-12:30	-0.08	0.048	0.116
DUM_$ Treasury Bonds	2.65	0.709	0.000
DUM_CB Intervention day -1	0.60	0.285	0.036
DUM_CB Intervention day 0	1.36	0.308	0.000
Daily Effect of the Lagged Market Friction	0.54*		
Daily Effect of the Volume of Trades per 1000 Billions of Bs	0.10*		
Daily Effect of the Order Flow per 1000 Billions of Bs	-0.19*		
Daily Effect of the Rate of Unconstrained Trades (in percentage points)	0.01*		
Ratio of Non-Traded Competitive Buy Orders (CC1)	0.46	0.094	0.000
Ratio of Expensive Constrained Trades (CC2)	-0.31	0.045	0.000
Ratio of Collateralized Seller Initiaded Trades	-0.26	0.051	0.000
Ratio of Collateralized Buyer Initiaded Trades	-0.10	0.051	0.060
CC1*Absolute Unexpected Net Government Deposits (in 1000 Billions of Bs)	0.02	0.000	0.031
CC2*Absolute Unexpected Net Government Deposits (in 1000 Billions of Bs)	-0.04	0.000	0.000
Daily Volatility of the Unexpected Net Government Deposits (in 1000 Billions of Bs)	0.92	0.000	0.001
Daily Volatility of the Rate of Unconstrained Trades (in percentage points)	0.06	0.020	0.002
Conditional Variance Equation			
C	0.047	0.022	0.030
Squared Market Friction Error (-1)	0.197	0.047	0.000
Lagged Conditional Variance	0.438	0.089	0.000
Ratio of Non-Traded Competitive Buy Orders (CC1)	0.133	0.069	0.055
Daily Volatility of the Unexpected Net Government Deposits (in 1000 Billions of Bs)	0.382	0.000	0.016
Daily Volatility of the Rate of Unconstrained Trades (in percentage points)	0.069	0.018	0.000
GED PARAMETER	1.51	0.070	0.000
R-squared	0.453		
Adjusted R-squared	0.441		
S.E. of regression	0.683		
Mean dependent var	0.003		
S.D. dependent var	0.914		
Durbin-Watson stat	2.002		

* The value corresponds to the sum of the significant coefficients for the lagged variable (from 1 up to 10 lags)

[29] The model presented in each case is derived from the elimination of not significant coefficients from a general autoregressive model for the mean and variance equations. Final estimations were tested for serial autocorrelation of residuals and squared residuals in order to ensure a proper model specification.

Tabla 8. Results for the GARCH Estimation of the Measure of Market Activity

Dependent Variable: Market Activity (standarized units)			
Method: ML - ARCH (Marquardt) - Generalized error distribution (GED)			
	Coefficient	**Std. Error**	**Prob.**
Mean Equation			
C	-0.42	0.037	0.000
DUM_8:30-9:00	0.40	0.054	0.000
DUM_9:00-9:30	0.32	0.054	0.000
DUM_11:00-11:30	0.10	0.048	0.043
DUM_$ Treasury Bonds	2.31	0.386	0.000
DUM_CB Intervention day -1	0.76	0.249	0.002
DUM_CB Intervention day 0	1.09	0.267	0.000
DUM_CB Intervention day 1	0.57	0.293	0.051
Daily Effect of the Lagged Market Activity	0.46*		
Daily Effect of the Order Flow per 1000 Billions of Bs	7.90*		
Daily Effect of the Rate of Unconstrained Trades (in percentage points)	0.03*		
Ratio of Non-Traded Competitive Buy Orders (CC1)	-0.28	0.077	0.000
Ratio of Expensive Constrained Trades (CC2)	0.31	0.047	0.000
Ratio of Collateralized Seller Initiaded Trades	0.16	0.054	0.002
Ratio of Collateralized Buyer Initiaded Trades	0.18	0.057	0.001
CC2*Absolute Unexpected Net Government Deposits (in 1000 Billions of Bs)	0.04	0.000	0.000
Daily Volatility of the Rate of Unconstrained Trades (in percentage points)	0.08	0.020	0.000
Conditional Variance Equation			
C	0.341	0.029	0.000
Squared Market Activity Error (-1)	0.239	0.056	0.000
Ratio of Non-Traded Competitive Buy Orders (CC1)	-0.147	0.079	0.064
CC2*Absolute Unexpected Net Government Deposits (in 1000 Billions of Bs)	0.015	0.000	0.091
Daily Volatility of the Rate of Unconstrained Trades (in percentage points)	0.079	0.025	0.001
GED PARAMETER	1.182	0.047	0.000
R-squared	0.517		
Adjusted R-squared	0.507		
S.E. of regression	0.760		
Mean dependent var	0.091		
S.D. dependent var	1.082		
Durbin-Watson stat	1.948		

* The value corresponds to the sum of the significant coefficients for the lagged variable (from 1 up to 10 lags)

The estimation of the market friction measure (table 7) indicates that the second distortion associated to credit constraints (CC2, i.e. the proportion trades occurring at elevated interest rate), although increases the effective spread in the market, causes a net reduction in the levels of market friction. This is the case because the rise in the probability of execution of funds more than compensates the increase in the spread. The contrary takes place in relation to the first type of distortion (CC1, i.e. the proportion of non traded competitive buy orders). That is, when the market does not allow the exchange of funds in spite of a considerable willingness to pay by demanders of funds, the level and variance of the market friction measure grows importantly, since it causes both an increase in the effective spread and a reduction in the likelihood of exchanges.

A similar result to the measure CC2 is obtained for the request of collateral in the exchange of funds: although collaterals tend to increase the spread, its net effect is that of reducing frictions because of its favorable impact on the probability of execution of funds. A higher daily volatility in unexpected net government deposits and average price of unconstrained trades raise both, the mean and volatility of market frictions, indicating not only a detrimental impact on spreads, but also on the probability of execution of funds.

Results on the estimation model for market activity (table 8) are consistent with the intuition provided in prior results. Credit restrictions expressed in the inability of competitive buy orders to find a match (CC1) reduce the variance of market activity, but around a considerably lower level. On the contrary, credit restrictions expressed in the consummation of expensive trades and request of collaterals induce greater market activity, because of the reduction in the waiting time of orders and the increase in their probability of matching.

When the market experiences a boost in the volatility of the unconstrained trades rate, the mean of market activity increases, suggesting that efficiency gains are probably explained by a considerable reduction in the waiting time of orders. This could be rationalized in a context in which noise signals from the unconstrained segment of the market will tend to raise the turnover of standing orders in the market, but at the expense of higher spreads (and a mixed effect on the observed likelihood of matching).

It is interesting to note that although the variable that measures order flow in the market has been significant to explain effective spread and market friction, it has a particularly high positive coefficient in the market activity estimation model. This might indicate that bigger volumes of buy orders possibly induce an important reduction in the waiting time of standing orders, and especially buy orders, which end up finding a match in the market but at the cost of a higher interest rate.

<u>Interval Characterization</u>

Based on the values of the synthetic variables, friction and activity levels, we can characterize time intervals according to the predominant behavior of these variables. We characterize intervals according to the frequency of cases (days) that belong to each of the following categories: positive activity and friction; negative activity and positive friction; negative activity and negative friction; and positive activity and negative friction. Results are shown in table 9.

Roughly speaking, we observe that the first interval might be characterized as of low activity, but high friction. From the second interval up to the middle morning interval, i.e. 10:00 – 10:30 a.m. interval, levels of activity rise and friction in the market drop to low (negative) levels. From the market efficiency point of view, these intervals represent the best hours of the trading day for market participants. Afterwards, characterization of intervals becomes harder, since observations are more uniformly spread across cases. Nonetheless, one could argue that generally activity levels in the market drop, but trading costs become positive. This is consistent with the intuitive idea already pointed that, in the second part of the morning in spite of the lower volumes of exchanges and orders, market activity tend to be motorized by a segment of the market (buyers of funds), which tend to suffer more heavily the distortions associated to credit restrictions.

Table 9. Frequency of Intervals according to Market Activity and Friction

	8:00 - 8:30	8:30 - 9:00	9:00 - 9:30	9:30 - 10:00	10:00 - 10:30
Activity>0, Friction>0	16%	23%	12%	16%	15%
Activity<0, Friction>0	70%	26%	11%	11%	23%
Activity<0, Friction<0	9%	6%	9%	21%	27%
Activity>0, Friction<0	5%	45%	68%	52%	35%

	10:30 - 11:00	11:00 - 11:30	11:30 - 12:00	12:00 - 12:30	12:30 - 1:00	Total
Activity>0, Friction>0	21%	19%	19%	15%	15%	**17%**
Activity<0, Friction>0	36%	30%	36%	29%	35%	**31%**
Activity<0, Friction<0	24%	26%	24%	29%	22%	**20%**
Activity>0, Friction<0	18%	24%	21%	28%	28%	**32%**

VI.- Policy Recommendations

A summary of the results discussed in the econometric analysis section are shown below in table 10. It can be argued that in terms of policy prescriptions, the distortions expressed as non-traded competitive buy orders are more detrimental to market performance than the distortions expressed as more expensive or collateralized trades. This is the case because, although all these distortions increase effective spreads for credit constraint participants, the second ones reduce other forms of market frictions, i.e. the probability of not finding a match or the waiting time for execution. This interpretation of the results suggests that improving market performance necessarily involves the elimination of credit lines and the introduction of an alternative mechanism for reducing the exposure to the risk of a loan default. One way to do so is by promoting the use of collaterals for all transactions. If collaterals are used universally, the market default risk disappears and interest rate premiums from market segmentation should tend to zero. As a byproduct of this policy, the market of collaterals represented by Venezuelan Treasury Bonds, might also suffer a positive externality in terms of increasing market depth, the turnover rate of bonds and improving efficiency in the price formation process.

Results obtained in terms of unexpected government interventions to the financial system have differentiated effects on each of the dimensions of market performance. However, it could be generalized that the impacts on the mean and variance of the variables are mostly related to the existence of market constraints. That is, unexpected behavior of government funds (measured as levels or volatility) could be harmful in terms of the effective spread and market friction, especially when these withdraws or deposits take place in credit constraint institutions. Theoretically, since unexpected government interventions increase trading costs as a result of asymmetric information, it would be desirable to reduce the market participants' uncertainty by simply making the schedule of public payments more predictable.

A very particular outcome for this market indicates that the volatility of average interest rates of unconstrained trades is significant in explaining the mean and variance of all of the dimensions of market performance. In particular, it is interesting that the conditional variance of the effective spread, market friction and activity grow in the presence of more volatile unconstrained trade prices. Since information coming from the unconstrained segment of the market directly translates in noisy market performance, it might be the case that unconstrained participants are perceived to have superior information. Since this process is rooted on the existence of at least two market segments, enforcing the homogeneity of participants and anonymity should reduce such phenomenon.

Table 10. Summary of the Effects on Market Performance

	EFFECTIVE SPREAD	MARKET FRICTION	MARKET ACTIVITY
	Mean Effect		
Ratio of Non-Traded Competitive Buy Orders (CC1)	positive	positive	negative
Ratio of Expensive Constrained Trades (CC2)	positive	negative	positive
Ratio of Collateralized Trades	positive	negative	positive
Unexpected Government Interventions	withdrawns>0 deposits<0	net deposits*CC1>0 net deposits*CC2<0	net deposits*CC2>0
Daily Volatility of the Unexpected Government Interventions	withdrawns & deposits>0	net deposits>0	--
Daily Volatility of the Rate of Unconstrained Trades	positive	positive	positive
	Conditional Variance Effect		
Ratio of Non-Traded Competitive Buy Orders (CC1)	--	positive	negative
Ratio of Expensive Constrained Trades (CC2)	negative	--	with net deposits>0
Daily Volatility of the Unexpected Government Interventions	withdrawns<0	net deposits>0	--
Daily Volatility of the Rate of Unconstrained Trades	positive	positive	positive

VII.- Conclusions

Because the overnight fund market can be defined as the starting point of the transmission mechanism of monetary policy, it is important that its rate contains more signals related to the state of the fundamentals of the money market and less noise coming from existing distortions or frictions that increase trading costs.

The existence of credit lines in this market not only reduces the amount of potential trades in the market (diminishes market depth) but also translates effectively in market discriminating practices, which have expressed in short run interest rate distortions and misled market performance evaluation.

Results show that the greater the distortions associated to the existence of credit constraints, the bigger the trading costs in the form of higher effective spreads. This finding has two immediate consequences: the first one is that credit constraints distort the observed levels of interest rate in the market, which introduces noise to the price signal extraction undertaken by market participants. The second consequence is that there are bigger rents appropriated by those market participants that are able to intermediate funds between the constraint segment of the market and the unconstrained one.

The application of principal component analysis to combine information on the effective spread, the probability of execution and waiting time for orders into two new variables, denominated *friction* and *activity* levels, allows analyzing market performance from a broader perspective. This new analysis leads to conclude that distortions associated to observing non-traded competitive buy orders are more detrimental to market performance than the distortions expressed as more expensive or collateralized trades. This is the case because, although all these distortions increase effective spreads and therefore trading costs for credit constraint participants, the second ones reduce other forms of market frictions, i.e. the probability of not finding a match or the waiting time for execution. This interpretation of the results suggests that improving market performance necessarily involves the elimination of credit lines and the introduction of an alternative mechanism for reducing the exposure to the risk of a loan default.

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