A Systemic Measure of Liquidity Risk

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Abstract

This paper analyzes systemic liquidity risk by assessing the behavior of aggregate banking variables and policies related to the management of liquid assets. The basic premise is that liquidity is not only related to the ability to meet interbank debt obligations, but also the availability of sufficient liquid assets to cover other short-term liabilities, such as those arising from commercial banks interaction with the central bank. To measure liquidity risk, we use the contingent claims approach of Merton (1974) and Gray, and Malone (2008). Data produced by the model (probability of default) explains and improves prediction of the amounts and interest rates negotiated in the interbank market. In the case of Venezuela, given the importance of fiscal expenditure in the

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primary creation of money, fiscally induced monetary expansion tends to reduce the likelihood of illiquidity events. Meanwhile, an increase in reserve requirements increases the probability of default by raising banks' short-term liabilities.

Keywords: contingent asset analysis, interbank market, systemic risk, macroprudential regulation.

JEL classification: G00, G13, G18.

1. INTRODUCTION

This paper aims to contribute to measuring systemic liquidity risk and understanding the factors influencing it.

Liquidity risk for an individual bank can be understood as the likelihood of it not being able to meet its payment obligations or cash flows with other banks as described by Cao (2015).[1] The literature typically describes systemic risk associated with liquidity issues as the contagion that takes place among institutions in the system after closely interconnected banks (or systemically important) report default problems. Given that network models allow analysts to understand to what degree a single event might cause domino type effects, they have become key to the analysis of systemic liquidity risk. A summary of this type of studies can be found in Upper (2011). Meanwhile, Smaga (2014), and Drehmann and Tarashev (2011) show that these estimations of individual risk contagion represent a bottom-up measure of systemic risk.

However, given the complexity of the factors contributing to systemic risk, Smaga (2014) also shows how there is still no consensus regarding its definition. This has opened up the possibility for measuring systemic risk from a bottom-up point of view, i.e., associating systemic risk to aggregate variables or

[1] This definition refers to the illiquid funds event, which differs from market illiquidity. The latter can be understood as the risk of an institution not being able to buy and sell assets immediately without forcing changes in their prices due to a lack of depth or distortions in the market.

macroeconomic factors, which can reveal the status of the financial system as a whole. This perspective is important if we consider the existence of exogenous factors that can affect the whole banking system but might remain invisible when analysis focuses on individual institutions just as pointed out in Elsinger et al. (2002). Moreover, Brunnermeier et al. (2009) argue that to properly regulate systemic risk it is necessary to abandon the predominant view which asserts that a system is sound if all the institutions within it are sound (macroprudential approach). In other words, it is essential to adopt a macroprudential approach that includes important macroeconomic data to analyze the stability of the system as a whole.

This paper estimates systemic liquidity risk based on the behavior of aggregate banking variables and policies related to banks' liquidity management. The basic premise is that liquidity is not only related to the ability to meet interbank debt obligations, but also the availability of sufficient liquid assets to cover other short-term liabilities, such as those arising from commercial bank interactions with the central bank. To pay any of these obligations banks typically reduce their liquid assets, be they those that are available immediately (such as cash) or less liquid assets that must first be sold in the market (such as Treasury bills). Given that the market value of less liquid assets fluctuates they are subject to possible losses. Hence, total liquid assets–the sum of highly liquid and less liquid assets–can be treated as a stochastic variable. Under this context, systemic liquidity risk arises due to the potential losses involved in market transactions that might jeopardize the fulfillment of short-term liabilities. This risk becomes greater as the need to transform less liquid assets into liquid ones in the market increases. Given that this idea of liquidity risk is systemic, it is also crucial to include the central bank's impact on commercial bank funds.

To measure the risks associated with changes in liquidity we apply the contingent claims approach originally developed for firms by Merton (1974) and applied to different microfinancial sectors by Gray and Malone (2008). This methodology rearranges the assets of an entity to define the probability of default as the likelihood that the (stochastic) value of its assets falls below that of the highest priority debt (or senior debt). The spread between the value of the assets and the value of the senior debt is named residual liability (or junior debt). Given that the value of assets is not clearly visible in this methodology the residual liabilities item is of utmost importance. In our study of the liquidity problem, we define residual liabilities as capital stocks and liquid asset flows that are available, such as cash and holdings in central bank policy instruments. We also include expected flows from new deposits related to the primary money creation. One characteristic of available liquid assets is that they can be immediately decumulated to meet short-term senior debt obligations if there are losses (expected or unexpected) in other assets. This definition of residual liabilities is in line with the fact that, during periods of liquidity shortage (when there are low levels of cash), adverse market conditions exist for selling assets and, therefore, the expected amount of total liquid assets tends to be low. On the other hand, short-term senior debt includes payments required by the central bank (such as legal capital requirements and disbursements for currency sales or other loans). We also consider withdrawals from the banking system as short-term liabilities.

The interpretation of default probability proposed here is that, if the desired accumulation of liquid assets (such as cash) exceeds the flow of new funds entering the banking system it increases the likelihood of an event that interrupts –to some extent– payments between banks or with the central bank. This likelihood reflects the risks (potential losses) arising from a generalized translation of less liquid assets into cash.

In the strict sense, default probability calculated in aggregate terms, more than an objective measure of risk, can be considered an indicator of overall banking system vulnerability, as suggested by Gapen et al. (2004) and Kozak et al. (2006). This is because there is no clear system-wide definition of a default event. Nevertheless, probability as a systemic risk concept can be useful for understanding the accumulation (observed) of highly liquid assets by the banking system as a whole. Such decisions are also linked to conditions seen in the interbank market, where banks seek to satisfy their immediate liquidity needs. We attempt to explain these ideas based on a stylized optimization problem that uses estimated default probability as an input for banks' decisions.

Our application to the case of Venezuela shows that the probability of default obtained from the model allows for explaining the aggregate amount of funds traded in the interbank market as well as their average agreed interest rate. In particular, a higher probability of default tends to signal larger transaction amounts due to the central bank's increased need for funds. Meanwhile, a higher probability of default explains higher interest rates, possibly reflecting larger risk premiums associated with the behavior of systemic liquidity. Furthermore, the mean squared error prediction for amounts and interest rate improves considerably when the results are included in the model.

According to the model presented in this paper, the vulnerability associated to changes in liquidity can be influenced to varying degrees by monetary, exchange rate and fiscal policy decisions, depending on their interactions inside a country's institutional framework. For Venezuela's case, given the importance of fiscal management in the creation of new money, we show that greater fiscal influence in the money supply tends to reduce the likelihood of illiquidity events. Conversely, when the central bank intervenes to a greater extent by selling currencies to the economy, illiquidity events tend to become more likely. Moreover, an increase in reserve requirements raises the probability of default by increasing banks' short-term obligations.

The paper is divided into four sections. The first corresponds to the introduction. The second describes the application of the contingent claims approach to liquidity management, interprets the probability of default obtained and outlines a stylized model to understand linkages with the interbank market. The third shows the application to the case of Venezuela, and the coherence and robustness of the outcomes, as well as counterfactual exercises that allow for understanding how changes in major policies (fiscal and exchange rate) would affect systemic liquidity risk. The fourth section presents some final remarks.

2. LIQUIDITY RISK

Assets and liabilities can be classified according to their planned maturity date. These classifications can provide central banks with an estimate of their maturity mismatch. However, referring to liquidity management means comparisons are not necessarily between total assets and liabilities, but rather between liquid assets and payment obligations with those liquid assets. Moreover, liquidity shortages can arise as a result of asset reallocations stemming from attempts to transform less liquid assets into more liquid ones. As a consequence, the ideas of senior and junior debt as traditionally applied in the liabilities or contingent claims approach (CCA) need to be reconsidered. Table 1 shows bank balance sheets classified according to the standard CCA. We will now analyze how the CCA should be applied to the liquidity management problem and how said problem can be framed. Annex A describes the mathematical approach related to implementing the contingent claims methodology.

Table 1

BANK BALANCE SHEET CLASSIFICATION ACCORDING TO THE STANDARD CONTINGENT CLAIMS APPROACH

Assets	*Liabilities*
Unobservable	*Senior debt:* Short-term deposits + a fraction of long-term deposits *Junior debt:* Capital at market value

Liquidity management tackles the problem of having sufficient liquid assets ready immediately to meet short-term obligations. There are two items that should be considered when applying the contingent claims approach to an analysis of liquidity. First, the amount of liquid assets is somewhat uncertain given that they are not clearly observable in the short term. Second, liquidity management needs to include the behavior of expected flows, which are related to changes in the central bank's balance sheet (monetary base) but are unobservable in commercial bank balance sheets.

Asset uncertainty. It is possible to think of two types of liquid assets. One part of them is readily available and clearly observable: Refers to cash holdings at banks, and all deposits at the central bank (such as reserves more than legal requirements and certificates of deposit). The other part is represented by assets that can be transformed into cash via market transactions, for instance, securities negotiated in secondary markets. The latter share is precisely the part of liquid assets whose value is uncertain. Estimation of said assets is generally subject to market conditions. Thus, total liquid assets can be treated as a stochastic variable just as in the standard contingent claims approach because of possible market losses (or gains).

Expected monetary base flows. Given that we try to study the problem of liquidity management from a systemic point of view, it is important to take into account the role played by the central bank. For instance, banks' positions in monetary policy instruments reflect funds lent by or requested from the central bank in the past. Although these balances have an impact on systemic liquidity, they are already considered in bank balance sheets. Expected inflows and outflows in a banking system are unobservable on bank balance sheets. These flows of funds (in domestic currency) take place through the primary money creation (changes in the monetary base) and should also be considered when assessing systemic liquidity. That is to say, banks' real liquidity is increased or reduced by the creation or destruction of domestic currency. These changes in monetary base typically refer to exchange rate interventions and money creation produced by disbursements or revenues of other organizations with accounts at the central bank, such as the central government. Our analysis only takes into account monetary base flows that are not related to specific monetary policy actions taken by the central bank to offset other flows. In other words, we only want to consider money creation stemming from currency flows or other entities other than the central bank. This is the reason why we assume banks' decisions to hold larger or smaller balances in monetary policy instruments will depend on the evaluation of systemic liquidity risk. Hence, changes in the amount of the monetary policy instrument cannot be used as an input for estimating said risk. This point is related to the description in Section 2.3.

2.1 Applying the Contingent Claims Approach to Liquidity Management

In the standard CCA, residual liabilities are modeled as a European call option because their value increases as the estimated value of assets with respect to the value of a senior debt rises. Just as in most applications presented in Gray and Malone (2008), the value of residual liabilities and senior debt are considered observable, while the implicit amount of assets has to be estimated.

In the liquidity management problem, we classify as residual or junior debt all cash and liquid flows banks can use immediately to meet short-term senior obligations when there are reductions (expected or unexpected) in other assets. The higher these residual liabilities, the greater the total liquid assets estimated by the model, given a fixed number of senior claims. This implies that the stochastic properties of residual liabilities are transferred to estimated total liquid assets. This idea is also consistent with the fact that during periods of liquidity shortage cash levels are low and there are adverse market conditions for selling assets. Hence, inadequate liquidity is associated with low expected amounts of total liquid assets.

What, therefore, are the specific components of those liquid residual liabilities and major obligations for liquidity management? Table 2 shows the balances and flows that should be considered.

One important component of residual debt is the balance of unlent cash deposits. Banks hold such cash deposits in their vaults or as excess reserves (to legal capital requirements) at the central bank. These two items represent the real amount of cash accumulated in the past and, potentially, an important buffer for unexpected increases in senior claims. Nonetheless, this cash inventory should be adjusted by the amount of funds in the interbank market in order to be able to estimate the part of reserves that are not committed during liquidity shocks. That is to say if interruptions occur in interbank debt payments by one or more institutions, only the net cash of loaned amounts can be considered as actually available. Meanwhile, subtracting the total amount of loans due also seeks to control for excessive cash accumulation during liquidity crises. For instance, during periods of liquidity shortage, but substantial banking activity, although cash reserves might seem high, unlent cash reserves might reflect systemic liquidity conditions more appropriately.

As for the monetary authority, the balance of funds loaned to the central bank, i.e., the balance of buffer instruments, is considered a residual liability because it is generally available for banks to use. On the other hand, the balance of funds borrowed from the central bank are considered a senior debt because they must be repaid to the monetary authority in the short-term.[2] Likewise, flows stemming from the primary money creation (changes in the sources of the monetary base) can be considered residual liabilities or senior claims, depending on whether they lead to newly available funds for banks or whether they represent payments to the central bank (or an entity with an account at the central bank).

[2] If there are different maturities for the instruments, only the portion of the balance related to the shortest maturities (or most important) should be considered.

Table 2

CLASSIFICATION OF SHORT-TERM LIABILITIES FOR LIQUIDITY MANAGEMENT

Total liquid assets	*Total liquid liabilities*
Unobservable	*Senior debt, D:* Balance + interest on monetary policy injection instruments Expected destruction of money in local currency (contraction of monetary base) Expected change in reserve requirements Interest on debt in the interbank market Expected cash withdrawals *Junior debt, E:* Balance + interest on monetary policy absorption instruments Expected money creation in domestic currency (expansion of monetary base) The balance of unlent cash reserves[1]

[1] Balance of unlent cash reserves = cash in the banks + excess reserves at the central bank − amount (past) of funds negotiated in the interbank market.

Concerning senior claims in liquidity management, interest payments owed in the interbank market represent additional funds the banking system needs to generate to keep the market functioning. Expected changes in legal or required reserves are considered liabilities because, despite representing assets for the banks, the central bank does not allow them to be used. This means that an increase in reserve requirements implies disbursements by banks that can increase the need for liquidity in the short-term, even if those reserves can be used as a contingency during liquidity shortages.

Another component of senior debt is the number of expected withdrawals from the banking system. This amount can be estimated by net cheque clearing and electronic transactions, which represent the amount of deposits leaving the system and immediately available deposits, respectively.

2.2 Interpreting Probability of Default

Due to the fact that the CCA is based on a reclassification of assets and liabilities, we can rewrite a simplified version of Table 2 as follows:

1 $$A_t - D_t = E_t,$$

2 $$A_t - E(\Delta RR_t) - E(R_t) - i^O_{t-1}Q^O_{t-1} = E(FBM_t) + BC^{abs}_{t-1} + \\ + efectivo_{t-1} - Q^O_{(t-1)},$$

where A, D and E are liquid assets, senior claims and residual debt, respectively. RR, R, and FBM refer to reserve requirements, withdrawals and monetary base flows, respectively. BC^{abs} and *cash* are credits (net absorption) at the central bank and cash, respectively, and represent available balances (highly liquid). Q^O and i^O are the amounts negotiated and average interest rate in the interbank market (overnight). For any variable X, $\Delta X_t = X_t - X_{t-1}$. Expectations regarding the flows occurring in time t are formed with information available at $t-1$.

One direct interpretation of the probability of default *(PrD)* can be obtained indifferently from each one of the two sides of Equation 2:

3 $$PrD = Pr(A_t < D_t) = Pr\left[A_t < E(\Delta RR_t) + E(R_t) + i^O_{t-1}Q^O_{t-1}\right],$$

4 $$PrD = Pr(E_t < 0) = Pr\left[E(FBM_t) + BC^{abs}_{t-1} + efectivo_{t-1} < Q^O_{t-1}\right].$$

Equation 3 suggests that if the total value of liquid assets is lower than senior debt flows; then the probability of systemic default would increase. Equation 4, on the other hand, depicts that if the balance of available assets (BC^{abs} and *cash*) plus new funds is lower than the last amount negotiated in the interbank market, the probability of default will increase.

Another interpretation of default probability can be obtained by subtracting *desired* (not actual) amounts of cash and the central bank absorption commercial banks would wish to maintain at time *t*. Equation 2 can be rewritten as follows:

5
$$\begin{aligned}&A_t - E(\Delta RR_t) - E(R_t) - i_{t-1}^{O} Q_{t-1}^{O} - efectivo_t - BC_t^{abs} = \\ &= E(FBM_t) - \Delta BC_t^{abs} - \Delta efectivo_t - Q_{t-1}^{O}.\end{aligned}$$

In this case the probability of default can be written as:

6
$$\begin{aligned}PrD &= Pr(A_t < D_t) \\ &= Pr\left[A_t - E(\Delta RR_t) - E(R_t) - i_{t-1}^{O} Q_{t-1}^{O} < efectivo_t + BC_t^{abs}\right],\end{aligned}$$

7
$$PrD = Pr(E_t < 0) = Pr\left[E(FBM_t) - Q_{t-1}^{O} < \Delta BC_t^{abs} + \Delta efectivo_t\right].$$

Equation 6 suggests that if the remaining portion of total liquid assets–once debt flows have been paid–is lower than the desired amount of available assets (BC^{abs} and *cash*), then the probability of systemic default increases. This is due to the fact that reaching the desired amount of highly liquid assets would imply transforming less liquid assets into cash by selling them in the market. At the aggregate level, such conversions would tend to diminish the overall expected value of assets and, therefore, would increase the likelihood of the assets being insufficient to cover obligations.

Meanwhile, Equation 7 suggests that if banks' new fund flows (money creation) are insufficient with respect to interbank debts, cash or absorption should be reduced by at least the same amount in order to prevent an increase in the probability of default. In other words, if the desired accumulation of cash in highly liquid instruments exceeds the flow of new funds in the system, the probability of default increases due to risks stemming from a generalized transformation of less liquid assets into cash.

Assuming the existence of *desired amounts* of available assets is just one tool to obtain economic insight into an increase in aggregate probability of default. However, in the statistical model, probability of default is given by implied asset volatility and their distance to senior claims. In the strict sense, therefore, said probability does not depend on the desired amounts of available assets.

That said, can default probability be linked to aggregate accumulation (observed) of available (highly liquid) assets? Alternatively, can default probability be related to market variables, such as the amounts and rates negotiated in the interbank market? Below we propose a highly stylized model to answer these questions.

2.3 Stylized Model for Modelling Available Assets

Here we present an optimization problem for a period when aggregate amounts of available liquid assets (cash and central bank absorption) are determined based on a given liquidity risk. That is to say, given the (past) information on assets and on expected flows, a probability for systemic default is generated. This probability, in turn, defines two possible states of nature: one state with some degree of interruption to banks' payments (with other banks or the central bank), and another one of normal asset and interbank market functioning. In both states, the costs of holding available liquid assets are different. The total expected costs *E(CT),* for both states of nature, related to holding these liquid assets are:

8
$$\begin{aligned} E(CT_t) = PrD_t\left(LGD_t - \Delta efectivo_t - \Delta BC_t^{abs}\right) + \\ + \left(1 + PrD_t\right)\left[i_t^O efectivo_t + \left(i_t^O - i_t^{BC}\right) BC_t^{abs}\right], \end{aligned}$$

where LDG is losses in assets traded in the markets in the event of an interruption to payments, and i^{BC} is the interest rate set by the central bank for its absorption instrument. Equation 8 reveals that, in the case of interruption of payments, expected losses include losses in less liquid assets (stochastic) and losses related to the reduction of available assets. The greater the accumulation of available liquid assets, the lower are the total losses associated to the payment interruption event. In the normal market functioning state, the observable costs of holding liquid assets are the opportunity costs with respect to the interbank rate. The aggregate optimization problem consists of minimizing the total expected cost when choosing the amount of cash and BC^{abs} in t, subject to the aggregate restriction: $\Delta efectivo_t + \Delta BC_t^{abs} \leq FBM$, which denotes that the actual accumulation of both available assets cannot exceed inflows of new funds to the system. This is due to the fact that once cash has been redistributed through the interbank market or the sale of less liquid assets by some banks, only money creation can translate into new available liquid assets.

We also assume that there is an implied positive function between i^O and the aggregate amount of cash, $i^O = f(cash)$. If $f'(cash) > 0$, it means that high aggregate levels of cash are associated with high interbank interest rates because banks, individually, try to increase their holdings of cash through the interbank market. That is to say, the behavior of the market reflects to a greater extent the behavior of those demanding funds. If $f'(cash) < 0$, it implies that high aggregate levels of cash are consistent with lower interest rates in the interbank market given that banks try to channel said cash as fund supply. In this case, the behavior of fund suppliers prevails to explain the interbank interest rate. We also assume that i^{BC} is related to BC^{abs}, i.e., for $i^{BC} = f\left(BC^{abs}\right)$, where $f'(BC) \lesseqgtr 0$.[3]

[3] Assumptions $f'(cash) > 0$ and $f'(BC) < 0$, or alternatively $f'(cash) < 0$ and $f'(cash) < 0$ satisfy both second order conditions for minimizing, if $f''(cash) = f''(BC) = 0$.

Because *PrD* and *LGD* in t are calculated with past information, the first order conditions for the optimization problem are given by:

$$i_t^O + f'(cash)\, cash_t = \frac{PrD}{1-PrD}, \tag{9}$$

$$i_t^O - i_t^{CB} + f'(BC)\, BC_t^{abs} = \frac{PrD}{1-PrD}. \tag{10}$$

Equality Equation 9 shows that for $f'(cash) > 0$, a higher (relative) probability of systemic default implies observing a greater demand for cash and, consequently, higher interbank interest rates. In this case, because banks turn to the interbank market in an attempt to satisfy their demand for cash, interbank lenders would also be positively related to the probability of default.[4] Likewise, condition 10 shows that a higher probability of default implies a greater demand for the instrument, if $f'(BC) < 0.$ In this case, greater demand for the instrument would lead to a reduction in the central bank's interest rate. Higher demand for cash, as well as for absorption instruments, could only materialize at the aggregate level if new funds enter the system, i.e., if $FBM > 0,$ just as shown by the restriction of the optimization problem. Otherwise, an increase in the probability of default is only associated with upward movements in the interbank interest rate.

[4] Given the constant probability of default, the relation between aggregate cash and the interbank rate is negative, i.e., an increase in the interbank rate reduces the demand for cash.

3. APPLICATION TO VENEZUELA

3.1 Estimating Probability of Default

The application we perform for Venezuela uses weekly data from between January 2004 and December 2014. This selection was made in order to deal with a homogeneous period with regards to the exchange rate regime because Venezuela implemented exchange controls in 2003.[5]

In Venezuela's case, due to the institutional arrangement of public policies, monetary base creation and destruction flows are substantially conditioned by fiscal and exchange rate actions related to oil revenues. That is to say, the public sector (tax authorities and the oil industry) is responsible for the amount of money entering circulation in the economy. On the one hand, the oil industry converts a significant share of oil revenues into domestic currency by selling most of its foreign currency to the central bank. On the other, the tax authority, through domestic spending financed with resources from the oil business, channels the money back into the economy as transfers or in exchange for goods and services. The central bank, by becoming the main holder of foreign currency, reduces the amount of money circulating in the economy each time it agrees with private banks the sale of oil revenues.[6] These public-sector actions have their monetary counterparty

[5] At the start of 2003 the National Executive and the Banco Central de Venezuela adopted currency control measures where commercial bank transactions are channeled at a pre-established exchange rate regime and capital transactions can be financed at a parallel or unofficial exchange rate. In general terms, the implementation of currency controls can be understood as the appearance of dual foreign exchange markets, where the unofficial price of the currency represents a significant premium as compared to the official price.

[6] Foreign currency sales are generally not accompanied by sterilization operations. During foreign exchange controls, sales of currency are decided by the government.

in two variables (or monetary impacts): IF, which is the creation of money through the tax authority and oil industry, and IC, which refers to demonetization through the central bank's sale of currency. Whereas IF represents flows that increase residual liabilities, IC constitutes payments (senior obligation) banks must make to the central bank in domestic currency.

With respect to stocks of central bank instruments, for the period considered (2004-2014), absorption operations were only carried out through the central banks' own instruments. Thus, residual liabilities related to the central bank only include the balance of certificates of deposit (CD). Expected cash withdrawals from the system are estimated by using net cheque clearing among banks.

Table 3 presents a summary of the items used for calculating probability of default.

Table 3

COMPONENTS OF SHORT-TERM LIABILITIES FOR THE CASE OF VENEZUELA

Total liquid assets	*Total liquid liabilities*
Unobservable	Senior obligations Weekly currency sales (IC) Weekly variation in reserve requirements Interest on interbank operations from the previous week Weekly net cheque clearing Residual liabilities Previous week's balance of central bank certificates of deposit + weekly interest Weekly creation of fiscal money (IF) The balance of cash reserves from the previous week (adjusted by interbank operations)

The volatility of residual liabilities (σ_E) is calculated for the weekly growth of (log) E, which has a standard deviation equal to 2.5%. The average value of the risk-free rate (μ_A) is assumed to be equal to 0.3%, which corresponds to the weekly growth of (log) IF. This rate is calculated based on the annualized rate of growth of (log) IF, which is 14%. We use this risk-free rate because interest rates in Venezuela are controlled, while the central bank's policy rate is also fixed most of the time. Meanwhile, the average rate of growth of IF represents the rate at which primary money is created. For Venezuela this also represents the rate at which banks receive new deposits. Hence, this rate can be interpreted as a constant growth, representing commercial bank assets.

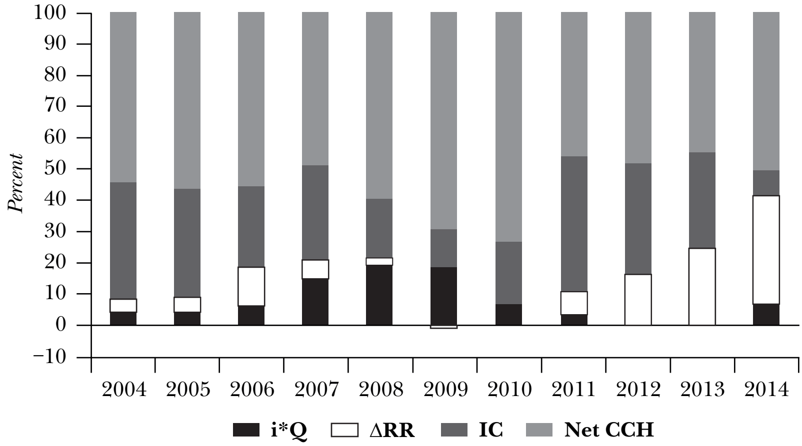
The time horizon used to calculate default probability is generally considered fixed and equal to $T = 1$, which in our case will be interpreted as one week. Default probability is calculated weekly. Balance values refer to those observed at the end of the preceding week. Flows are also measured on a weekly basis. We assume that expected flows are equal to those observed.

Figure 1 presents the composition of senior claims *(D)*. In senior debt, net cheque clearing and currency sales are the components mostly explaining its performance. As of 2012, the participation of reserve requirements in senior debt begins to grow in response to increases in the cash reserve ratio.

Figure 2 shows the composition of junior debt or residual liabilities *(E)*. Between 2004 and 2009, its performance follows the behavior of central bank certificates of deposit. During those years, absorption operations were important because of the implementation of foreign exchange controls in 2003 limited currency transactions and allowed liquidity in the economy to increase through higher government expenditure (increase in IF). This liquidity was channeled by banks towards central bank instruments. After 2009, the weight of CDs drops sharply due to restrictions (ceilings on the amounts) imposed on financial institutions' holdings of CDs. As of 2010, the behavior of junior

Figure 1

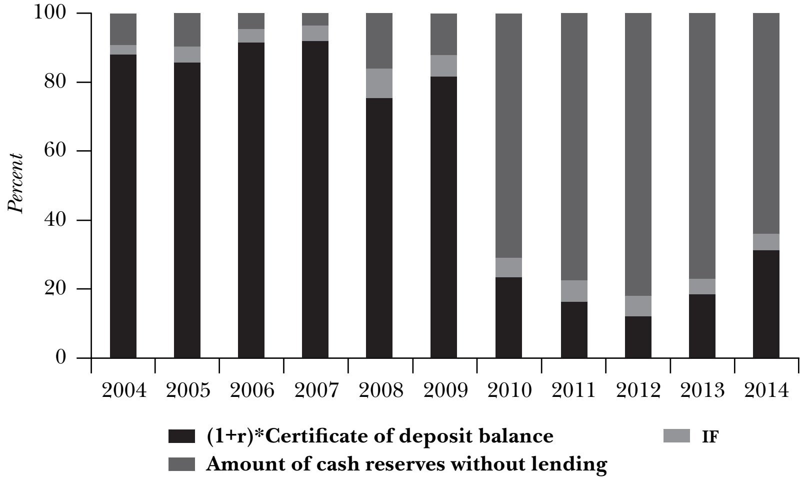
COMPOSITION OF SENIOR DEBT (*E*)[1]



[1] Each component is expressed as a percentage of the average total (in millions of bolivars) of each year.

Figure 2

COMPOSITION OF JUNIOR DEBT (*E*)[1]



[1] Each component is expressed as a percentage of the average total (in millions of bolivars) of each year.

debt mainly depends on the cash balances held by banks (in vaults or in excess reserves at the central bank).

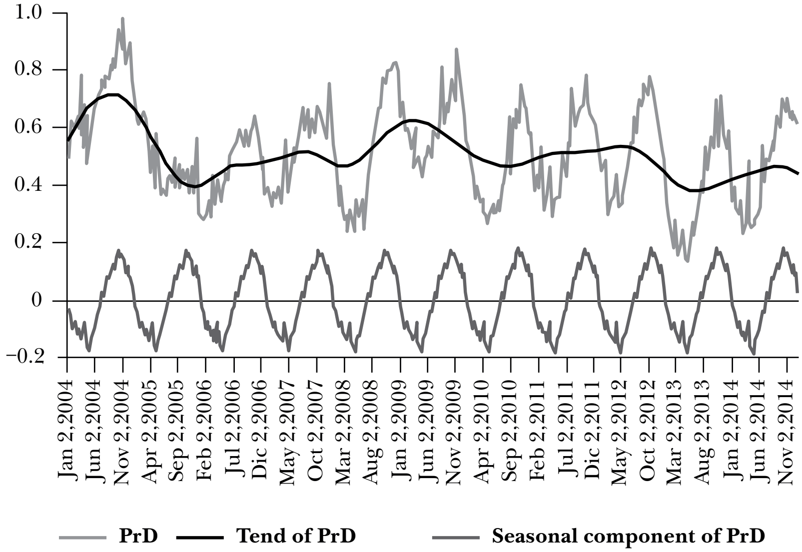
Figure 3 depicts the probability of default calculated, as well a breakdown of its holdings and seasonal component.

The path of default probability allows for identifying the periods in which structural changes take place in senior and junior debt. According to Figure 3, the periods of highest liquidity are 2004-2005 and 2008-2009. In 2004, economic activity and central bank currency sales began to grow substantially after having undergone a sharp contraction during the first year of currency controls (2003). Such increases in both variables generated significant growth in senior debt due to greater cash withdrawals (net cheque clearing), as well as higher exchange rate incidence (IC). Nevertheless, this increased demonetization in 2004, associated to foreign currency sales, was not offset until 2005, when higher fiscal expenditure began to materialize. In fact, during 2006 and 2007, the significant growth of fiscal impacts allowed high levels of liquidity that were reflected in a substantial growth of CDs (and residual liabilities) and a reduction in default probability. During 2008-2009, senior debt levels started to increase again, partly in response to interest rates and larger amounts negotiated in the interbank market. Although in this case a reduction in net money creation was not produced, the increase in the probability of default appears to be related to redistribution processes within the interbank market itself. After 2012, growth in junior debt, generated by greater money creation and cash accumulation by commercial banks, produce lower levels of default probability in the sample.

The seasonal component has a significant weight in the probability of default and represents approximately ±0.15 additional percentage points to the trend. Said component exhibits the following behavior: It tends to peak around October and then decreases gradually to minimum values in April the following year. This seasonality is associated to the seasonal behavior exhibited by net cheque clearing, which in turn reflects the

Figure 3

PROBABILITY OF WEEKLY DEFAULT FOR THE VENEZUELAN CASE



seasonal pattern of economic transactions. That is to say, the economy's cash requirements grow during the third quarter of the year, and decline substantially during the first, in parallel with economic activity. These cash requirements translate into an increase in default probability by raising the amount of senior debt.

3.2 Relation with the Interbank Market

According to the stylized model in Section 2.2, the banking system adjusts its holdings in cash and central bank instruments in order to minimize costs arising from situations defined by the probability of default. Our estimation of said probability contains all the data collected at the start of each period.

Assuming that the demand for funds in the interbank market is positively related to the demand for cash, it is possible to make two predictions. First, that interbank interest rates should be positively related to the probability (relative) of default. Second, that amounts negotiated in the market should also be positively associated with a growing probability of default. In this section, we attempt to verify these two predictions empirically by estimating models for average weekly interbank rates and amounts negotiated as functions of default probability. We then test whether these models improve the predictions as compared to the reference autoregressive models.

We begin by presenting diagrams of the dispersion between interbank variables and default probability estimated by the model (Figures 4 and 5)

Figure 4 depicts a positive relation between the overnight market interest rate and the probability of default. This might reflect that higher interest rates include greater risk premiums associated to the behavior of system liquidity.

Meanwhile, Figure 5 shows a positive relation between amounts traded in the overnight market and the probability of default. A higher probability of default might be associated with a greater need for available liquid funds by commercial banks and, therefore, increase the amounts traded in the interbank market.

Can the probability of default improve forecasting in models for interest rates and real amounts negotiated in the interbank market? To answer this question, we compare three alternative models for the variables: the weekly amount traded (Q^O) and average agreed rates (i^O).

First is the reference model that explains the overnight market variables only considering an autoregressive process in the mean. The second model includes the probability of default for modeling the mean and a GARCH (1,1) model for a variance.[7] The

[7] Generalized autoregressive conditional heteroscedasticity (GARCH) models are used because we are working with high frequency financial series in which volatility is an inherent characteristic and

Figure 4

CONTEMPORARY RELATION BETWEEN THE PROBABILITY OF DEFAULT (AXIS X) AND THE INTEREST RATE OF OVERNIGHT (Y AXIS)

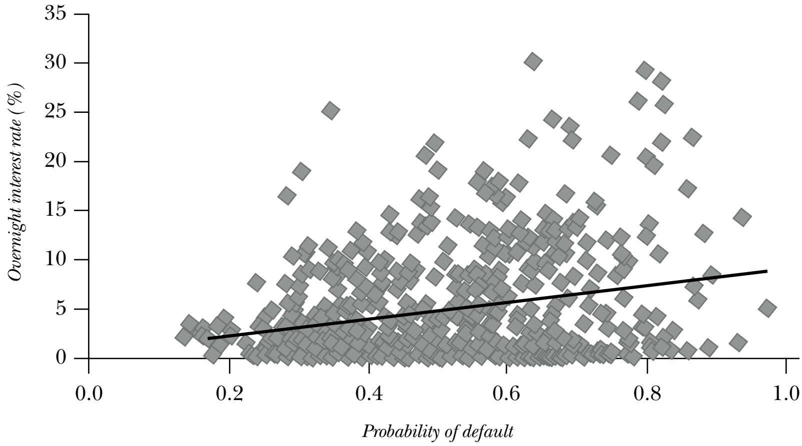
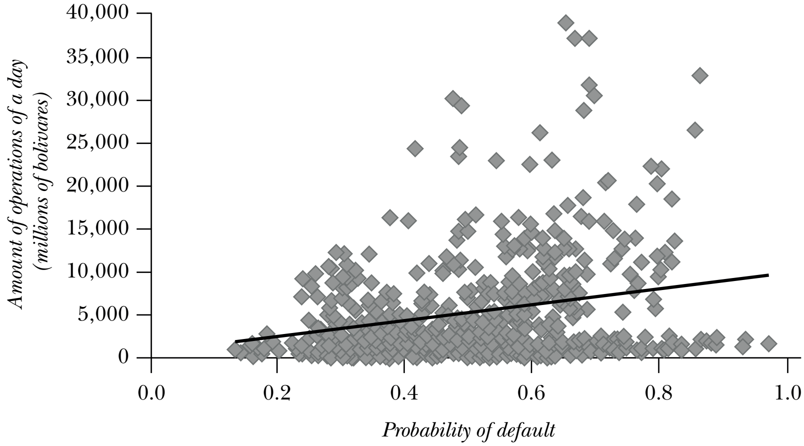


Figure 5

CONTEMPORARY RELATION BETWEEN THE PROBABILITY OF DEFAULT (AXIS X) AND THE AMOUNT AGREED ON ONE-DAY OPERATIONS (Y AXIS)



third model expands the second one by including the probability of default as an explanatory variable for a variance. In the case of interest rates those models are:

Model 1. Autoregressive in the mean (reference)

11 $$i_t = 0.01 + 0.63 i_{t-1} - 0.11 i_{t-2} + 0.13 i_{t-3} + 0.20 i_{t-4} + \varepsilon_{t.}$$

Model 2. With explanatory variables in the mean and GARCH for variance

12 $$i_t = 0.004 + 0.57 i_{t-1} - 0.05 i_{t-2} + 0.08 i_{t-3}$$

$$+ 0.25 i_{t-4} + 0.01 PrD_t + \varepsilon_t,$$

where $\varepsilon_t \sim D(0, h_t)$ with variance

$$h_t = -2.6 \times 10^{-5} + 0.07 \varepsilon_{t-1}^2 + 0.90 h_{t-1}.$$

Model 3. With explanatory variables in the mean and in the GARCH:

13 $$i_t = 0.005 + 0.56 i_{t-1} - 0.04 i_{t-2} + 0.061 i_{t-3}$$

$$+ 0.26 i_{t-4} + 0.01 PrD_t + \varepsilon_t,$$

where $\varepsilon_t \sim D(0, h_t)$ with variance

cannot be considered homoscedastic. For further information see Engle (1982) and Bollerslev (1986).

$$h_t = -2.2\times 10^{-5} + 0.07\varepsilon_{t-1}^2 + 0.90h_{t-1} + 1\times 10^{-4} PrD_t.$$

Models for amount traded only show two possible variations given that the probability of default was only significant for modeling the mean. The regressions estimated are:

Model 1. Autoregressive in the mean (reference)

14 $$Q_t = 46.51 + 0.65Q_{t-1} - 0.01Q_{t-2} + 0.09Q_{t-3} + 0.18Q_{t-4} + \varepsilon_t.$$

Model 2. With explanatory variables in the mean and GARCH for variance:

15 $$Q_t = 4.68 + 0.54Q_{t-1} + 0.05Q_{t-2} + 0.14Q_{t-3}$$
$$+ 0.18Q_{t-4} + 41.82PrD_t + \varepsilon_t,$$

where $\varepsilon_t \sim D(0, h_t)$ with variance $h_t = 190.3 + 0.1\varepsilon_{t-1}^2 + 0.8h_{t-1}$.

Tables 4 and 5 display mean absolute percentage errors (MAPE) of the different models. The forecasts (dynamic) were performed for the first three months of the subperiods: 2007, 2011 and 2015. The models are estimated using the above information in the prediction period, i.e., 2004-2006, 2004-2010 and 2004-2014, respectively. Moreover, and by way of comparison, we calculate the MAPE using static forecasts for the subsample 2005-2009.

A comparison of the equations' forecasts for the amount traded and agreed interest rate in the overnight market reveals successive improvements in the MAPE with respect to the reference forecast in the equation for the amount as well as that for the interest rate, especially when the default probability is included for modeling the mean.

To corroborate the above results, we apply the Diebold and Mariano (1995) test, which analyzes whether the difference

Table 4

EQUATION FOR OVERNIGHT RATES

Comparison of forecasts using the

MAPE ***adjustment indicator to forecast:***

	First three months (January to March) of years			*Subsample*
Cases	*2007*	*2011*	*2015*	*2005-2009*
Model 1	52.62025	12.46301	654.2557	121.1801
Model 2	48.06451	11.05222	108.8856	111.3088
Model 3	43.03569	11.04099	108.5249	111.2405

Table 5

EQUATION FOR THE OVERNIGHT AMOUNT IN MILLION 1997 BOLIVARS

Comparison of forecasts using the

MAPE ***adjustment indicator to forecast:***

	First three months (January to March) of years			*Subsample*
Cases	*2007*	*2011*	*2015*	*2005-2009*
Model 1	21.62721	61.04253	1757.320	32.10837
Model 2	20.40863	35.07300	1228.376	29.59481

between the loss functions (sum of absolute values) of the errors between two models is significantly different from zero. Details of this test can be found in Annex B.

Tables 6, 7 and 8 show the constant of the Diebold-Mariano test and corresponding p values. The comparison is performed in pairs.

When comparing Models 2 and 3 with Model 1 we find evidence to reject the null hypothesis of equal forecast accuracy between the models. In both cases, the value estimated for the constant is negative, i.e., forecast errors of Model 1 (autoregressive) are significantly larger than those of Models 2

Table 6

DIEBOLD-MARIANO TEST AND ASSOCIATED *P* VALUES

Model 2 against Model 1 for rates

H_0	*2007*	*2011*	*2015*	*2004-2009*
$\lvert e_{Model\ 2t}\rvert - \lvert e_{Model\ 1t}\rvert = 0$	-1×10^{-4} (0.11)	-0.003 (0.00)	-0.015 (0.00)	-0.002 (0.003)
$(e_{Model\ 2t})^2 - (e_{Model\ 1t})^2 = 0$	-2×10^{-5} (0.09)	-1×10^{-4} (0.00)	-1.25×10^{-4} (0.03)	-9.62×10^{-5} (0.01)

Table 7

DIEBOLD-MARIANO TEST AND ASSOCIATED *P* VALUES

Model 3 against Model 1 for rates

H_0	*2007*	*2011*	*2015*	*2004-2009*
$\lvert e_{Model\ 3t}\rvert - \lvert e_{Model\ 1t}\rvert = 0$	-0.001 (0.11)	-2×10^{-4} (0.00)	-0.015 (0.00)	-0.002 (0.001)
$(e_{Model\ 3t})^2 - (e_{Model\ 1t})^2 = 0$	-5.23×10^{-5} (0.10)	-1.2×10^{-5} (0.08)	-1.26×10^{-4} (0.03)	-1.04×10^{-4} (0.005)

Table 8

DIEBOLD-MARIANO TEST AND ASSOCIATED *P* VALUES

Model 2 against Model 3 for rates

H_0	*2007*	*2011*	*2015*	*2004-2009*
$\lvert e_{Model\ 3t}\rvert - \lvert e_{Model\ 2t}\rvert = 0$	-8.97×10^{-4} (0.2175)	-3×10^{-4} (0.00)	-2.56×10^{-4} (0.0092)	-9.5×10^{-5} (0.09)
$(e_{Model\ 3t})^2 - (e_{Model\ 2t})^2 = 0$	-2.55×10^{-5} (0.2344)	-1.6×10^{-5} (0.00)	-0.002 (0.042)	0.00 (0.00)

Table 9

DIEBOLD-MARIANO TEST AND ASSOCIATED *P* VALUES Model 2 against Model 1 for amounts				
H_0	*2007*	*2011*	*2015*	*2004-2009*
$\left\|e_{Model\ 2t}\right\|-\left\|e_{Model\ 1t}\right\|=0$	−27.75 (0.0008)	−56.55 (0.008)	−56.70 (0.0000)	−4.85 (0.10)
$\left(e_{Model\ 2t}\right)^2-\left(e_{Model\ 1t}\right)^2=0$	−3,380.334 (0.0234)	−17,755.23 (0.0057)	−15,359.61 (0.0000)	−3,003.031 (0.1244)

and 3 (GARCH). These outcomes prove the predictive gains from incorporating default probability into the mean. When we compare loss functions of Models 2 and 3, we find, in all the forecasts except 2007, that the null hypothesis of equal forecast accuracy between them is rejected.

We now perform a similar procedure for comparing the models presented in Table 5 with respect to amounts.

In the amount equation, we also find evidence to reject the null hypothesis of equal forecast accuracy between the GARCH model and the autoregressive one in the forecasts, except for the period 2004-2009.

3.3 Policy Exercises

In this section we perform simulations to calculate the probability of default, focusing on the impacts of monetary base components (IF and IC). To do this we assume that such flows of money creation or destruction not only affect default probability, but also cash holdings in the financial system (equations 20 and 21). We also include autoregressive equations for IF and IC to determine the differing impact of changes in the mean and variance of those variables (Equations 22 and 23). Given that interbank market amounts and rates are affected by the probability of (*PrD*), we also incorporate behavioral equations for said variables (equations 18 and 19). We do not model the behavior of CDs because of the low variability of monetary policy rates throughout the period as a whole. All the behavioral equations are estimated with data from between 2004 and 2007, which corresponds to the period with greatest interbank market depth. The simulation model is represented by equations 17 to 23.

The probability of default is given by:

17 $$PrD = f\left(A\left(E,\sigma_E\right), \sigma_A\left(E,\sigma_E\right), D, T, \mu_A\right).$$

Behavioral equations for overnight market amounts and rates in accordance with risk indicators are:

18 $$Q_t = a_0 + a_1 Q_{t-1} + a_2 DD_t,$$

19 $$i_t = b_0 + b_1 i_t + b_2 PrD_t - b_3 DD_t.$$

Autoregressive equations for variation of excess reserves (ΔRE) and cash in vaults (ΔEB) are:

20 $$\Delta RE_t = c_0 + c_1 \Delta RE_{t-1} + c_2 IF_{t-1} - c_3 IC_t,$$

21 $$\Delta EB_t = d_0 + d_1 \Delta EB_{t-1} + d_2 IF_t - d_3 IC_t,$$

Autoregressive equations for fiscal and exchange rate influence are given by:

22 $$IF_t = e_0 + e_1 IF_{t-1} + \mathcal{E}_{1t},$$

23 $$IC_t = \lambda_0 + \lambda_1 IC_{t-1} + \mathcal{E}_{2t},$$

where $a_j, b_j, c_j, d_j, e_j, \lambda_j > 0$ for all $j = 1, 2, 3$; y $\mathcal{E}_{1t}$ and $\mathcal{E}_{2t}$ have a normal distribution with mean zero and variance one. The reserve requirement ratio is considered as a multiple of monetary base in the preceding period. Monetary base is considered as the sum of excess and required reserves. Finally, to tie the model into the time horizon, the initial conditions were assumed as those observed at the beginning of 2006. The performed simulations are shown in Annex C.

The outcomes suggest that, on average, increases (reductions) in the unconditional mean and persistence of fiscal events tend to reduce (increase) the probability of default, while increases (reductions) of the ordinate and persistence in the equation for exchange rate effects imply an increase (reduction) in the probability of default. Changes in the variance of fiscal events have a greater impact on the probability of default than changes in the variance of exchange rate events. Finally, if the legal capital requirement ratio increases (decreases), the probability of default tends to rise (fall) by raising (lowering) banks' short-term obligations.

4. FINAL REMARKS

In this paper, we use risk indicators derived from the contingent claims approach (probability and distance to default) to evaluate liquidity risk in the banking system as a whole. These ideas are easy to calculate because they use readily available aggregate banking and monetary policy variables, in general.

The probability of default can be a useful instrument for central banks to improve predictions on the interbank market, as well as potentially contribute to modeling the behavior of some (or all) liquid assets available to commercial banks.

In the case of Venezuela, the behavior of default probability would seem to depend, among other factors, on the monetary impacts of fiscal and exchange rate actions. One interpretation that emerges from the counterfactual exercises performed on the properties of such policies is that the vulnerability of Venezuela's interbank market could increase substantially in the face of greater dynamism in currency sales and conservative fiscal expenditure trends. This outcome is consistent with another paper on the Venezuelan financial system: Carvallo and Pagliacci (2016). According to the latter, combinations of said policies that generate restrictive monetary conditions will tend to increase bank instability. In general terms, both outcomes point towards the necessity for performing a review of the framework of regulations that enhance the significant monetary effects of these policy actions.

ANNEXES

Annex A. Contingent Claims Approach

The contingent claims approach is a methodology that generalizes the Black-Scholes (1973) and Merton (1974) option pricing theory, combining market-based data and balance sheet information to obtain financial risk indicators such as distance to default and default probability.[8]

The conceptual framework can be represented mathematically as follows. Assets $A_t \in \mathbb{R}_+$, are assumed to follow a geometric Brownian motion with volatility, σ_A. Senior debt is $D_t \in \mathbb{R}_+$. Hence, the process governing the behavior of asset prices is assumed given by:

$$dA_t = A_t\left(\mu_A dt + \sigma_A dW_t\right). \tag{A.1}$$

Equivalently,

---

[8] Other financial risk indicators obtained using this methodology are: risk-neutral credit risk premia and expected losses on senior debt. For further information see Saldías (2012) and Gray et al. (2006)

A.2 $$A_t = A_o \exp\left(\left(\mu_A - \frac{\sigma_A^2}{2}\right)t + \sigma_A \varepsilon \sqrt{t}\right),$$

where $\varepsilon \sim \mathcal{N}(0, \Delta t)$; and μ_A is the expected average return on the assets. With the risk-neutrality hypothesis, μ_A means there can be no arbitrage in the financial derivative during an infinite period. W_t is a standard Brownian motion, i.e.:

A.3 $$W_{t+\Delta t} - W_t \sim \mathcal{N}(0, \Delta t).$$

This assumption considers that assets and senior debt (its derivative) follow a log-normal distribution.

However, D_t being the value of senior debt in t, the probability of default or system vulnerability at time T, conditional on known information in t, is defined as:

A.4 $$\text{Prob}(A_t \leq D_t) = \text{Prob}\left(A_o \exp\left(\left(\mu_A - \frac{\sigma_A^2}{2}\right)(T-t) + \right.\right.$$
$$\left.\left. + \sigma_A \varepsilon \sqrt{T-t}\right) \leq D_t\right).$$

This probability captures system vulnerability when assets are below the threshold represented by hard or high priority debt.

The two equations used for estimating assets and their volatility are as follows. The first comes from the basic formulation of the expected value of junior debt *(E),* which is obtained using Itō's lemma. This expected value is equal to the price of a European call option on the assets, so that:

A.5 $$E_t = A_t \sim \mathcal{N}\left(d_1\right) - D_t e^{-\mu_{A_t}} \mathcal{N}\left(d_2\right),$$

where

A.6 $$d_1 = \frac{\ln\left(\frac{A_t}{D_t}\right) + \left(\mu_A + \frac{\sigma_A^2}{2}\right)(T-t)}{\sigma_A \sqrt{T-t}} \text{ and}$$

A.7 $$d_2 = \frac{\ln\left(\frac{A_t}{D_t}\right) + \left(\mu_A - \frac{\sigma_A^2}{2}\right)(T-t)}{\sigma_A \sqrt{T-t}} = d_1 - \sigma_A \sqrt{T-t}.$$

Since, $\mathcal{N}(x)$ is the value of the cumulative standard normal distribution in x and $\mathcal{N}\left(0, \sigma^2\right)$ is the univariate normal probability density function with mean μ and variance σ^2.

But, Equation 5 has two unknown variables, A and σ_A; meaning a second equation is necessary. The model of Merton (1974) obtains an equation that links the volatility of junior debt, σ_E, and that of assets using:

A.8 $$\sigma_E = \frac{A_t}{E_t} \frac{\partial E}{\partial A} \sigma_A.$$

As well as,

A.9 $$\frac{\partial E_t}{\partial A_t} = \mathcal{N}\left(d_1\right).$$

Hence, the volatility of junior debt can be calculated as:

A.10 $$\sigma_E = \frac{A_t}{E_t} \mathcal{N}\left(d_1\right) \sigma_A.$$

Finally, using Equations 5 and 10 we obtain the following system of non-linear equations, formed by two equations and two unknowns.

A.11
$$f = \begin{bmatrix} A_t \mathcal{N}(d_1) - D_t e^{-\mu_{A_t}} \mathcal{N}(d_2) - E_t \\ \frac{A_t}{E_t} \mathcal{N}(d_1) \sigma_A - \sigma_E \end{bmatrix}.$$

Making $f \begin{bmatrix} 0 \\ 0 \end{bmatrix}$ we can use quadratic optimization or similar techniques to estimate the value of assets and their volatility, $\hat{A}$ and $\hat{\sigma}_A$, respectively. Once these values have been calculated, the number of standard deviations (d_t) of insolvency is precisely, d_2.

A.12
$$d_1 = \frac{\ln\left(\frac{A_t}{D_t}\right) + \left(\mu_A + \frac{\sigma_A^2}{2}\right)(T-t)}{\sigma_A \sqrt{T-t}}.$$

That is to say, in a single measure, distance to default combines the difference between the value of assets (A_t) and the distress barrier (D_t), standardizing with asset volatility.

Using Equations 4 and 7, we obtain that the probability of default or system vulnerability is, therefore, the standard normal cumulative distribution of negative distance to default:

A.13
$$pd_t = \mathcal{N}(-d_t).$$

That is, the one that intermediates between distance-to-default and probability of default is the normal distribution.

Annex B. Diebold and Mariano Test (1995) Methodology

We consider two forecasts, $\{y_{1t}\}_{t=1}^{T}$ and $\{y_{2t}\}_{t=1}^{T}$, of the series $\{y_t\}_{t=1}^{T}$ with T as a positive integer and define the prediction error as:

B.1 $$e_{it} = \hat{y}_{1t} - y_t, \quad i = 1, 2.$$

The loss associated with the forecast of model i will be a function of the forecast errors, e_{it}, and be denoted by $g(\cdot)$, which is typically considered as the absolute value function or quadratic function. Meanwhile, the function of the loss differential between two forecasts is given by,

B.2 $$d_t = g(e_{1t}) - g(e_{2t}).$$

According to the abovementioned, we can have

B.3 $$d_t = |e_{1t}| - |e_{2t}|,$$

B.4 $$d_t = (e_{1t})^2 - (e_{2t})^2.$$

Moreover we say that both forecasts have the same predictive ability if and only if the loss differential is expected to be 0 for all t. The null hypothesis is, therefore:

B.5 $$H_0 = E(d_t) = 0 \ \forall\ t.$$

Versus the alternative hypothesis:

B.6 $$H_a = E(d_t) \neq 0.$$

Annex C. Figures

Figure C.1

SCENARIOS OBTAINED BY MODIFYING THE UNCONDITIONAL AVERAGE IN TAX INCIDENCES

Probability of default

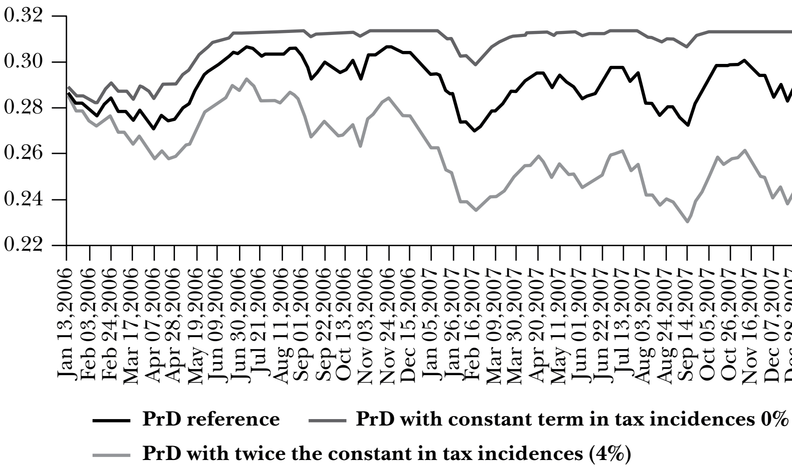


Figure C.2

SCENARIOS OBTAINED BY MODIFYING THE UNCONDITIONAL AVERAGE IN THE EXCHANGE RATE INCIDENCES

Probability of default

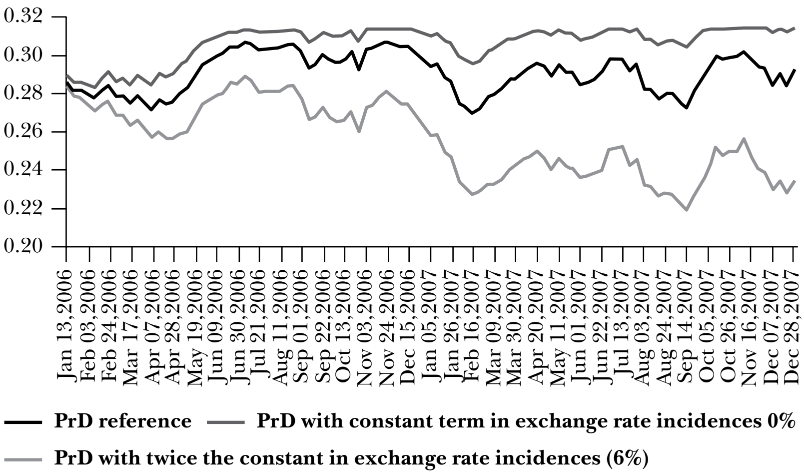


Figure C.3

SCENARIOS OBTAINED BY MODIFYING THE VARIANCE IN THE RESIDUALS OF THE TAX INCIDENCES EQUATION

Probability of default

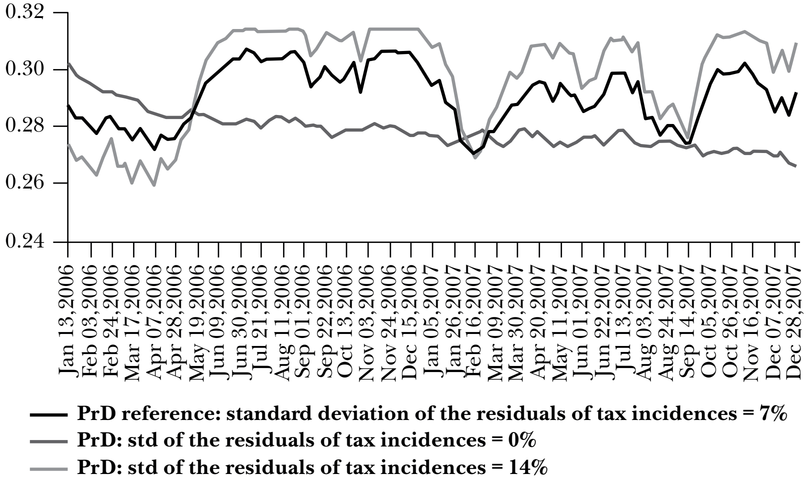


Figure C.4

SCENARIOS OBTAINED BY MODIFYING THE VARIANCE IN THE RESIDUALS OF THE EQUATION OF THE EXCHANGE RATE INCIDENTS

Probability of default

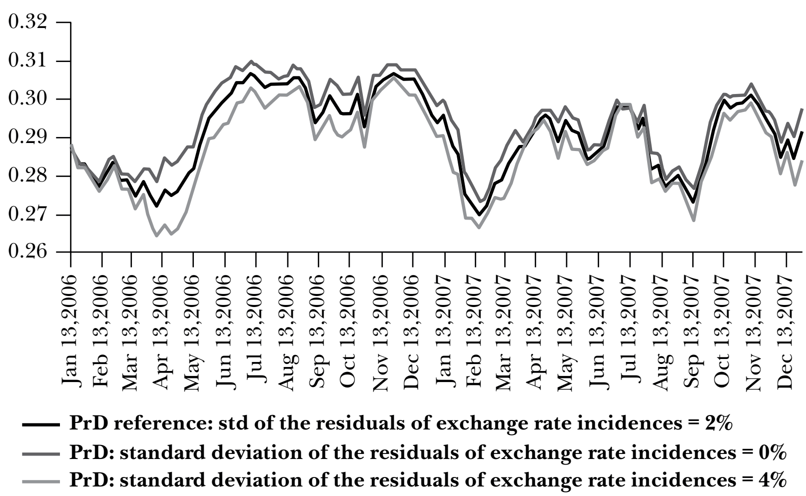


Figure C.5

SCENARIOS OBTAINED BY MODIFYING THE PERSISTENCE IN THE TAX INCIDENCES EQUATION

Probability of default (PrD)

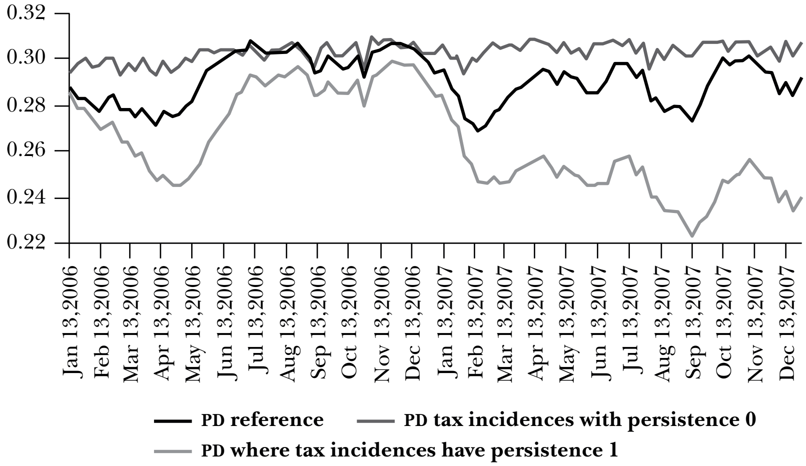


Figure C.6

SCENARIOS OBTAINED BY MODIFYING THE PERSISTENCE IN THE EQUATION OF EXCHANGE RATE INCIDENTS

Probability of default (PrD)

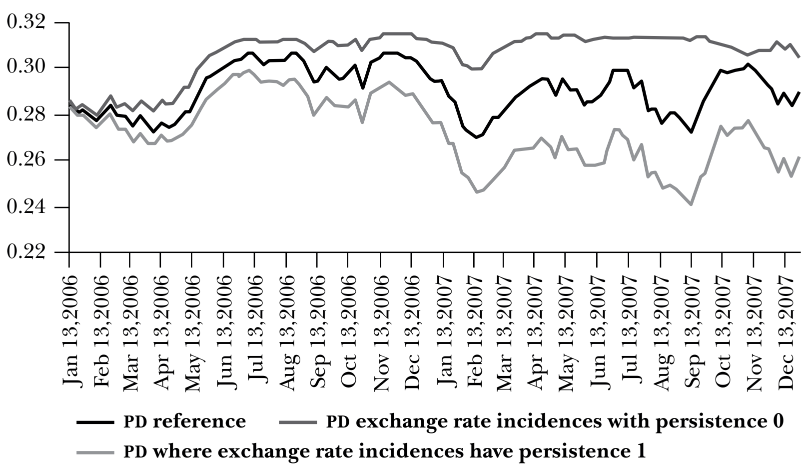
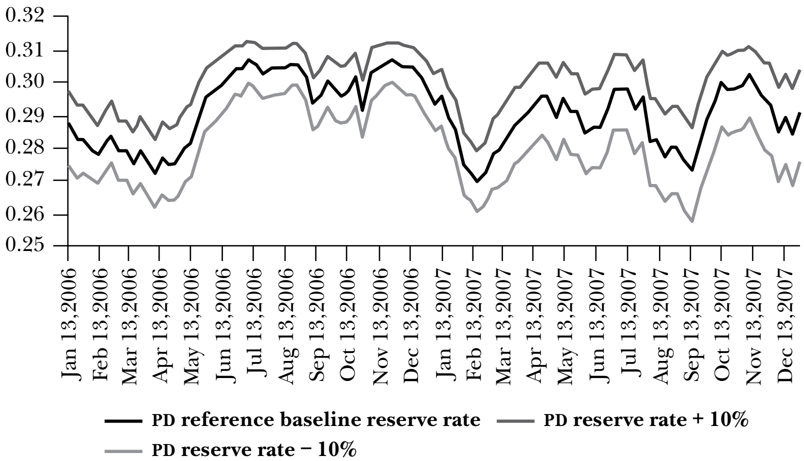


Figure C.7

SCENARIOS OBTAINED BY MODIFYING THE RESERVE RATE

Probability of default (PrD)



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