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Identifying Interbank Loans, Rates, and Claims Networks from Transactional Data¹

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Abstract

We identify interbank (i.e. non-collateralized) loans from the Colombian large-value payment system by implementing *Furfine's method*. After identifying interbank loans from transactional data we obtain the interbank rates and claims without relying on financial institutions' reported data. Contrasting identified loans with those consolidated from financial institutions' reported data suggests the algorithm performs well, and it is robust to changes in its setup. The weighted average rate implicit in transactional data matches local interbank rate benchmarks strictly. From identified loans we also build the interbank claims network. The three main outputs (i.e. the interbank loans, the rates, and the claims networks) are valuable for examining and monitoring the money market, for contrasting data reported by financial institutions, and as inputs in models of financial contagion and systemic risk.

Keywords: Furfine's method, interbank, IBR, TIB

JEL Codes: E42, E44

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1. Introduction

The interbank funds market plays a central role in monetary policy transmission: it allows financial institutions to exchange central bank money in order to share liquidity risks (Fricke and Lux, 2014). For that reason they are the focus of central banks' implementation of monetary policy and have a significant effect on the whole economy (Allen, Carletti, & Gale, 2009; p.639), whereas the interbank rate is commonly regarded as central bank's main target for assessing the effectiveness of monetary policy transmission. In addition, the absence of collaterals in the interbank funds market creates powerful incentives for participants to monitor each other, thus it also plays a key role as a source of market discipline (Rochet and Tirole, 1996; Furfine, 2001). Therefore, the interbank funds market is an important element for an efficiently functioning financial system (Heijmans, Heuver, & Walraven, 2010).

Reliable and comprehensive data from the interbank funds market is somewhat elusive, with restrictions on the consistency, granularity, and opportunity of the corresponding databases. This explains the numerous research articles that aim at identifying unsecured (i.e. non-collateralized) interbank funds loans from large-value payment systems' transactional data. The first of such articles is credited to Furfine (1999), who developed an algorithm for identifying interbank overnight loans for the US money market from Fedwire data. The procedure in Furfine (1999) is straightforward: matching payments in day t from Bank A to Bank B greater than one million dollars rounded to the nearest integer of \$100,000 (i.e. the loans), with payments from Bank B to Bank A in day $t + 1$ (i.e. the overnight refund) such that the implicit interest rate between both payments is reasonable (i.e. it falls inside a ± 50 basis points corridor with respect to publicly available measures of the federal funds rate). This general approach is commonly referred as *Furfine's method* or *Furfine's algorithm*.

After Furfine (1999) several authors have attempted to apply similar algorithms. Enhancements have come in the form of including additional rules or parameters to filter out interbank overnight funds transactions. For instance, Demiralp, Preslopsky,

and Whiteshell (2004) include smaller size loans (i.e. greater than \$50,000, with equal-sized increments) and include an interest rate 1/32-rounding rule for discarding interbank overnight transactions that are incompatible with market practices. Millard and Polenghi (2004) apply Furfine's algorithm to the UK's large value payment system (CHAPS), including a threshold on one million pounds. Hendry and Kamhi (2007) apply Furfine's algorithm to data from the Canadian large value transfer system with a half a basis point rounding rule for filtering transactions. Some authors have considered interbank non-overnight transactions for the Dutch, Swiss, and Euro interbank markets (see Heijmans et al., 2010; Guggenheim, Kraenzlin, & Schumacher, 2010; Arciero, Heijmans, Heuver, Massarenti, Picillo, & Vacirca, 2013).

Regarding the validity of the Furfine's method, Armantier and Copeland (2012) have questioned the results obtained when implementing Furfine's method. On the other hand, Arciero et al. (2013) contrast results reported by Armantier and Copeland, and confirm the validity of Furfine's method conditional on a deep knowledge of the underlying data and the technical attributes of the system under analysis.

This paper implements the Furfine's method on a dataset from the Colombian large-value payment system (CUD – *Cuentas de Depósito*), which is the only large value payment system in the country. Our objectives are the following: First, to filter out interbank funds transactions in the Colombian market in order to identify loans without relying on data reported by financial institutions.⁵ Second, to contrast the loans identified by our algorithm with those identified from reports by financial institutions, and to contrast our implicit interbank overnight interest rate (IIR_{ON}) with the publicly available interbank overnight reference rate (IBR_{ON}) and interbank overnight funds average rate (TIB). Third, to construct the interbank claims networks, a key input for examining financial contagion under recent approaches to systemic risk and financial stability.

⁵ We do not include intraday interbank funds transactions. Despite these transactions are sizeable in the Colombian case, some identification problems in the local large-value payment datasets deter us from including them in this version. We expect to address this shortcoming in the near future.

By accomplishing these three objectives we expect to provide evidence on the usefulness of large-value payment systems' data for monitoring, overseeing, and analyzing the interbank funds market. Some uses are worth emphasizing. First, as this type of exercise provides the opportunity to evaluate the interbank funds market without relying on reports from financial institutions, lags and potential errors arising from consolidating, processing and transmitting reports by financial institutions and financial authorities may be conveniently avoided. As financial authorities have to rely on delayed and costly sources of data (i.e. reported data, on-site and off-site analyses), it is warranted to have potential alternatives (Kyriakopoulos, Thurner, Pühr, & Schmitz, 2009).

Second, transactional data grants financial authorities the ability to contrast surveys and reports by financial institutions. As the Libor panel scandal demonstrated, the ability to contrast is rather limited when relying on reports and surveys only.⁶ Also, as stressed by Kyriakopoulos et al. (2009), using financial transaction records is particularly useful to uncover financial misconduct and rogue trading.

Third, using transactional data allows monitoring the interbank overnight funds market in a continuous manner. Therefore, as suggested by Heijmans et al. (2010), it should be used as an early warning indicator tool, both at macro level (the whole market) and at the individual (financial participant) level.

It is important to state that our implementation of Furfine's method is somewhat easier than in other markets. Interbank transactions settled in large-value payment systems are not labeled as such in most systems around the world (Heijmans et al., 2010), whereas the Colombian large-value payment system obliges financial institutions to use specific codes when registering interbank transactions. Before March 2013 there was a single code for interbank funds transactions, which did not allow distinguishing between loans and refunds. After March 2013 separate codes for intraday and non-intraday loans and refunds were enacted. Therefore, unlike most

⁶ As documented by Guggenheim et al. (2010), in March 2008 Libor panel banks were accused of talking up their creditworthiness by reporting lower rates in order to avoid negative signals about their refinancing conditions.

attempts to implement Furfine’s method, we already have identified loans and refunds, and our task is to match converse transactions at a reasonable implicit rate in the future. As described below, such matching requires defining an area of interest rate plausibility (i.e. an interest rate corridor) with respect to publicly available interbank reference rates, defining a procedure for solving multiple refund matches for a single loan, and defining the transactions’ maximum reliable time-to-maturity.

An interesting methodological contribution of our implementation is worth stating. By running the algorithm backwards (i.e. starting with the last date of the sample until reaching the first one) we attained a practical method for mitigating the over-identification of long-term interbank loans. To the best of our knowledge, this backwards-run setup has not been attempted in related literature before, and may be worth exploring in further implementations of Furfine’s algorithm.

This paper is structured as follows. The second section describes the dataset. The third section presents the algorithm designed for the Colombian case. The fourth section presents the main results. The fifth section discusses results, and presents some challenges and forthcoming applications.

2. The Dataset

As usual in other implementations of Furfine’s method, the data source is the local large-value payment system. This method relies on the premise that all interbank loans will eventually result in a converse payment between financial institutions in the large-value payment system. Such premise may be questionable whenever financial institutions tend to settle their interbank transactions outside the large-value payment system, say on the books of a common settlement bank, or by the physical delivery of cash or checks between them.

In the Colombian case there is a single large-value payments system (CUD), and it is owned and operated by the Central Bank (*Banco de la República*). It is the financial

market infrastructure where all cash settlement (in local currency) takes place, for all types of financial transactions –including interbank funds transactions.

To the best of our knowledge, there is no information about the significance of interbank loans and refunds settled outside the local large-value payment system. We presume that the non-tiered access scheme of the Colombian large-value payment system, and the corresponding absence of settlement banks, should make the settlement of transactions in the book of a common financial institution unnecessary, therefore rare. However, as there are no limitations to this kind of external settlement, or to the settlement of transactions by the physical delivery of cash or checks, we can't rule out that some interbank loans and refunds are settled outside the large-value payment system. All in all, we expect external settlements of interbank loans and their refunds to be unimportant.

The local large-value payment system obliges financial institutions to classify their transactions based on a set of codes determined by the Central Bank. Regarding the interbank funds market transactions, after March 2013 financial institutions use distinct codes for registering interbank loans and refunds when executing the transfer of funds. Nonetheless, there is no tracking or earmarking between each loan and its corresponding refund.

Financial institutions do not register some interbank funds transactions in the large-value payment system. Interbank funds transactions corresponding to the interbank reference rate formation program (*IBR – Índice Bancario de Referencia*⁷) are registered in the large-value payment system by a second financial market infrastructure, DCV (*Depósito Central de Valores*)⁸. The codes used by DCV when

⁷ Technical details on the interbank reference rate formation program (*IBR*) are presented and discussed by Cardozo and Murcia (2014) and Asobancaria et al. (2015).

⁸ DCV is a financial market infrastructure owned and operated by the Central Bank. It is the securities settlement system and the central securities depository for sovereign securities. It provides a technical platform for the interbank reference rate formation program (*IBR*). The sole central counterparty in the local market (*Cámara Central de Riesgo de Contraparte de Colombia S.A.*) provides clearing and settlement for transactions agreed for the formation of the one- and three-month *IBR* rates, which are not quoted as typical loans and refunds, but as non-delivery interest rate swaps.

reporting interbank transactions are different from those used by financial institutions, but they also distinguish between loans and refunds.

Hence, unlike most implementations of Furfine's method, the dataset is already filtered out. All non-interbank funds transactions may be easily discarded, and the remaining data is already classified as a loan or as a refund.

The dataset consists of all interbank funds transactions between 1 April, 2013 and 30 December, 2014 (i.e. 428 business days); intraday interbank transactions are not considered. This dataset comprises 27,200 interbank funds transactions. 13,504 correspond to interbank transactions registered by financial institutions directly, whereas 13,696 correspond to interbank transactions registered by DCV on behalf of the interbank reference rate formation program. The value of the interbank transactions corresponding to the reference rate formation program (i.e. registered in CUD by DCV) represents about 21.6% during the period under analysis.

3. The algorithm

As stated before, the dataset is already filtered out. All non-interbank funds transactions may be easily discarded, and the remaining data is already classified as a loan or as a refund. Thus, the algorithm's design and setup should reflect the favorable particularities of the dataset.

Unlike Furfine (1999) and most of the related literature on Furfine's method, our algorithm should not filter interbank transactions out from (raw) large-value payments data. This feature of the dataset avoids making some assumptions for identifying loans and refunds. For instance, following the algorithm's setup by Arciero et al. (2013), we do not need to define minimum loan values and increments in loan values to filter out potential loans. As defining these two parameters is critical for minimizing false negatives and false positives (Arciero et al., 2013), working with filtered data should mitigate some serious sources of error.

Yet, some steps in the setup of the algorithm remain. First, defining the implicit interest rates' plausibility (i.e. the interest rate corridor). Second, excluding plausible rates that do not conform market practices. Third, defining a solving procedure in case of multiple refund matches for a single loan. Fourth, defining the transactions' maximum reliable time-to-maturity.

Regarding the first remaining step, as not all financial institutions can trade liquidity at the same rates, an area of plausible interest rates has to be defined (Heijmans et al., 2010). Related literature favors a symmetrical or quasi-symmetrical corridor around a representative publicly available interbank rate. For the US Furfine (1999) uses a corridor of 50 basis points below (above) the minimum (maximum) of each day's federal funds' 11:00 rate, closing rate, and value-weighted funds rate. Demiralp et al. (2004) uses a wider ± 100 basis points corridor with a minimum rate of 1/32. Heijmans et al. (2010) use a ± 100 basis points corridor with respect to Eonia (European Overnight Index Average) and Euribor throughout the European Central Bank's liquidity injection and interest rate decrease (i.e. September 2008 – September 2009), and a ± 50 basis point corridor for the rest of their sample. Guggenheim et al. (2010) use a ± 15 basis points corridor with respect to the Libor fixing in the Swiss Franc, but adjust this corridor based on day-specific volatility of the overnight rate on the Swiss Franc repo market. Arciero et al. (2013) use three corridors (± 25 , ± 50 and ± 200 basis points) with respect to Eonia.

The area of plausibility should be chosen in such a way that it minimizes the probability of Type 1 and Type 2 errors (Heijmans et al., 2010). Type 1 error results when a transaction is mistakenly identified as an interbank transaction (i.e. a false positive), whereas Type 2 error results when an interbank funds transaction is erroneously omitted (i.e. a false negative). In our case the occurrence of Type 1 error is low due to the features of the dataset (i.e. interbank funds transactions only). About Type 2 error, omitting actual interbank funds transactions may result from the choice of the area of plausibility: The narrower the corridor, the more likely it is to misclassify actual interbank funds transactions as implausible.

As in our case the occurrence of Type 1 error is expected to be low due to the features of the dataset, choosing a significantly wide area of plausibility may definitely minimize Type 2 error. However, a wide corridor may cause a Type 3 error, in which the algorithm yields a “wrong match” from multiple matches (see Arciero et al., 2013). Therefore, a too-lax plausibility area is to be avoided as it may result in an unwarranted recurrence of multiple potential refund matches for a single loan.

Akin to Arciero et al. (2013), we use several corridors in order to test whether the results, along with the occurrence of Type 2 and 3 errors, are robust to the change of plausibility area, or not. We use three corridors, of ± 50 , ± 100 and ± 200 basis points with respect to the maximum and minimum *IBR* publicly available interbank reference rates (*IBR*) for the overnight, one-month and three-month time-to-maturities. A minimum plausible interest rate is set at 100 basis points.

About solving for multiple potential matches, we use a recursive procedure. In case two or more potential refunds are available as plausible matches for a single loan, the algorithm estimates the interbank funds market term structure for all maturities from overnight to 90 days based on the three available interbank reference rates (i.e. overnight *IBR*, one-month *IBR*, and three-month *IBR*). The estimation of the term structure is done by cubic spline interpolation. The resulting term structure is used as a benchmark for deciding which of the competing plausible rates is the closest in absolute terms to the interpolated market price for liquidity. Afterwards, if two or more potential refunds persist the one with the lowest time-to-maturity is chosen. This is consistent with interbank funds market’s maturities in the Colombian case, in which most transactions are very short term; based on reports by the Financial Superintendency for the period under analysis, the interbank funds market maximum maturity is 35 days. Finally, if the competing plausible refunds share the same absolute difference with respect to the interbank funds term structure, and have the same time-to-maturity, we use a *first in first out* (i.e. FIFO) rule that privileges the first occurring refund in the day.

Finally, we determine the loans' maximum reliable time-to-maturity. As stated before, Financial Superintendency's data discloses that the maximum time-to-maturity reported by financial institutions is 35 days during the period under analysis, in May 29, 2013. Therefore, one of our scenarios consists of limiting the maturity of potential refunds to 35 days. However, as one the advantages of using transactions data is to contrast other sources of information, and because longer maturities occurring in the future should not be disregarded, we also use a 90-day maximum reliable time-to-maturity scenario. Comparing both maturity scenarios will be useful for testing whether (or not) the algorithm is robust to different specifications.

Please note that in designing the setup of the algorithm we do not consider excluding plausible rates that do not conform to market practices. This is a step that uses market practices or anecdotal evidence (e.g. rounding rules, minimum loan values, typical increments in value) to discard implausibly complicated loans or interest rates that do not follow standard interbank funds transactions (see Arciero et al. 2004; Demiralp et al. 2004;). As before, because in our case the dataset is limited to interbank funds transactions, such exclusion procedure is unwarranted.

4. Main results

The main results of the implementation of the Furfine's method for the Colombian interbank funds market are presented in three subsections. The first subsection compares the results obtained with different scenarios of plausible interest rates (i.e. corridors) and different transactions' maximum reliable time-to-maturities. After selecting the most convenient scenario for analytical purposes, the second subsection contrasts the resulting identified loans with those identified from financial institutions' reported data. The third section contrasts our implicit interbank overnight interest rate (IIR_{ON}) with the publicly available interbank overnight reference rate (IBR_{ON} - *Índice Bancario de Referencia Overnight*) and interbank overnight funds average rate (TIB - *Tasa Interbancaria*). The last subsection presents a sample of the interbank claims networks available as a byproduct of the algorithm.

4.1. Examining the scenarios

Six different scenarios are designed to examine the algorithm and its robustness to its setup. Different choices of plausible interest rates (i.e. the corridor) and transactions' maximum reliable time-to-maturities are considered for the following scenarios:

- $S_{(50|90)}$: ± 50 basis points corridor, 90-day maximum maturity
- $S_{(100|90)}$: ± 100 basis points corridor, 90-day maximum maturity
- $S_{(200|90)}$: ± 200 basis points corridor, 90-day maximum maturity
- $S_{(50|35)}$: ± 50 basis points corridor, 35-day maximum maturity
- $S_{(100|35)}$: ± 100 basis points corridor, 35-day maximum maturity
- $S_{(200|35)}$: ± 200 basis points corridor, 35-day maximum maturity

The algorithm was run forwards, starting with transactions occurring in April 1, 2013, day by day, through December 30, 2014. Although our dataset covers the April 1, 2013 – December 30, 2014, we discard some observations at the end of the sample when comparing among scenarios. As the first three scenarios consider a 90-day maximum time-to-maturity, comparisons will correspond to April 1, 2013 – September 30, 2014 period (i.e. the last 3 months of observations are discarded). All rates are annualized rates with an actual/365 day-count convention.⁹ A lower bound for the corridor is set to 100 basis points in all scenarios.

Table 1 compares how the scenarios matched actual transactions (by number of transactions and their value), and presents how they differ in terms of implicit interest rates and maturities.

⁹ The local day-count convention for the interbank market is actual/360 annualized rates. We use the actual/365 annualized rate convention because it is the one used by the Central Bank for calculating the *TIB*, and the one required by the Financial Superintendency for financial institutions' reports.

		$S_{(50 90)}$	$S_{(100 90)}$	$S_{(200 90)}$	$S_{(50 35)}$	$S_{(100 35)}$	$S_{(200 35)}$
Matched ^a	Transactions	83.45%	83.49%	83.80%	83.45%	83.49%	83.78%
	Value	89.51%	89.54%	90.11%	89.51%	89.54%	90.10%
Implicit interest rate	Average ^b	3.41%	3.41%	3.40%	3.41%	3.41%	3.40%
	Minimum	2.78%	2.28%	1.20%	2.78%	2.78%	1.20%
	Maximum	4.72%	4.72%	6.51%	4.72%	4.72%	4.72%
Time-to-maturity (days ^c)	Average ^b	2.63	2.64	2.68	2.62	2.63	2.64
	Minimum	1	1	1	1	1	1
	Maximum	49	85	90	35	35	35

This table shows that matched transactions' number and value are rather representative for all scenarios, and fairly stable in cross-section. Likewise, the average implicit interest rates, average maturity, and minimum maturity are robust to changes in the setup of the algorithm. Non-negligible differences arise in the maximum and minimum implicit interest rates, and in maximum maturity. ^a Matched transactions and matched value correspond to the number of actual transactions and value of transactions (in percentage) that are identified by the algorithm, respectively. ^b Corresponds to the simple average. ^c Calendar days.

Table 1 shows that the number and value of transactions matched from the large-value payment system's data are rather representative, slightly above 83% and 89%, respectively. Interestingly, changes in the interest corridor and the maximum reliable maturity do not affect the number and value of matched transactions: increasing the corridor by 150 basis points and the maximum reliable maturity by 55 days results in a -negligible- 0.35% and 0.60% increase in the number and value of matched transactions. This points out that some traits of the data may explain the fraction of transactions that could not be captured by the algorithm. These traits may include the separate refund of principal and interests; the aggregation of refunds into a single settlement; and the settlement of the loan (or the refund) outside the large-value payment system (i.e. by the physical delivery of cash or checks).

Table 1 also shows that the main overall outcomes of the algorithm are rather robust to its setup. There are trivial differences in the number and value of transactions matched from actual data, in the average implicit interest rates, and in the average time-to-maturities. However, there are non-negligible differences in the range (i.e. from minimum to maximum) of implicit interest rates and time-to-maturities. Moreover, all scenarios corresponding to the 90-day maximum reliable maturity tend to over-identify transactions, especially when the corridor widens. For instance, despite the maximum observed time-to-maturity reported by the Financial Superintendency for the period under analysis is 35 days, the first three scenarios identified interbank funds transactions at maturities of 49, 85 and 90 days, in which the wider the corridor the longer the maturity. This concurs with Arciero et al. (2013) statement about how the amount of noise (i.e. falsely identified loans) tends to increase with the selected maximum reliable maturity. Again, as emphasized by Arciero et al., a deep knowledge of the underlying data and technical details of the system is essential to avoid spurious results.

To examine the robustness of the algorithm to its setup we attempted a straightforward test. As mentioned, the algorithm was run forwards, meaning that we start matching interbank loans occurring in April 1 with refunds happening after April 1, then matching loans occurring in April 2, until –recursively- reaching the last date of our sample (i.e. September 30, 2014). Our test is to run the algorithm backwards, starting with the last date of the sample until reaching the first one. In short, we start matching loans contracted in September 30, 2014 with the refunds registered after that date; afterwards, we match the loans contracted in September 29, 2014 with the refunds registered and available (i.e. not already matched before) after that date; and so on until reaching the first day of the sample (April 1, 2013).

By running the algorithm backwards short-term matches will be more likely because spurious long-term potential refunds will tend to be scarce (they will be matched by short-term plausible transactions first). Thus, running the algorithm backwards should mitigate the over-identification of long-maturity transactions and of false

positives (i.e. Type 1 error), whilst the results should converge to those attained by defining an adequate maximum reliable time-to-maturity.¹⁰

The backwards scenarios will be identified as follows:

- $Z_{(50|90)}$: backwards, ± 50 basis points corridor, 90-day maximum maturity
- $Z_{(100|90)}$: backwards, ± 100 basis points corridor, 90-day maximum maturity
- $Z_{(200|90)}$: backwards, ± 200 basis points corridor, 90-day maximum maturity
- $Z_{(50|35)}$: backwards, ± 50 basis points corridor, 35-day maximum maturity
- $Z_{(100|35)}$: backwards, ± 100 basis points corridor, 35-day maximum maturity
- $Z_{(200|35)}$: backwards, ± 200 basis points corridor, 35-day maximum maturity

The backwards-run scenarios in Table 2 exhibit some interesting features. First, as before, the number and value of transactions matched from the large-value payment system's data are rather representative, slightly above 83% and 89%, respectively, and they are robust to changes in the setup of the algorithm. Second, the main outcomes of the scenarios are robust in cross-section, with trivial differences in the average implicit interest rates, average time-to-maturity, minimum time-to-maturity, and number and value of captured transactions. Third, concurrent with forward-run scenarios in Table 1, the widest corridor (± 200 basis points) results in non-negligible differences in the maximum and minimum implicit interest rates, and the maximum maturities. Fourth, as expected, the over-identification of long-maturities is mitigated in the backwards-run scenarios: $Z_{(50|90)}$ and $Z_{(100|90)}$ result in a maximum time-to-maturity equal to that reported by the Financial Superintendency for the sample under analysis (i.e. 35 days in 29 May, 2013), whereas analogous forwards-run $S_{(50|90)}$ and $S_{(100|90)}$ resulted in 49 and 85 days maturities. However, $Z_{(200|90)}$, which is the

¹⁰ Other authors have addressed the over-identification of long-term loans. The algorithm designed by Guggenheim et al. (2010) searches the whole dataset for each possible maturity, starting with one-day loans; they also exclude transactions with a maturity of more than three months. Heijmans et al. (2010) let the algorithm select the most plausible maturity from a set consisting of determined maturities (i.e. one-day, full week(s) and full month(s)); if the maturity does not match any of these plausible maturities, the shortest maturity is selected.

scenario with the widest corridor (± 200 basis points) under a lax time-to-maturity limit (90 days), still results in maturities well beyond reported ones (i.e. 85).

Table 2
Comparison of backwards-run selected scenarios ^d

		$Z_{(50 90)}$	$Z_{(100 90)}$	$Z_{(200 90)}$	$Z_{(50 35)}$	$Z_{(100 35)}$	$Z_{(200 35)}$
Matched ^a	Transactions	83.45%	83.49%	83.79%	83.45%	83.49%	83.78%
	Value	89.51%	89.54%	90.11%	89.51%	89.54%	90.10%
Implicit interest rate	Average ^b	3.41%	3.41%	3.40%	3.41%	3.41%	3.40%
	Minimum	2.78%	2.28%	1.42%	2.78%	2.28%	1.42%
	Maximum	4.72%	4.72%	6.37%	4.72%	4.72%	6.11%
Time-to-maturity (days ^c)	Average ^b	2.62	2.63	2.64	2.62	2.63	2.64
	Minimum	1	1	1	1	1	1
	Maximum	35	35	80	35	35	35

This table shows that matched transactions' number and value are rather representative for all scenarios, and fairly stable in cross-section. Likewise, the average implicit interest rates, average maturity, and minimum maturity are robust to changes in the setup of the algorithm. Non-negligible differences arise in the maximum and minimum implicit interest rates, and in maximum maturity. ^a Matched transactions and matched value correspond to the number of actual transactions and value of transactions (in percentage) that are identified by the algorithm, respectively. ^b Corresponds to the simple average. ^c Calendar days. ^d Instead of running the algorithm from the first to the last date, we run the algorithm backwards to mitigate the over-identification of long maturity transactions and examine the robustness of results.

For simplicity, because of the overall robustness of all backwards-run algorithm to changes in its setup, and due to its ability to mitigate the over-identification of long-term transactions, we choose to analyze a single scenario: $Z_{(100|90)}$. This backwards-run scenario, consisting of a ± 100 basis points corridor and a 90-day maximum time-to-maturity, may be considered representative because it concurs with most features of all twelve scenarios. Moreover, $Z_{(100|90)}$ may be considered convenient as well because it attains the highest number and value of matched transactions without imposing a restrictive maximum maturity based on historical data.

The graphical outcome of the algorithm is displayed in Figure 1. Dots correspond to loans identified by the algorithm, whereas the line corresponds to our weighted average implicit interbank interest rate (*IIR*). All time-to-maturities available are displayed. The corridor corresponds to the selected scenario $Z_{(100|90)}$, and it is non-symmetrical due to its design (i.e. ± 100 basis points with respect to the maximum and minimum *IBR* for the overnight, one-month and three-month time-to-maturities).

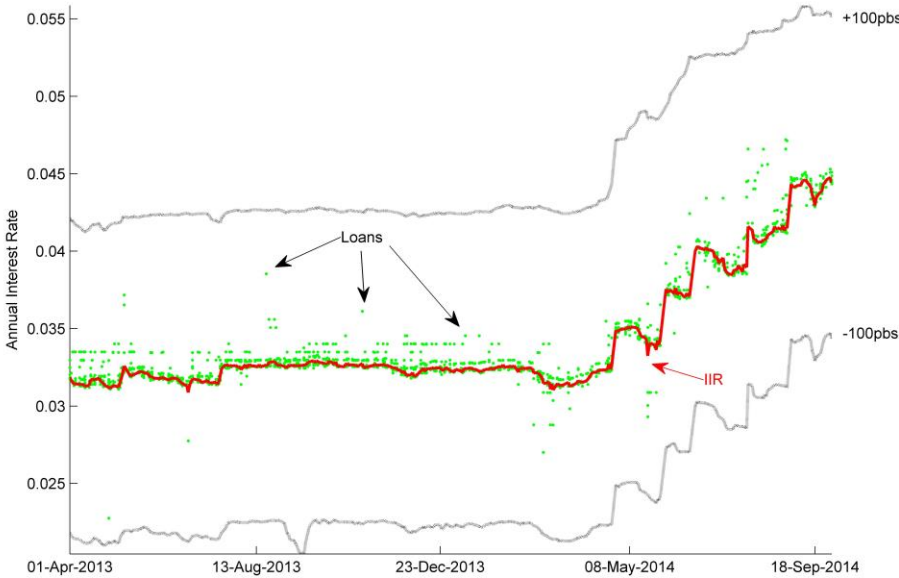


Figure 1. The implicit interbank rate (*IIR*). Dots represent the overnight loans identified by the algorithm for any time-to-maturity. *IIR* corresponds to the weighted average of all loans for each business day. The non-symmetrical corridor corresponds to a ± 100 basis points with respect to the maximum and minimum *IBR* for the overnight, one-month and three-month maturities.

Other information valuable for monitoring purposes may be available as well. Figure 2 exhibits the average time-to-maturity of loans at their inception. As expected, most loans have a low time-to-maturity at inception, with 78.87% being overnight loans. Figure 3 displays the total value of contracted loans for each day in the sample.

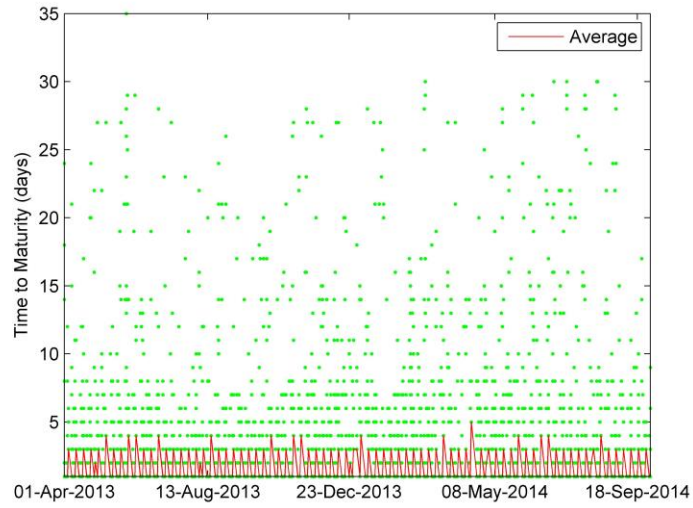


Figure 2. Time-to-maturity of loans (at inception). The average maturity of interbank loans is about 2.6 calendar days, with most deviations from the 1-day maturity due to weekends and holidays. In terms of business days, 78.87% of the loans are overnight at inception.

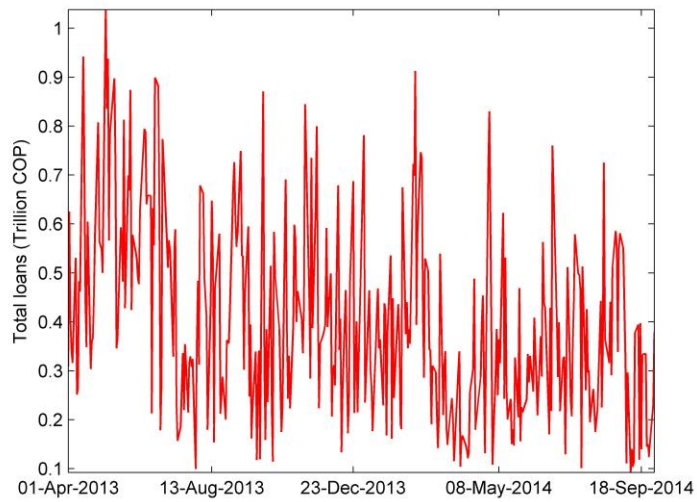


Figure 3. Value of new loans. The average value of loans extended each day during the period under analysis is about 0.4 Trillion \$COP, ranging from 0.1 to 1.0 Trillion \$COP.

4.2. Contrasting the selected scenario with reported data

Reports or surveys from financial institutions are the most common source of interbank data. Two types of reports are available from the Colombian Financial Superintendency, both containing different information reported by local financial institutions.

The first type is a report on the interbank funds transactions occurred during the previous business day. It is aggregated by lender, and reports the total value and weighted average interest rate of the loans for three maturities (i.e. overnight, 2-5 days, more than 5 days). After an exhaustive validation process, this report is used by the Central Bank to calculate the interbank overnight funds average rate (*TIB*). However, it does not contain information about the borrower; it is aggregated by maturity; and does not include the pending amount (i.e. the value of the claim). Hence, this type of report is useless for examining and monitoring individual loans and their financial conditions, or for calculating the exposures between financial institutions and building the corresponding interbank claims networks. Consequently, this type of report is discarded for the purpose of this article.

The second type of report discloses each outstanding interbank loan separately, reports the lender, borrower, and pending amount. Each outstanding interbank loan is identified by a unique code, which we use to determine the date in which the loan was contracted. Although the data has a daily frequency, it is made available to the Central Bank in batches transmitted with a lag between one and two weeks.

As with most reports by financial institutions to financial authorities, the steps involved (i.e. consolidating, processing, transmitting) may result in lagged information and potential errors. Also, as contrasting the reported data is difficult and costly –if possible– for financial authorities, it is uncertain to what extent the information reported is reliable and complete. Furthermore, as the Colombian Financial Superintendency only requires credit institutions to report their interbank funds transactions, other financial institutions that are allowed to participate in the interbank funds market (e.g. brokerage firms) may not be considered.

On the other hand, transactional data is available with a minimum lag (i.e. right after the market closes for overnight loans), and it may be monitored in real-time (i.e. as transactions are registered). Though, as the algorithm requires the refunds to match the loans, there is at least a 1-day lag for the overnight loans. Unlike reports required by the Financial Superintendency, due to the non-tiered (i.e. direct) nature of the local large-value payment system, interbank funds transactions with or among non-credit institutions are captured and readily available.

Unfortunately, reliability and completeness of interbank funds transactional data in our case is uncertain as well. The quality of transactional data depends on how careful and truthful financial institutions are when using the codes assigned for registering transactions in the large-value payment system. As with reported data, it is difficult and costly –if possible- for financial authorities to verify that all interbank funds transactions are properly registered.

As the reliability and completeness of both data sources (i.e. transactional and reports) is uncertain, contrasting our results is not straightforward. We are trying to assess the quality of an algorithm run on a dataset whose quality cannot be verified by contrasting its results with financial institutions' reports whose quality has not been verified either. Thus, under the –unverifiable- assumption of reliability and completeness of financial institutions' raw reported data, we expect to find minor and reasonable differences when contrasting transactional data.

The contrast is as follows. We use the second type of report provided by the Colombian Financial Superintendency for the corresponding period (April 1, 2013 – September 30, 2014). From this source of raw reported data we build a consolidated and revised dataset containing the original loan and its main financial features (i.e. contracting date, lender, borrower, loan value, interest rate, maturity).

Based on the consolidated and revised version of raw reported data we make four contrasts. First, we contrast the number and value of loan transactions identified from both sources; the less dissimilar the datasets, the less disparate the number and value of loan transactions. Second, we calculate the proportion of loan transactions

identified from transactional data that coincide with those identified from reported data by date, lender, borrower, and loan value; the higher the proportion, the lower the occurrence of Type 1 errors (i.e. false positives). Third, we discriminate the interest rate matching precision of transactions coinciding from reported and transactional data; we discriminate between exact matches (i.e. zero two-decimal digit absolute difference) and approximate matches (i.e. absolute difference between 1 and 30 basis points). Fourth, we calculate the proportion of loan transactions from reported data that are also identified from transactional data by date, lender, borrower and loan value; the higher the proportion, the lower the occurrence of Type 2 errors (i.e. false negatives).

Table 3 presents the outcome of the contrast. The number and value of identified loans from each data source is rather dissimilar, with reported loans about 1.46 and 1.25 times that from transactional data, respectively. A reasonable explanation for such disparity is related to the loan-by-loan nature of reports required by the Financial Superintendency, even if the conditions (i.e. date, interest rate, maturity) could allow some aggregation. On the other hand, as the large-value payment system charges a per-transaction fee¹¹, financial institutions may find optimal aggregating loans into a single registry, and may also aggregate refunds occurring in a same day. An alternative explanation may be the settlement of interbank loans and refunds outside the large-value payment system (e.g. by the delivery of cash or checks). Likewise, the separate settlement of the principal and interest may further complicate the identification of loans and their refunds; yet, the per-transaction fee charged by the large-value payment system should dissuade financial institutions from such separation. Therefore, such disparity may not be surprising, and should also increase the occurrence of Type 2 errors (i.e. false negatives).

¹¹ The large-value payment system charges \$COP 2,580 (around \$USD 1.2) per-transaction occurring between 00:00 and 17:00. From 17:00 to 24:00 the per-transaction fee is \$COP 2.5 per million, with a minimum of \$COP 3,730 (around \$USD 1.6).

Table 3
Contrasting transactional and reported data

Parameter		By number of loans ^a	By value of loans ^b
Identified loans	Transactional data	10,020	142.93
	Reported data	13,923	177.99
Proportion of loans from transactional data that match reported data ^c		99.70%	99.83%
<i>Exact interest rate matches (i.e. two-decimal digit absolute difference precision)</i>		91.51%	88.56%
<i>Approximate interest rate matches (i.e. absolute difference between 1 and 30 basis points)</i>		8.19%	11.27%
Proportion of loans from transactional data that do not match reported data ^c		0.30%	0.17%
Proportion of loans from reported data that match transactional data ^c		71.81%	80.25%

This table shows that the number and value of loans identified from reported data are higher. The number and value of loans identified from transactional data that match reported data is higher than 99%, and most matches are rather accurate; only a fraction of matches do not comply with a two-decimal digit precision. Loans identified from transactional data that do not exist in reported data are scarce, about 0.30% and 0.17% in terms of number and value of loans, respectively; hence, Type 1 errors (i.e. false positives) are rare. Most loans identified from reported data match transactional data, about 71.81% and 80.25% in terms of number and value of loans, respectively. ^a Number of loans, unless otherwise stated. ^b Trillion \$COP, unless otherwise stated. ^c A match is based on the exact coincidence of date, lender, borrower, and loan amount, whereas the interest rate match considers exact and approximate coincidences.

The number and value of loans from transactional data that match reported data by date, lender, borrower, loan amount and interest rate is high, 99.70% and 99.83%, respectively; conversely, the number and value of loans from transactional data that do not match reported data is rather low, 0.30% and 0.17%, respectively. Exact interest rate matches (i.e. two-decimal digit precision) occur for 91.51% and 88.56% of the number and value of loans from transactional data, respectively. 8.19% and 11.27% correspond to approximate matches, which have an average absolute difference about 2 basis points. All in all, the proportion of loans from transactional

data that match reported data suggests that Type 1 errors (i.e. false positives) are rare. Furthermore, as wrong matches can be considered a subset of false positive errors (Arciero et al., 2013), the low occurrence of Type 1 errors and the dominance of exact matches may be interpreted as a signal of a low occurrence of Type 3 errors (i.e. wrong matches).¹²

Concurrent with the number and value of loans from reported data exceeding those from transactional data, the proportion of loans from reported data that match transactional data is 71.81% and 80.25%, respectively. This suggests that Type 2 errors (i.e. false negatives) are non-negligible. A typical source of Type 2 error is a narrow corridor of plausible rates; however, tables 1 and 2 show that widening the corridor does not increase the number or value of matched loans notably. Alternatively, as stated before, misusing large-value payment system's registering codes; the aggregation of loans in a single register in transactional data; the separate settlement of principal and interests; and the settlement of loans and refunds outside the large-value payment system, may explain differences in the number and value of loans. Still, as the reliability and completeness of reported data is not verifiable, it is uncertain to what extent the excess of reported data and the occurrence of Type 2 errors is related to the quality of both reported and registered information.

4.3. Contrasting the implicit interbank interest rate with market data

As customary in the literature (see Millard and Polenghi, 2004; Heijmans et al., 2010; Arciero et al., 2013), we contrast our implicit interbank interest rate with the existing interbank interest rate benchmarks. In the Colombian case there are two publicly available benchmarks: First, the interbank overnight funds average rate (*TIB - Tasa Interbancaria*), which is calculated and reported by the Central Bank based on financial institutions' reports to the Colombian Financial Superintendency. *TIB* is

¹² As suggested by Arciero et al. (2013), a wrong match is always related to a false positive (i.e. a wrong match will unavoidably result in a false positive), whereas a wrong match is not always related to a false negative.

calculated after an exhaustive validation process of financial institutions' raw reported data, thus it is a reliable and comprehensive benchmark. Second, the interbank overnight reference rate (IBR_{ON} - *Índice Bancario de Referencia Overnight*), which is the overnight rate of the interbank reference rate formation program. As IBR_{ON} results from the interest rate formation program, it is a reliable and comprehensive benchmark as well.

As both benchmarks are overnight rates, we build the corresponding implicit interbank overnight interest rate (IIR_{ON}). This is, from the selected scenario ($Z_{(100|90)}$) we discard all loans with maturities greater than one business day. Figure 4 displays IIR_{ON} , IBR_{ON} and TIB for the period under analysis (1 April, 2013 - 30 September, 2014). Due to the reliability and comprehensiveness of TIB and IBR_{ON} , divergences displayed by the implicit interbank overnight interest rate (IIR_{ON}) should correspond to the features and limitations of our algorithm and datasets.

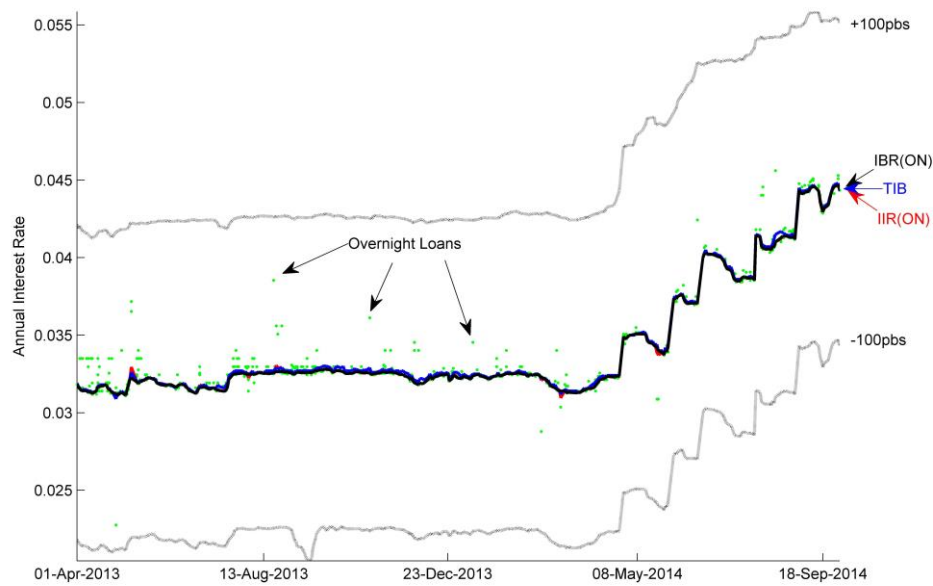


Figure 4. Interbank overnight interest rates comparison. Dots represent the overnight loans identified by the algorithm, whereas the three lines in the middle of the ± 100 corridor correspond to the implicit interbank overnight interest rate (IIR_{ON}), interbank overnight reference rate (IBR_{ON}), and the interbank overnight funds average rate (TIB). The three interbank overnight interest rates do not deviate significantly from each other. Most loans (i.e. dots) have implicit interest rates that do not deviate too much from the three interbank overnight interest rates.

The similarity between the three interbank overnight interest rates is evident. Differences are scarce, and they are not prominent. The implicit overnight loans (the dots) do not deviate too much from the three interest rates in the middle of the corridor. Table 4 confirms the linear dependence (i.e. correlation) among the three overnight interest rates' level and serial differences, above and below the main diagonal, respectively. As in Heijmans et al. (2010), this correlation decreases the chance of Type 1 and Type 2 errors.

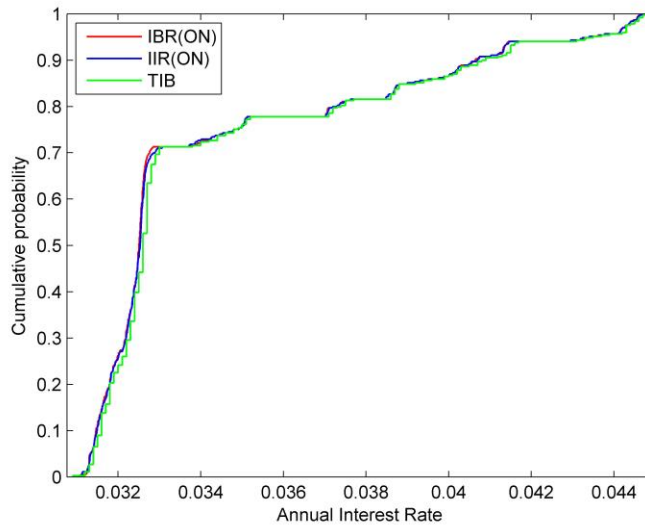
	IBR_{ON}	TIB	IIR_{ON}
IBR_{ON}	1	0.9997	0.9998
TIB	0.9674	1	0.9997
IIR_{ON}	0.9715	0.9704	1

The correlation of the three overnight interest rates' level (above the main diagonal, shadowed) and serial differences (below the main diagonal) shows that the linear dependence across the three overnight interest rates is particularly high.

Likewise, Figure 5 confirms the correspondence of the cumulative distributions of interbank overnight interest rates and their differences. The two-sample Kolmogorov-Smirnoff test does not reject the null hypothesis that data in IBR_{ON} and IIR_{ON} are from the same continuous distribution at any typical significance level, either for interest rates ($p\text{-value} = 0.87$) or their differences ($p\text{-value} = 0.82$). However, this test is rejected when the two samples are TIB and IBR_{ON} or TIB and IIR_{ON} .¹³

¹³ As visual inspection of cumulative distribution reveals (Figure 5), TIB 's level and variation appear to follow discrete changes. Therefore, a preliminary conjecture may relate the rejection of the null hypothesis in the Kolmogorov-Smirnoff test for TIB to its distributions' divergence from a continuous distribution.

Interest rates



Differences in basis points

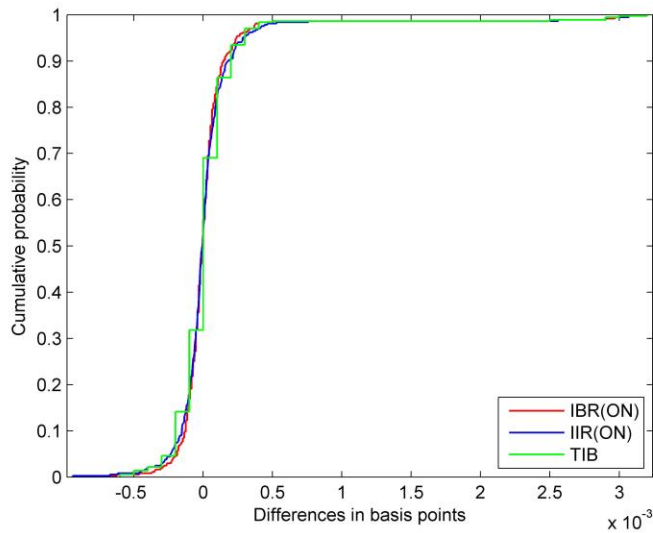


Figure 5. Cumulative distributions of interbank overnight interest rates and their differences. Visual inspection of the cumulative distributions reveals that the distributions of the three interbank overnight interest rates are rather similar. The two-sample Kolmogorov-Smirnoff test does not reject the null hypothesis that data in IBR_{ON} and IIR_{ON} are from the same continuous distribution at the 1% significance level, either for interest rates or their differences.

4.4. Interbank claims networks

The algorithm does not only allow obtaining the interbank interest rate from transactional data, or the loans' time-to-maturity and value. It also allows building the corresponding interbank claims networks in a straightforward manner.

The procedure added to the typical Furfine's method consists of organizing loans in matrix form, building a hypermatrix (i.e. a cube) of loans, with dimensions $N \times N \times T$. T corresponds to the number of days in the sample ($t = 1, 2, \dots, T$), and N corresponds to the number of observed participants all over the sample ($n = 1, 2, \dots, N$). Each t -layer of the hypermatrix will accommodate the cumulated loans granted from financial institution i to financial institution j up to day t . Conversely, all refunds should be organized accordingly. Subtracting each layer in the refunds hypermatrix from the loans hypermatrix will yield the exposure (i.e. outstanding loan) hypermatrix, with each t -layer containing the interbank claims that i holds from j at day t (i.e. j has an outstanding loan from i at t). Hence, each resulting layer is the weighted adjacency matrix of interbank claims.

The graph corresponding to a randomly selected weighted adjacency matrix of interbank claims is portrayed in Figure 6 (and figures A1 and A2 in the appendix). Nodes or vertexes (in rectangles) correspond to a financial institution that participated at some time t throughout the sample; for the period under analysis (1 April, 2013 – 30 September 2014) there are 31 participating financial institutions. The height (width) of each node corresponds to its contribution to the total claims of the market as a lender (borrower). The direction of the arrows (i.e. arcs) represents the existence of an interbank claim (i.e. from the lender to the borrower), whereas their width represents its contribution to the total claims of the system.

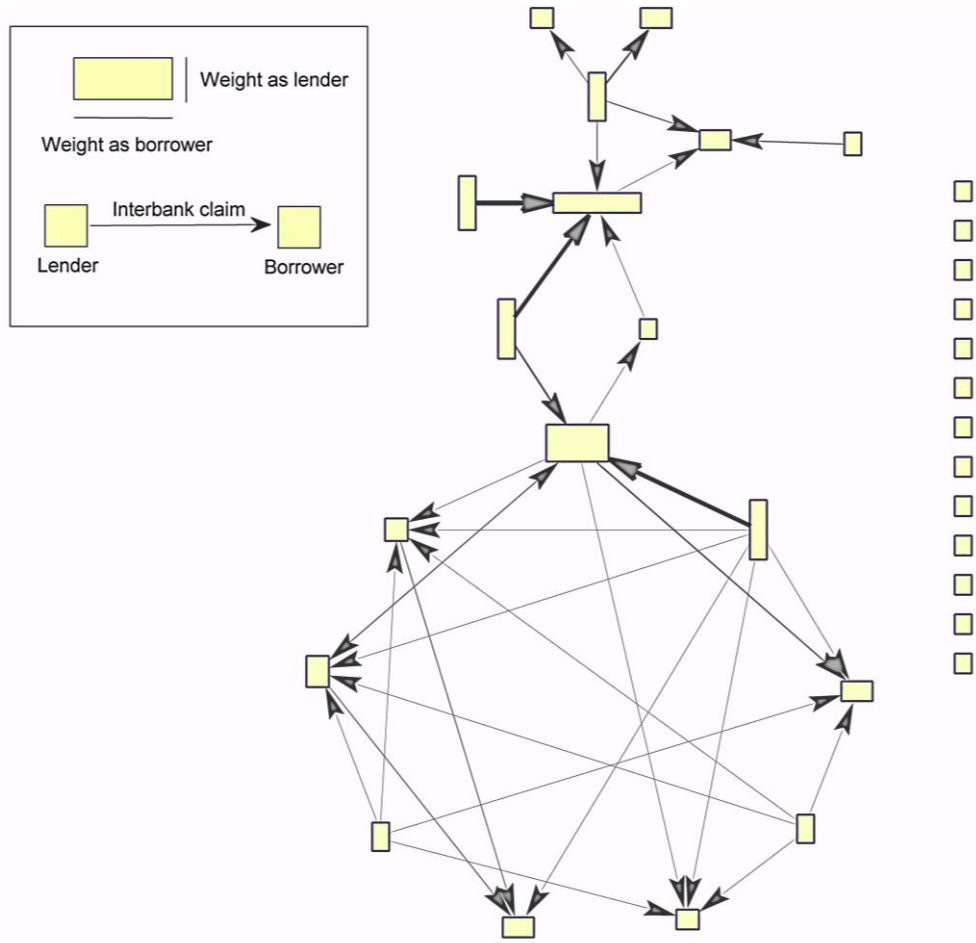


Figure 6. Interbank claims network for a randomly selected date. Nodes in (rectangles) correspond to participating financial institutions. The height (width) of each node corresponds to its contribution to the total claims of the market as a lender (borrower). The direction of the arrows represents the existence of an interbank claim (i.e. from the lender to the borrower), whereas their width represents its contribution to the total claims of the system.

Despite a formal and comprehensive analysis of the statistical properties of the interbank claims networks is beyond the scope of this paper, there are some obvious features in Figure 6 (and in figures in the Appendix) that are worth stating. First, as expected, not all financial institutions are connected, which results in 13 non-connected financial institutions. Second, concurrent with related literature, the interbank claims network is sparse: The number of observed linkages is a fraction of potential linkages (i.e. about 3.44% if all nodes are considered, and 10.46% if only

connected nodes are considered), which may be related to the existence of under-insurance in interbank markets (see Castiglionesi and Wagner, 2013). Third, also concurrent with related literature, the distribution of links, their values, and the roles of financial institutions as lenders and borrowers is heterogeneous.

5. Final remarks

By implementing Furfine's method on a dataset from the Colombian large-value payment system this paper attained three main objectives. First, we filtered out interbank funds transactions in the Colombian market in order to identify interbank loans without relying on data reported by financial institutions. Second, we contrasted the loans identified by our algorithm with those identified from reports by financial institutions, and contrasted our implicit interbank overnight interest rate (IIR_{ON}) with the publicly available interbank overnight benchmark rates. Third, we constructed a hypermatrix containing the interbank claims network for each day in the sample from transactional data.

Results suggest that the algorithm is useful as an alternative source of interbank data. The algorithm is rather robust to changes in its setup. Interestingly, by running the algorithm backwards we mitigated the over-identification of long-term interbank loans in a straightforward manner. To the best of our knowledge, this backwards-run setup has not been attempted in related literature before, and may be a configuration worth exploring in further implementations of Furfine's algorithm.

All in all, the selected setup of the algorithm performed well. Most loans identified by the algorithm coincide with reported data (i.e. 99.70% by number of loans and 99.83% by value of loans), and most of these coincidences are exact matches (91.51% and 88.56%, respectively). The backwards-run setup of the algorithm was able to accurately identify the single loan with the greatest maturity of the sample while avoiding the over-identification of long-maturity loans. The implicit overnight interest rates resulting from the loans identified by the algorithm match the publicly available

overnight rates benchmarks successfully by several measures (i.e. visual comparison of rates and their variation, and their cumulative distributions; their linear dependence; the Kolmogorov-Smirnoff non-parametric test of differences in the distribution of datasets). Due to the reliability and comprehensiveness of *TIB* and *IBR_{ON}*, the convergence of the implicit overnight interest is a fair test of the algorithm's goodness of fit. Also, a preliminary visual inspection of randomly selected claims networks suggests that they conform to the traits of other interbank networks, namely their sparseness and inhomogeneity.

There are three main outputs from our implementation: the interbank loans, the interbank rates, and the claims networks. Identifying the interbank loans from transactional data is a valuable alternative for financial authorities willing to have the ability to contrast surveys and reports by financial institutions. Also, with the benefit of hindsight, the protracted manipulation of benchmark interbank rates (e.g. the Libor scandal) may be avoided by continuously checking whether the rates quoted by financial institutions pertaining to the benchmark's panel conform to market conditions. Moreover, identifying loans and their financial conditions (i.e. borrower, lender, cost, maturity, and amount) may be valuable for monitoring purposes because of the market discipline content implicit in non-collateralized loans.

Regarding the interbank interest rates, the information available from this implementation allows examining and monitoring the aggregated dynamics of liquidity in the non-collateralized money market, including non-overnight maturities. Likewise, amid the granularity of the information available, individual financial institutions' liquidity dynamics may be examined and studied for prudential purposes. Furthermore, the relation between financial institutions' characteristics (e.g. size, leverage, profitability, connectedness, business line) and their borrowing or lending costs may be conveniently examined as well.

About the claims networks, it is important to highlight that they are vital for examining financial contagion and systemic risk. In this vein, financial networks' architecture conveys critical information for financial authorities contributing to

financial stability (see Allen & Gale, 2000; Battiston, Delli, Galletti, Greenwald, & Stiglitz, 2012a; Kambhu, Weidman, & Krishnan, 2007; Haldane, 2009; León and Berndsen, 2014). The interbank claims network is also vital for understanding financial intermediation and the formation of financial networks (see Craig and von Peter, 2014), studying lending relationships in interbank markets (see Cocco, Gomes, & Martins, 2009; Afonso, Kovner, & Schoar, 2013) and liquidity cross-insurance (see Castiglionesi and Wagner, 2013). Furthermore, combining network analysis and institution-centric data, as in DebtRank (Battiston, Puliga, Kaushik, Tasca, & Caldarelli, 2012b), is gaining attention as a comprehensive approach to assessing systemic risk.

Challenges arising from this methodological article come in several forms. First, implementing financial contagion and systemic risk models based on the three main outputs (i.e. interbank loans, rates, and claims networks). Two suggested implementations are DebtRank (Battiston et al., 2012b) on the local interbank claims network, and supplementing existing literature on the Colombian interbank market's architecture (e.g. León, Machado, & Sarmiento, 2014) by implementing network analysis on the claims network.

Second, as contrasting the loans from reported and transactional data evidenced non-trivial differences, it is important to address the sources of such differences in a rigorous and comprehensive manner. Being able to reconcile both data sources with a marginal error is desirable from financial authorities' point of view. As the continuous and efficient reconciliation of both data sources may be difficult and costly, a convenient alternative may be to oblige interbank funds' market participants to register their loans and their financial conditions (i.e. counterparty, amount, maturity, interest rate) in the large-value payment system, and allowing the system itself to settle the refund based on the registered conditions; other financial market infrastructures –besides the large-value payment system- may serve as well. This would result in the ultimate dataset for the interbank funds market: issues about the completeness, reliability, granularity, and opportunity of the information would be minimal –mainly related to settlements outside the large-value payment system.

Third, consolidating other sources of financial claims (e.g. derivatives, collateralized loans) into a multi-layer network may provide a broader view of financial contagion. Likewise, incorporating non-financial institutions (e.g. households, firms) into a multilayer network may provide a comprehensive view of systemic risk –as in de Castro and Tabak (2013).

Finally, articulating the outcomes of the algorithm (i.e. interbank loans, rates, and claims networks) for monitoring purposes is particularly convenient, yet challenging. Comprehensively tracking the dynamics of financial institutions' interbank loans (e.g. their cost, maturity, counterparties), amid the dynamics of the interbank claims network (e.g. density, distribution of links), may provide valuable information for authorities contributing to financial stability.

6. References

- Afonso, G., Kovner, A., & Schoar, A. (2013). "Trading Partners in the Interbank Lending Market". *Federal Reserve Bank of New York Staff Reports*, 620, May.
- Allen, F. & Gale, D. (2000). "Financial Contagion". *Journal of Political Economy*, 108 (1), 1-33.
- Allen, F., Carletti, E., & Gale, D. (2009). "Interbank Market Liquidity and Central Bank Intervention". *Journal of Monetary Economics*, 56, 639–652.
- Arciero, L., Heijmans, R., Heuver, R., Massarenti, M., Picillo, C., & Vacirca, F. (2013). "How to Measure the Unsecured Money Market? The Eurosystem's Implementation and Validation Using TARGET2 Data". *DNB Working Paper*, 369, De Nederlandsche Bank.
- Armantier, O. & Copeland, A. (2012). "Assessing the Quality of Furfine-Based Algorithms". *Staff Report*, 575, Federal Reserve Bank of New York.
- Asobancaria, Ministerio de Hacienda y Crédito Público, Banco de la República, & Superintendencia Financiera de Colombia. (2015). *Reglamento del Indicador Bancario de Referencia*. [retrieved from http://www.asobancaria.com/portal/page/portal/Asobancaria/publicaciones/economica_financiera/estudios_regulaciones_financieras/indicador_bancario_referencia/REGLAMENTO_IBR.pdf]
- Battiston, S., Delli, D., Gallegati, M., Greenwald, B., & Stiglitz, J.E. (2012a). "Default Cascades: When Does Risk Diversification Increase Stability?". *Journal of Financial Stability*, 8, 138-149.
- Battiston, S., Puliga, M., Kaushik, R., Tasca, P., & Caldarelli, G. (2012b). "DebtRank: Too Central to Fail? Financial Networks, the FED and Systemic Risk", *Scientific Reports*, 2 (541), DOI:10.1038/srep00541.

- Cardozo, P. & Murcia, A. (2014). "El IBR y la DTF como Indicadores de Referencia". *Reportes del Emisor, 187*, Banco de la República.
- Castiglionesi, F. & Wagner, W. (2013). "On the Efficiency of Bilateral Interbank Insurance". *Journal of Financial Intermediation, 22*, 177-200.
- Cocco, J.F., Gomes, F.J., & Martins, N.C. (2009). "Lending Relationships in the Interbank Market". *Journal of Financial Intermediation, 18*, 24-48.
- Craig, B. & von Peter, G. (2014). "Interbank Tiering and Money Center Banks". *Journal of Financial Intermediation, 23*, 322-347. [dx.doi.org/10.1016/j.jfi.2014.02.003](https://doi.org/10.1016/j.jfi.2014.02.003)
- de Castro, R. & Tabak, B. (2013). "Contagion Risk within Firm-Bank Bivariate Networks". *Working Paper Series, 322*, Banco Central do Brasil.
- Demiralp, S., Preslopsky, B., Whitesell, W. (2004). "Overnight Interbank Loan Markets". *Manuscript Board of Governors of the Federal Reserve*.
- Fricke, D. & Lux, T. (2014). "Core-Periphery Structure in the Overnight Money Market: Evidence From the e-MID Trading Platform". *Computational Economics*, DOI 10.1007/s10614-014-9427-x.
- Furfine, C. (1999). "The Microstructure of the Federal Funds Market". *Financial Markets, Institutions and Instruments, 8*, 24-44.
- Furfine, C. (2001). "Banks Monitoring Banks: Evidence From the Overnight Federal Funds Market". *Journal of Business, 74 (1)*, 33-58.
- Guggenheim, B., Kraenzlin, S., & Schumacher, S. (2011). "Exploring an Uncharted Market : Evidence on the Unsecured Swiss Franc Money Market". *SNB Working Papers, 2011-5*, Swiss National Bank.
- Haldane, A.G. (2009). "Rethinking the Financial Network". *Speech Delivered at the Financial Student Association (Amsterdam, Netherlands)*.

- Heijmans, R., Heuver, R., & Walraven, D. (2010). "Monitoring the Unsecured Interbank Money Market Using TARGET2 Data", *DNB Working Paper, 369*, De Nederlandsche Bank.
- Hendry, S. & Kamhi, N. (2007). "Uncollateralized Overnight Loans Settled in LVTS". *Bank of Canada Working Paper, 07-11*, Bank of Canada.
- Kambhu, J., Weidman, S., & Krishnan, N. (2007). "New Directions for Understanding Systemic Risk". *Federal Reserve Bank of New York Economic Policy Review, 13 (2)*, November.
- Kyriakopoulos, F., Thurner, S., Puhr, C., & Schmitz, S.W. (2009). "Network and Eigenvalue Analysis of Financial Transaction Networks". *The European Physical Journal B, 71*, 523-531.
- León, C. & Berndsen, R.J. (2014). "Rethinking Financial Stability: Challenges Arising From Financial Networks' Modular Scale-Free Architecture". *Journal of Financial Stability, 15*, 241-256. doi:10.1016/j.jfs.2014.10.006.
- León, C., Machado, C., & Sarmiento, M. (2014). "Identifying central bank liquidity super-spreaders in interbank funds networks". *Borradores de Economía, 816*, Banco de la República.
- Millard, S. & Polenghi, M. (2004). "The Relationship Between the Overnight Interbank Unsecured Loan Market and the CHAPS Sterling System". *Bank of England Quarterly Bulletin*, Bank of England.
- Rochet, J-C. & Tirole, J. (1996). "Interbank Lending and Systemic Risk". *Journal of Money, Credit and Banking, 4 (28)*, 733-762.

7. Appendix

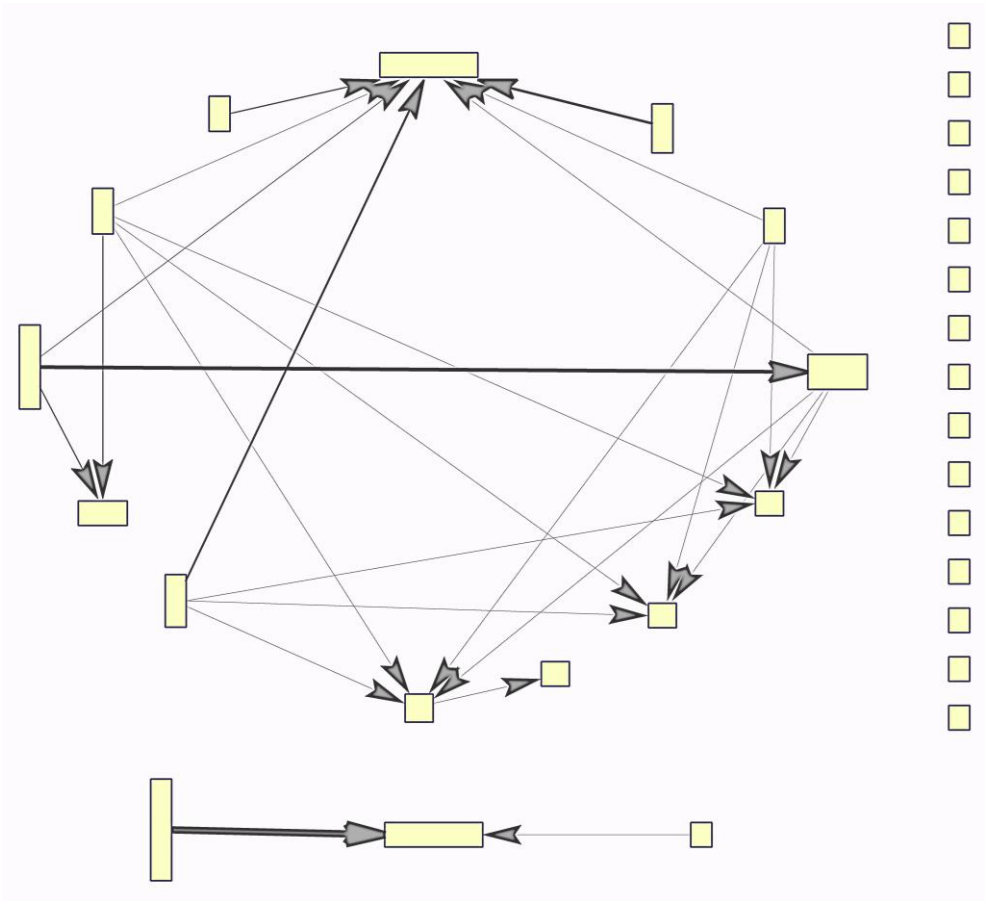


Figure A1. Interbank claims network for a randomly selected date. The height (width) of each node corresponds to the financial institution’s contribution to the total claims of the market as a lender (borrower). The direction of the arrows represents the existence of an interbank claim (i.e. from the lender to the borrower), whereas their width represents its contribution to the total claims of the system.

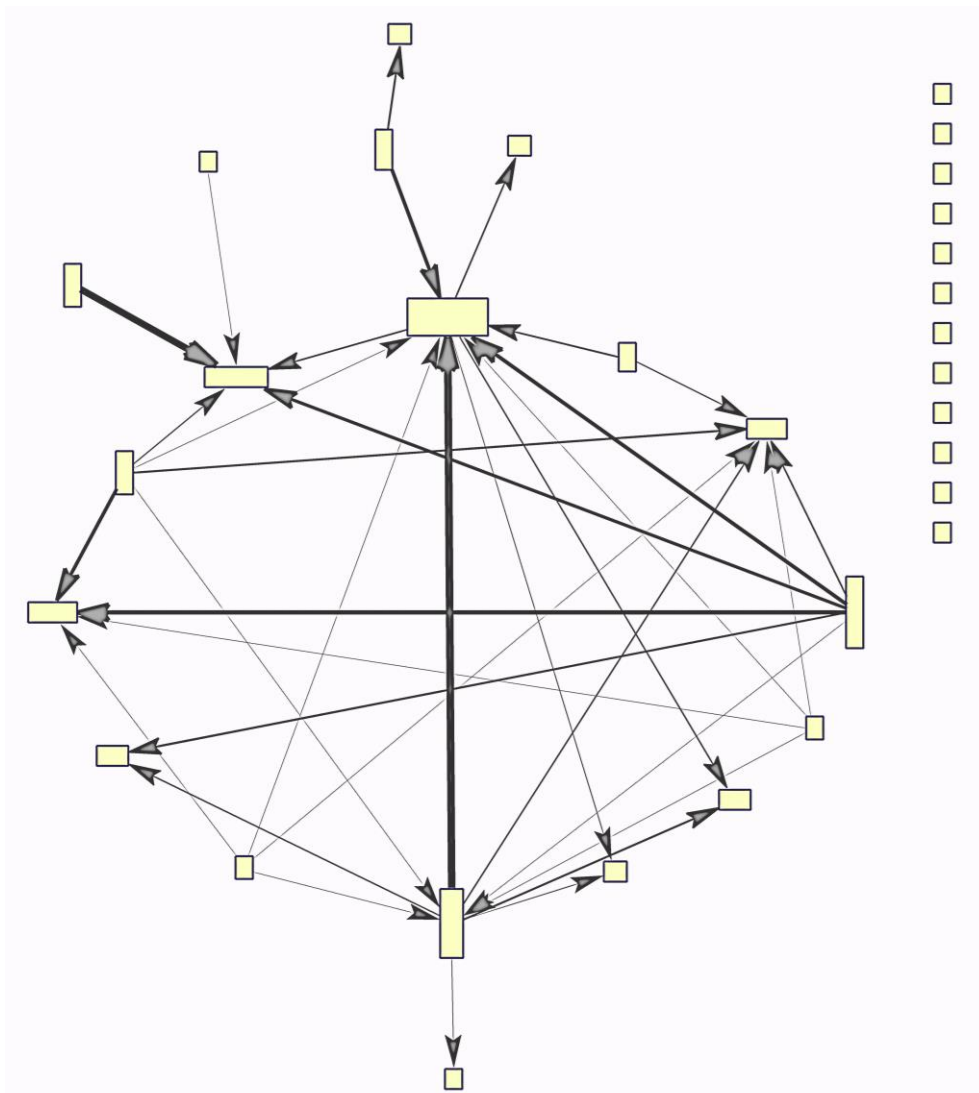


Figure A2. Interbank claims network for a randomly selected date. The height (width) of each node corresponds to the financial institution's contribution to the total claims of the market as a lender (borrower). The direction of the arrows represents the existence of an interbank claim (i.e. from the lender to the borrower), whereas their width represents its contribution to the total claims of the system.



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