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Abstract

The functioning of large-value payment systems (LVPSs) can be affected when some of its participants voluntarily decide to delay their payments until they can totally fund them with the payments received from other participants. This behaviour, known as the free-rider problem, can cause an under-provision of liquidity in LVPSs that operate under a RTGS (real-time gross settlement) mode. With the aim of determining whether there are free-riders in the Colombian LVPS (CUD), we empirically tested this payment strategy: firstly, using regression techniques (quantile regression models) and secondly, computing the empirical quantiles. Our results indicate that there is evidence of this problem in the Colombian case; however, their negative effects on CUD are negligible.

Keywords: Payment system, free riding on liquidity, liquidity hoarding, quantile regression models

JEL: C23, E42, G20

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1. Introduction

Financial institutions' payments, settled through a large-value payment system (LVPS), can be funded using loans (from the central bank and the money market), their own balances at the central bank, and the payments received from other system's participants (McAndrews and Potter, 2002). Amongst these sources of liquidity, only the last one is available free of charge. Money market instruments, such as repurchase agreements (repos) with the central bank or with other banks, are priced at interest rates given by the monetary policy in the first case, and the market's dynamics in the other case. But a repo, either with central bank or in the secured money market, additionally involves an opportunity cost for posting collateral.

As noted by Angelini (1998), when intraday liquidity is costly it creates an incentive for banks to free-ride on the liquidity provided by others, which consists in postponing their due payments until they can be fully funded with the payments collected from other system's participants. From an individual perspective (a system's participant), free-riding can be considered an optimal strategy of payments because the cost of liquidity is cut to zero. But from a wider perspective it may not be optimal as it can reduce the system's effectiveness to avoid liquidity risk.⁴

Some empirical studies on this topic have found evidence of free-riders in the UK's LVPS (Denbee, Garratt and Zimmerman, 2012 and 2015) and the German LVPS (Diehl, 2013). However, it has also been found evidence of system's participants (banks) that over-provide liquidity to the payment system (Denbee et al. 2015). When a system's participant has to send payments but lacks of any other funding source, free-riding on others' liquidity is the only way to fulfil its payments obligations. But when other liquidity sources are available, free ridding will evidence liquidity hoarding. To the extent that the under provision of liquidity that may arise from free-riders can threaten the functioning of payment systems, a formal evaluation of this payments strategy can be useful for oversight purposes, at the same time that it can be informative on how system's participants are really funding their payments, and when some additional rules on liquidity management might be required. Hence, the study of this topic will allow LVPS's owners and managers (e.g. central banks) to identify and monitor the financial

⁴ In this context we assume the definition of liquidity risk provided by the Bank for International Settlement (BIS-CPSS), which is exclusively related to the risk that a financial institution will not settle an obligation of payments in full when due.

institutions that are following this payments strategy, and determine the extent to which it can represent a problem for the safe and efficient functioning of the payment system as a whole.

A recent assessment on payments reaction functions for some of the financial institutions that use the Colombian LVPS (CUD) to process their funds transfers found that there is coordination in the sending of payments, but that the degree of such coordination is rather low (Martínez and Cepeda, 2015).⁵ This result, along with the levels of liquidity recycling within system's participants (during the first half of 2015 the percentage participation of incoming payments within the funding sources was beyond 40 per cent, see Banco de la República 2016), advocates for a formal evaluation of the free-rider problem in the large-value payments context. To this aim, we consider five measures of this payments strategy that have been proposed in previous studies (see Denbee et al. (2012) and Diehl (2013)) and test them using quantile regression models and empirical quantiles as suggested in Denbee et al. (2012) and Denbee et al. (2015), respectively. Our results obtained from payments data between November 2014 and April 2016 reveal the existence of free-riders on liquidity.

2. Free-riders in large-value payment systems

The decision that a financial institution takes on which funding source to use when making a payment essentially depends on how costly that source is compared to the others. Financial institutions can fund their payments using their own liquidity held on accounts with the central bank, the liquidity collected from counterparties, but they can also resort to the central bank or to other system's participants. The cost of liquidity in any of these last two cases is given by the interest rate charged by the lender, but it is also given by the existence of collateral requirements that apply to both repos with the central bank and with other financial institutions. For the financial institution looking for funds, the posting of collateral may be considered as an

⁵ The Colombian LVPS that processes the funds transfers between financial institutions that participate in the local financial markets is CUD, and it is owned and managed by the Colombian Central Bank (Banco de la República). CUD settles payments using a real time framework (RTGS) enhanced with liquidity-saving mechanisms that optimise the management of intraday liquidity. The liquidity-saving mechanisms (LSM) are algorithms that automatically process unsolved transactions, netting payments between system's participants. In CUD the LSM are executed five times per day CUD (see Martínez and Cepeda, 2015). As any LVPS that operates under RTGS mode, this system is more susceptible than others (deferred net settlement (DNS)) systems to coordination problems in the sending of payments, which can even provoke situations in which a payments delay can impede that a huge number of other participants execute their pending disbursements (Kahn and Roberds, 2009).

additional cost (opportunity cost in economic terms) that can make a funding source even more expensive.

Amongst these funding sources, re-using (recycling) the payments received from counterparties seems to be preferred above the others, which is not surprising, since this is the only one that involves no-cost for its users. But following this payments strategy, even if other funding sources are available, is what defines the free-rider problem. As noted by Angelini (1998), when the cost of daylight liquidity is high, the system's participants may feel tempted to postpone their payments. Hence, following the free-rider strategy may also imply conducting payments delays which can affect the payment system as a whole.

The free-riding behaviour is considered intentional when a payments delay arises as a strategic decision; however, it may also be non-intentional when it emerges from the type of business conducted by a financial institution (Denbee et al. 2012). In any case, and as noted by Bech, Galbiati and Tudela (2008), delaying payments could imply additional costs for the financial institution following this payments pattern, given by:

- The financial penalties that may arise for not sending time-critical payments at the agreed time;
- The reputational costs given by the delay of payments on behalf of clients;
- Other reputational costs that may take place when system's participants decide, as a punishment strategy, to stop sending payments to the financial institution that is being perceived as free-rider (FR).

Therefore, the individual decision regarding a timely release of payments (cooperate by sending payments) or its postponement depends on the relative cost of liquidity, but it may also depend on the cost of delaying them. However, whatever the source of the payments delay is, the cost of delay supposes -to some extent- the existence of complete (perfect) information of individual payments. And, as Bech et al. (2008) indicated, system's participants lack of full information on payment flows.

The existence of participants behaving as FRs does not represent a problem for a payment system, per se; but it could turn into a problem when it reaches a level that affects the system's efficiency. In fact, a payments delay will reduce the expected cost of liquidity for the FR, but it

will also increase the cost of liquidity for the financial institution expecting the funds. As a result, it may produce a deadweight loss at the system relative to the cooperative outcome (Nellen, 2011). This is the reason why this topic is of extreme importance for central banks that own and manage a LVPS operated under a RTGS mode, given its objectives of guaranteeing the smooth functioning of payments and the efficient use of liquidity.

Previous studies on this issue are scarce. In the payments economics literature the free-riding problem has been considered tangentially, mentioning mostly the negative consequences that it could produce on payment systems. Angelini (1998) and Galbiati and Soramäki (2010) coincide in that this behaviour is one of the main causes of inefficiencies in LVPSs that transfer funds in a RTGS mode, since it could generate an under-provision of liquidity to the system, and hence, lead to a reduction in its effectiveness to avoid the liquidity risk. Likewise, as Galbiati and Soramäki, (2010) indicate, the adverse effects that the FRs on liquidity may cause on LVPS-RTGS systems can be lessened, but not completely solved by means of the adoption of liquidity-saving mechanisms.

Other studies on this topic have been focused on developing, from different angles, specific measures that allow for empirically assessing the existence of FRs on payment systems. Denbee et al. (2012) proposed two measures of free-riding, based on cost and risk criteria, and noted from results that these measures do not allow separating the intentional from the non-intentional FR. To circumvent this limitation they executed some simulations carried out on their free-riding measures, and tested them using quantile regression models (Denbee et al. 2012) and empirical quantiles (Denbee et al. 2015). Under both empirical assessments, their results confirmed the existence of FRs in the U.K.'s LVPS (CHAPS), but also, that the banks that have followed this payments strategy have not affected the liquidity usage in a considerable manner.⁶ A similar result was found for the German component of the European LVPS (TARGET2-BBK), for which Diehl (2013), using a set of axiomatic postulates on five measures of free-riding (three indicators in addition to the two measures proposed by Denbee et al. (2012)) found that although some banks have behaved as FRs, their effects on this payment system have also been nil.

⁶ This result is also supported by the existence of throughput rules that may (at least, partially) discourage financial institutions from adopting this type of behaviour. These rules force all CHAP's participants to send 50 per cent of payments by value by 12:00 p.m., and complete 75 per cent of payments as an average of calendar month, by 2:30 p.m. (Becher et al., 2008).

3. Data description

The empirical appraisal of liquidity provision in CUD is based on the five measures proposed in related literature, which were computed using payments data of the financial institutions that explain the majority of payments sent through the system. These financial institutions are represented by 24 banks, 22 brokerage firms, 28 trust companies and 6 financial corporations. The business type they conduct present some differences. Banks and financial corporations are responsible for financial intermediation services that consist in channelling funds from depositors to borrowers. But while banks are oriented towards households and firms, financial corporations are specifically focused on providing loans to the industry. The remaining financial institutions are related to investments: Brokerage firms trade securities, while trust companies construct investment portfolios that may include securities as well as other assets.⁷

Table 1
Financial institution's size (in terms of payments)

| | |
|------------------------|--------------|
| Banks | 59.8% |
| Brokerage firms | 10.2% |
| Trust companies | 10.6% |
| Financial corporations | 6.5% |
| TOTAL | 87.2% |

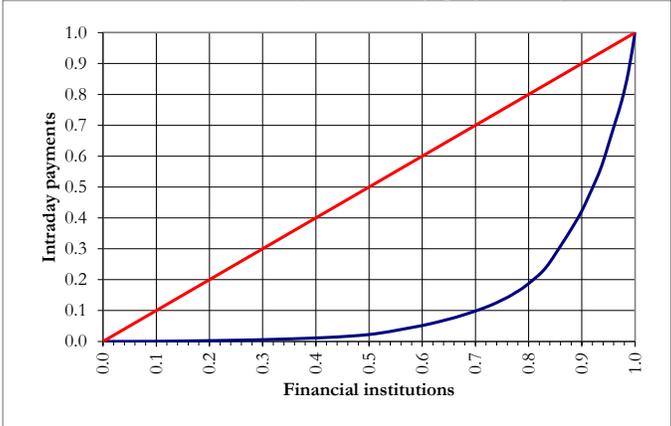
For a typical month representing the sample period (that goes from November 2014 to April 2016), these financial institutions jointly signify around 87.2 per cent of the total value of payments registered per day in CUD, where banks are the largest system's participants (59.8 per cent), and financial corporations the smallest ones (6.5 per cent). Brokerage firms and trust companies can be considered, in this context, as mid-size participants, each one representing more than 10 per cent of intraday payments.

The distribution of payments for the 80 financial institutions considered in the sample, reveal some degree of concentration. The Lorenz curve, constructed using the total value of sent out

⁷ See León, Machado, Cepeda and Sarmiento (2011) for a detailed explanation of the business type conducted by these financial institutions.

payments for a typical month, indicate that only 10 per cent of system’s participants execute 57.7 per cent of intraday payments (or, in other words, 42.3 per cent of payments come from 90 per cent of system’s participants).

Graph 1
Lorenz curve (on intraday payments)



The Gini coefficient computed for this data is 75 per cent, which also indicates some degree of payments concentration in few system’s participants.

3.1. Measures of free-riding

The following description of these measures is brief, and hence, we advise the reader interested in an in-depth explanation of them to consult the original sources: Denbee et al. (2012, 2015) for the cost and risks measures, and Diehl (2013) for the time-based indicators and the relative net sending indicator.

3.1.1. Cost-based measure

The cost based measure calculates the individual cost of liquidity provision, based on each financial institution’s shares on the payments activity (Denbee et al. 2015). Put another way, this criterion is determined by comparing the liquidity burden and the liquidity usage, on an individual basis. The liquidity burden (L_i^s) depends on the total liquidity that each system’s participant provides on day s (its net debit position, $N_i^s(t)$), and it can be computed subtracting

the total amount of payments received ($y_i^s(t)$) from the total amount of payments sent ($x_i^s(t)$) on that same day. Hence, the cost based measure for the *ith* financial institution will be given by the difference between its percentage participations in the total liquidity provision (largest net debit position, $L_i^s = \max_{t \in [0, T]} N_i^s(t)$), and the total liquidity usage:

$$\mu_i^s = \frac{L_i^s}{\sum_{j=1}^n L_j^s} - \frac{x_i^s(T)}{\sum_{j=1}^n x_j^s(T)} \quad [1]$$

Consequently, a financial institution will be considered as FR when the liquidity that uses from the system (second term in equation [1]) exceeds the liquidity that it provides to it ($\mu_i^s < 0$).

3.1.2. Risk based measure

The risk based measure assesses the individual exposure to the liquidity risk of counterparties. This, in other words, depends on the difference between the share of total risk per participant (first term in [2] that depends on the average risk: $\Lambda_i^s = \frac{1}{T} \sum_{t=0}^T \max[(x_i^s(t) - y_i^s(t)), 0]$), and the share of payments it makes on that same day (Denbee et al. 2015):

$$\gamma_i^s = \frac{\Lambda_i^s}{\sum_{j=1}^n \Lambda_j^s} - \frac{x_i^s(T)}{\sum_{j=1}^n x_j^s(T)} \quad [2]$$

Therefore, when the level of counterparty risk that a financial institution assumes is below the amount of liquidity that it uses from the system ($\gamma_i^s < 0$) is because the liquidity that it is providing to the system is lower than expected (it is under-providing liquidity), hence suggesting that it is free-riding.

3.1.3. Time-based measure

The time-based measure determines the percentage of the day required by a financial institution to receive (send) half of the payments. For the assessment of this measure, each business day is divided into the total number of minutes that exist within the thirteen hours in which CUD operates, which correspond to 780 time packages (13 hours times 60 minutes per hour). In addition to this adjustment, the time-based measure assumes that there is no difference between

the payments sent (received) in different seconds within the same minute, and consequently, they are regarded as if they were registered in the same time package. Thus, this measure depends on the difference between the average reception time index and the average payment time index:

$$\delta_i = \left(\begin{array}{c} \text{average reception} \\ \text{time index} \end{array} \right)_i - \left(\begin{array}{c} \text{average payment} \\ \text{time index} \end{array} \right)_i \quad [3]$$

Based on this measure's results, a financial institution could be considered as a FR when, according to Diehl (2013), requires a larger share of the day to send half of its payments than to collect half of the payments coming from other system's participants ($\delta_i < 0$).

3.1.4. Early payment time indicator

Alike to the time-based measure, the early payment time indicator calculates the time at which half of the total payments in value has been settled (see Diehl (2013)). But this indicator assigns a higher weight to the payments solved at early hours of a day than to those solved at later hours, using a decay factor that continuously decreases until it reaches a zero weight for the last time package of the day. The factor describing the weights will diminish consistently with a decay factor of 0.1% that determines a weighting factor per day $(1.001^{780-t}) - 1$. This weights factor, which also depends on the time packages per day (780), is used to calculate the early payment indicator and the early reception indicator. The early payment (reception) indicator will be equal to one when a participant sent (received) all its payments in the first time band of the day, or zero if that occurred in the last time band. Hence, this indicator can be considered as the weighted version of the time-based measure, given by:

$$\pi_i = \left(\begin{array}{c} \text{early reception} \\ \text{indicator} \end{array} \right)_i - \left(\begin{array}{c} \text{early payment} \\ \text{indicator} \end{array} \right)_i \quad [4]$$

Thus, a financial institution that under provides liquidity to the system (that free-rides) will correspond to a negative result of the criterion ($\pi_i < 0$), given by those cases in which the early sent of payments overpasses the early reception of payments.

3.1.5. Relative net sending indicator

The relative net sending indicator completes the set of measures suggested by Diehl (2013). In the same way as the measures based on cost and risk, this indicator depends on the largest net debit position (L_i^s), but it considers extreme situations in terms of liquidity (e.g. a participant with large liquidity needs). More formally, this indicator is given by the difference between the ratio of the largest net debit position (L_i^s) to the sum of all incoming payments ($\sum_{t=0}^T x_t^{rec}$), and the ratio of the largest accumulated amount of net reception to the sum of all outgoing payments ($\sum_{t=0}^T x_t^{sent}$).

$$v_i = \frac{L_i^s}{\sum_{t=0}^T x_t^{rec}} - \frac{Abs(\min_t(x_i^s(t) - y_i^s(t)))}{\sum_{t=0}^T x_t^{sent}} \quad [5]$$

Once more, a free-rider will correspond to a negative result ($v_i < 0$), which happens when the surplus of received payments relative to the total amount of all payments sent through the system (second term in equation [5]) exceeds its net debit position relative to the total amount of payments received in the system (the first term in equation [5]).

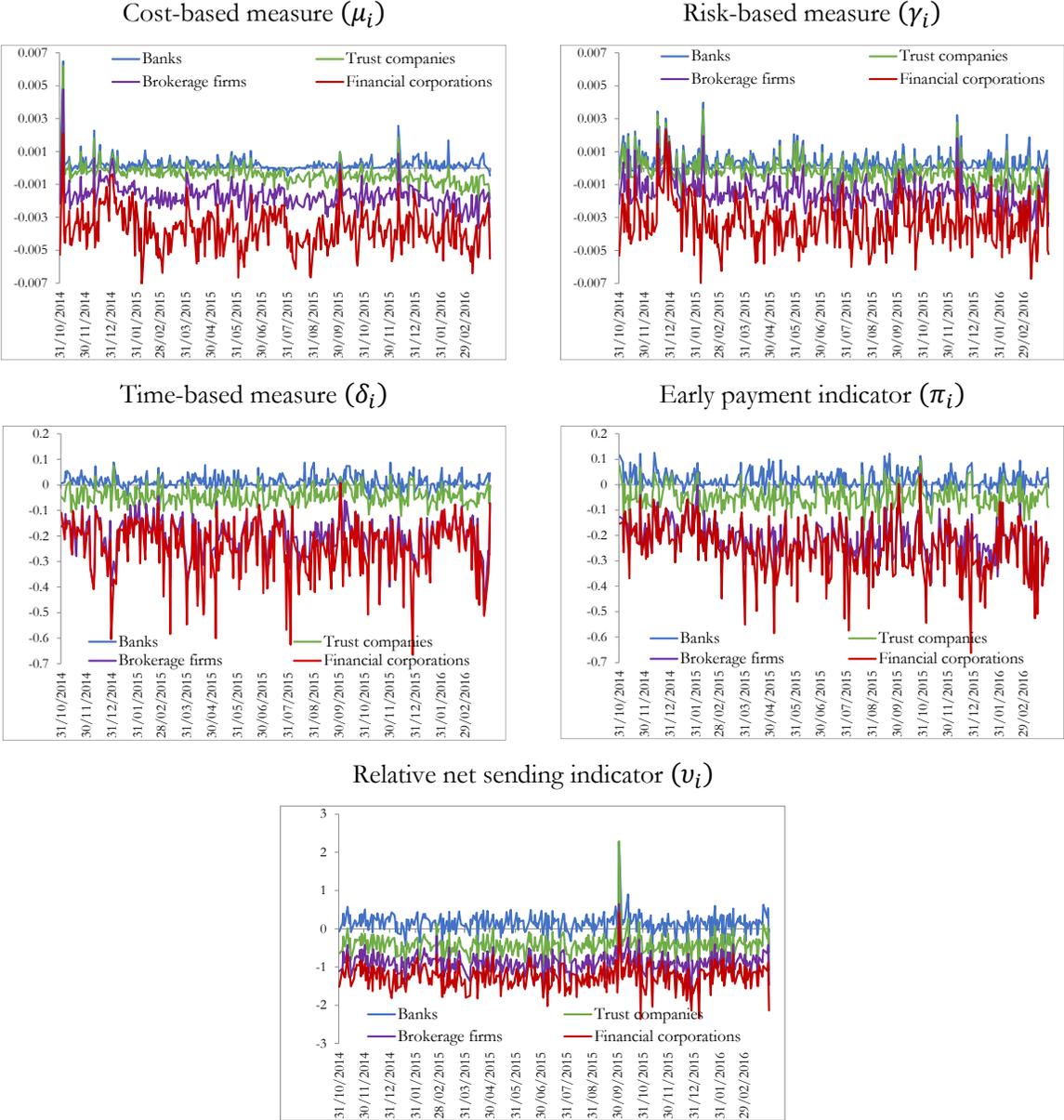
3.2. Measuring free-riding on liquidity in CUD

The five measures of free-riding were calculated using the payments registered per second during CUD's operating hours; that elapses between 07:00:00 and 19:59:59. The computed measures per day for the financial institution located in the median of the distribution (the 50th percentile) between November 2014 and April 2016 are presented in Graph 2. As noted in the literature, the individual payment behaviour is dynamic and consequently, it is very likely that the results obtained from the visual inspection of them do not coincide in concluding (rejecting) the existence of free-riders for different time periods.

As can be seen on the set of graphs, these measures do not share the same measurement scale, which can be attributed to the different criteria they are based on. In effect, the computed measures under the cost and risk criteria move within the same interval, which can be attributed to the fact that they both are centred on each institution's net debit position. Likewise, the time-based measure and the early payment indicator also share a similar measurement scale, since they both are adjusted for the number of minutes within the system's operating time (780 time

packages). Even so, considering the median value per day, the estimated measures produce negative results suggesting that some financial corporations, brokerage firms and trust companies, free-ridden on other's liquidity to settle their own payments. In a strict sense these results cannot be considered conclusive because they indicate, at most, the existence of apparent free-riders but not whether this conduct arises (or not) from individual's willingness to delay.

Graph 2
Computed measures of free-riding per type of financial institution
(Median)



Source: Banco de la República. Authors' calculations.

4. Methodology and estimation results

The estimation methodology that we follow is composed by a three-step procedure. In the first step we constructed a fictitious month of intraday payments by taking a random sample of observations from the entire period that goes from November 1, 2014 to April 12, 2016. Specifically, we randomly selected a day representing the position of a day in a month, using a vector of random numbers on the dates of the entire period, excluding holidays and banking days. The vector of random numbers was constructed setting a specific seed, so that the process can be replicated. In this procedure we additionally assume a continuous uniform distribution in the open interval (0, 1), such that there exists the same probability of choosing a certain day within the same types of days (a Monday from all Mondays, a Tuesday from all Tuesdays, and so on and so forth).⁸ Thus, assuming that our constructed month starts on a Wednesday, this month is given by the payments data corresponding to the following ordering:

Table 2
Randomly selected days

| Week | Wednesday | Thursday | Friday | Monday | Tuesday |
|------|------------|------------|------------|------------|------------|
| 1 | 18/02/2015 | 9/07/2015 | 21/08/2015 | 15/12/2014 | 6/10/2015 |
| 2 | 13/01/2016 | 4/12/2014 | 22/05/2015 | 28/03/2016 | 15/03/2016 |
| 3 | 30/03/2016 | 30/04/2015 | 19/02/2016 | 21/09/2015 | 24/02/2015 |
| 4 | 6/04/2016 | 20/11/2014 | 5/06/2015 | 27/04/2015 | 9/06/2015 |

Authors' calculations

In the second step we simulated a set of payments data by randomly re-arranging the payments that depend on the individual willingness, per second within each day, under the assumption that a financial institution could have sent out each payment in a different second from what was registered in the CUD. The re-ordering of payments is conducted with the aim of breaking any dependency that the payments variable may exhibit, but also with the purpose of defining, along the lines of Denbee et al. (2012), “*the amount of liquidity that every financial institution might use to make payments absent from behavioural biases*”. The assumed random sampling is based on the fact that each financial institution fulfils all its payments obligations within the same day, and so, the re-ordering of payments that depend on the individual will is possible. Accordingly, we set fixed all

⁸ Denbee et al. (2012) construct this simulated dataset using the payments registered in CHAPS during 102 days.

payments that cannot be settled at a different time of the day (time-critical payments and automatic payments) given that they are out of the sender's willingness to delay payments and, therefore, they do not reflect whether a financial institution will adopt (or not) a strategic payment behaviour. We also kept fixed all the payments solved in the netting cycles, the payments sent by financial infrastructures (automatic clearing houses⁹, payment networks, the central counterparty clearing house, and the foreign exchange clearing house), as well as those received from and sent to the Colombian central bank (*Banco de la República*). That is, we rearrange solely the payments that can be temporarily delayed within a same day, between 7:00 a.m. and 19:59 p.m. In the case of tax payments this rearrangement was done between the system's opening time (7:00 a.m.) and 11:00 a.m., since this is the last time in which they can be sent to the National Treasury Directorate.¹⁰ As a result, the rearranged payments correspond approximately to 31.8 per cent of the total number of payments settled in CUD.

In the third step we compute the measures of free-riding with the simulated data (obtained from the random re-arrangements of observed data). These measures were estimated almost 160.000 times, using simulated daily observations that correspond to the financial institutions that sent out payments in CUD (80 financial institutions), times 20 working days in our fictitious month, times 100 repetitions.¹¹

4.1. A model-based approach

As in Denbee et al. (2012), we used regression techniques to estimate individual models for each of the computed free-riding measures as a function of a set of explanatory variables (individual characteristics) that may have a say on financial institutions' funding decisions for the Colombian LVPS. Then, we computed the expected free-riding measures (\hat{y}_i) using quantile regression models in the 5th percentile of the empirical distribution. In this way, the expected free-riding measures are considered as the thresholds for determining whether a financial institution is following this behaviour or not, at 5% level of significance (probability of committing type I error that correspond to reject the null hypothesis when it is true). Thus, the 5th percentile of the

⁹ These clearing houses are ACH-CENT and ACH Colombia.

¹⁰ Within these tax payments are found the tax on sales, the income tax, the patrimony tax, the consumptions tax, the wealth tax and the tax collected on imports (import duties).

¹¹ Denbee et al. (2012) used 102 days of observed real data of payments, and randomly re-arranged each day 200 times.

distribution of a FR measure given the set of individual characteristics (y/X) indicates that 5% of the values of the FR measure computed from observed data are less than (or equal to) the specified function of X .¹²

We estimated individual models for each FR measure so that the expected level of free riding can be computed, and hence, used as benchmarks from which the existence of this payments strategy can be established. The explanatory variables included in the empirical estimations are: the ratio between payments sent and received, the value of sent out payments, the opening balance, the turnover ratio, the average size of payments sent, and the average size of payments received.

- The ratio between the payments sent and received is computed as the quotient of the total value of outgoing to incoming payments. A ratio higher than one will correspond to a system's participant who's sent out payments exceeds the amount of payments it collects from other system's participants. From this definition, we expect to find a positive relationship between this ratio and all FR measures.
- Financial institution's size corresponds to the individual share of the outgoing payments (in value) to the total value of payments executed per day. A negative relationship between this variable and the FR measures is foreseen, which, in the sense of Denbee et al. (2012), will reflect the fact that larger participants (in terms of payments) could be tempted to take advantage on other's liquidity to fund their own payments.
- The opening balance on each account at 7:00 a.m. is included as the individual share of the total amount registered for all system's participants, so as to identify the participants with the largest balances at CUD's opening time. As long as the opening balance is a source of liquidity alternative to incoming payments (that capture others liquidity), we postulate a positive relationship with the FR measures.

¹² As Koenker and Bassett (1978) noted, the parameter estimates of the relationship between a dependent variable and its explanatory variables in quantile regression models can be obtained for all parts of the distribution of the response variable. Hence, a given quantile Q_τ is the value such that τ per-cent of the mass of the distribution is less than (or equal to) Q_τ .

- The turnover ratio of liquidity was included with the aim of assessing the extent to which outgoing payments are backed with incoming payments. Hence, a positive relationship is conjectured between this variable and all the computed measures of free-riding. This ratio is given by the quotient between the total value of executed payments and the opening balance.
- The average sizes of payments sent and received were included, separately, as the daily mean value of the payments registered. We do not anticipate any hypothesis regarding these two variables, but instead, we let the models estimation tell us what relationships they may have with the measures of free-riding.

As can be seen from the summary table of results (Table 3), the goodness of fit measure surpasses 50% in three out of the five FR indicators: in the cost and risk based measures and in the relative net sending indicator. For the other two FR measures the pseudo-R² is somewhat low, 9% and 8%. The individual significance is reported in parenthesis and correspond to robust standard errors computed with the aim of correcting problems of heteroskedasticity that were detected with the Machado-Santos Silva tests in preliminary estimation results (not shown). Individual problems of multicollinearity are absent from our specifications, as the mean variance inflation factor (VIF) of the estimated models indicates (3.06).

For the fictitious month of payments used in models' estimation, the total liquidity that these financial institutions required to make payments ($L = \sum_{i=1}^N L_i^s/s$) averaged \$6.9 billion Colombian pesos (COP) per day, while from random walk simulations this value averaged \$7.6 billion COP. Therefore, as in Denbee et al. (2012), in aggregate terms, the liquidity usage computed from simulations result in approximately the same observed liquidity usage, which indicates the absence of substantial differences in the system's efficiency arising from strategic delays and randomized payments.¹³

¹³ We compute a simulation of random walk using bilateral institution's characteristics, and assuming an exponential distribution of payments with mean given by the average value of payments $\left(\frac{v_{ij}}{w_{ij}}\right)$.

Our estimation results for the ratio of payments sent and received are significantly and positively related with three out of the five FR measures, based in costs, risks and the relative net sending indicator. These results suggest that inasmuch as the market's participants provide more liquidity to the system the free-riding measures will increase (signalling less free-riding). Given that this variable represents the simplest way to determine whether a system's participant is underproviding (or not) liquidity to the system, a positive relationship with the FR measures is a reasonable outcome.

Table 3
5% Quantile regression results

| | Cost-based measure μ_i^s | Risk based measure γ_i^s | Time based measure δ_i | Early payment time indicator π_i | Relative net sending indicator ϑ_i |
|--|---------------------------------|------------------------------------|----------------------------------|---|---|
| Ratio of sent out payments to payments received | 0.000002 (9.51E-08)*** | 0.000002 (1.01E-07)*** | -0.000233 (1.53E-05)*** | -0.000302 (4.82E-05)*** | 0.753397 (2.27E-05)*** |
| Financial institution's size | -1.245 (0.0046)*** | -1.218 (0.0054)*** | 1.619 (3.00E-02)*** | 1.616 (0.0317)*** | 0.069 (0.0231) |
| Opening balance | 0.138 (0.0054)*** | 0.127 (0.0031)*** | 1.322 (0.0546)*** | 1.243 (0.0220)*** | 1.243 (0.0354)*** |
| Turnover ratio | 0.150 (0.0066)*** | 0.144 (0.0072)*** | 33.87 (3.4213)*** | 38.56 (1.644)*** | -4.993 (20.35) |
| Average size sent | 0.0000001 (1.17E-08)*** | 0.0000002 (1.63E-08)*** | -0.0000013 (2.37E-07)*** | -0.0000042 (6.15E-07)*** | -0.0000001 (1.22E-07) |
| Average size received | -0.0000001 (1.56E-08)*** | -0.0000002 (2.21E-08)*** | 0.0000117 (2.91E-08) | 0.0000098 (6.27E-07) | 0.0000001 (1.16E-07) |
| Constant term | -0.0002 (1.20E-05)*** | -0.0002 (7.83E-06)*** | -0.547 (1.98E-03)*** | -0.541 (0.0022)*** | -0.753 (0.0002)*** |
| Pseudo R² | 0.54 | 0.55 | 0.09 | 0.08 | 0.55 |
| Number of observations | 143255 | 143255 | 143255 | 143255 | 143255 |

Robust standard errors in parenthesis. Statistical significance at 1%, given by ***

The individual size (defined in terms of payments) negatively affects the cost and risk based measures of free-riding as in Denbee et al. (2012) which indicates that financial institutions with higher payments obligations may increase the extent of free-riding on liquidity. In fact, financial institutions with large payments are precisely those that have higher balances because they are obliged to maintain reserve requirements (banks and other depository financial institutions such as financial corporations). However, the effect that this variable exerts on the time-based measure and the early payment indicator is positive signifying an effect in the opposite direction. These contrasting results enlighten a substantial difference between the FR measures used:

whereas the measures based on cost and risk and the early payment indicator can be considered as ‘full-day’ indicators of free-riding, the time-adjusted indicators can be considered as ‘mid-day’ indicators because they are related to a specific part of the day and to a specific portion of payments (i.e. the average of payments). Consequently, when comparing these measures it is possible to find financial institutions that might be labelled as free-riders at a certain moment of the day, but not being regarded that way when full-day measures are considered. So, under the assumption that this variable is indicative of the individual size of market participants, the positive relationships found with the time based-measures suggest that financial institutions with large payments size may prefer to transfer half of its payments using their own funds. But when it comes to understand their full-day funding of payments, it is very likely that because of their huge liquidity needs they were more willing to free-ride on others’ liquidity.

In regard to the opening balance, the positive sign suggest that to the extent that financial institutions are more willing to send payments financed with their own funds, the magnitude of free-riding will be reduced. In other words, the higher the opening balances the less likely will be the under-provision of liquidity to the payment system. Nevertheless, such inference only applies to system’s participants that count with balances amounts that allow them make an early execution of payments. In fact, there are considerable differences about the opening balances of financial institutions that participate in CUD: banks typically have the highest levels of opening balances, while brokerage firms usually have the lowest balances levels at the beginning of the day (zero in almost all cases). Likewise, there was found a positive relationship with the turnover ratio of liquidity, signifying, as expected, that the free-riding on liquidity will be reduced to the extent that more payments are backed with financial institution’s own funds. This result goes in line with intuition, in the sense that a high turnover ratio signals a high liquidity use pertaining - perhaps- to a financial institution that over-provides liquidity to the system.

The average sizes of payments sent and received enter in models’ estimation with similar coefficients but extremely low values, and with opposite signs. Consequently, although significant, these variables are considered of low explanatory power to understand the provision of liquidity at individual level.

The under-provision of liquidity that may arise from this strategy of payments can be related to different individual characteristics of the system’s participants, but determining whether it may

become a problem for the entire payment system may depend on the number of financial institutions behaving this way. Hence, the overall extent of free-riding is inferred comparing the observed measures (y_i) with the model's results (\hat{y}_i) and counting the number of times in which each FR measure obtained from payments simulations exceeds the measures computed from models' estimation.

Table 4
5% Threshold values obtained from model's results

| | Cost based measure μ_i^S | Risk based measure γ_i^S | Time based measure δ_i | Early payment indicator π_i | Relative net sending indicator θ_i |
|---|---------------------------------|------------------------------------|----------------------------------|------------------------------------|--|
| Threshold value exceeded across all financial institutions | 4.9% | 5.0% | 6.7% | 6.7% | 5.0% |
| Banks | 4.8% | 4.9% | 4.1% | 3.8% | 2.3% |
| Financial Corporations | 16.9% | 17.5% | 4.3% | 3.5% | 3.1% |
| Trust companies | 1.4% | 1.4% | 5.1% | 6.6% | 7.7% |
| Brokerage firms | 4.3% | 4.3% | 4.3% | 3.0% | 3.1% |
| Financial institutions that never exceeded the threshold | 57.5% | 57.5% | 18.8% | 18.8% | 1.3% |

According to our models' results, financial institutions exceeding the threshold that determines the free-riding behaviour indicates from the time-based measure (6.7%) and the early payment indicator (6.7%) the existence of free riders in CUD, since they both exceed the 5% level that should have been found for the computed quantile. However, this is not the case when considering the results obtained for the cost based measure (4.9%), the risk based measure (5.0%) and the relative net sending indicator (5.0%). Hence, according to the results that come from mid-day measures related to a certain percentage of payments (50% of payments under the time-based measure and the early-payment indicator) some financial institutions can be labelled as free-riders on liquidity, but they may not be regarded that way according to full-day measures. Similar results were obtained when we estimated the same specification used by Denbee et al. (2012), see Table 6 in the appendix. These results per type of financial institutions also indicate that financial corporations is the only group that free-rides in the system, as can be noted from the measures based on cost (16.9%) and risk (17.5%).

Another interesting result from the full-day measures (based on cost and risk criteria) is that more than half of system's participants (57.5%) never underprovided liquidity to the system,

which may explain why (under normal circumstances or normal days) despite the existence of some free-riders, their negative effects on the CUD are nil.

4.2. A model-free approach

The extent of liquidity provision can also be assessed using only the empirical quantiles. As in Denbee et al. (2015), these results indicate the number of times in which each FR measure was below the 5th percentile or above the 95th percentile. Accordingly, the results below 5% reflect the financial institutions that under-provide liquidity (as a result of their free-riding), while those above 95% correspond to financial institutions that over-provide liquidity to the system.

At the aggregate level, the computed quantiles for the 5% indicate that the degree of free-riding is normal under the measures based on cost (4.2%) and risk (3.6%) criteria, and the relative net sending indicator (0.5%); but it becomes worrying when considering the time-based measure (76.4%) and the early payment indicator (25.7%). In general terms, the inferences that can be made from these results coincide with those obtained from the model-based approach: some financial institutions prefer relying on others' liquidity to fund a certain level of payments at a certain moment of the day, but in general terms, they behave similar to their peers (sharing liquidity) according to full-day measures.

Table 5
Thresholds values obtained from empirical quantiles at 5% and 95%

| | Cost based measure μ_i^s | | Risk based measure γ_i^s | | Time based measure δ_i | | Early payment indicator π_i | | Relative net sending indicator ϑ_i | |
|---|---------------------------------|--------------|------------------------------------|--------------|----------------------------------|-------------|------------------------------------|--------------|---|--------------|
| | Threshold | | Threshold | | Threshold | | Threshold | | Threshold | |
| | 5% | 95% | 5% | 95% | 5% | 95% | 5% | 95% | 5% | 95% |
| Threshold value exceeded across all financial institutions | 4.2% | 19.6% | 3.6% | 21.8% | 76.4% | 9.2% | 25.7% | 26.4% | 0.5% | 14.5% |
| Banks | 4.3% | 41.5% | 4.1% | 41.3% | 64.6% | 10.0% | 18.2% | 31.3% | 0.2% | 36.8% |
| Financial corporations | 15.5% | 0.0% | 11.7% | 1.4% | 89.3% | 6.7% | 24.0% | 12.2% | 0.2% | 2.8% |
| Trust companies | 1.1% | 0.0% | 0.9% | 13.5% | 86.4% | 6.9% | 33.4% | 20.0% | 0.7% | 0.6% |
| Brokerage firms | 5.0% | 13.2% | 4.3% | 16.5% | 72.1% | 12.0% | 24.1% | 32.9% | 0.5% | 11.0% |

At the individual level the results vary per type of financial institution. Banks and brokerage firms behave alike those observed at the aggregate level: some of them act as free-riders according to mid-day FR measures (time-based and early-payment), but not under full-day

measures (cost-based and risk-based). In the case of brokerage firms, these results can be explained, to some extent, by the fact that they usually have no liquidity at the beginning of the day. Therefore, it is very likely that the under-provision of liquidity identified from mid-day measures is non-intentional for these financial institutions, but that it partially reflects the way brokerage firms manage their liquidity (given by their business type). In contrast, according to four out of the five criteria the group represented by financial corporations are labelled as FRs. Although this result can be related to their obligation to maintain reserve requirements, the identified FR behaviour represent only the largest two financial corporations.

As long as the time at which an incoming payment coincides with the time at which a payment should be executed, the recycling of payments may not be worrying. But, when there is a considerable mismatch between these two payment flows, reusing others' liquidity may signify several payments delays, and became a serious problem for the entire payments system. Hence, keeping a close watch of these measures can be very informative about the way in which the system's participants are funding their payments, and the moment in which the extent of liquidity hoarding deserves attention.

The empirical quantiles at the 95% indicate, at the other extreme, the financial institutions that are overproviding liquidity to the system. As can be seen from the obtained results, this group is mainly composed by banks, followed by some brokerage firms, and trust companies.

Summing up, we found evidence of the existence of free-riders in CUD, mainly supported by the relative measures associated to a certain amount of payments and a certain moment of the day (mid-day measures). However, when considering results per type of system's participants, the empirical quantiles point to financial corporations as the group that hoarded liquidity the most. As long as these results are obtained from a fictitious month of payments (constructed with observed data), there are not worrisome; however, a call for a close oversight of these measures on an individual basis on real data may be of some interest not only for the system's manager but also for oversight purposes.

Conclusions

Financial institutions' intraday payments can be funded using loans (from the central bank and the money market), their own deposits at the central bank, and the payments that they receive from other system's participants. Within these liquidity sources, only the last one is available free of charge, and hence, it is usually preferred above the others.

The strategy of funding payments using only the disbursements received from counterparties is known as the free-rider strategy. Although it is considered optimal from an individual perspective, it is not for the entire payment system because it may imply payments-delays produced by the mismatch between the moment in which a financial institution has to send a payment and the moment in which it receives a payment. In LVPSs that operate under a RTGS mode the existence of several financial institutions behaving as free-riders may cause under-provision of liquidity, impeding, as a result, that a considerable amount of payments be completed in a timely manner.

Our results for the financial institutions that participate in CUD evidence the existence of the free-riders on liquidity, most commonly found in financial corporations. However, within groups there is also evidence of this payments strategy. As long as this problem may even generate difficulties to system's participants that are expecting to collect payments on time, a call for some actions should be considered so as to discourage the adoption of this strategy. Some possible solutions to the free-rider problem may require the design of a scheme, either based on penalisations (fees), incentives (discounts), or deterrence measures (as the throughput rules that were adopted in the U.K's LVPS).

Some interesting extensions on this subject could include an empirical assessment on what drives the free-riding behaviour, as well as considering the extent to which the existence of free-riders can be related to a rise in the volatility of liquidity, the monetary stance of the central bank, risk aversion, amongst many others.

Appendix

Table 6
5% Threshold values obtained from model's results

| | Cost based measure μ_i^S | Risk based measure γ_i^S | Time based measure δ_i | Early payment indicator π_i | Relative net sending indicator ϑ_i |
|---|------------------------------------|---------------------------------------|-------------------------------------|---------------------------------------|--|
| Threshold value exceeded across all financial institutions | 9.70% | 9.62% | 5.01% | 5.01% | 5.03% |
| Banks | 5.41% | 5.54% | 4.08% | 3.94% | 1.62% |
| Financial corporations | 40.80% | 37.97% | 5.12% | 4.41% | 7.25% |
| Trust companies | 9.15% | 9.30% | 6.01% | 7.37% | 7.26% |
| Brokerage firms | 6.48% | 6.65% | 4.68% | 3.29% | 5.28% |

Estimation results obtained from specification proposed by Denbee et al. (2012)

References

- Angellini, P. (1998). "An analysis of competitive externalities in gross settlement systems", *Journal of Banking and Finance*, Vol. 22, issue 1, pp. 1-18.
- Banco de la República (2016). Payment System Report, June.
- Bech, Ch.; Galbiati, M.; and Tudela, M. (2008). "The Timing and Funding of CHAPS Sterling Payments" Reserve Bank New York, Economic Policy Review, September, pp. 113–133.
- Bernal, J.; Cepeda, F.; and Ortega, F. (2012). "Estimating the contribution of liquidity sources in the Colombian large-value real-time gross settlement payment system: A preliminary approach" *Journal of Payments Strategy and Systems*, Vol. 6, num. 2, pp.159-182.
- Denbee, E.; Garrat, R.; and Zimmerman, P. (2012). "Methods for evaluating liquidity provision in real-time gross settlement payment systems" pp. 53-76, in Diagnostics for the financial markets- computational studies on payment system, Bank of Finland, Scientific Monographs, Simulator Seminar Proceedings 2009-2011.
- Denbee, E.; Garrat, R.; and Zimmerman, P. (2015). "Identification of over and under provision of liquidity in real-time payment systems", *Journal of Financial Market Infrastructures*, Vol. 4, num. 2, pp. 1-20
- Diehl, M. (2013). "Measuring free riding in large-value payments systems: the case of TARGET2", *Journal of Financial Market Infrastructures*, Vol. 1, num. 3, pp. 31-53.
- Galbiati, M.; and Soramäki, K. (2010). "Liquidity-savings mechanism and bank behaviour" Bank of England, Working Paper number 400, July.

Kahn, Ch.; and Roberds, W. (2009). “Why pay? An introduction to payments economics”, *Journal of Financial Intermediation*, Vol. 18, issue 1, pp. 1-23.

Koenker, R.; and Hallock, K. (2001). “Quantile Regression: An Introduction”, *Journal of Economic Perspectives*, Vol. 15, num. 4, pp. 143-156.

León, C.; Machado, C.; Cepeda F.; and Sarmiento, M. (2011). “Too-connected-to-fail Institutions and Payments System’s Stability: Assessing Challenges for Financial Authorities”, *Borradores de Economía*, Banco de la República, num. 644.

Manning, M.; Nier, E.; and Schanz, J. (2009). “The Economics of Large-Value Payments and Settlement: Theory and Policy issues for central banks”, Oxford University Press.

Martínez, C.; and Cepeda, F. (2015). “Reaction functions of the participants in Colombia’s large-value payment system”, *The Journal of Financial Market Infrastructures*, Vol. 4, num. 2, pp. 21-47.

McAndrews, J.; and Potter, S. (2002). “Liquidity effects of the events of September 11, 2001”, Federal Reserve Bank New York, *Economic Policy Review*, November, pp. 59–79.

Nellen, T. (2011). “Essays in Payment Economics”, Swiss National Bank, unpublished.

Shleifer, A.; and Vishny, R. (2011). “Fire sales in Finance and Macroeconomics”, *Journal of Economic Perspectives*, Vol. 25, num. 2, pp. 29-48.

