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Which bank is the "central" bank?[☆]

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1. Introduction

ABSTRACT

Liquidity flows through a financial network cannot be accurately described using external processing constraints alone. Behavioral aspects of participants also matter. A method similar to Google's PageRank procedure is used to produce a ranking of participants in the Canadian Large Value Transfer System in terms of their daily liquidity holdings. Accounting for differences in banks' processing speeds is essential for explaining why observed distributions of liquidity differ from the initial distributions, which are determined by the credit limits selected by banks. Delay tendencies of banks are unobservable in the data and are estimated using a Markov model.

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The ongoing financial crisis has shown the importance of liquidity and exposed how crucial interconnections are within the financial system. Illiquidity whereby agents either pull away from trading or refuse to provide funding for others have impaired many markets and have had devastating consequences for a number of financial institutions. Events have shown that focusing only on specific institutions or segmented parts of the financial system can obscure vulnerabilities that may prove very important. Regulators are pushing for tougher liquidity requirements. Unease about the increasing complexity of inter-linkages in financial systems is in part motivating the calls for a systemic risk regulator in the United States. One goal of a systemic risk regulator would be to ascertain overall system liquidity and determine which banks are "central" to the smooth functioning of the financial system and which are not.

Liquidity in financial markets is a burgeoning field (see Brunnermeier and Pedersen, 2009; Amihud et al., 2005 as well as references in the latter) and recently, economists have focused increasing attention on understanding the importance of

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different network structures within the financial system (see Allen and Gale, 2000; Gale and Kariv, 2007; Allen and Babus, 2008). However, little is understood about the relationship between liquidity and interconnectedness (Bech and Garratt, 2007). Empirical work in the latter area is generally hampered by a lack of data on linkages between financial institutions and across the components of the financial system. Not only is there virtually no data available on the actual (and ever changing) exposures between financial institutions, but also, very little is known about the counterparty limits that are a key component of risk management practices across the industry.¹ One exception to this drought of data are large-value payment systems. These payment systems have detailed records on individual transactions between participants and in some cases on the risk control parameters employed by both the system itself as well as the participants. As such, payment systems can provide a mini cosmos of the financial system and serve as a testing ground for new theories and methodologies while progress is being made on collecting data from other sources.^{2,3}

In this paper, we investigate the relationship between interconnectedness and liquidity in the Canadian Large Value Transfer System (LVTS). The LVTS provides information not only on flows, but also on bilateral credit limits set by the participants in order to manage exposure vis-à-vis other participants. Bilateral credit limits (BCLs) determine the maximum amount of money any one participant can transfer to any other without offsetting funds. As such, these limits determine the potential banks have for transferring liquidity to one another. Analytically speaking, the BCLs specified by banks define a network, where the weights on outgoing links are determined by the BCLs granted to a bank, and the weights on incoming links are determined by the BCLs granted by a bank. Since almost all banks are connected in the LVTS,⁴ the important structural properties of the network relate to differences in the weights on the links, which can be substantial (see Section 2).

Our objective is to use the network structure to predict the daily distribution of liquidity in the LVTS. This is complicated by the fact that flows of liquidity depend not only on capacity restrictions that are reflected by the network structure (i.e., the BCLs), but also on a "behavioral" component that reflects the willingness of participants to turnaround and redistribute incoming liquidity. The behavioral aspects are captured by translating the network structure defined by the BCLs into a transition probability matrix and estimating the diagonal components, which specify the probabilities that banks delay in processing payment requests.

Our approach is based on the premise that money flows out of a bank in proportions given by the relative magnitudes of the BCLs that the bank has granted to it by other banks. The simple idea is that if bank A grants bank B a BCL that is twice as large as the BCL bank C grants bank B, then money that flows out of bank B is twice as likely to go to bank A as it is to go to bank C. The possibility that banks will hold onto money is captured by our assignment of positive probability that money stays put. These probabilities cannot be determined from data available to the Bank of Canada. The Bank of Canada observes when payments are processed by banks, but does not know when the underlying payment requests arrive at the banks. However, we are able to estimate these delay parameters by finding values that provide the best match over the sample period between the stationary vector of the implied transition probability matrix and the observed daily distributions of liquidity.⁵

The stationary vector of the transition probability matrix that includes our estimates of the delay probabilities is our prediction for the distribution of daily liquidity. The bank with the highest value in the stationary vector is predicted to hold the most liquidity throughout the day and is thus the "central" bank. Processing speed plays a significant factor in explaining the liquidity holdings of banks throughout the day and causes the ranking of banks to be different from the one suggested by the initial distribution of liquidity. In particular, the bank which is central based on initial liquidity holdings is not central in terms of liquidity flows over the day.

Our approach has much in common with Google's PageRank procedure, which was developed as a way of ranking web pages for use in a search engine by Sergey Brin and Larry Page.⁶ In the Google PageRank system, the ranking of a web page is given by the weighted sum of the rankings of every other web page, where the weights on a given page are small if that page points to a lot of places. The vector of weights associated with any one page sum to one (by construction), and hence the matrix of weights is a transition probability matrix that governs the flow of information through the world wide web. Google's PageRank ranking is the stationary vector of this matrix (after some modifications which are necessary for convergence). In PageRank the main diagonal elements of the transition probability matrix are all zeros. In contrast, we allow these elements, which represent the probabilities that banks delay in processing payment requests, to be positive. By doing so, we improve upon the performance of the PageRank algorithm (see Tables 3 and 4 of Section 7.2).

The potential usefulness of Markov theory for examining money flows was originally proposed by Borgatti (2005). He suggests that the money exchange process (between individuals) can be modeled as a random walk through a network,

¹ Boss et al. (2004) use Austrian data on inter-bank liabilities from a central bank loan register.

² The cons of utilizing payment systems data include the need to have at least a rudimentary understanding of the institutional details and intricacies of operations in order to able to evaluate the significance and applicability of the results.

³ Others have looked at network topologies of banking systems defined by observed payment flows. For example, Soramäki et al. (2007) used U.S. data on payment flows and volumes to characterize the topology of interbank networks. Interestingly, payment flow networks share structural features (degree distributions, clustering, etc.) that are common to other real world networks.

⁴ Only one pair of banks in the LVTS is missing a link in our sample.

⁵ Assuming money flows through the banking system in a manner dictated by our proposed transition probability matrix, the values of its stationary vector represent the fraction of time a dollar spends at each location in the network.

⁶ The PageRank method has also been adapted by the founders of Eigenfactor.org to rank journals. See Bergstrom (2007).

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