Intraday Liquidity and Delays in the European Payments System

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Payment Delays in the European Gross Settlements System

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Standard Disclaimer:
This represents only the views of the authors, not the views of Federal Reserve Bank of Cleveland, Board of Governors of the Federal Reserve System, IMF, Deutsche Bundesbank, Banque de France, EDB nor the Eurosystem.
Second, Obligatory Slide actually has some punch in this case:

WHO CARES?
After all...

• Haven’t we conquered payments? Surely it is a mute issue!
  – Further, couldn’t we just slap more rules on the system, should it become an issue?
• Delays surely are small in number!?
• Have we ever heard of a payments gridlock ever happening in practice?
• Couldn’t computers resolve delays by quickly netting out things?
Perhaps, but...

- Delays still happen throughout the day in the payments system. They occur in about 15% of all payments.
- They are intrinsic to the liquidity strategies of banks. One could characterize them as the shortest point of the maturity transformation.
  - Given the attention devoted to extension of the yield curve from the overnight to longer term securities, it is interesting that we do not study the extension of the yield curve in the other direction. It may be that overnight lending is driven by intraday liquidity needs for which delays serve as one of our best indicators. (Actually there is some evidence of this.)
The interest is behavioral, but also technical

- Delays force one to think of identification within the context of a continuous-time series of shocks.
- Do not overestimate the ease with which computers can solve our problems.
- Economist’s caveat: how does one slap on quick rules and assess the success and cost without understanding the underlying behavior?
Technical Aims of our work

• We develop methods that use the payments network to identify causality within a continuous time context.
• We determine whether on several days of stressed liquidity banks engaged in punishing behavior towards delayers and whether the delays were “explosive.”
• We establish a discrete heterogeneity in the liquidity behavior of the banks. We develop an indicator “alpha” that measures this heterogeneity.
• We use this measure to develop a simple and easily computed indicator that estimates the probability of gridlock from delays.

• Other papers have documented delays in payment systems: Massarenti et al. (2013) for T2, Bartolini et al. (2010) for Fedwire
In the Interest of Full disclosure

Work in progress.
Delays are defined as

\[(\text{Settlement Time}) - (\text{Introduction Time}) - [5 \text{ min}]\]*

* Massarenti et al. (2013) suggest 5 min as technical time

Source: TARGET2 data. Only interbank and customer payments.
Outline

• Data descriptive graphs
• Hypothesis proposed in the literature: banks delay on a payment-by-payment basis as reaction to their counterparties delaying
• New Hypothesis: Delays are related to banks’ liquidity management
### Data

<table>
<thead>
<tr>
<th>Payement type</th>
<th>Volume</th>
<th>Value</th>
<th>Delayed Volume</th>
<th>Delayed Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Customer payments</td>
<td>56,56%</td>
<td>4,32%</td>
<td>14,41%</td>
<td>9,03%</td>
</tr>
<tr>
<td>Interbank payments</td>
<td>19,7%</td>
<td>19,56%</td>
<td>22,34%</td>
<td>10,64%</td>
</tr>
<tr>
<td>Central bank payments</td>
<td>9,13%</td>
<td>8,98%</td>
<td>6,82%</td>
<td>6,23%</td>
</tr>
<tr>
<td>Ancillary systems</td>
<td>10,3%</td>
<td>19,47%</td>
<td>4,86%</td>
<td>9,99%</td>
</tr>
<tr>
<td>Liquidity transfers</td>
<td>4,3%</td>
<td>47,66%</td>
<td>5,73%</td>
<td>2,07%</td>
</tr>
<tr>
<td>Total</td>
<td>100%</td>
<td>100%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Intraday patterns

Source: TARGET2 data. Only interbank and customer payments at introduction time.
Data: delay intraday patterns

Source: TARGET2 data. Only interbank and customer payments. Only payments that are delayed.
Data: delay patterns over time

Volume of delayed payments in total volume settled during the day

Percentage of the delayed payments value in total value settled during the day

Source: TARGET2 data. Only interbank and customer payments.
So what does this mean in terms of behavior?

• Theoretical literature: very concerned with the prevention of free riding of the liquidity.
  – Garrett, et al., Martin, and McAndrews focus on the lack of distinction between gross and net settlements systems with delays. What strategies can the banks use to prevent strategic delays?

• Intrinsic to this is the idea of a reaction: when a strategic partner develops a recent history of delays, then a bank will react by delaying more value to the culprit.
Note: while called a “punishment,” “reaction” is probably the more appropriate term.
So we develop two right hand endogenous variables to explain whether a payment is delayed and its value.
• Reaction: does the bank react to the past history of a bank delaying to it by delaying more?

• Pass-through: does the bank pass “upstream” payments delays “downstream.” This can be simply mechanical.
Identification

- Really a problem of defining the right hand variables correctly: what is a reaction to a history of delays? What is pass-through?
- How do we establish causality?
Payments in Delay at $t_0$

Cleared Payments initiated in between $t_0-k$ and $t_0$
Payments in Delay at $t_0$

Cleared Payments initiated in between $t_0-k$ and $t_0$

Delayed Payments
Payments in Delay at $t_0$

Cleared Payments initiated in between $t_0 - k$ and $t_0$

time of the transaction
Payments in Delay at $t_0$

Cleared Payments initiated in between $t_0-k$ and $t_0$

Pass-through
Payments in Delay at $t_0$:

Cleared Payments initiated in between $t_0-k$ and $t_0$
Clearly these two concepts have a non-empty intersection

- I have tried several different approaches to making the concepts distinct within the variables. For example, using the portion of the history of $B$ that is orthogonal to the non-$B$ payers to $C$. 
Payments in Delay at \( t_0 \)

Cleared Payments initiated in between \( t_0-k \) and \( t_0 \)
Identification

• Really a problem of defining the right hand variables correctly: what is a reaction to a history of delays? What is pass-through?
• How do we establish causality?

This is more subtle
Payments in Delay at $t_0$

Cleared Payments initiated in between $t_0-k$ and $t_0$

These two nodes share a relationship. B might an error that is reflected back onto C.
Due to Manski

• Reflection problem was posed as impossible in the context of a complete network, for such topics as team effects on labor productivity.
• For incomplete networks, sparsity can buy some identification.
  – Not entirely surprising given that identification is often formulated in terms of a directed graph.
  – Ongoing and exciting research in econometrics.
These two nodes share a relationship. B might an error that is reflected back onto C.

One Possible Solution
One Possible Solution:
Use these transactions as instruments
It is clear that there is a wide set of choices for instruments.

Note that the set of instruments is dynamic and changes from transaction to transaction, as opposed to the time slices proposed by Cohen-Coles, et. al. and others.
Results:

• Until this last week, I had a very robust set of results: Without instruments there is a small reaction effect that disappears (or is of the wrong sign) when one uses instrumental variables. There is a small pass-through effect that is not explosive
But...
But…

• This week I found a bug and recalculated. Now I seem to have a significant and positive reaction effect.
But...

- This week I found a bug and recalculated. Now I seem to have a significant and positive reaction effect in some of the specifications.
- I must confess to being somewhat skeptical. When we have given earlier versions of this work to payments technicians they have said the result of no reaction is not surprising. The intraday liquidity decisions are made at the beginning of the day, not on a transaction by transaction basis.
Further...

• We looked at other mechanisms that are allowed by the Target 2 system, such as bilateral limits. These should be used as strategic tools, and Martin has given the optimal bilateral limit strategies to prevent free-riding.

• Yet
  – These are used only by a tiny fraction of the participants, and in only ten cases or so are these used more than a handful of times. (The ten cases are not the ten largest banks, by the way.)
Technical Aims of our work

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So if I were asked to give an answer to whether delays propagate explosively.

The answer so far is robustly no. They propagate but dampen quickly.
On the other hand, the issue of reaction is less robust. However, if you have a strong prior that there is no reaction, then this gives a strong benchmark with which to examine identification.
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Banks’ liquidity management and delays

• Banks make most of the decisions on how much liquidity to put into the system at the beginning of the day and then the process runs mechanically through out the day.

• Sources of liquidity to make payments:
  - Beginning-of-day balances
  - Credit lines
  - Incoming payments
  - Delaying while waiting for incoming payments

• Need a method that measures the sufficiency of initial liquidity for conducting outgoing payments.
Banks face an unexpected stream of different payments throughout the day.

Each day is different. While a bank may be fairly clear about what payments will come and go, for a single stream the timing of the payments will be different.

We approximate the uncertainty by running a block bootstrap on the realized payments of the day.
Methodology

• For each month from Nov 2007 to Dec 2014
• The estimation is done only for active banks, more than 100 in- and out- payments per month and more than 30 payments per day.
• Only payments between 8am and 4pm are used
• Minimum 10 payments by block and 10,000 bootstrap samples. Otherwise, the optimal block size.
• Then bootstrap is combined with bank’s initial liquidity to compute an estimation "error" made by the bank when it allocates its initial liquidity.
• It is analogous to the classical type I error, $\alpha$, where a high value implies a large error.
Results: two groups of banks

Source: TARGET2 data. Only interbank and customer payments.
Some of the high alpha earlier in the sample was the result of a difference in liquidity procedures allowed to a subset of banks. However, our bimodality of alpha is robust to removing these from the sample.
High-alpha banks and delays

1 – low-alpha banks; 2 – high-alpha banks; 12 – flow among the groups
Several things to note:

• It is not a great idea to call the liquidity management system of the high alpha banks “free riding.” It may well be that they have a business model that allows easier access to liquidity throughout the day.
  – We are correlating alpha with network and bank characteristics. The network characteristics that matter most for a high alpha is that high alpha banks seem to be centrally located in the network at the beginning of the day.

• Alpha is easy to compute, and the burden of computation can be accomplished the night before from the previous day’s transactions. Then the current day’s liquidity is used to make a very quick calculation.
The simple form of the heterogeneity allows a gridlock probability indicator based on a simple contagion model. From this one can run a continuous check on the payment system to assess whether it is getting “close” to gridlock.
In conclusion

• We have developed a continuous time set of instruments for measuring delays and assessing intraday liquidity.

• So far, on stressed days, delays do not propagate explosively. It is less clear but probable that banks do not discipline counterparties that delay with their own delays.

• The payments system is heterogeneous with respect to liquidity management. This can be expressed with a simple division into two groups.

• This allows the use of classic contagion analysis to assess the probability of gridlock in a simple model.