Interbank Networks

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Outline

- Overview: quality of the algorithm’s output
- Comments: How to Measure the Unsecured Money Market?
- Comments: A Network View on Money Market Freezes.

A brief history of the algorithm's application to payments data

- Lending between banks is often over-the-counter and so hard to observe
- Craig Furfine observed that unsecured lending between banks is typically settled on LVPS
- He came up with the novel idea of using an algorithm to identify loans in these payments data
- Algorithm is intuitive, but its output was not formally evaluated and made public until very recently
  - Armantier and Copeland (2012) [US],
  - current paper [Europe],
  - Kovner and Skeie (2013) [US].

Illustration of the algorithm

Observe payments ($\longrightarrow$) but not purpose.

Use algorithm to link payments, to divine which are loans

date t			date t+1		
Bank A	$\longrightarrow$ $\longrightarrow$ $\longrightarrow$ $\longrightarrow$	Bank B	Bank A	$\longleftarrow$ $\longleftarrow$ $\longleftarrow$	Bank B

algorithm "finds" pairs [$\rightleftarrows$] that "look like loans"

In US for May 2013: selected 30,802 out of 605,826 (5 percent)

Quality of algorithm output

- Not easy to validate, because data are scarce
- But especially important, because financial crisis focused spotlight on interbank markets
  - Surge of policy / research papers using output
- Armantier and Copeland (2012)
  - Focus at transaction level (most disaggregate)
  - Compare to data on federal funds (narrow definition)
  - Result: algorithm performs abysmally (in US)
    - Type I error > 80% & false positives are NOT white noise
    - Nothing to say about false positives
  - Larger lesson: validate before starting research/policy

What does Arciero et al. find about quality?

- Different environment (Target2 versus Fedwire Funds)
- More positive results
- Validate algorithm output with 2 sources
  - Italian data (eMid)
    - At transaction level
    - 200,000 plus loans
  - EONIA panel data
    - At bank level (43 banks)
    - Total amount sold
    - Weighted average rate of loans

Main takeaways on quality

- Italian comparison (transaction level)
  - Type II error is < 2%; algorithm is not missing loans
  - Payments paired incorrectly < 1% of the time
- EONIA comparison (bank level)
  - Large type I error / many false positives
    - Algorithm quantity roughly 150% of EONIA
    - Similar problem as US, but less extensive (>500% in US)
  - Algorithm rate (for loans made) biased downwards
    - Similar problem to US

Main takeaways on quality

- What are these “extra” loans (the false positives)?
- Best case: Rollovers, tomorrow or spot-next loans
  - *Algorithm’s output can be used at transaction level*
- Okay case:
  - Intra-group transactions
    - mixing competitive and non-competitive loans
  - Transactions on behalf of clients
    - incorrect counterparties
  - *Algorithm’s output can be used at an aggregate level*
- Worst case: Not unsecured loans, improperly linked payments
  - *Algorithm’s output should only be used with much caution*

Comments on analysis

- Paper plays to algorithm's strength by looking at aggregate measures
  - So client or intra-group trades are not problematic
- But paper puts up a lot of descriptive statistics without motivation
- Found it hard to walk away with a punch line

Comments on analysis

- An aggregate level analysis of this general market is important and publishable at a high level
- How to get there?
  - separate out the analysis of quality
  - find an important policy-related question, e.g.,
    - ECB monetary policy and its impact on liquidity in unsecured money markets
    - Counterparty risk in unsecured money markets
    - E.g., see “Repo runs: evidence from tri-party repo” or “The evolution of a financial crisis: Collapse of the ABCP market” (Covitz, Liang, and Suarez)

Comments on Network paper: Overview

- Use the algorithm's output to:
  - Describe change in maturity structure of loans
  - Describe the network structure of loans
- Argue a freeze occurred in the term segment
- Use regression analysis and find that network characteristics predict banks' borrowing & lending behavior

Discussion of quality of algorithm's output

- Currently little discussion of quality
  - Relying heavily on algorithm output at a disaggregated level
    - Rates, quantities, and counterparties
- Need to discuss large type I errors, which are problematic for the analysis used in the paper
  - In footnote 2: authors claim to have improved the algorithm
  - Need to formally show EONIA comparisons (in appendix).
- Ideally, incorporate algorithm's errors in paper's network and regression analysis.
  - How to do this formally? Not clear to me.
    - Not a standard mismeasurement problem.
  - Perhaps develop an informal approach (robustness analysis)?
  - Unfortunately, no examples to follow.

Networks and policy makers

- Main regression

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- Interesting because of mix of
  - Micro-prudential (balance sheet & loans)
  - Macro-prudential (network & loans)
- Do networks matter?
- Is there a macro-prudential interest in having central bankers monitor networks?

Econometrics

- Main regression

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- Hard to interpret the estimated coefficients (esp. on network characteristics)
  - What do you expect to see?
  - What is the theory underlying the regression?

Econometrics

- Regression's right-hand variables characteristics are likely highly correlated
  - network and balance sheet characteristics
- In US, using algorithm's output (May 2013)
  - corr(in-degree, out-degree)=0.51
  - corr(in-degree, assets) = 0.65
  - corr(out-degree, assets) = 0.62
- Should do robustness checks
  - Subsample of banks
  - Change time periods

Conclusion

- Commend Aciero et al. for thankless task of formally validating algorithm's output
  - There is potential for a top-level publication
- The Network paper is tackling an important question in general and in particular for central bankers

- Thank you for your time and attention