Identifying Bank Runs in Payment Systems

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SUOMEN PANKKI EUROJÄRJESTELMÄ FINLANDS BANK EUROSYSTEMET

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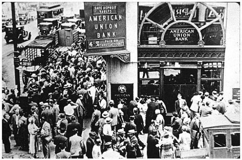
Important Definitions

- **Bank run** occurs when (in a fractional-reserve banking system) a large number of customers withdraw cash from deposit accounts with a financial institution at the same time because they believe that the financial institution is, or might become, insolvent.
  - keep the cash;
  - transfer it into other assets, such as government bonds, precious metals or gemstones;
  - transfer funds to another institution (capital flight).



Important Definitions

- **Silent run** (Rockoff, 2003) depositors simply write checks on a bank they consider weak and deposit them in another bank they consider stronger. (= deposit currency ratio)
- **Noisy run** (Rockoff, 2003) depositors literally run down to the bank, stand in line with their scared fellow depositors, and withdraw cash, perhaps forcing the bank to close its doors. ($\neq$ deposit currency ratio)

> These **"silent runs"** have been neglected in many accounts of the banking crises. But evidence from the **Gold Settlement Fund** and from regional deposit movements suggests that silent runs were important, especially in the crucial year 1930.
>
> —Rockoff (2003) - 1929 Great Contraction

Important Definitions

Slow run (Gertler and Kiyotaki, 2015) creditors began a steady stream of withdrawals and became increasingly reluctant to roll over short-term loans. As the market probability of a run increases, creditors withdraw some but not all of their funds.

Fast run (Gertler, Kiyotaki and Prestipino, 2016; Bernanke, 2010 and 2012) complete collapse of the banking system as depositors coordinate on a no rollover equilibrium. As a result, banks liquidate all their assets leading to a sharp drop in asset prices and rise in spreads.

In August 2007 a steady contraction of Asset Backed Commercial Paper (ABCP) market began, something akin to a **"slow run"**, in Bernankes terminology. Indeed if the first wave of distress hitting the ABCP market had the features of a **"slow run"**, the second, which led to the dissolution of the entire investment banking system had the features of a traditional **"fast run"**.

— Gertler, Kiyotaki and Prestipino (2016) - 2008 Great Recession

"Overall, the emergence of **run-like phenomena** in a variety of contexts helps explain the remarkably sharp and sudden intensification of the financial crisis, its rapid global spread, and the fact that standard market indicators largely failed to forecast the abrupt deterioration in financial conditions."

— Ben Bernanke (2012) - 2008 Great Recession

Background and Literature

- **Policy**
  - **Bank Run and Deposit Insurance** Government can provide deposit insurance and produce superior deposit contracts (Diamond and Dygvig, 1983; Bryant 1980).
  - **Bank Run and Liquidity Provision** Particular central bank liquidity provision policy can prevent bank panics without moral hazard problems. (Martin 2006).
  - **Bank Run and Suspension of Convertibility** The bank can suspend convertibility of deposits into cash (Engineer, 1989).
  - **Bailouts and Bank Runs** If there are effective regulation and supervision, then allowing intervention is always optimal (Keister and Narasiman, 2016).
- **Macro and systemic risk**
  - **Systemic Bank Run** The 2008 financial crisis is reminiscent of a bank run. Outright purchase of troubled assets by the government (Uhlig, 2010).
  - **Macroeconomic Models with Bank Runs** Macroeconomic models that consider bank runs include Gertler and Kiyotaki (2015) and Ferrante (2015).
  - **Wholesale and Shadow Banking Runs** Retail markets may remain relatively stable while wholesale funding markets experience dry-ups and runs. Runs on the shadow banking system were a salient feature of the crisis, culminating with the collapse in September 2008 of Lehman Brothers (Gertler, 2016).

Background and Literature

- **Interaction with financial markets**
  - **Bank Runs, Interbank Markets and Reserve Requirements** Coexistence of a central bank, which determines banks reserve requirements, and an interbank market, which redistributes reserves, leads to a smaller probability of a bank run (Canon and Margaretic, 2014).
  - **Bank Runs and Interest Rates** Riase of short-term interest rates during bank runs (Waldo, 1985).
  - **Bank Runs, Liquidity Costs and Investments** Banks offer contracts preventing runs, but may accept some risk of run to achieve higher returns (Cooper and Ross, 1998; Ennis and Keister, 2006).
  - **Bank Runs and Spillovers** A bank run may have significant effects on the rest of the banking system. Banks that rely on funding from wholesale markets may be significantly affected (Goldsmith-Pinkham and Yorulmazer, 2010). One bank may trigger a panic-based depositor-run at another bank (Brown et al., 2014)
- **Depositors behavior**
  - **Bank Runs and Social Networks** Depositors observe the other depositors action. When withdrawals are observed, bank runs are more likely (Kiss, 2014).
  - **Expectations vs. Fundamentals-driven Bank Runs** Bank run may still occur when depositors expectations on the banks fundamentals do not change (Chen and Hasan, 2008; Keister and Narasiman, 2016).

Framing

- **Bank runs** lead to the build-up of systemic risks to financial stability;
- After the **financial crisis** it became relevant to **real-time monitoring** stability of banks;
- With the **digitalization of banking services** runs can materialize electronically and be "silent";
    - **Home-banking runs**
- **Modern payment systems** provide a source of information
    - to timely detect difficulties
    - if information is well organized and smoothly interrogable
- Our **goal** is to build an **econometric tool** that identifies runs
    - focus on customers distrust
    - the tool can be generalized to other forms of runs

Contribution

- **Use payment systems** to early get information about runs;
- Propose a **new methodology** to identify silent or slow runs;
- **Empirically test** the method;
- **Characterize** silent runs.

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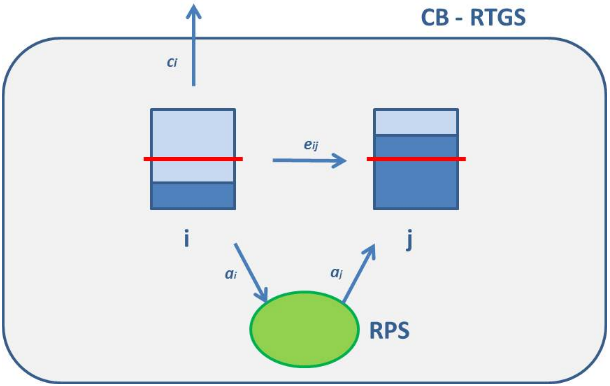
Payment System (LVPS) Information

Customer behavior proxies

- Multilateral balances settled by domestic and international retail payment systems (RPS) [a_i]
  - BI-COMP, operated by Banca d'Italia
  - STEP2, operated by EBA
  - include transactions, money transfers, card payments, etc
- Gross money transfer settled directly in the RTGS on behalf of customers [$e_{i.}$]
  - MT103
  - include money transfers, electronic payments, etc
- Net Cash withdrawal [c_i]
  - Bank's net withdrawal of cash from the Central Bank
  - under the assumption of constant bank's inventory
  - sudden changes generated only by customers

LVPS Information



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Methods in the Early Warning Literature

Mostly from banking, currency and BoP crises early warning literature

- Minimization of the noise-to-signal ratio (Kaminsky and Reinhart 1999)
- Fully-parametric (Logit/Probit) models (Berg and Patillo, 1999)
- Semiparametric models (Arduini et al, 2012)
- Classification trees and Random Forest (Alessi and Detken, 2017)

Which Approach?

- **All these approaches (previous slide)**

  1. **Observe** ex-post $W_{ct} = 1$ when a crisis occured;
  2. **Choose** ex-post covariates X_{ct} that should predict a specific type of crises;
  3. **Specify** $f(X_{ct})$ as a valid function of observables;
     - ex: fully-parametric $W_{ct} = \Lambda(\gamma X_{ct})$
  4. **Select** a crises threshold τ for f;
  5. Binary choice **prediction**: $f > \tau \rightarrow$ crisis;
  6. **Assess**.

		True	
		1	0
Predicted	1	α	β
	0	γ	δ

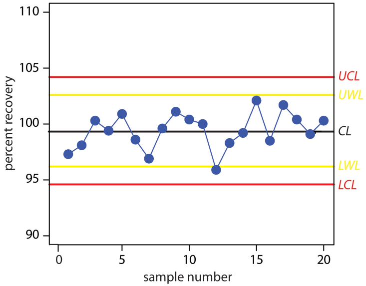
Peculiarities of our problem

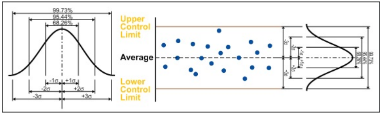
- **Main features**
  - No clear definition and **public information** about silent or slow runs (W_{ct}?);
  - **Bank-level analysis** to be useful (W_{ict});
  - **Binary indicator** may be too sharp and not timely;
  - **High-frequency data**, and we can exploit their continuous nature;
  - **Hard data** (operations settled in payment systems) are quite volatile and difficult to model time series;
  - **Distributional assumptions** on the unobserved factors are inadequate;

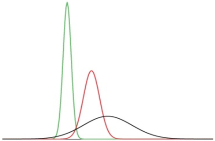
Shewhart Charts (also known as Control Charts)

- **Background**
  - The control chart was invented by Walter A. Shewhart while working for Bell Labs in the 1920s;
  - Shewhart framed the problem in terms of Common- and special-causes of variation and, on May 16, 1924;
  - Shewhart Charts is now the most used tool in industrial production processes control;
- **What is a Control Chart?**
  - Statistical tool born in industrial statistical control to monitor quality;
  - The parametric CC assumes the outcome has a normal distribution;
  - Check whether the outcome is under control using the mean and the standard deviation ($\mu + / - 3\sigma$).

- **How do they look like?**







Source: `http://www.learneasy.info/MDME/MEMmods/MEM15001B-StatQual/charts/control-charts.html` and `https://chem.libretexts.org/LibreTexts/Northeastern/153A_Quality_Assurance/15.43A_Evaluating_Quality_Assurance_Data` and `http://onlinestatbook.com/2/normal_distribution/intro.html`

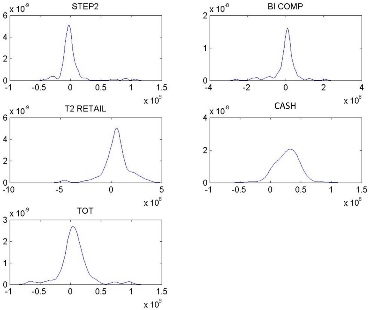
- **Appealing Features**
  - Designed to be applied on **real-time data** (as RTGS systems), **not ex-post**;
  - Does not need an ex-post and **known definition of crises** (W_{ict});
  - Does not provide a strictly **binary indicator**;
  - Detect timely 'special-causes' with **high-frequency data**;
  - Nice graphical representation and **easy to read and understand**.
- **Undesired Features**
  - Designed for a controlled process (**standardized** output);
  - Strong **distributional** assumption (usually normality);
  - Ad-hoc tuned for a **specific** economic agent (firm);
  - Not **seasonal** data.

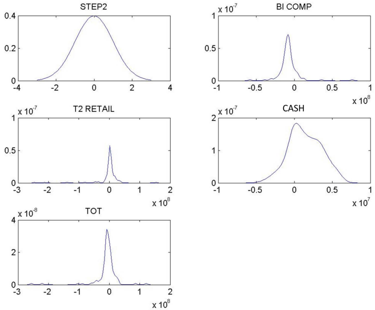
Main Issues in our Framework

- Non normality
- Structural unbalances on these channels
  - Banks can have persistent positive or negative positions on these channels
    - customer heterogeneity (merchant vs buyers)
    - technical platforms adoption
    - intermediaries in ancillary systems
- High seasonality and complex idiosyncratic time patterns
  - systemic seasonality
    - cash withdrawals before leisure (like holidays)
    - fiscal payments and taxes
  - idiosyncratic cyclicality
- Definition of Warning
  - Binary vs continuous
  - Definition of criticality, sudden and normality
  - Model Cross Validation and Robustness
- Technical Change
  - Change in RPS participation
  - Outsourcing
  - New routing of payments
  - Payment system operator (L2) Cross Validation

Issues, Visually (1/2)

Issues, Visually (2/2)





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Our Solution

Regularized Nonparametric Shewhart Charts (ReNoSCh)

1. Regularize the data
   - Adding knowledge about the monetary phenomena under analysis
   - Using an appropriate model
2. Derive nonparametrically critical thresholds
   - Avoiding inadequate distributional assumptions
3. Propose Thresholds
   - Subjectively or using maximization

ReNoSCh
First Step: Regularization

- Regularize time series using
  $\min_f \sum_T^{t=1} V(f(z_i), y_i) + \lambda R(f)$
  where V is an underlying loss function that describes the cost of predicting $f(x)$ when the label is y, such as the square loss or hinge loss; and λ is a parameter which controls the importance of the regularization term. $R(f)$ is typically chosen to impose a penalty on the complexity of f. Concrete notions of complexity used include restrictions for smoothness and bounds on the vector space norm.

  - Very simple time series regularization
    $Y \rightarrow \tilde{Y} = M_X Y = (I - X(X'X)^{-1}X')Y$
    where
    - $Y = A, C, E$;
    - the element of Y is y_{it};
    - X captures systemic and idiosyncratic seasonality and patterns (mostly time dummies).

    tackling
    - High seasonality and complex idiosyncratic time patterns
    - Structural unbalances on these channels

ReNoSCh in practice

- **We construct an algorithm:**
  1. Regularize (with model R) data $Y_T \to \tilde{Y}_T$ on a big time support T;
  2. Take a recent time interval t;
  3. Estimate the distribution of $\tilde{Y}_t$ (by simple sorting or non parametric methods, D);
  4. Estimate a threshold for the p percentile such that $P(\tilde{y}_{it} < \psi_p) = p$;
  5. A warning can be defined
     - as binary: $W_{it}^{k,p} = 1$ if $\sum_{t-k}^{t} I(\tilde{Y}_t < \psi_p) > s$, where $s < k$;
     - as continuous $W_{it}^{k,p} = \sum_{t-k}^{t} I(\tilde{Y}_t < \psi_p)/k$

Observe that the number of choices involved is inevitably pretty big $C = (R, T, t, D, p, s, k)$.

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Evidence from our Sample

1. Take r ex-post known cases of difficulty for the Italian banking system from 2007 to 2017 (bad news popping up).
   - No noisy runs
   - Potential silent runs
2. Regularize data via simple OLS on a time support T between 2 and 7 years.
   - Constant and Trend
   - Monthly and daily dummies
   - Pre/Post/During holiday periods FE
   - Start/Middle/End of the month dummies
3. Take a smaller time interval t of six months;
4. Estimate the distribution of $\tilde{Y}_t$ by simple sorting;
5. Estimate a threshold for the p percentile such that $P(\tilde{y}_{it} < \psi_p) = p = 7.5$;
6. A warning defined as a sequence $s \geq 3$ of observations below the threshold on $k = 5$ consecutive days.

Results

- The methodology is able to **early find silent bank runs**;
  - **Liquidity drains**
- **Both digital transfers (*A* and *E*) and cash withdrawals (*C*)**;
- **Transfers mostly domestic** to **big banks** ("intraregional silent runs");
  - **Home banking runs**
- **Cash mostly withdrawn from ATMs** instead of bank tellers.

Table: Runs - Digital transfers vs Cash

Dependent: Daily bank-specific net position in			
	(1)	(2)	% increase (2)
	Raw data		
Digital transfers	-121,587,321 ***	-251,740,297 ***	194 (s)
	(47,500,855)	(40,299,189)	
Cash withdrawals	12,557,830 ***	-7,951,568 ***	38 (s)
	(4,762,268)	(2,486,092)	
	Regularized data		
Digital transfer	-289,895,457 ***	-261,295,973 ***	942
	(41,201,901)	(42,376,381)	
Cash withdrawals	-10,125,804 ***	-8,879,669 ***	718
	(1,971,173)	(1,985,025)	
Run FE	No	Yes	
Month Dummies	Yes	Yes	
Day Dummies	Yes	Yes	
Holiday FE	Yes	Yes	
Part of the month FE	Yes	Yes	
Trend	Yes	Yes	

- Digital **transfers** are **bigger** in magnitude
- and have a raw percentage increase much bigger than cash.
- Nevertheless, when controlling for regular pattern in the data the **relative increase** in unexpected withdrawals is **comparable**

Table: Cash - ATMs vs Bank Tellers

Dependent: Bank-specific withdrawals		
		% increase
ATM ($\leq$ 50)	9,088,699 ***	355
	(1,955,436)	
100	813,993 ***	362
	(276,710)	
200	39,005	10(s)
	(32,001)	
500	383,347	20(s)
	(264,093)	
Run FE	Yes	
Month Dummies	Yes	
Day Dummies	Yes	
Holiday FE	Yes	
Part of the month FE	Yes	
Trend	Yes	
Regularized data	Yes	

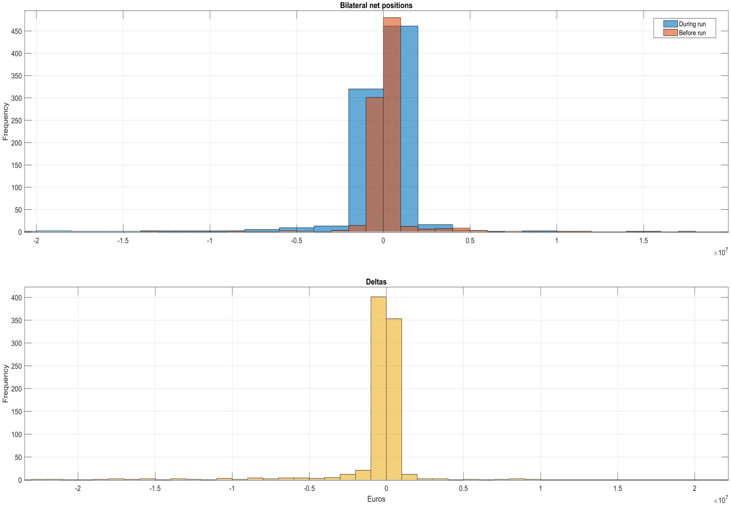
- Cash is more demanded via **ATMs**
  - Less comfortable to go to the bank teller and ask big amounts of money;
  - Furthermore, large withdrawals in big denominations are subject to bank's reporting to the FIU;
  - Big amounts probably moved electronically.

Table: Bilateral Digital Transfers - Nationality and Size

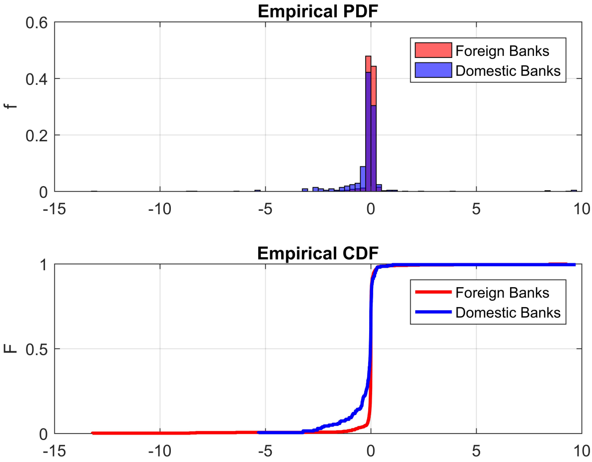
Dependent: Δ pair-specific customer payments net position			
	All (1)	Negative (2)	% ratio
Foreign banks	737,136,37 **	1,661,214,77 ***	2.3
	(373,510,10)	(450,276,29)	
Domestic banks	-543,658,68	-740,596,17	1.4
	(401,784,84)	(461,260,79)	
Size of domestic banks	-2,57E-09 ***	-5,57E-09 ***	2.2
	(6,77E-10)	(6,32E-10)	
Run FE	Yes	Yes	

- Money transfer are mostly directed **to domestic banks**;
  - Risk is mostly idiosyncratic, probably not seen as country-wide
  - inconsistent with a "contagion of fear."
- **Bigger banks** are preferred as 'safe havens'.

Customer payments net position



Δ pair-specific customer payments net position



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In a Nutshell

- Argued that **payment systems** can be used to timely get information about bank runs;
- Proposed a method (ReNoSCh) to **early identify silent runs**;
- Provided evidence that **the method works**;
- Show **silent runs features**.

Final Remarks

- **Limits and caveat**
  - We are not able to identify runs generated by conversion in assets, bitcoins, metal or gemstones if they do not involve customer payments (for example different custodians).
  - We cannot measure I and II type error.
  - Lots of subjective decisions to be made.
- **Potential Extensions**
  - Early detection of other types of runs or crises
    - Repo runs
    - Interbank markets freezes
    - Bop crises
    - ....
  - Methodology improvements
    - Bayesian SC
    - LASSO Regularization
  - Information expansion
    - Using more granular (and text) data
    - New data from "New RTGS Services" and other FMIs ?

THANK YOU!

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