PREDICTING SELF-FULFILLING FINANCIAL CRISES

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MOTIVATION & AIMS

Policymaking Problem:

Why are we bad at predicting financial crises?

Financial crises are often **self-fulfilling**: a crisis occurs when actors believe it is occurring.

- Multiple equilibria in financial crises (Diamond and Dybvig 1983; Obstfeld 1994; Chang and Velasco 1998; Morris and Shin 20XX)

Despite widespread agreement on existence of self-fulfilling crises, **little analysis of implications for prediction**.

This paper:

Proposes a model of prediction to explore consequences of self-fulfilling dynamics for “our” ability to predict crises.

Derives novel predictions about exactly when we can predict crises.

Empirically tests the implications of the model with a **new text-based measure** of financial market stress.

THEORETICAL MODEL

Core features of financial markets

1. Players have private information about their vulnerability to crises, i.e. liquidity demands, their willingness to cooperate.
2. Market sentiments or conditions vary across periods.
3. An observer uses behavior in time t to predict crises in period $t+1$.

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A **two-player** game of strategic complements (*Hold* or *Sell*) with

1. Player types' σ_i drawn from single-peaked distribution F_σ, with support on the interval of $(\underline{\sigma}, \overline{\sigma})$.
2. Common shock κ representing market conditions.

NB: F_σ and κ are common knowledge. Only the realization of σ_i is private information.

Normalize the value of holding when the other player holds at 0, denote “sucker’s punishment” as $\alpha > 0$, and “first mover advantage” as $\beta > 0$. We then have:

Table: The Private Information Game

		Player B	
		Hold	*Sell*
Player A	*Hold*	κ, κ	$-\alpha$, $\beta - \sigma_B$
	Sell	$\beta - \sigma_A$, $-\alpha$	$-\sigma_A$,$-\sigma_B$

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Sensible features of private σ_i and common shocks κ:

1. Larger σ_i increase the value of holding for each player.
2. Larger κ increase the value of holding for both players.

MODEL: A GENERALIZED STAG HUNT

- Given common knowledge of F_σ, α, and β, strategies depend entirely on the values of σ_i and κ.
- The equilibrium is unique (Baliga and Sjöström 2012): players play a "cut-off" strategy where they sell iff $\sigma_i < \sigma^*$.

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Model the *Observer* as another player who predicts whether a crisis will take place in the future given the absence of a crisis today.

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We show

If types are sparse and shocks are moderate, then ***larger common shocks*** *κ_t in period 1 imply a* ***higher variance in player types*** *in period 2 for any for any log-concave distribution F_σ.*

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We show

If types are sparse and shocks are moderate, then ***larger common shocks*** κ_t *in period 1 imply a* ***higher variance in player types*** *in period 2 for any for any log-concave distribution* F_σ.

Good times in period t mean that there is a **greater set of possible states** of the world in period $t+1$ that will feature crises.

1. Shocks *screen types* by placing more bounds on $\sigma_{i,j}$.
2. Shocks *increase confidence* that each player's opponent is a strong type.

Novel Predictions:

1. Wider range of future states given “good” fundamentals today.
2. If there is no crisis today, “bad” fundamentals should predict no crisis in the future; “good” fundamentals should be uninformative.

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Extension:

- If shocks are positive enough, then multiple equilibria are possible, creating epistemic uncertainty (Knight 1921).

EMPIRICAL TESTS

Measure the Variance in Future States of the World

- Many indicators of financial crises (e.g. Laeven & Valencia 2013; Reinhart & Rogoff 2010) are **binary**.
- Many indicators of financial crises (e.g. Laeven & Valencia 2013; Reinhart & Rogoff 2010; Rosas 2009; Andrianova et al. 2015, Z-Scores) are **annual**.
- Continuous sub-annual pricing measures (e.g stock market returns Danielsson 2015) have **varying importance across countries/years**.

Gandrud & Hallerberg (2015)

Economist Intelligence Unit (EIU) **monthly** country reports are:

- **comparable** (from 2003) for 180+ countries,
- **contemporaneous** summaries of information **in context**.

Process (ask us how later) to generate summary of qualitative assessments of quantitative **data in context**.

Prediction: **More variance** in future states of the world when economic conditions are **more favourable**.

So...

Use $\mathrm{Var}(\mathit{FinStress}_{t+1})$ as the **dependent variable**, where t is either a year or quarter.

- GDP Growth$_t$ (WDI 2015) & OECD (2015): higher growth $\implies$ better economic conditions.
- Stock Price Volatility$_t$ (GFDD 2015): Higher volatility $\implies$ worse economic conditions.
- $\log(\text{Impaired Loans})_t$ (Andrianova et al. 2015): More impaired loans $\implies$ higher probability of bank insolvency.
- $\frac{\text{LiquidAssets}}{\text{TotalAssets}}_t$ (Andrianova et al. 2015): Counterintuitive-ly, more liquid assets $\implies$ more stressed financial system (especially in developing countries).
- $\text{FinStress}_{\bar{t}}$: Lower FinStress $\implies$ better financial market conditions.

RESULTS

Table: Regression result from predicting FinStress Variance using annual explanatory variable data (Full Sample)

	Dependent variable:				
	$\text{Var(FinStress)}_{year+1}$				
	Full Sample	Full Sample	Full Sample	Full Sample	Full Sample
	(1)	(2)	(3)	(4)	(5)
$\text{Var(FinStress)}_{year+0}$	0.014	−0.011	−0.083*	0.076**	0.054
	(0.029)	(0.030)	(0.047)	(0.038)	(0.035)
GDP Growth (%)	0.046**	0.028			
	(0.022)	(0.023)			
$\text{FinStress Mean}_{year}$		−5.347***	−6.263***		
		(1.299)	(2.404)		
Stock Price Volatility			−0.061***		
			(0.022)		
Impaired Loans (log)				−0.277	
				(0.196)	
Liquid Assets Ratio					0.026*
					(0.015)
Fixed Effects	y	y	y	y	y
Observations	1,349	1,349	599	833	939
R^2	0.004	0.018	0.044	0.009	0.007
Adjusted R^2	0.003	0.016	0.038	0.008	0.006
Note:					*p<0.1; **p<0.05; ***p<0.01

Table: Regression result from predicting FinStress Variance using annual explanatory variable data (OECD Sample)

	Dependent variable:				
	$\text{Var(FinStress)}_{year+1}$				
	OECD	OECD	OECD	OECD	OECD
	(1)	(2)	(3)	(4)	(5)
$\text{Var(FinStress)}_{year+0}$	0.036	−0.027	−0.048	0.052	0.089
	(0.068)	(0.070)	(0.072)	(0.077)	(0.074)
GDP Growth (%)	0.336***	0.207**			
	(0.083)	(0.090)			
$\text{FinStress Mean}_{year}$		−10.146***	−6.916*		
		(3.150)	(3.531)		
Stock Price Volatility			−0.144***		
			(0.039)		
Impaired Loans (log)				−1.636***	
				(0.530)	
Liquid Assets Ratio					0.043
					(0.055)
Fixed Effects	y	y	y	y	y
Observations	248	248	231	205	216
R^2	0.077	0.119	0.153	0.061	0.011
Adjusted R^2	0.067	0.103	0.132	0.052	0.009

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table: Regression result from predicting FinStress Variance using quarterly explanatory variable data (OECD only)

	Dependent variable:	
	$\text{Var(FinStress)}_{quarter+1}$	
	(1)	(2)
$\text{Var(FinStress)}_{quarter+0}$	0.090***	0.066**
	(0.027)	(0.027)
GDP Growth (%)	0.102***	0.043
	(0.027)	(0.029)
$\text{FinStress Mean}_{quarter+0}$		−5.569***
		(1.065)
Fixed Effects	y	y
Observations	1,237	1,237
R^2	0.023	0.045
Adjusted R^2	0.022	0.043
Note:	*p<0.1; **p<0.05; ***p<0.01	

CONCLUSIONS

Central innovation: explicit model of the prediction problem during self-fulfilling crises:

1. Observable economic conditions today help us to learn about players' types given their actions.
2. However, we can learn less about crises in the future as the conditions today improve.
3. Empirically tested these implications with a new text-based measure of financial market stress.

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More general contribution: a new model of **why social scientists should be bad at predicting changes** in equilibrium behavior when players coordinate with private information (cf. Kuran 1991). E.g. coups, revolutions.

Given the findings in our paper, financial regulators should focus on trying to discern **types** (e.g. with stress tests), rather than focusing primarily on **macro-economic conditions**.

EXTRAS

1. Nature **draws** σ_A, σ_B and reveals them to players A and B.
2. Nature **draws** κ_t from distribution F_κ and reveals it to A, B, and the Observer.
3. A and B **play** the game.
4. The Observer and A and B **update** their beliefs about the values of σ_A, σ_B conditional on what they observe.
5. The Observer **predicts** whether a financial crisis will occur given possible future realizations of the common shock κ_{t+1}.

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2. the values of σ_A, σ_B lie in the range $\sigma^* < \sigma_A, \sigma_B < \overline{\sigma}$. Denote this range $r(\kappa_t)$.

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Proposition

If types are sparse and shocks are moderate, then ***larger common shocks*** κ_t *result in* ***larger*** $r(\kappa_t)$*. This implies a* ***higher variance in player types*** *in period 2 for any for any log-concave distribution* F_σ*.*

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Two mechanisms:

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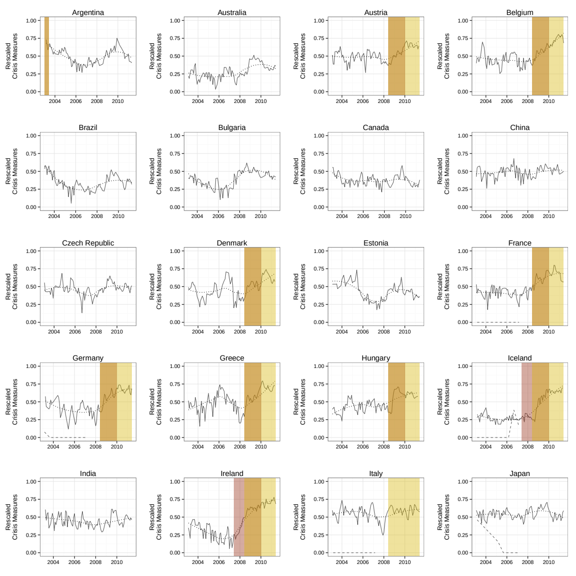
FINSTRESS (SELECTION)



EIU reports contain information about more than banking market conditions. So ...

Selected portions of texts based on keywords such as: *balance sheet*, *bank*, *credit*, and *finance*.

Results: 12,377 texts.

Use kernel principal component analysis (PCA) to summarise the texts on a more–less stressed scale $[0, 1]$.

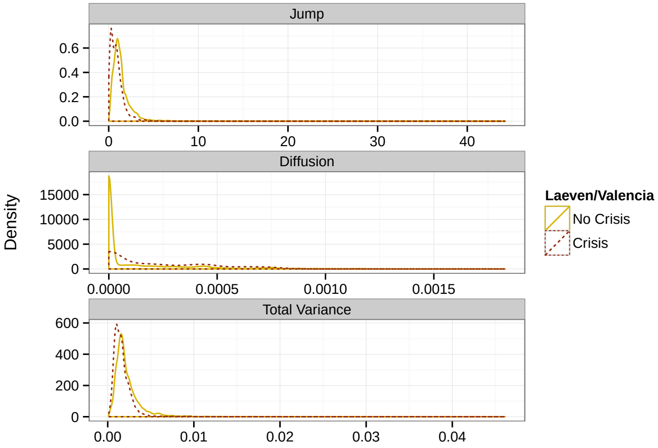
- Allows us to preserve word order, so that phrases like 'expand credit' and 'slow credit' distinguishable.
- Summary of qualitative assessments of quantitative data in context.

Also examined FinStress with a Drift, Jump, Diffusion Approach often used in time-series forecasting.

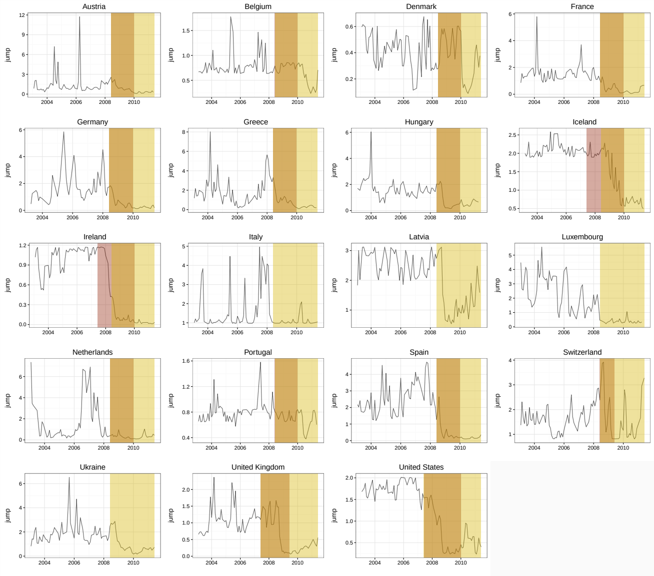
$$dx_t = f(x_t,\ \theta_t)dt + g(x_t,\ \theta_t)dw + dJ_t \tag{1}$$

- **Drift** $f(x_t,\ \theta_t)dt$: measures the local rate of change.
- **Diffusion** $g(x_t,\ \theta_t)dw$: small changes that happen at each time increment
- **Jump** dJ_t: large shocks that occur intermittently and are uncorrelated in time.

MORE JUMPS IN NON-CRISIS TIMES



JUMPS FOR SELECTED COUNTRIES WITH CRISIS



OTHER HYPOTHESIS

Bad conditions are not indicative of future crises.

$t+0$ conditions predict banking crises (Laeven/Valencia 2013)?