PREDICTING SELF-FULFILLING FINANCIAL CRISSES

Christopher Gandrud and Thomas Pepinsky
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City, University of London/Hertie School of Governance and Cornell University
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 $t + 1$. 
A **crisis** occurs when market actors simultaneously *Sell* their assets, e.g. in a bank run.
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A two-player game of strategic complements (Hold or Sell) with

1. Player types’ $\sigma_i$ drawn from single-peaked distribution $F_\sigma$, with support on the interval of $(\sigma, \bar{\sigma})$.
2. Common shock $\kappa$ representing market conditions.

NB: $F_\sigma$ and $\kappa$ are common knowledge. Only the realization of $\sigma_i$ 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

<table>
<thead>
<tr>
<th>Player A</th>
<th>Player B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hold</td>
<td>Hold: $\kappa, \kappa$</td>
</tr>
<tr>
<td>Sell</td>
<td>$\beta - \sigma_A, -\alpha$</td>
</tr>
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<tbody>
<tr>
<td></td>
<td></td>
<td>$\kappa, \kappa$</td>
<td>$-\alpha, \beta - \sigma_B$</td>
</tr>
<tr>
<td>Hold</td>
<td></td>
<td>$\beta - \sigma_A, -\alpha$</td>
<td>$-\sigma_A, -\sigma_B$</td>
</tr>
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</table>

Sensible features of private $\sigma_i$ and common shocks $\kappa$:

1. Larger $\sigma_i$ increase the value of holding for each player.
2. Larger $\kappa$ increase the value of holding for both players.
• Given common knowledge of $F_\sigma$, $\alpha$, and $\beta$, strategies depend entirely on the values of $\sigma_i$ and $\kappa$.

• The equilibrium is unique (Baliga and Sjöström 2012): players play a “cut-off” strategy where they sell iff $\sigma_i < \sigma^*$. 
MODEL: A GENERALIZED STAG HUNT

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Notice:

- Given $\kappa$, we know $\sigma^*$
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· The equilibrium is unique (Baliga and Sjöström 2012): players play a “cut-off” strategy where they sell iff $\sigma_i < \sigma^*$. 

Notice:

· Given $\kappa$, we know $\sigma^*$

Model the Observer as another player who predicts whether a crisis will take place in the future given the absence of a crisis today.
The observer makes inferences about $\sigma_{i,j}$ given $\kappa$. 
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**We show**

*If types are sparse and shocks are moderate, then larger common shocks $\kappa_t$ in period 1 imply a higher variance in player types in period 2 for any log-concave distribution $F_\sigma$.***
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**We show**

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

**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 $\text{Var}(\text{FinStress}_{t+1})$ 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(Impaired Loans)$_t$ (Andrianova et al. 2015): More impaired loans $\implies$ higher probability of bank insolvency.

· $\frac{\text{Liquid Assets}}{\text{Total Assets}}_t$ (Andrianova et al. 2015): Counterintuitively, more liquid assets $\implies$ more stressed financial system (especially in developing countries).

· FinStress$_t$: Lower FinStress $\implies$ better financial market conditions.
RESULTS
### Table: Regression result from predicting FinStress Variance using annual explanatory variable data (Full Sample)

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Full Sample (1)</th>
<th>Full Sample (2)</th>
<th>Full Sample (3)</th>
<th>Full Sample (4)</th>
<th>Full Sample (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Var(FinStress)_{year+1}</td>
<td>0.014 (0.029)</td>
<td>−0.011 (0.030)</td>
<td>−0.083* (0.047)</td>
<td>0.076** (0.038)</td>
<td>0.054 (0.035)</td>
</tr>
<tr>
<td>GDP Growth (%)</td>
<td>0.046** (0.022)</td>
<td>0.028 (0.023)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FinStress Mean_{year}</td>
<td>−5.347*** (1.299)</td>
<td>−6.263*** (2.404)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stock Price Volatility</td>
<td>−0.061*** (0.022)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Impaired Loans (log)</td>
<td></td>
<td></td>
<td>−0.277 (0.196)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Liquid Assets Ratio</td>
<td></td>
<td></td>
<td></td>
<td>0.026* (0.015)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>y</th>
<th>y</th>
<th>y</th>
<th>y</th>
<th>y</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observations</td>
<td>1,349</td>
<td>1,349</td>
<td>599</td>
<td>833</td>
<td>939</td>
</tr>
<tr>
<td>R²</td>
<td>0.004</td>
<td>0.018</td>
<td>0.044</td>
<td>0.009</td>
<td>0.007</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.003</td>
<td>0.016</td>
<td>0.038</td>
<td>0.008</td>
<td>0.006</td>
</tr>
</tbody>
</table>

Note: * p<0.1; ** p<0.05; *** p<0.01
Table: Regression result from predicting FinStress Variance using annual explanatory variable data (OECD Sample)

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Var(\text{FinStress})_{\text{year}+1}</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OECD (1)</td>
</tr>
<tr>
<td>Var(\text{FinStress})_{\text{year}+0}</td>
<td>0.036 (0.068)</td>
</tr>
<tr>
<td>GDP Growth (%)</td>
<td>0.336*** (0.083)</td>
</tr>
<tr>
<td>FinStress Mean_{\text{year}}</td>
<td>-10.146*** (3.150)</td>
</tr>
<tr>
<td>Stock Price Volatility</td>
<td>-0.144*** (0.039)</td>
</tr>
<tr>
<td>Impaired Loans (log)</td>
<td>-1.636*** (0.530)</td>
</tr>
<tr>
<td>Liquid Assets Ratio</td>
<td>0.043 (0.055)</td>
</tr>
</tbody>
</table>

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)

<table>
<thead>
<tr>
<th></th>
<th>Dependent variable:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Var(FinStress)_{quarter+1}</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Var(FinStress)_{quarter+0}</td>
<td>0.090***  (0.027)</td>
</tr>
<tr>
<td></td>
<td>(2)</td>
</tr>
<tr>
<td>GDP Growth (%)</td>
<td>0.102***  (0.027)</td>
</tr>
<tr>
<td></td>
<td>0.043  (0.029)</td>
</tr>
<tr>
<td>FinStress Mean_{quarter+0}</td>
<td>-5.569***  (1.065)</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>y</td>
</tr>
<tr>
<td>Observations</td>
<td>1,237</td>
</tr>
<tr>
<td>R²</td>
<td>0.023</td>
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<tr>
<td>Adjusted R²</td>
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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.
“Surprise” crises after booms: **Not (just) ignorance**, bias, or heuristics by stupid and naive social scientists.
CONCLUSIONS

“Surprise” crises after booms: Not (just) ignorance, bias, or heuristics by stupid and naive social scientists.

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*.
THE COURSE OF PLAY

1. Nature draws $\sigma_A, \sigma_B$ and reveals them to players $A$ and $B$.
2. Nature draws $\kappa_t$ from distribution $F_{\kappa}$ 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 $\sigma_A, \sigma_B$ conditional on what they observe.
5. The Observer predicts whether a financial crisis will occur given possible future realizations of the common shock $\kappa_{t+1}$. 
Conditional on observing \{\textit{Hold}, \textit{Hold}\} in period $t$, the Observer and \(A\) and \(B\) know that:

1. if $t + 1 > t$, then the probability of a crisis outcome in period $t + 1$ is zero, otherwise it is positive.

2. the values of \(A; B\) lie in the range \(0 < A; B < 1\). Denote this range \(r(t)\).

Proposition: If types are sparse and shocks are moderate, then larger common shocks result in larger \(r(t)\). This implies a higher variance in player types in period 2 for any log-concave distribution \(F\).
Conditional on observing \( \{Hold, Hold\} \) in period \( t \), the Observer and \( A \) and \( B \) know that:

1. if \( \kappa_{t+1} > \kappa_t \), then the probability of a crisis outcome in period \( t + 1 \) is zero, otherwise it is positive.
Conditional on observing \{Hold, Hold\} in period $t$, the Observer and $A$ and $B$ know that:

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

If types are sparse and shocks are moderate, then larger common shocks \(\kappa_t\) result in larger \(r(\kappa_t)\). This implies a higher variance in player types in period 2 for any log-concave distribution \(F_\sigma\).
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Two mechanisms:

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.
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.

\[ dx_t = f(x_t, \theta_t) dt + g(x_t, \theta_t) dw + dJ_t \] (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

Laeven/Valencia

No Crisis
Crisis
JUMPS FOR SELECTED COUNTRIES WITH CRISIS
Bad conditions are not indicative of future crises.
Do $t+0$ conditions predict banking crises (Laeven/Valencia 2013)?