PREDICTABLE FINANCIAL CRISES

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How predictable are crises?

- *"Financial crises can't be reliably anticipated or preempted."* –Tim Geithner
- *"My strong belief is that these crises are unpredictable in terms of cause or timing or the severity when they hit."* –Hank Paulson
- *"This crisis involved a 21st century electronic panic by institutions... It was an old-fashioned run in new clothes."* –Ben Bernanke

How predictable are crises?

- **Recognized that crises preceded by weak economic fundamentals**
  - Kaminsky 1990, Goldstein-Kaminsky-Reinhart 2000
- **But, still widely believed that crises largely unpredictable**
  - Gorton (2012) "crises are sudden, unpredictable events"
  - Literature in the late 1990s and 2000s using country characteristics to forecast a currency and/or banking crisis
- **Emerging alternate: Crises predictable byproducts of rapid expansions of credit accompanied by asset booms (Minsky, Kindleberger)**
  - Recent papers arguing credit expansions, growth of risky credit as share of total, tight credit spreads, predict financial fragility & worse macro outcomes
    - Borio-Lowe 2020, Schularick-Taylor 2012, Greenwood-Hanson 2013, Baron-Xiong 2017, Lopez-Salido-Stein-Zakrajšek 2017, Mian-Sufi-Verner 2017, Krishnamurthy-Muir 2020
- **Yet, precise and straightforward estimates of the probability of a crisis following credit and asset price booms remain unavailable.**
  - Open debate about how high probability of a crisis should be permitted to climb before prompting early policy action

This paper

- **Estimate probability of financial crises as a function of past credit and asset price growth.**
  - Panel of 42 countries from 1950–2016
  - Historical data on growth of outstanding credit to businesses and households.
  - Data on the growth of equity and home prices.
  - Chronology of financial crises: Baron-Verner-Xiong (2021) use hand-collected historical data on bank stock returns to improve existing crisis chronologies.
- **Construct indicator variables capturing "overheated" credit markets**
  - Overheated = **Joint occurrence** of rapid asset price growth and credit growth
  - Do so separately for the household and business sector
- **How predictable are crises?**
  - When credit markets are overheated in this sense, Prob(Crisis with 3 years) > 40%
- **How much lead time does a policymaker have?**
  - A decent amount.
  - Predictability is much stronger at 2- and 3-year horizons than at a 1-year horizon.

Main Findings (1)

1. **Consistent with Schularick and Taylor (2012) and others, crises can be predicted using past credit growth in simple linear regressions.**
   - But predictability is modest, even at horizons up to five years.

2. **Predictability rises substantially when we focus on large credit expansions that are accompanied by asset price booms.**
   - Prob(Crisis) is high when:
     - Nonfinancial business credit growth is high + stock prices have risen sharply.
     - Household credit growth is high and home prices have risen sharply.
   - "Red-Zone" = Joint occurrence of rapid asset price growth and credit growth
     - Natural signal of an outward shift in the supply of credit, which then sows the seeds of its own destruction
   - Prob(Crisis) cumulates for 3-4 years after overheating: Ample early warning

3. **Overheating in business and household credit = Separate things**
   - Both independently predict the arrival of future crises.
   - Particularly dangerous in the rare instances when they occur in tandem.

Main Findings (2)

4. **Overheating in credit markets naturally has a global component and is correlated across countries.**
   - Construct global business Red-zone variables: Fraction of countries in our sample that are in the Red-zone in each year.
   - Including global variables substantially increases predictability.

5. **How high should probability of a financial crisis be allowed to climb before prompting early action on part of policymakers?**
   - "Back-of-the-envelop" model
   - Answer turns on (1) statistical tradeoff between false negative and false positive errors and (2) costs of these two policy mistakes.
   - Argue that early action warranted unless costs of false negatives is very low—implausibly in our view—relative to false positives.

Previous literature

- **Forecasting the credit cycle**
  - Schularik and Taylor 2012; Greenwood and Hanson 2013; Baron Xiong 2017; Lopez-Salido, Stein, Zakrajsek 2017; Mian, Sufi, Verner 2017; Kirti 2020
  - Our contributions:
    - Simplicity and transparency of approach
    - Highlighting strong interaction between credit growth and asset prices
    - Documenting a higher degree of predictability than normally assumed
    - Calibrating simple model of policy tradeoff

- **Behavioral view of credit cycles**
  - Minsky 1977, 1986; Kindleberger 1978
  - Gennaioli, Shleifer and Vishny 2012; Greenwood and Hanson 2013; Bordalo et al. 2018; Gennaioli and Shleifer 2018; Greenwood, Hanson, and Jin 2019; Maxted 2020; Krishnamurthy and Lu 2020
  - Our findings favor this behavioral view of crises.

Data

- **Unbalanced panel dataset covering 42 countries from 1950 to 2016**

- **Key dependent variable = Financial crisis indicators**
  - Baseline = Baron-Verner-Xiong (2021) indicator
  - Reinhart-Rogoff (2011) and Jorda-Schularick-Taylor (2017) as robustness

- **Independent variable #1 = Growth in business/household credit**
  - Change in Credit-to-GDP for Businesses and Households
  - Focus 3-year change
  - Primarily drawn from IMF

- **Independent variable #2 = Asset price growth**
  - Equities: 3-year real price growth from Global Financial Data
  - Residential Housing: 3-year real price growth from BIS

- **Focus on the postwar period**

Crisis data

- Painstakingly collected by Reinhart-Rogoff (2011), Jorda-Schularik-Taylor (2017), and Baron-Verner-Xiong (2021)

- BVX (2021)
  - Combine narrative data on bank failures and bank panics with data on bank stock prices
  - "Bank crisis" when either:
    - "Equity crisis" = bank stocks fall by >30% + widespread failures
    - "Panic crisis" = severe withdrawals from banks
  - Unconditional probability of a crisis in a given year is 4.0%
    - Roughly a crisis every 25 years
  - BVX actually classify every country year into bank equity crisis/panic, and so on, so we can (and have) looked at predictability of different crisis genres

Forecasting with credit growth only

- Jordá-style (2005) linear forecasting regressions of the form:

$$Crisis_{i,t+1\text{ to }t+h} = \alpha_i^{(h)} + \beta^{(h)} \cdot \Delta_3 X_{it} + \varepsilon_{i,t+1\text{ to }t+h}$$

for $h = 1, 2, 3, \text{and } 4$ where $\alpha_i^{(h)}$ is a country fixed effect, and Δ_3 is the change in predictor X_{it} over three years ending in t. $Crisis_{i,t+1\text{ to }t+h}$ is an indicator variable that equals one if a crisis begins in country i in any year between $t+1$ and year $t+h$

	Dependent Variable											
	Crisis within 1 year				Crisis within 2 year				Crisis within 3 year			
	(1.1)	(1.2)	(1.3)	(1.4)	(2.1)	(2.2)	(2.3)	(2.4)	(3.1)	(3.2)	(3.3)	(3.4)
Δ_3 (Debt^{Priv} / GDP) (Normalized)	2.6*				4.0***				5.3**			
	[1.7]				[2.9]				[2.6]			
Δ_3 (Debt^{Bus} / GDP) (Normalized)		2.0				2.8**				3.4*		
		[1.5]				[2.6]				[2.1]		
Δ_3 (Debt^{HH} / GDP) (Normalized)			2.8**				6.1***				9.2***	
			[2.2]				[2.9]				[3.4]	
Δ_3 log(Debt^{Priv}/CPI) (Normalized)				1.3				2.3				3.5
				[1.2]				[1.6]				[1.7]
R^2 *(within)*	1.5	0.9	1.7	0.4	1.9	0.9	4.4	0.6	2.5	1.0	7.3	1.0
N	1,281	1,258	1,107	1,281	1,281	1,258	1,107	1,281	1,281	1,258	1,107	1,281

Forecasting with credit growth only

- Jordá-style (2005) linear forecasting regressions of the form:

$$Crisis_{i,t+1 \text{ to } t+h} = \alpha_i^{(h)} + \beta^{(h)} \cdot \Delta_3 X_{it} + \varepsilon_{i,t+1 \text{ to } t+h}$$

  - One Standard Deviation rise in $\Delta_3(Debt^{Priv}/GDP)_{it}$ associated with a 2.6 and 5.3 percentage point increase in Prob (Crisis) within 1 and 3 year.

	Dependent Variable											
	Crisis within 1 year				Crisis within 2 year				Crisis within 3 year			
	(1.1)	(1.2)	(1.3)	(1.4)	(2.1)	(2.2)	(2.3)	(2.4)	(3.1)	(3.2)	(3.3)	(3.4)
Δ_3 (Debt^{Priv} / GDP) (Normalized)	2.6*				4.0***				5.3**			
	[1.7]				[2.9]				[2.6]			
Δ_3 (Debt^{Bus} / GDP) (Normalized)		2.0				2.8**				3.4*		
		[1.5]				[2.6]				[2.1]		
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N	1,281	1,258	1,107	1,281	1,281	1,258	1,107	1,281	1,281	1,258	1,107	1,281

Incorporating Asset Price Data

- Probability of Financial Crisis ***onset*** within 3 years
  - *Business Debt and Equity Prices*

	Crisis Frequency Debt Quintile					*Diff. from Median* Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	4.2	4.9	4.1	7.1	19.3	-3.7	-3.1	-3.8	-0.9	11.3
2	3.5	5.3	8.0	9.5	19.4	-4.4	-2.7	0.0	1.6	11.4*
3	11.5	9.3	11.1	19.3	**45.3**	3.5	1.4	3.2	11.3	**37.4*** **

  - *Household Debt and House Prices*

	Crisis Frequency Debt Quintile					*Diff. from Median* Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	9.5	4.8	11.1	8.2	28.3	6.1**	1.5	7.8	4.9	24.9**
2	7.2	4.0	3.3	16.2	13.1	3.9	0.7	0.0	12.9**	9.8*
3	2.7	3.2	1.4	17.4	**36.8**	-0.6	-0.2	-1.9	14.1**	**33.5*** **

- Simple way of understanding nonlinear multivariate relationship

Incorporating Asset Price Data

- Probability of Financial Crisis ***onset*** within 3 years
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1	4.2	4.9	4.1	7.1	19.3	-3.7	-3.1	-3.8	-0.9	11.3
2	3.5	5.3	8.0	9.5	19.4	-4.4	-2.7	0.0	1.6	11.4*
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3	2.7	3.2	1.4	17.4	**36.8**	-0.6	-0.2	-1.9	14.1**	**33.5*****

- Very strong interaction between past credit and asset price growth

Incorporating Asset Price Data

- Probability of Financial Crisis ***onset*** within 3 years
  - *Business Debt and Equity Prices*

	Crisis Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	4.2	4.9	4.1	7.1	19.3	-3.7	-3.1	-3.8	-0.9	11.3
2	3.5	5.3	8.0	9.5	19.4	-4.4	-2.7	0.0	1.6	11.4*
3	11.5	9.3	11.1	19.3	**45.3**	3.5	1.4	3.2	11.3	**37.4*****

  - *Household Debt and House Prices*

	Crisis Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	9.5	4.8	11.1	8.2	28.3	6.1**	1.5	7.8	4.9	24.9**
2	7.2	4.0	3.3	16.2	13.1	3.9	0.7	0.0	12.9**	9.8*
3	2.7	3.2	1.4	17.4	**36.8**	-0.6	-0.2	-1.9	14.1**	**33.5*****

- ***Red-Zone or "R-zone"*** = Asset price growth and credit growth both high

The Red-Zone

- Define three indicator variables:

  $High\text{-}Debt\text{-}Growth_{it} = 1\{\Delta_3(Debt/GDP)_{it} > 80^{\text{th}} \text{ percentile}\})$

  $High\text{-}Price\text{-}Growth_{it} = 1\{\Delta_3 \log(Price_{it}) > 66.7^{\text{th}} \text{ percentile}\}$

  $R\text{-}zone_{it} = High\text{-}Debt\text{-}Growth_{it} \times High\text{-}Price\text{-}Growth_{it}$

- To assess how elevated credit and asset price growth shape Prob(Crisis), estimate Jordá-style (2005) forecasting regressions:

$$Crisis_{i,t+1 \text{ to } t+h} = \alpha_i^{(h)} + \beta^{(h)} \cdot High\text{-}Debt\text{-}Growth_{it} + \delta^{(h)} \cdot High\text{-}Price\text{-}Growth_{it} + \gamma^{(h)} \cdot R\text{-}zone_{it} + \varepsilon_{i,t+1 \text{ to } t+h}$$

  - Results similar with or without country fixed-effects
  - We estimate LPMs, but marginal effects nearly identical with logit or probit
  - Driscoll-Kraay (1998) standard errors (panel analog of Newey-West)
  - Conservative *p-values* using Kiefer-Vogelsang's (2005) "fixed-b" asymptotics

Forecast with R-Zone (Business)

$$Crisis_{i,t+1\text{ to }t+h} = \alpha_i^{(h)} + \beta^{(h)} \cdot High\text{-}Debt\text{-}Growth_{it}$$
$$+ \delta^{(h)} \cdot High\text{-}Price\text{-}Growth_{it} + \gamma^{(h)} \cdot R\text{-}zone_{it} + \varepsilon_{i,t+1\text{ to }t+h}$$

	Crisis within 1 year				Crisis within 3 years			
	(1.1)	(1.2)	(1.3)	(1.4)	(3.1)	(3.2)	(3.3)	(3.4)
High Debt Growth$^{Bus.}$ ($\beta^{(h)}$)	6.9**		5.3**		16.8***		11.5**	
	[2.3]		[2.1]		[3.3]		[2.7]	
High Price Growth$^{Bus.}$ ($\delta^{(h)}$)		0.4	-0.4			10.5	7.4	
		[0.1]	[-0.2]			[1.4]	[1.1]	
R-Zone$^{Bus.}$ ($\gamma^{(h)}$)			5.3	9.0			19.4**	33.7***
			[0.8]	[1.1]			[2.8]	[3.3]
Sum of coefficients ($\beta^{(h)} + \delta^{(h)} + \gamma^{(h)}$)	6.9	0.4	10.2	9.0	16.8	10.5	38.2	33.7
R^2 *(within)*	1.6	0.0	1.9	1.1	3.8	2.4	7.8	6.1
N	1,258	1,258	1,258	1,258	1,258	1,258	1,258	1,258

- Degree of predictability rises significantly with horizon: Crises slow to develop

Forecast with R-Zone (Business)

$$Crisis_{i,t+1\text{ to }t+h} = \alpha_i^{(h)} + \beta^{(h)} \cdot High\text{-}Debt\text{-}Growth_{it}$$
$$+ \delta^{(h)} \cdot High\text{-}Price\text{-}Growth_{it} + \gamma^{(h)} \cdot R\text{-}zone_{it} + \varepsilon_{i,t+1\text{ to }t+h}$$

	Crisis within 1 year				Crisis within 3 years			
	(1.1)	(1.2)	(1.3)	(1.4)	(3.1)	(3.2)	(3.3)	(3.4)
High Debt Growth$^{Bus.}$ ($\beta^{(h)}$)	6.9**		5.3**		16.8***		11.5**	
	[2.3]		[2.1]		[3.3]		[2.7]	
High Price Growth$^{Bus.}$ ($\delta^{(h)}$)		0.4	-0.4			10.5	7.4	
		[0.1]	[-0.2]			[1.4]	[1.1]	
R-Zone$^{Bus.}$ ($\gamma^{(h)}$)			5.3	9.0			19.4**	33.7***
			[0.8]	[1.1]			[2.8]	[3.3]
Sum of coefficients ($\beta^{(h)} + \delta^{(h)} + \gamma^{(h)}$)	6.9	0.4	10.2	9.0	16.8	10.5	38.2	33.7
R^2 *(within)*	1.6	0.0	1.9	1.1	3.8	2.4	7.8	6.1
N	1,258	1,258	1,258	1,258	1,258	1,258	1,258	1,258

- Coefficient on R-zone interaction is economically large, statistically significant

Forecast with R-Zone (Household)

$$Crisis_{i,t+1\text{ to }t+h} = \alpha_i^{(h)} + \beta^{(h)} \cdot High\text{-}Debt\text{-}Growth_{it}$$
$$+ \delta^{(h)} \cdot High\text{-}Price\text{-}Growth_{it} + \gamma^{(h)} \cdot R\text{-}zone_{it} + \varepsilon_{i,t+1\text{ to }t+h}$$

	Crisis within 1 year				Crisis within 3 years			
	(1.1)	(1.2)	(1.3)	(1.4)	(3.1)	(3.2)	(3.3)	(3.4)
High Debt Growth^{HH} ($\beta^{(h)}$)	7.3**		2.4		20.5***		9.1**	
	[2.2]		[1.6]		[3.3]		[2.3]	
High Price Growth^{HH} ($\delta^{(h)}$)		3.6*	0.4			8.1	0.0	
		[1.7]	[0.3]			[1.5]	[0.00]	
R-Zone^{HH} ($\gamma^{(h)}$)			8.9*	11.2**			20.9***	28.6***
			[1.8]	[2.2]			[3.2]	[3.4]
Sum of coefficients ($\beta^{(h)} + \delta^{(h)} + \gamma^{(h)}$)	7.3	3.6	11.7	11.2	20.5	8.1	30.1	28.6
R^2 *(within)*	1.8	0.7	2.8	2.7	5.6	1.4	7.6	7.0
N	1,107	1,107	1,107	1,107	1,107	1,107	1,107	1,107

- Degree of predictability rises significantly with horizon: Crises slow to develop

Forecast with R-Zone (Household)

$$Crisis_{i,t+1\text{ to }t+h} = \alpha_i^{(h)} + \beta^{(h)} \cdot High\text{-}Debt\text{-}Growth_{it}$$
$$+ \delta^{(h)} \cdot High\text{-}Price\text{-}Growth_{it} + \gamma^{(h)} \cdot R\text{-}zone_{it} + \varepsilon_{i,t+1\text{ to }t+h}$$

	Crisis within 1 year				Crisis within 3 years			
	(1.1)	(1.2)	(1.3)	(1.4)	(3.1)	(3.2)	(3.3)	(3.4)
High Debt Growth^{HH} $(\beta^{(h)})$	7.3**		2.4		20.5***		9.1**	
	[2.2]		[1.6]		[3.3]		[2.3]	
High Price Growth^{HH} $(\delta^{(h)})$		3.6*	0.4			8.1	0.0	
		[1.7]	[0.3]			[1.5]	[0.00]	
R-Zone^{HH} $(\gamma^{(h)})$			8.9*	11.2**			20.9***	28.6***
			[1.8]	[2.2]			[3.2]	[3.4]
Sum of coefficients $(\beta^{(h)} + \delta^{(h)} + \gamma^{(h)})$	7.3	3.6	11.7	11.2	20.5	8.1	30.1	28.6
R^2 *(within)*	1.8	0.7	2.8	2.7	5.6	1.4	7.6	7.0
N	1,107	1,107	1,107	1,107	1,107	1,107	1,107	1,107

- Coefficient on R-zone interaction is economically large, statistically significant

Additional Questions

1. How robust are these core results?
   a) Driven by look-ahead bias?
   b) Driven by just the 2007–2008 global financial crisis?
   c) Hold for other crisis chronologies?
   d) Sensitive to the specific thresholds for "high"?

2. Do overheating in the markets for business and household credit reflect a single underlying factor, or are these separate phenomena?

3. How much of the predictability is driven by global overheating in credit markets, as opposed to local, country-level credit market overheating?

4. How likely do crises need to become before warranting pre-emptive action by policymakers?

Business and Household Credit

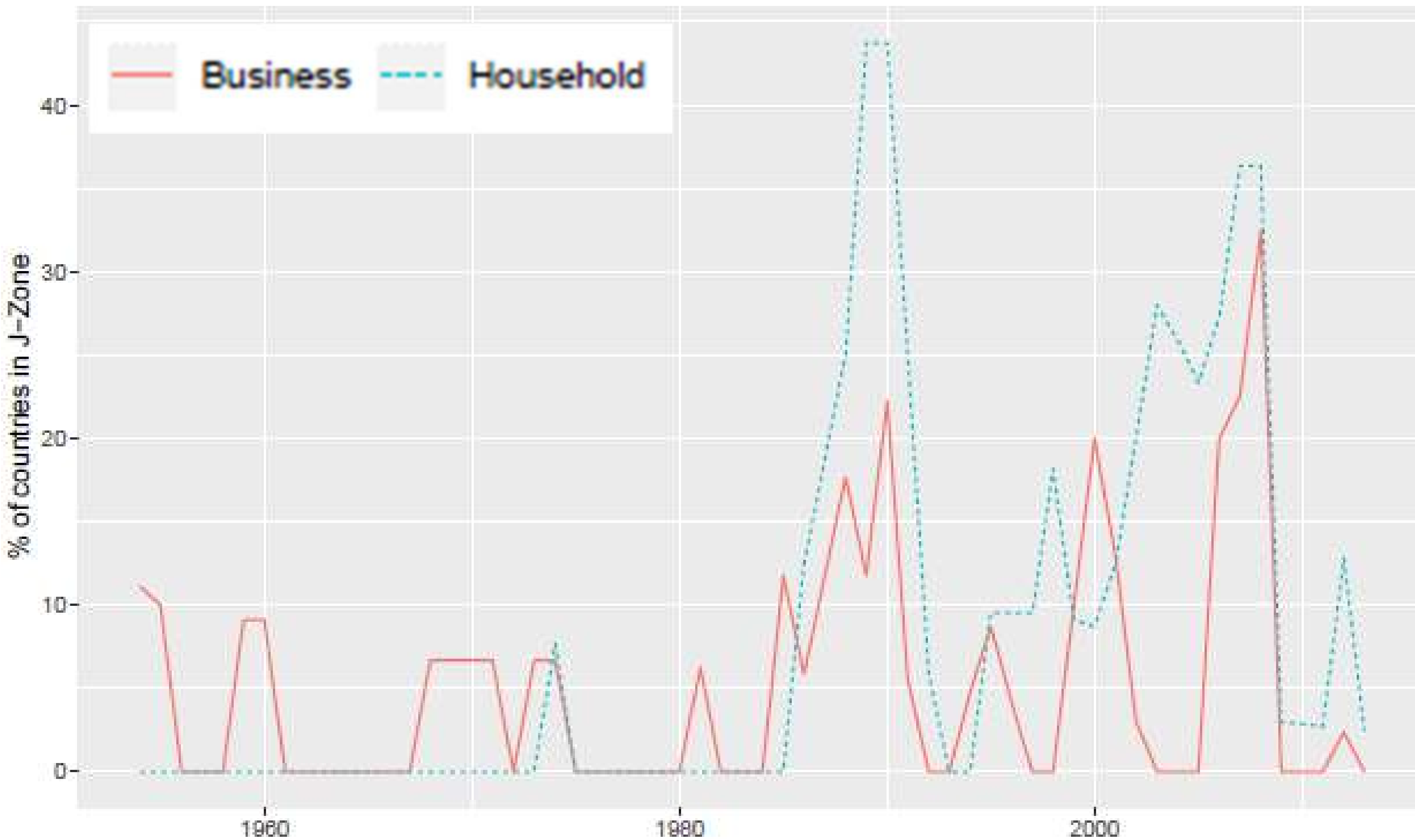
$$Crisis_{i,t+1\text{ to }t+h} = \alpha_i^{(h)} + \gamma^{Bus(h)} \cdot R\text{-}zone_{it}^{Bus} + \gamma^{HH(h)} \cdot R\text{-}zone_{it}^{HH} + \gamma^{Both(h)} \cdot R\text{-}zone_{it}^{Both} + \gamma^{Either(h)} \cdot R\text{-}zone_{it}^{Either} + \varepsilon_{i,t+1\text{ to }t+h}$$

	Crisis within 3 years			
	(3.1)	(3.2)	(3.3)	(3.4)
R-Zone^{Bus} ($\gamma^{Bus(h)}$)	28.7***	22.2*		
	[3.2]	[2.0]		
R-Zone^{HH} ($\gamma^{HH(h)}$)	24.8***	21.6***		
	[3.5]	[2.7]		
R-Zone^{Bus} × R-Zone^{HH} ($\gamma^{Both(h)}$)		24.8	65.4***	
		[1.7]	[8.0]	
max{R-Zone$^{Bus.}$,R-Zone^{HH}} ($\gamma^{Either(h)}$)				28.1***
				[3.4]
R^2 (within)	11.1	11.7	6.7	8.7
Observations	1,084	1,084	1,084	1,281

- Overheating in business and household credit markets are separate phenomena.
  - Correlation between household R-zone and the business R-zone just 16%.
- Independently predict the arrival of future crises, but they are particularly dangerous in rare instances—e.g., Japan in 1988—when they occur in tandem.

Local versus Global Overheating

- Credit cycles share an important global component
  - Schularick-Taylor (2012), Mian-Sufi-Verner (2017), Agrippino-Rey (2020)
- Simple measure: $Global\ R\text{-}zone_t \; = \% \,(Countries\ in\ R{-}zone\ in\ year\ t)$



Local versus Global Overheating

$$Crisis_{i,t+1\text{ to }t+h} = \alpha_i^{(h)} + \gamma^{Bus(h)} \cdot Local\ R\text{-}zone_{it}^{Bus} + \xi^{Bus(h)} \cdot Global\ R\text{-}zone_{t}^{Bus} + \gamma^{HH(h)} \cdot Local\ R\text{-}zone_{it}^{HH} + \xi^{HH(h)} \cdot Global\ R\text{-}zone_{t}^{HH} + \varepsilon_{i,t+1\text{ to }t+h}$$

	Crisis within 3 years		
	(3.1)	(3.2)	(3.3)
Local R-Zone^{Bus} ($\gamma^{Bus(h)}$)	18.3**		16.0
	[2.4]		[1.9]
Global R-Zone^{Bus} ($\xi^{Bus(h)}$)	116.0***		77.0*
	[4.7]		[1.8]
Local R-Zone^{HH} ($\gamma^{HH(h)}$)		14.3***	13.1**
		[3.1]	[2.9]
Global R-Zone^{HH} ($\xi^{HH(h)}$)		76.6***	39.4**
		[4.9]	[2.4]
R^2 *(within)*	14.3	14.5	19.2
Observations	1,258	1,107	1,084

- Including these global variables in our forecasting regressions substantially increases the predictability of crises.
  - R^2 when forecasting crises at a 3-year horizon is 19.2% in column (3.3), far exceeds R^2 reported in prior Tables.

Crisis prediction & financial stability

- While Red-zone indicator has substantial predictive power for arrival of a crisis, still fails to signal some crises and also generates false alarms.
  - How strong must the predictability be to warrant taking early policy actions to either avert or mitigate the severity of financial crises?
- Different ways of defining R-zone events are associated with a natural statistical tradeoff between false negative errors and false positive errors
  - For instance, many of the crises not preceded by a R-zone event are “near misses” in the sense that credit and asset price growth fall just short of our assignment thresholds
  - So, they are preceded by a Yellow-zone or “Y-zone” in which credit and asset price growth are elevated, but not as high as in the R-zone.
  - So, Y-zone has fewer false negatives, but generates more false alarms than R-zone.
- Use our data to construct a “policy possibility frontier,” which provides a more formal summary of the statistical tradeoff faced by policymakers.
  - Develop a simple framework to quantify how a policymaker tasked with promoting financial stability should trade off false positive and false negative errors—e.g., when setting her threshold for acting to “lean against the wind” of credit-market overheating.
  - Taking policy possibility frontier as given, optimal choice depends on relative costs of these two types of policy errors.
  - While neither the R-zone nor the Y-zone are perfect predictors, argue there is a strong quantitative case for taking early policy action.

Crisis prediction & financial stability

- **Contingency table:** A simple representation of the predictive efficacy of the Business R-zone indicator

	Crisis within 3 years $Crisis_{i,t+1 \text{ to } t+3} = 1$	No crisis within 3-years: $Crisis_{i,t+1 \text{ to } t+3} = 0$
R-zone: $R\text{-}zone_{it} = 1$	True Positives ($\#TP$)	False Positives ($\#FP$)
No R-zone: $R\text{-}zone_{it} = 0$	False Negatives ($\#FN$)	True Negatives ($\#TN$)

- Looking at rows:
  - Positive Predictive Value: $PPV = \#TP/(\#TP + \#FP)$
  - Negative Predictive Value: $NPV = \#TN/(\#TN + \#FN)$

Crisis prediction & financial stability

- **Contingency table:** A simple representation of the predictive efficacy of the Business R-zone indicator

	Crisis within 3 years $Crisis_{i,t+1\text{ to }t+3} = 1$	No crisis within 3-years: $Crisis_{i,t+1\text{ to }t+3} = 0$
R-zone: $R\text{-}zone_{it} = 1$	True Positives (34)	False Positives (41)
No R-zone: $R\text{-}zone_{it} = 0$	False Negatives (117)	True Negatives (1,066)

- Looking at rows:
  - Positive Predictive Value: $PPV = 34/(34 + 41) = 45.3\%$
  - Negative Predictive Value: $NPV = 1{,}066/(1{,}066 + 117) = 90.1\%$

Crisis prediction & financial stability

- **Contingency table:** A simple representation of the predictive efficacy of the Business R-zone indicator

	Crisis onset: $Crisis_{i,t} = 1$	No crisis onset: $Crisis_{i,t} = 0$
R-zone in prior 3 years	True Positives (20)	False Positives (131)
No R-zone in prior 3 years	False Negatives (30)	True Negatives (1,077)

- Looking at columns:
  - True Positive Rate: $TPR = 20/(20 + 30) = 40.0\%$
  - True Negative Rate: $TNR = 1{,}077/(1{,}077 + 131) = 89.2\%$

Crisis prediction & financial stability

	Type			
	Business	Household	Either	Both
#R-Zone Events followed by a Crisis	34	42	61	15
#R-Zone Events	75	114	170	19
%R-Zone Events followed by a Crisis (PPV)	45.3	36.8	35.9	78.9
#Crises Preceded By R-Zone	20	21	32	7
#Crises	50	44	50	44
% of Crises preceded by R-Zone (TPR)	40.0	47.7	64.0	15.9
#Non-crises not Preceded By R-Zone	1077	897	969	1010
#Non-Crises	1208	1063	1231	1040
% of Non-Crises not preceded by R-Zone (TNR)	89.2	84.4	78.7	97.1
Time to Crisis	2.9	3.7	3.6	3.0

- Household *R-zone* is a more sensitive indicator ($TPR = 48\%$) than business, but is slightly less specific ($TNR = 84\%$).
- If allow **either** household or business *R-zone* to signal a crisis, sensitivity rises significantly ($TPR = 64\%$), but specificity ($TNR = 79\%$) falls
- If require **both** the business and the household sectors to be in *R-zone*, sensitivity falls significantly ($TPR = 16\%$), but a large improvements in specificity ($TNR = 97\%$).

Crisis prediction & financial stability

	Type			
	Business	Household	Either	Both
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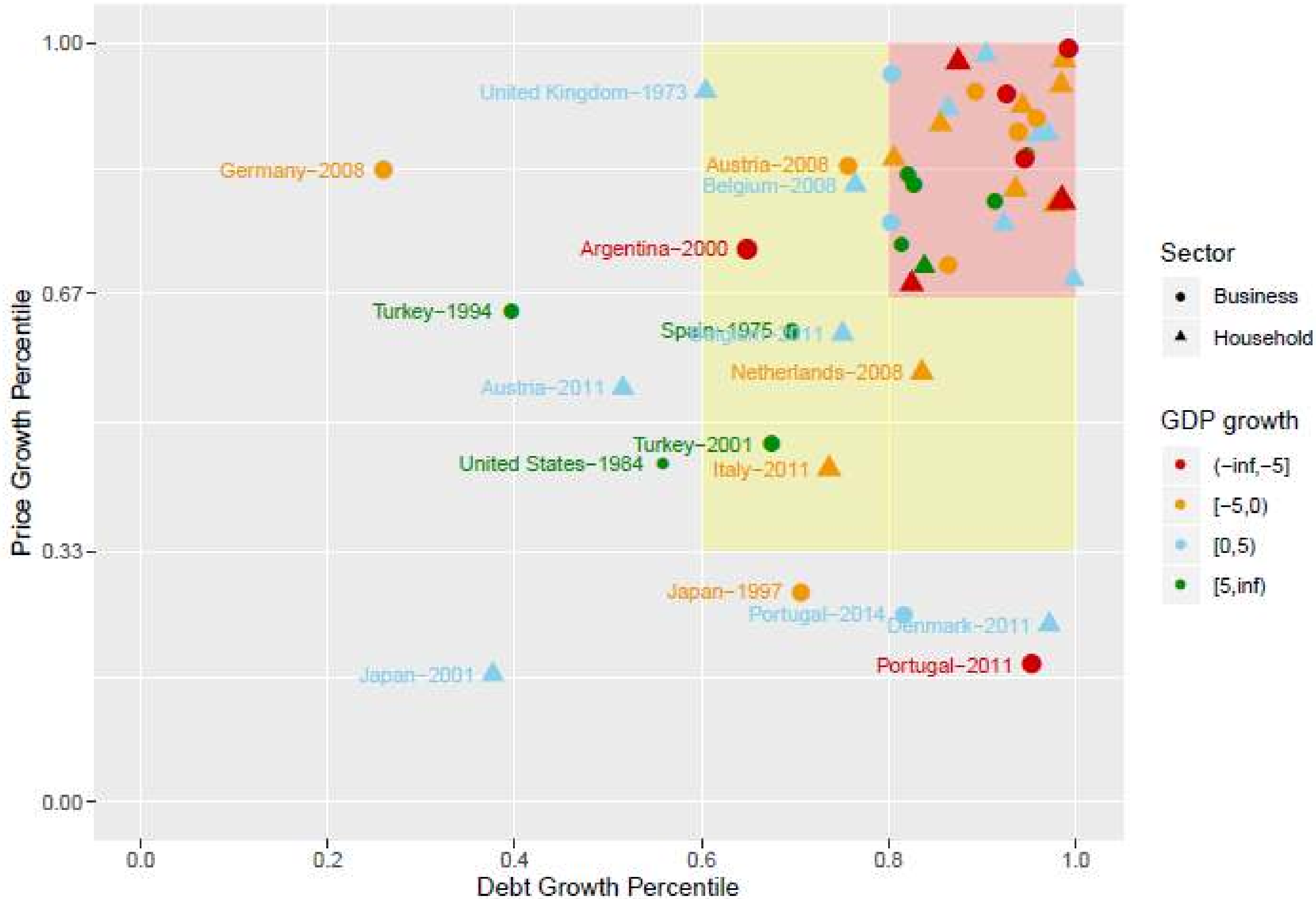
- A general statistical trade-off.
- Using a <u>less stringent</u> indicator of credit market over-heating:
  - Raises the True Positive Rate (TPR).
  - Reduces the True Negative Rate (TNR)

    [Also reduces the Positive Predictive Value (PPV)]

Crises in and out of the *R-zone*



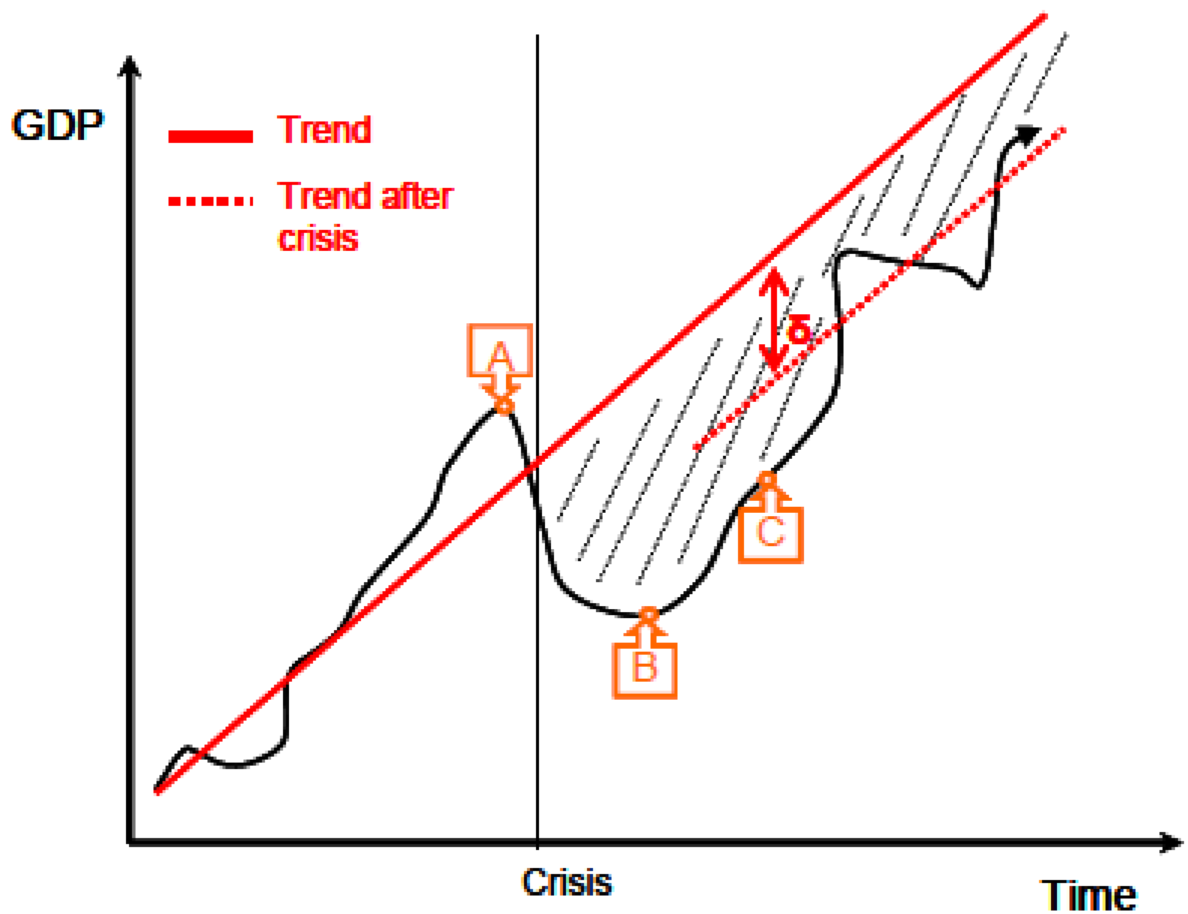
- *TPR* = 32/50 = 64% of crises preceded by Red-zone (either Bus or HH)
- *TPR* = 41/50 = 81% of crises preceded by Yellow-zone (either Bus or HH)
- 7/9 crises not preceded by Yellow-zone are "double-dips"

The policy tradeoff

- What point on the policy possibility frontier should a policymaker choose?
  - Given the statistical tradeoff between false positives and false negatives, what should a policymaker concerned with financial stability do?
  - How high of a threshold should set for taking early actions.
- Tradeoff:
  - Taking steps to avert crises, the policymaker runs the risk of leaning against the wind based on false alarms.
  - But, if they set too high of a threshold they will fail to act.
- Optimal threshold for taking early action depends on the cost of acting based on a false alarm, compared to the cost of failing to act when the risk of a crisis is truly elevated.

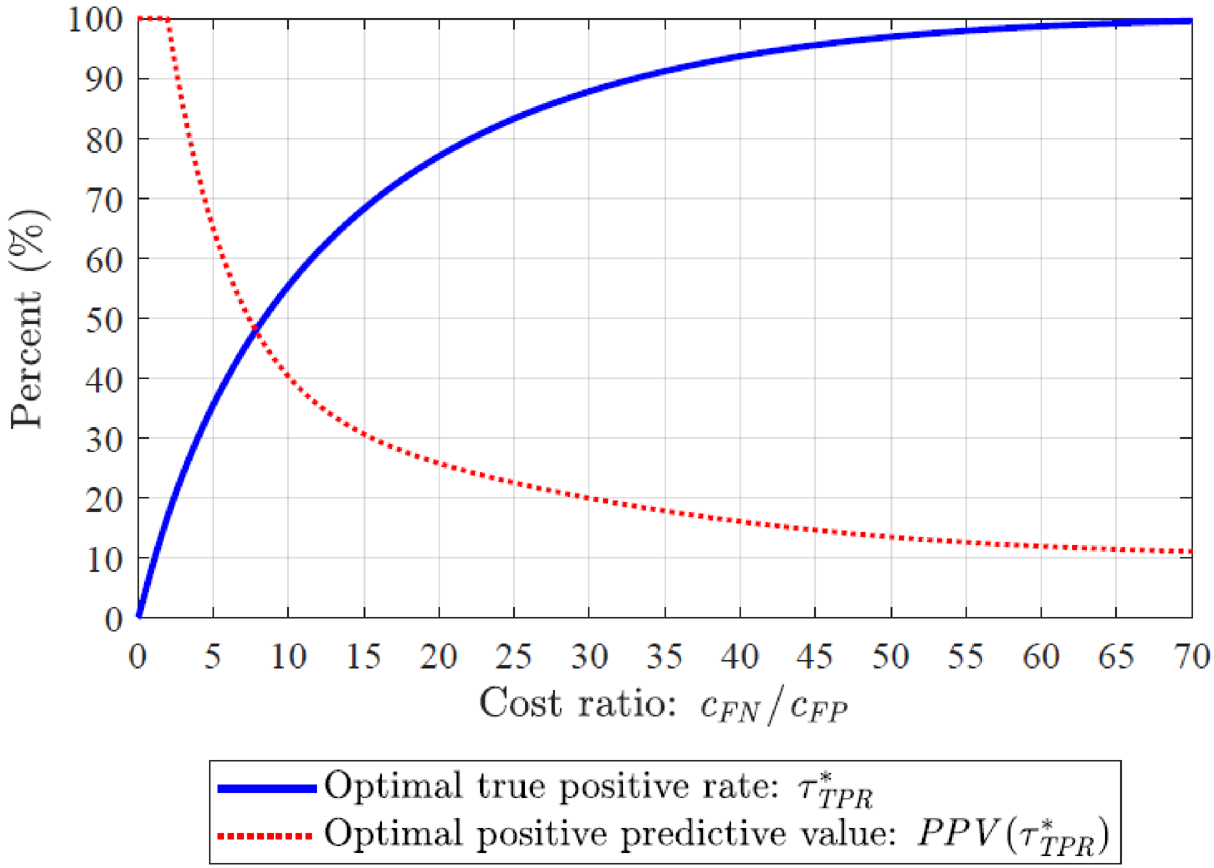
Crude back-of-the-envelope

- **Financial crises are incredibly costly.**
  - Cerra and Saxena (2008) and Basel (2010).



Crude back-of-the-envelope

- Example: $c_{FN}/c_{FP} = 30\%/2\% = 15$: Forceful early action to lean against the wind, lowers expected severity of incipient crisis by 30%, but reduces GDP by 1 percentage point for two years if there is no crisis
  - $\tau^*_{TPR} = 68\%$: Act once Prob[Crisis arrives within three years] > 31%.



Crude back-of-the-envelope

- Predictability we observe is sufficiently strong that policymakers should only adopt a "do nothing" strategy if they hold fairly extreme views about costs of failing to respond to financial stability threats vs. costs of false alarms
  - Based on our estimates, policymakers should only set $\tau^*_{TPR} \leq 10\%$ if they believe c_{FN}/c_{FP} is less 1.1.
  - Policymaker would need to believe a leaning-against-the-wind policy, which would reduce GDP by 1 percentage point for two years if there is no crisis, would only reduce the expected severity of an incipient crisis by 2.2%.

Conclusion

- **How predictable are crises?**
  - When credit markets are overheated in the sense that credit growth and asset growth are jointly elevated:

    Prob(Crisis with 3 years) > 40%

- **Sufficiently predictable to warrant early action?**
  - We certainly think so!