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Financial Crises: A Survey

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ABSTRACT

Financial crises have large deleterious effects on economic activity, and as such have been the focus of a large body of research. This study surveys the existing literature on financial crises, exploring how crises are measured, whether they are predictable, and why they are associated with economic contractions. Historical narrative techniques continue to form the backbone for measuring crises, but there have been exciting developments in using quantitative data as well. Crises are predictable with growth in credit and elevated asset prices playing an especially important role; recent research points convincingly to the importance of behavioral biases in explaining such predictability. The negative consequences of a crisis are due to both the crisis itself but also to the imbalances that precede a crisis. Crises do not occur randomly, and, as a result, an understanding of financial crises requires an investigation into the booms that precede them.

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1. Introduction

Economists have recently become more engaged with the study of financial crises and with good reason. As the 2008 Global Financial Crisis unfolded, the profession and the wider world got an overdue reminder of the importance of these events, both in terms of their historic tendency to recur over time, their capacity to strike rich as well as poor countries, and the deep and lasting damage they can inflict on economies, societies, and polities.

Just looking back now on the decade 2009–19 we have seen in many countries an aftermath of sluggish recovery, stagnant real wages, persistent output gaps and unemployment, low investment, and deteriorating fiscal positions (IMF, 2018). And though not a focus of this paper, beyond purely macroeconomic outcomes we have seen patterns in financial crises of broader social damage now, and in the past, as health suffered (Stuckler, Meissner, Fishback, Basu, and McKee, 2012; Parmar, Stavropoulou, and Ioannidis, 2016; Karanikolos, Heino, McKee, Stuckler, and Legido-Quigley, 2016), trust in institutions eroded (Stevenson and Wolfers, 2011), and political sentiments polarized (Funke, Schularick, and Trebesch, 2016; Mian, Sufi, and Trebbi, 2014). Disturbing as such consequences were to many observers in real time after 2008, advances in research have revealed that such phenomena are very typical responses, with quantitative evidence dating back 100 years or more.

For financial crises to be seen as a distinct, important, and disastrous type of event, we might first ask: how damaging are they? and how frequent? The associated downturns are much more adverse than a typical normal recession. We present a headline summary in Table 1. Using local projections (LPs, see Jordà, 2005), the deviation of real GDP per capita y is estimated h years after a crisis event. In the first two panels, the event is a crisis year and the baseline is trend; in the last two panels the event is the peak of a financial recession (a crisis within ± 2 years) and the baseline is a normal recession. To start, using the simpler crisis year definition, Table 1a shows that at a 6 year horizon, real GDP per capita is lower by about 5%–6% following crises, relative to trend. Table 1b shows the result is not driven by the great global crises, the synchronized distress in many countries seen in the interwar depression and the 2008 Global Financial Crisis. Next, aligning events using business cycle peaks as in Jordà, Schularick, and Taylor (2013), Table 1c shows that over 6 years, real GDP per capita is lower by about 4% after financial peaks, relative to normal peaks. Table 1d shows this is also not driven global crises, with a deviation of about 3% still seen.[1]

Large growth costs motivate the study of financial crises, and similar large, persistent losses are found in other studies (Bordo, Eichengreen, Klingebiel, and Martínez-Pería, 2001; Cerra and Saxena, 2008; Reinhart and Rogoff, 2009b). However, the other key metric is

[1] Arguably, the baseline using normal recessions in the last two panels is a stricter test, as it compares a crisis scenario to a reference downturn period, not just the unconditional growth trend.

Table 1: *Costs: the path of real GDP per capita after financial crises: crisis years and crisis peaks*

The table shows local projections of cumulative log real GDP per capita $y_{t+h} - y_t$ with indicators for financial crisis years (first two panels) and normal and financial recession peaks (last two panels) in advanced economies for the full non-war sample (1870–2015 ex. war) and also excluding the great global crises (1870–1913 and 1946–2006 ex. war). Classifications as in Jordà, Schularick, and Taylor (2013). Data from latest JST dataset (R5). Authors' calculation. See text. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

(a) *Deviation from trend after a crisis year*

	$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 5$	$h = 6$
$\mathbb{1}$(Crisis)	-3.29^{***}	-4.38^{***}	-5.01^{***}	-5.77^{***}	-5.68^{***}	-5.69^{**}
	(0.44)	(0.53)	(0.71)	(0.88)	(1.14)	(1.54)
Observations	2049.00	2031.00	2013.00	1995.00	1977.00	1959.00

(b) *Deviation from trend after a crisis year, ex. great global crises (1870–1913 & 1946–2006)*

$\mathbb{1}$(Crisis)	-2.79^{***}	-3.93^{***}	-5.04^{***}	-5.76^{***}	-5.01^{***}	-5.55^{**}
	(0.65)	(0.82)	(0.86)	(1.05)	(1.17)	(1.61)
Observations	1846.00	1846.00	1846.00	1846.00	1846.00	1846.00

(c) *Deviation from normal recession trend after a crisis peak*

$\mathbb{1}$(Peak, financial)	-0.75^{*}	-2.54^{**}	-3.42^{***}	-3.76^{**}	-3.86^{**}	-4.19^{**}
	(0.30)	(0.80)	(0.84)	(1.06)	(1.17)	(1.30)
Observations	2032.00	2014.00	1996.00	1978.00	1960.00	1942.00

(d) *Deviation from normal recession trend after a crisis peak, ex. great global crises (1870–1913 & 1946–2006)*

$\mathbb{1}$(Peak, financial)	-0.31	-1.64	-2.51^{*}	-2.68^{*}	-2.76^{*}	-3.01
	(0.44)	(0.92)	(0.93)	(1.12)	(1.10)	(1.46)
Observations	1829.00	1829.00	1829.00	1829.00	1829.00	1829.00

how frequently such crises are observed. Ultimately, to first order, the welfare costs of any type of rare disaster will depend on frequency times expected loss per event (Barro, 2006, 2009). In the JST data employed above, advanced economies experienced over 200 peacetime recession events since 1870 but one in four (25%) of these recessions were of the financial crisis type. Financial crisis events are the salient form disaster: more common than wars, pandemics, and the like. The raw event frequency summary for the onset of financial crises is given in Table 2, and it is also noteworthy that, despite the unusually calm period from 1946 to 1970, when no financial crisis events were seen in advanced economies and very few in emerging economies, the incidence of financial crisis recessions has been large in recent decades, and comparable to outcomes in the turbulent 1870 to 1939 period.

These stylized facts form the backdrop for macroeconomists studying financial crises. In this survey we provide detail about the definition of crisis events, as well as our ability to predict them and document their consequences. We consider open issues and directions for future research. The rest of this introduction sets the scene and frames the discussion.

Table 2: *Frequency: empirical probabilities of normal and financial crisis recessions*

The table shows the frequency of normal and financial crisis recessions in advanced economies for various samples, based classifications and data in Jordà, Schularick, and Taylor (2013). The sample in the final column is the overall peacetime sample period covered by the previous columns. Authors' calculation. See text.

	Fraction of country-year observations with onset of recession type				
	1870–1913	1919–1938	1946–1972	1973–2008	Overall
Normal recessions	0.17	0.10	0.06	0.09	0.11
Financial crisis recessions	0.06	0.05	0.00	0.03	0.04
All recessions	0.23	0.16	0.06	0.12	0.15

Definition: what is a financial crisis? In section 2 of the paper we review the various ways of defining a financial crisis that have been adopted. By far the most commonly used classification method could be said to be a mix of narrative and quantitative, focusing on events characterized by large-scale macro distress in the banking system, including the closure or suspensions of a large fraction of the system and/or the need for substantial government interventions to protect the system from acute failure. This approach dates back to definitions developed at the World Bank and IMF in the 1980s and 1990s, at first primarily for use in emerging markets and developing countries, but the idea has been refined over time to reduce subjectivity and increase the use of hard data (Caprio and Klingebiel, 1996; Laeven and Valencia, 2020).

Some key features of this approach are worth noting. It is typically used to construct a binary 0-1 indicator of a crisis, but nothing finer. It implicitly equates a financial crisis to a banking crisis, which may be historically sensible given dominant bank-centered financial systems in the last 200 years, but this is not incontrovertible, especially in the U.S. case. And for the method to be truly objective it would require hard data on many covariates to capture different dimensions of distress. But as one goes back in historical time, the application of these methods may inevitably lean more narrative and less quantitative, and potentially more subjective, an unavoidable hazard when there is scant availability of hard data in the distant past to measure crisis intensity (Bordo, Eichengreen, Klingebiel, and Martínez-Pería, 2001; Reinhart and Rogoff, 2009b; Schularick and Taylor, 2012).

Some other caveats will also warrant discussion. A measurement concern is that a binary classification is somewhat crude, and recent efforts have been made to develop either finer narrative classifications (Romer and Romer, 2017), or classifications augmented by market data (Baron, Verner, and Xiong, 2021). Such metrics capture variations in crisis intensity but, limited to historical epochs with adequate supporting data, may never fully replace the standard indicator. Another concern is the confounding of financial crisis events with other types of crises, such as sovereign default crises and currency crises (Kaminsky and Reinhart, 1999). It is important to take into consideration other types of crises which are often coincident, especially in emerging markets.

An overarching result that emerges through this discussion is that the economic consequences of a financial crisis are negative and substantial, however a financial crisis is measured. The variations in the approach to measurement generate important debate in the literature; however, the debate does not undermine this central conclusion.

Build-up: crisis prediction and causality We saw unconditional frequencies of crises in Table 2. A naïve interpretation would be that of a random Bernoulli event driven by probability draw. But this would be inappropriate if the risk of a crisis event were time varying and, in particular, state dependent. This matters for the correct interpretation of the economic mechanisms that trigger crisis events.

At the risk of over simplification, two very different views, not necessarily mutually exclusive, can be discerned in the broader theoretical and empirical literatures. A pure random-draw view is clearly aligned with the basic "rare disaster" models in macroeconomics (Barro, 2006, 2009). It is also implicit in multiple-equilibrium views of banks runs (Diamond and Dybvig, 1983) which are often associated with a banking crisis. Randomness may be the arrival of "news" such as a bad productivity level or growth draw (Gorton and Ordoñez, 2019). Asset prices may then move, damaging debtor and intermediary balance sheets, with potential for amplification via financial accelerator mechanisms compared to non-financial macro models (Bernanke, Gertler, and Gilchrist, 1999).

Alternatively, state dependence may be at work. In older, descriptive models key candidates were—often coincident—credit booms and asset price bubbles (Kindleberger, 1978; Minsky, 1986). These might be accompanied by overbuilding and malinvestment, stressed by the Austrian School (von Hayek, 1939; von Mises, 1949). This literature often put non-rational beliefs or behavior at the center of the explanation for financial crises. However, many mechanisms can generate credit booms and asset price bubbles, and associated risks, even in rational models: for example, rational bubble models, incentive misalignments, government bailouts, heterogeneous beliefs, strategic complementarities, or pecuniary externalities arising from constraints in the financial system (Brunnermeier and Oehmke, 2013; Farhi and Tirole, 2012; Aikman, Haldane, and Nelson, 2014; Dávila and Korinek, 2017). In behavioral models a sequence of optimism shocks, with extrapolation, might drive the boom—via borrower credit demand or lender credit supply shocks, or both—only to be later undercut by a pessimism draw (Bordalo, Gennaioli, and Shleifer, 2018).

The empirical evidence we survey supports the view that financial crises are indeed predictable, especially by credit and asset price growth. Support has also built up for the view that deviations from rational expectations are an important component in explaining this predictability. In general, the findings in the literature fit a broader trend in macroeconomics towards the study of the booms that precede economic downturns; or, as (Beaudry, Galizia, and Portier, 2020) put it, "putting the cycle back into business cycle analysis."

Aftermath: consequences of crises The unconditional path of economies is more adverse after a recession with an associated financial crisis. Various mechanisms could be at work here, such as impairments to the financial system that lead to inefficient flows or allocations of the supply of credit, or scars left by debt overhang on firms and/or households on the borrower side, all of which might depress aggregate demand and/or supply (Myers, 1977; Bernanke, 1983; Mian and Sufi, 2018).

The literature has made inquiries into the consequences of crises for a broad range of outcome variables, with conditional LPs, attention to robustness, and efforts to tease out causal interpretations. An important identification problem is that factors causing a financial crisis may also independently explain the severity of the economic downturn associated with financial crises. Credit booms, for example, may distort the economy toward unproductive investment projects. They may also lead to debt overhang and weak growth even in the absence of a financial crisis. This identification problem has been a tough nut to crack, but we note that the findings in the literature to date suggest that both factors, the preceding imbalances and the crisis itself, are important in explaining the painful economic consequences. This is a fruitful avenue for future research, especially given the importance to policy-makers.[2]

These findings also raise the question of why the factors that lead to financial crises may have negative consequences for growth. We discuss how research has identified household debt, rather than business debt, as the most salient form of debt overhang, and most dangerous for the probability of a crisis and future economic output, which helps us discriminate among contending economic models and mechanisms (Jordà, Schularick, and Taylor, 2016; Mian, Sufi, and Verner, 2017). For example, we might draw a distinction between credit that is designed to boost the productive capacity of the economy, and credit that is designed to boost the consumption of final goods. This may help resolve a difficult question in the literature: in the long run, countries with higher private credit to GDP ratios have higher per-capita income levels. But in the short-run, a rapid rise in credit portends economic difficulty. Perhaps the type of credit matters in explaining this discrepancy. We discuss this and other questions in the final section of the chapter.

[2]For example, in the aftermath of the Great Recession, there has been an active debate in the United States on whether policy achieved the correct balance between addressing the banking crisis and addressing the collapse of house prices and household balance sheets.

2. Measurement: defining a financial crisis

At first glance, identifying financial crisis events may seem to be a rather straightforward matter, a case of "I know it when I see it." We certainly have many well-documented instances of recognizable banking panics, stock market crashes, and other such events dating back several centuries. Historians, economists, and policymakers have recognized such discrete events in qualitative terms for centuries, when trying to improve theory and policy prescriptions in the immediate aftermath (e.g., Thornton, 1802; Bagehot, 1873) or when retrospectively looking back to take stock of the broader array of such events across time and space (e.g., Kindleberger, 1978; Grossman, 1994, 2010).

In modern quantitative research, more precise definitions have been sought as the basis for comparable classifications in long and wide comprehensive panel databases. In line with common usage, and reflecting the dominance of bank-based finance systems around the world in the modern era, we keep a focus on the term financial crisis as meaning a *financial crisis in the banking sector*, i.e., synonymous with systemically-large banking crises, like most authors (e.g., Bordo and Meissner, 2016). In this chapter, space dictates that we keep to our narrow remit, and set aside other types of financial market disruptions such as stock market crashes, manias and bubbles in commodity or asset prices, default and debt crises, and currency or exchange rate crises.[3] Yet the broader macroeconomic implications of these other events appear, as yet, to be less clear and consequential compared to the very severe damage now seen to be associated with banking crises, whether in advanced or emerging and developing economies (Reinhart and Rogoff, 2009b, 2013; Jordà, Schularick, and Taylor, 2013).

This section describes the main approaches to the problem of binary classification for the dates of financial crises. We start first with mostly-narrative indicators, where a systemically-large banking crisis is in most cases quite obvious, given sufficient scale. The problem is largely with borderline crises, where some judgement calls inevitably intrude, such as whether many banks or deposits were affected, or whether state interventions were significant. Without hard data to ground such measurements, which is especially a problem in the more distant past, such quibbles can account for most differences between the multiple prevailing classifications currently in wide use. We then discuss how more recently narrative binary indicators can be replaced with continuous measures of severity or augmented with financial real-time data to create more granular classifications—clearly a worthwhile aspiration, even if data availability hampers the scope of such efforts.

[3] Of course, many of these other phenomena have been widely studied and classified. See, e.g., Kindleberger (1978); Eichengreen, Rose, and Wyplosz (1995); Kaminsky and Reinhart (1999); Garber (2000); Bordo, Eichengreen, Klingebiel, and Martínez-Pería (2001); Reinhart and Rogoff (2009b); Laeven and Valencia (2020).

The extensive literature focused on the definition of a financial crisis may suggest more disagreement than there really is. Over time, different sources have used more or less strict criteria, and inevitably some close calls can be quite subjective. That said, there is a consistent finding that financial crises are associated with a large decline in economic output, regardless of the precise manner in which crises are measured. For example, in the case of 19th century U.S. banking panics, Jalil (2015) documents wide disagreements in several sources, and then revisits primary historical documentation to revise the event chronology and confirm the steep downturns associated with crisis events. Such deep data construction and revision has underpinned progress in recent decades, and this important work should continue, as a consensus chronology of events will help us better identify outcomes and underlying mechanisms.

2.1. Combining data and narrative criteria

As recently as the 1990s comprehensive panel databases on banking crises did not exist. Seminal work at the World Bank by Caprio and Klingebiel (1996) documented over 100 bank insolvency events in 90 countries from the 1970s to the 1990s. However, detailed information was only available for 26 countries, e.g., the intensity of the crisis and its resolution cost. Large crises afflicted 70%–90% of the banking system, but smaller crises covering 20%–60% were also documented. Following quickly, others expanded the idea to more countries and as far back as 1870 (see, e.g., Kaminsky and Reinhart, 1999; Bordo, Eichengreen, Klingebiel, and Martínez-Pería, 2001). Later, work at the IMF by Laeven and Valencia (2008, 2020) helped refine the quantitative and subjective criteria. Their approach is now the principal baseline used to declare a systemic banking crisis, so it is worth quoting them at length so that we understand how a mix of data and narrative, or quantitative and subjective, criteria are combined in the standard definition:

> Under our definition, in a systemic banking crisis, a country's corporate and financial sectors experience a large number of defaults and financial institutions and corporations face great difficulties repaying contracts on time. As a result, non-performing loans increase sharply and all or most of the aggregate banking system capital is exhausted. This situation may be accompanied by depressed asset prices (such as equity and real estate prices) on the heels of run-ups before the crisis, sharp increases in real interest rates, and a slowdown or reversal in capital flows. In some cases, the crisis is triggered by depositor runs on banks, though in most cases it is a general realization that systemically important financial institutions are in distress.

> Using this broad definition of a systemic banking crisis that combines quantitative data with some subjective assessment of the situation, we identify the starting year of systemic banking crises around the world since the year 1970. Unlike prior work. . ., we exclude banking system distress events that affected isolated banks but were not systemic in nature. As a cross-check on the timing of each crisis, we examine whether the crisis year coincides with deposit runs, the introduction of a deposit freeze or blanket guarantee, or extensive liquidity support or bank interventions. This way we are able to confirm about two-thirds of the crisis dates. Alternatively, we require that it becomes apparent that the banking system has a large proportion of nonperforming loans and that most of its capital has been exhausted. This additional requirement applies to the remainder of crisis dates. (Laeven and Valencia, 2008, p. 5)

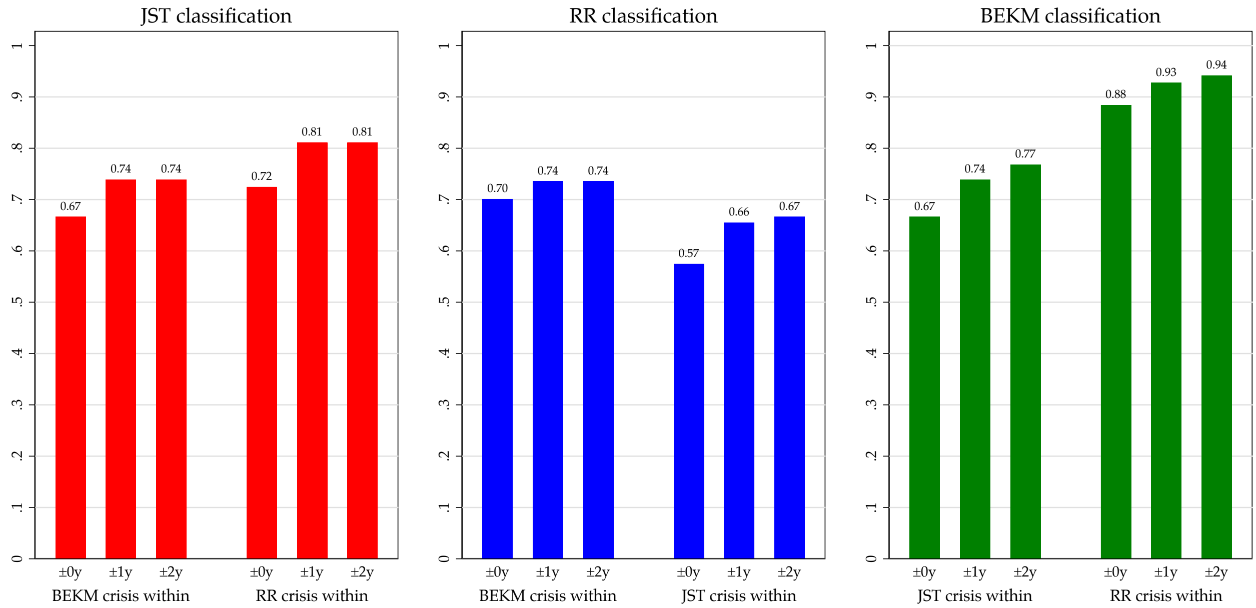
Recent classifications that broadly adhere to this mix of quantitative and subjective principles include those of Reinhart and Rogoff (2009b) and Schularick and Taylor (2012). The former also identified not only the start year of crises, but also duration; the latter also went on to develop a classification of recessions into normal and financial types based on the proximity of the recession peak to the start of a financial crisis event (Jordà, Schularick, and Taylor, 2013). In this section, we will not explore those extensions but simply focus on the start-year dating that is common to all classifications now in widespread use. It should be understood that as one goes back in time the availability of quantitative details about any given event will fade, and so any classification is likely to get more subjective, and hence correlate less with other classifications, in the more distant past.

2.2. Standard binary classification

We can examine several influential binary classifications, using criteria like those discussed above, to see how consistently financial crisis events have been classified using the most widely used methods to date. We split this discussion in two to reflect the different breadth and span of the datasets. We first consider three datasets that provide a long-narrow panel for the advanced economies from 1870 to recent times (Bordo, Eichengreen, Klingebiel, and Martínez-Pería, 2001; Reinhart and Rogoff, 2009b; Jordà, Schularick, and Taylor, 2017). We then turn to an alternate set of three datasets that provide a short-wide panel for advanced and emerging economies from 1970 onwards (Bordo, Eichengreen, Klingebiel, and Martínez-Pería, 2001; Reinhart and Rogoff, 2009b; Laeven and Valencia, 2020). We should also note that the overlap is often limited: for example, in the former case Reinhart and Rogoff (2009b) seek to document crises as far back as 1800, when others start in 1870 or

Figure 1: *The long panel: advanced economy crisis coincidence, 1870–2016*

The figure considers 3 classifications, one in each panel, and refers only to the common sample of all three datasets. For each classification the panel shows the frequency with which the other two classifications produce a coincident crisis event within 0,1, or 2 years. Note that the classifications differ in sample coverage and in the unconditional event frequency. See text.



1880; in the latter case Laeven and Valencia (2020) cover a much wider range of emerging economies after 1970 compared to the others. We focus on areas of overlap in these sets of classifications to demonstrate the consistency of different methods, while highlighting some divergences that emerge.

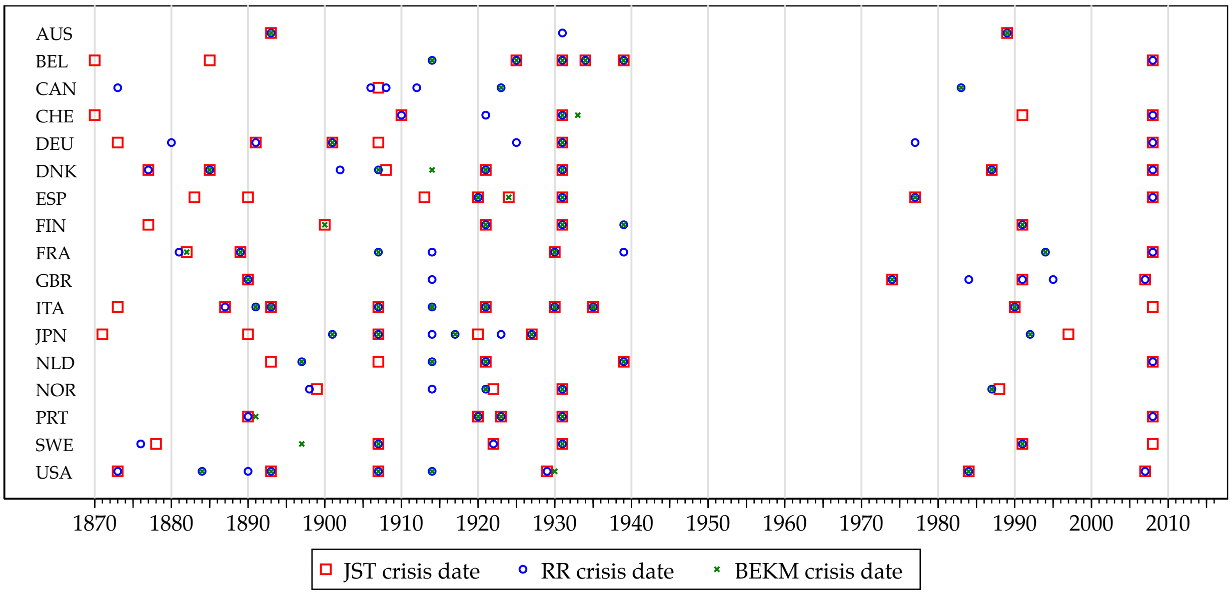
Crises in advanced economies since 1870 First we turn to the three long-narrow datasets, denoted respectively BEKM, RR, and JST (Bordo, Eichengreen, Klingebiel, and Martínez-Pería, 2001; Reinhart and Rogoff, 2009b; Jordà, Schularick, and Taylor, 2017). From these sources we draw a crisis onset indicator $Crisis_{ct}$ marking the first year of a financial crisis event. For this indicator, we first show measures of coherence in Figure 1 and raw event classification data in Figure 2.

First note that the datsets have different coverage: JST runs from 1870 to 2016, BEKM from 1880 to 1997, RR from 1870 to 2010. However, all three cover all 17 countries in JST, on which we focus. With that proviso, JST counts 90 crises, BEKM counts 69, and RR counts 102 (frequencies are 3.6%, 3.4%, 4.3%). Thus RR declare significantly more crisis events, meaning BEKM and JST are more strict.[4] Also, since the BEKM sample is smaller it counts fewer than JST. This is apparent from raw data in Figure 2, where more RR events

[4]However, in a later paper Reinhart and Rogoff (2014) constructed a new dataset, with a more strict set of crisis events which excludes smaller and likely non-systemic events.

Figure 2: *The long panel: advanced economy crisis events, 1870–2016*

The figure considers 3 classifications, and shows the country-year crisis events for each. Note that the classifications differ in sample coverage and in the unconditional event frequency. All countries are present in all samples. Authors' calculation. See text.



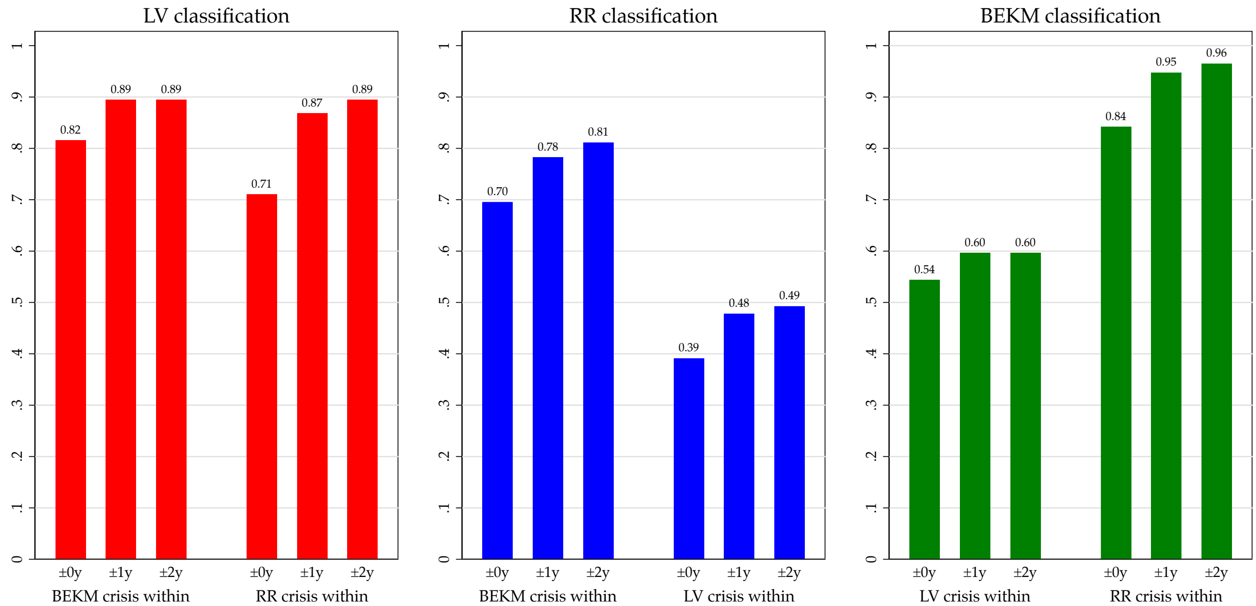
are clearly seen. After WW2 the differences are few. RR call systemic crises in Germany in 1977, and Britain in 1984 and 1995, but the others do not. Some crises differ by a year or two, although the drawn out Japanese crisis is dated differently by JST. JST call more crises in 2008, in Italy and Sweden, and also 1991 in Switzerland. Before WW2 more differences emerge, as expected in more distant periods. The three classifications generally agree strongly in the 1929–33 global distress period, and more generally in the interwar period as a whole. JST do not count banking crises during wars, when financial systems are often under a degree of government control, and the character of these events is somewhat different. That said, no classification records any crises in the 1939–45 window. Before WW1 the classifications differ the most, with many JST events in Europe and Japan not picked up by others. Conversely, RR record more events in the U.S. and Canada than JST.

The coherence measures in Figure 1 refer only to the common sample of all three datasets, and suggest an 70%–80% agreement is typical among these three classifications if we allow a ± 2 year window. For RR the agreement is lower simply because the RR event frequency is higher, so it has to disagree more, by construction. Both JST and BEKM, conversely, agree more with RR, also by construction.

Overall, differences among the advanced economy classifications are not great and they typically concur within a couple of years. On the other hand, the inherently subjective element of these classifications is revealed by the nontrivial extent of disagreement.

Figure 3: *The short panel: advanced and emerging economy crisis coincidence, 1970–2016*

The figure considers 3 classifications, one in each panel, and refers only to the common sample of all three datasets. For each classification the panel shows the frequency with which the other two classifications produce a coincident crisis event within 0,1, or 2 years. Note that the classifications differ in sample coverage and in the unconditional event frequency. Authors' calculation. See text.



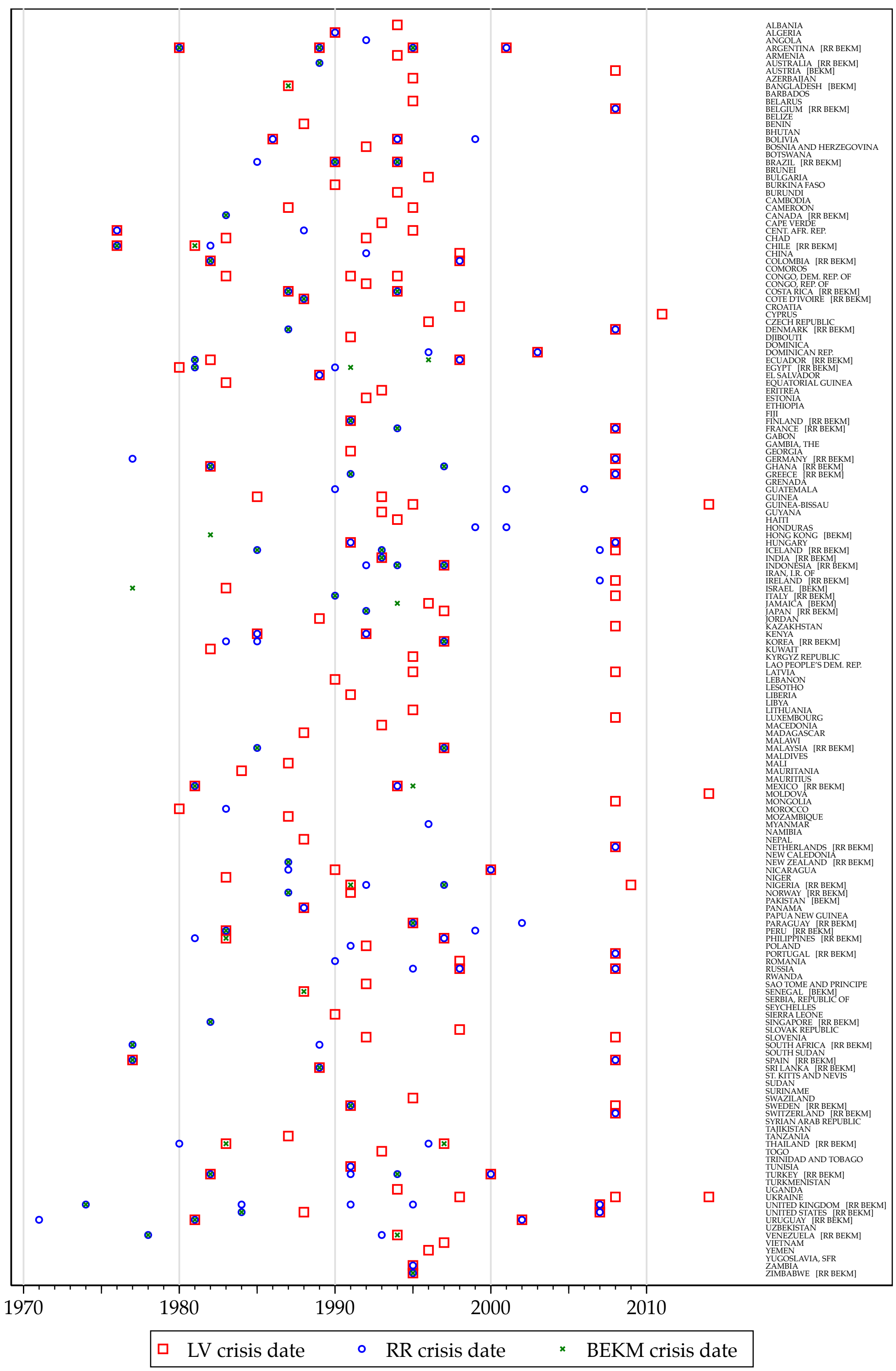
Crises in advanced and emerging economies since 1970 The availability of historical data for emerging markets is more limited and this means that classification datasets here take the form of short-wide panels, typically starting around 1970 and running up to the present. This was true for pioneering studies (Caprio and Klingebiel, 1996; Kaminsky and Reinhart, 1999; Bordo, Eichengreen, Klingebiel, and Martínez-Pería, 2001), although the RR dataset covers a more limited range of emerging markets all the way back to 1800, taking into account any relevant date of independence.

For our purposes we will compare three datasets that run from 1970 onwards, and which span advanced and emerging economies: namely BEKM and RR, plus the addition of LV, denoting Laeven and Valencia (2020). We show measures of coherence in Figure 3 and raw event classification data in Figure 4.

First note that the wide datasets have different coverage in this window: LV runs from 1970 to 2017, BEKM from 1973 to 1997, RR from 1970 to 2010. In addition, BEKM and RR cover a subset of less than half the countries spanned by the newer LV dataset. With that noted, we find that LV counts 151 crises, BEKM counts 62, and RR counts 120 (frequencies are 1.9%, 4.2%, 4.3%). Thus from a frequency perspective, LV have a tendency to declare significantly fewer crisis events. This may reflect a stricter definition being used, or it might just be that their larger sample, with many more emerging economies, contains fewer financially fragile (or, more financially repressed) economies. These patterns can also be

Figure 4: *The short panel: advanced and emerging economy crisis events, 1970–2016*

The figure considers 3 classifications, and shows the country-year crisis events for each. Note that the classifications differ in sample coverage and in the unconditional event frequency, and overlap is limited. All countries are present in LV sample, other samples are denoted by RR and BEKM in brackets on the right axis. Authors' calculation. See text.



gleaned from Figure 4, where the raw data are shown. The coherence measures in Figure 3 again refer only to the common sample of all three datasets, and suggest an 80%–90% agreement is typical among these three classifications if we allow a ±2 year window. The exception is the lower level of overlap from BEKM and RR crises when looking for a nearby LV crisis, but given the much lower event frequency in the LV dataset this is entirely to be expected. Overall, that apart, coherence is a little higher than in the long panel of advanced economies, perhaps suggesting slightly less subjectivity in more recent years.

Ending on a positive note, in the last 30 years the systematic classification of financial crisis events has progressed from essentially nothing to a consensus approach with broad coverage. Established databases now extend to many countries, cover most of the recent decades for the entire world and even stretch back into the 1800s for a wide panel. They may disagree on certain specific historical events given the sometimes subjective judgements involved, but agreement on the same criteria results in substantial overlap.

2.3. Finer classifications using narrative and data-driven criteria

From a theoretical perspective some might have the hope, possibly forlorn, that with sufficient detail the range of crisis outcomes can be encompassed as a continuum of endogenously modeled distress, rather than as a separate regime in a more complex nonlinear or state-dependent world.

From that standpoint, the above binary classifications may be seen as lacking nuance, having no granular detail to allow the researcher to discriminate between more or less severe events. An intense financial crisis is coded as 1, but so are much milder crises. We would expect these differences to matter when analyzing causes and consequences.

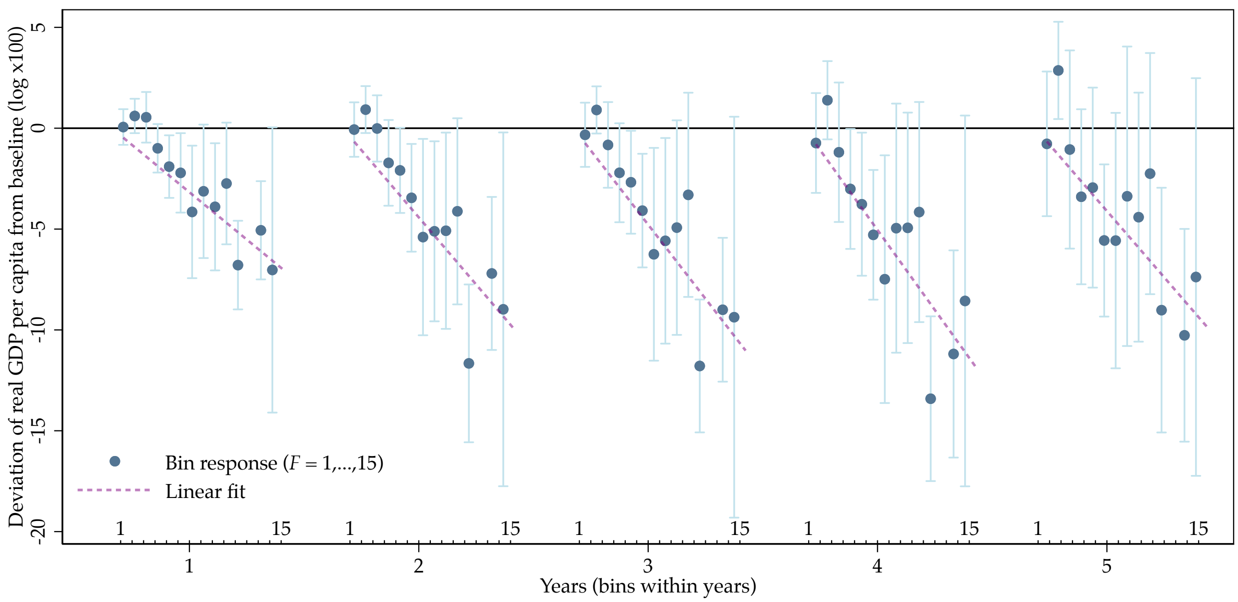
Some recent progress has been made filling this gap using both narratives and data.

Finer classification using narrative criteria One way to make a finer classification is to parse narrative records more carefully, sorting events in to more than just two bins, on and off as in Romer and Romer (2017). They built semiannual series on financial distress in 24 advanced countries for the period 1967–2012, using the *OECD Economic Outlook*. They base judgements on accounts of the health of countries' financial systems and classify distress with an indicator F on a 16-bin scale, where 0 means no distress.

Using LP methods, a key finding is that, sensibly, higher levels of distress F_{ct}, in country c at time t, are associated with slower growth going forward, as well as higher unemployment and lower industrial production. A typical local projection for the cumulative real GDP

Figure 5: *Finer classification using narrative criteria: RR 15-bin classification*

The figure shows local projections of the deviation of real GDP per capita $h = 1, \ldots, 5$ years after a financial distress event of intensity F based on the Romer and Romer (2017) narrative classification. The baseline estimating equation is $y_{c,t+h} - y_{c,t-1} = \alpha_k^h + \gamma_t^h + \beta^h F_{ct} + A(L)F_{ct} + B(L)y_{ct} + \epsilon_{ct}^h$ as in the original. That is, the conditional mean effect is estimated as a restricted linear function of F. We also show an alternative with a fixed-effect estimate for each bin. Authors' calculation. See text.



outcome y after h periods is

$$y_{c,t+h} - y_{c,t-1} = \alpha_k^h + \gamma_t^h + \beta^h F_{ct} + A(L)F_{ct} + B(L)y_{ct} + \epsilon_{ct}^h ,$$

where $A(L)$ and $B(L)$ are 4-lag polynomials and fixed country and time effects are included.

Representative baseline estimates of the response $\hat{\beta}^h$ are shown in Figure 5 for real GDP at 1–5 year horizons, as F varies across bins of increasing distress intensity from 1 to 15. There are no observations in bins 12 and 15. The linear fit, preferred by Romer and Romer (2017) is shown along with bin-specific estimates at each horizon h. The baseline estimates assume a linear form in F, with no effect as $F \to 0$; the figures show why this is hard to reject given the precision available, and quadratic and spline forms look similar.

Out of 2,183 country-year observations, 248 (11%) have $F > 0$. This is much more frequent than the raw binary crisis frequency of about 3% in the long panel since 1870. However, truncating to values with $F \geq 7$ yields just 61 observations, about 3% of the sample, with a median value of $F = 8$, which Romer and Romer (2017) see as the analog of "moderate or systemic crisis" events. Judging from Figure 5 it is the $F \geq 7$ events that are significantly damaging, and which correspond to the moderate or systemic crisis events picked out by the traditional binary classifications. The responses here conform to priors.

They are uncannily close to the Jordà, Schularick, and Taylor (2013) estimates, and the summary estimates shown in Table 1, even though these estimates allow variable distress $F \neq 0$ across periods.[5]

Finer classification using data-driven criteria An alternative route to a finer classification is to use observable financial data to infer stress in the financial system. In principle, this could produce crisis indicator completely divorced from qualitative or narrative information. This might be a valuable a step if some narrative events suffer from categorization bias, for example, if an historical event is more likely to be classified by the observer as a systemic crisis when it happens to be followed by a bad downturn, leading to spurious inferences.

An example of a data-augmented classification is Baron, Verner, and Xiong (2021), who measure the health of the banking system for 46 countries for the years 1870–2016, including both advanced and emerging countries. They propose that: "As there is no single correct definition of a banking crisis, our goal is to provide one possible construction of clear-cut crisis episodes based on three systematic measures: bank equity declines, bank failures, and panics." They collect market data on the first, and build new narrative indicators of the latter two, building on prior work.

In particular, they use bank equity declines to adjust earlier narrative lists. BVX refer to additions as "forgotten" and deletions as "spurious" and their primary filter is evidence on bank equity declines. Table 3 shows the differences with three other narrative classifications, BEKM, RR and ST (Bordo, Eichengreen, Klingebiel, and Martínez-Pería, 2001; Reinhart and Rogoff, 2009b; Schularick and Taylor, 2012). (Note: ST differs from the updated JST list used earlier.) Specifically, making a joint list of the three older lists and the BVX list yields 140 potential crises. The BEKM list is smallest with 64, followed by ST with 84, RR with 113; in contrast BVX count 108, but there are disagreements, as the table shows.[6]

We highlight two interesting findings in Baron, Verner, and Xiong (2021), notably: first, declines in real bank equity returns R^B are the best coincident classifier of conventional narrative financial crisis binary events, compared to many macroeconomic and financial variables; second, bank equity returns are a strong predictor of subsequent growth slow-

[5]Recall that in Table 1, the real GDP deviation was about 3%–5% from 2 to 5 years, similar to the effect is seen in Figure 5 for bins 7 or 8. This is as expected: in Romer and Romer (2017, Figure 1) an episode is typically a sequence of nonzero F events: most are in the low bins, a few peak in the moderate or systemic range, and some get into the severe bins; but that peak lasts typically just one year, so the main drag will come from the effect in that peak, if in the upper range of bins, leading the two methods to match on average in those cases.

[6]The highest agreement in column 1 is with the ST dataset. The BVX data suggest that BEKM is most likely to omit "forgotten" crises in BVX (column 2), perhaps a result of a higher bar for crisis calls; and that RR is most likely to include "spurious" crises not in BVX (column 3), although that would likely not be the case if one used the narrower systemic crisis list in Reinhart and Rogoff (2014).

Table 3: *Finer classification using data-driven criteria: coincidence of BVX crises*

This table shows the agreement frequency (count) between the Baron, Verner, and Xiong (2021) crisis list and other narrative lists (Bordo, Eichengreen, Klingebiel, and Martínez-Pería, 2001; Reinhart and Rogoff, 2009b; Schularick and Taylor, 2012) for the long panel. The first column uses the joint list from all sources, i.e., the union of all 4 lists, which consists of 140 potential crises. The second and third columns refer to subset of this union, those included and excluded from the BVX list. BVX refer to additions as "forgotten" and deletions as "spurious" and their primary filter is evidence on bank equity declines. The highest agreement in column 1 is found with the ST dataset. Authors' calculation. See text.

Subsample of joint list (BEKM,RR,ST,BVX)	All observations	$Crisis^{BVX} = 1$	$Crisis^{BVX} = 0$
$Crisis^{BVX} = 1$	0.75	1.00	0.00
	(108.00)	(108.00)	(0.00)
$Crisis^{BVX} = 0$	0.25	0.00	1.00
	(36.00)	(0.00)	(36.00)
$Crisis^{BVX} = Crisis^{BEKM}$	0.64	0.65	0.61
in BEKM sample period	(68.00)	(49.00)	(19.00)
$Crisis^{BVX} = Crisis^{RR}$	0.62	0.76	0.13
in RR sample period	(85.00)	(81.00)	(4.00)
$Crisis^{BVX} = Crisis^{ST}$	0.71	0.71	0.69
in ST sample period	(94.00)	(72.00)	(22.00)

downs and credit crunches, based on an LP analysis, even controlling for real nonfinancial equity returns R^N, a result we discuss in more detail below.

A third result also bears mentioning: banking panics (runs by depositors/creditors) on their own have small macro-financial consequences—it is the bank failures that matter most. Obviously, panics can happen without failures, and failures without panics, in theory and in the data. This finding is important since much debate centered on whether the key locus of the crisis problem is runnable funding outbreaks (roughly, liquidity), or systemic failures (roughly, solvency). The empirical record points to the latter as the more serious issue in terms of macroeconomic consequences, and justifies the central use of solvency and failure criteria in the traditional narrative definition of a financial crisis.

To see if information on bank equity declines is a substitute or complement to the traditional narrative indicator, we can replicate and extend some results in Baron, Verner, and Xiong (2021). Estimates for the primary real GDP outcome measure are shown in Table 4. The baseline estimating equation here is

$$y_{c,t+h} - y_{ct} = \alpha_k^h + \beta^h F_{ct} + \theta^h X_{ct} + \epsilon_{ct}^h ,$$

where here F is a narrative crisis indicator for a joint-list (BEKM,RR,LV,ST) crisis in a ± 3-year window. This excludes additions and deletions in BVX.

Estimates of $\hat{\beta}_h$ from this specification are reported in Table 4a. The results conform to prior work: crisis events are followed by negative output deviations, and the gap rises

Table 4: *Finer classification using data-driven criteria: outcomes with Narrative and Bank Equity indicators*

The table examines real GDP per capita outcomes (log ×100) using local projections, based on Table A8 in Baron, Verner, and Xiong (2021). The first panel uses only an indicator based on a narrative crisis (from a joint-list of BEKM,RR,LV, and ST) within ±3 years, the second uses the full specification as in the original. The baseline estimating equation here is $y_{c,t+h} - y_{ct} = \alpha_k^h + \beta^h F_{ct} + \theta^h X_{ct} + \epsilon_{ct}^h$. Added controls as in the original, 3 lags of both crash indicators and current plus 3 lagged difference of log real GDP and credit-to-GDP. Standard errors as in the original, clustered by country and year. Authors' calculation. See text.

(a) *LP using narrative crisis indicator only: real GDP per capita outcomes (log ×100)*

	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$
Narrative crisis	−0.29	−1.20 *	−3.01***	−5.24***	−6.76***	−6.78***
(±3 yr.)	(−0.99)	(−1.84)	(−3.27)	(−4.71)	(−5.76)	(−4.92)
Observations	2548.00	2548.00	2548.00	2466.00	2384.00	2302.00

(b) *LP using narrative crisis and bank equity crash indicator: real GDP per capita outcomes (log ×100)*

	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$
Narrative crisis	−0.29	−1.16	−3.04***	−5.29***	−6.87***	−6.94***
(±3y)	(−0.87)	(−1.68)	(−3.10)	(−4.30)	(−5.36)	(−4.77)
Bank equity crash	−2.11***	−1.86 **	−2.56***	−2.45***	−1.77 **	−1.51
	(−4.54)	(−2.14)	(−3.07)	(−3.01)	(−2.05)	(−1.53)
Bank equity crash	−0.60	−1.12	−0.46	−0.62	−0.56	0.21
× Narrative crisis	(−0.95)	(−1.03)	(−0.33)	(−0.34)	(−0.29)	(0.11)
Nonfinancial	−2.13***	−2.62***	−2.83***	−3.32***	−4.11***	−4.63***
equity crash	(−4.15)	(−3.40)	(−3.07)	(−3.42)	(−3.63)	(−3.25)
Observations	2548.00	2548.00	2548.00	2466.00	2384.00	2302.00

to around 5% after 5 years. Estimates from an augmented specification are reported in Table 4b. Additional controls are an indicator of a crash (return $< -30\%$) in bank equities and nonfinancial equities, and an interaction term for bank equity crash times the narrative crisis indicator. The interaction term is small and insignificant, but the other two added controls matter. A bank equity crash does contain some useful information about adverse outcomes beyond the traditional narrative indicator, and Baron, Verner, and Xiong (2021) show that the larger is the crash the larger is the drag. However, the magnitude and significance of the effect of the narrative indicator is the same here as before: the first row in each panel is virtually identical.

In sum, both measures—bank equity crashes and the traditional narrative indicator—reflect emergent problems on bank balance sheets. They are not perfectly correlated, and the failure-based narrative indicator still provides the most discriminating information:

BVX count 197 narrative failure events, and out of these 193 are called as crises (98%); but out of a count of 269 bank equity crashes, only 138 are called as crises (51%). This shows that the inclusion of data on bank equity declines complements the narrative approach with useful auxiliary information.

Summary Finer classifications are feasible and can produce sensible results which complement the binary approach. They can reveal how more intense stress episodes line up with more adverse outcomes. However, milder episodes may not be associated with significant drag. These findings remind us that the binary classifications will yield only measures of average effects, and that in reality financial crises come in varying levels of intensity, which are correlated with key outcomes.

Finer narrative measures can be built but this is a time-intensive, bespoke activity. The paucity of widespread, continuous, high-frequency, consistent narrative sources for many countries or periods is a formidable obstacle. The difficulty of ensuring comparability across sources with varying textual content to allow the datasets to be pooled for large-scale panel analysis may also keep the traditional binary indicator in business.

Finer data-based measures present different tradeoffs. Data availability is broader and easier, at least where financial data are already compiled. Comparability across historical episodes is better ensured by a hard definition grounded in observable market data. Yet it is clear that even this measure can't capture everything related to a crisis and fully substitute for the narrative information on failures in the traditional binary indicator.

As a final note, it is worth noting that almost all measures of financial crises point to the conclusion that financial crises are associated with a sharp decline in real economic activity. It is unlikely that such a finding is the result of look-back biases or subjective evaluation of what constitutes a crisis. The severe economic downturns associated with financial crises warrants a further consideration of their causes. The next section turns to this question.

3. Financial crisis predictability and causality

Financial crises are associated with severe and protracted downturns in economic activity. So it is no surprise that a large body of research is dedicated to the question of the sources of financial crises. For the sake of argument, it is useful to separate views on this question into two extremes. Are financial crises random events that strike an otherwise stable economy? Or, in contrast, is there a set of factors that systematically predict financial crises? This section shows that the evidence strongly favors the second view: financial crises are indeed predictable which raises challenging questions for the theory of business cycles.

3.1. Credit expansion and asset price growth

Pre–Global Financial Crisis research The idea that asset price growth and credit expansion are crucial to the prediction of financial crises is an old one in economics, showing up prominently in the work of Kindleberger (1978) and Minsky (1986). The modern approach of using large data sets and econometric tools to detect predictability began in the aftermath of the banking crises of the 1980s and 1990s. This initial wave of research focused mostly on data sets covering the 1970s through 2000.

Illustrative of this literature is Borio and Lowe (2002) who focus on a sample of 34 countries from 1970 to 1999. They conclude that "sustained rapid credit growth combined with large increases in asset prices appears to increase the probability of an episode of financial stability." The statistical analysis in the study compares the statistical power of asset prices, credit growth, and investment growth in predicting financial crises using the Bordo, Eichengreen, Klingebiel, and Martínez-Pería (2001) crisis classification. These findings follow upon the influential work by Kaminsky and Reinhart (1999), who condition on financial crises and show that rapid credit growth is a salient feature of the pre-crisis period. Kaminsky and Reinhart (1999) point to the importance of financial liberalization in explaining the rapid credit growth, a factor explored in more detail in subsection 3.2.

Other notable contributions among this first wave of research on the predictability of financial crises are Caprio and Klingebiel (1996), Demirgüç-Kunt and Detragiache (1998), Glick and Hutchison (2001), Hutchison and McDill (1999), Hardy and Pazarbaşioğlu (1999), Gourinchas, Valdes, and Landerretche (2001), and Eichengreen and Arteta (2002), among others. Table 5 contains a brief overview of all of these articles, listing the number of countries covered, the sample years, whether the study includes emerging markets, and a brief summary of the factors that the study finds help statistically predict crises. A rise in private credit, measured either using private credit growth or the change in the private credit to GDP ratio, emerges as a central factor in many of these studies. Asset price corrections, following a period of elevated valuations, also often appear as a theme.

However, this earlier wave of research emphasizes open economy issues to a larger degree than in the later literature written after the Global Financial Crisis.[7] This is in part due to a focus on crisis countries in the 1980s and 1990s that were small open-economy advanced economies, or Latin American and East Asian emerging economies. Open economy issues were naturally a greater focus of this literature, given the important role that factors like cross-border capital flows and real exchange rate movement played in the run-up to crises in these countries, and also in the subsequent adjustment process, aspects

[7] Although, as shown below, open economy issues do play an important role in evaluation of the Global Financial Crisis.

Table 5: *Literature Review*

#	Authors (Year)	No. of countries	Sample years	EME	Significant predictors
1	Caprio and Klingebiel (1996)	29 studied in-depth (69 discussed overall).	Country-specific instances identified, earliest in 1977 for Spain.	✓	**- Macro:** Volatility in terms of trade; High inflation; Large interest rate spread. **- Regulatory and accounting frameworks:** Poor incentives for reporting losses; Low bank capitalization levels; Political suasion over underwriting decisions.
2	Demirgüç-Kunt and Detragiache (1998)	Max. 65 and min. 45 from IMF's IFS database.	1980–94	✓	**- Banking sector:** Capital outflows; High private-sector share of credit; Explicit deposit insurance scheme. **- Macro:** Low GDP growth; High real interest rates; High inflation; Terms of trade deterioration
3	Glick and Hutchison (2001)	Unbalanced panel of 90 countries.	1975–97	✓	**- Currency crisis:** Greater real exchange rate overvaluation; Higher ratio of M2/foreign reserves; Lower export growth; Lagged banking crisis. **- Banking crisis:** Decline in GDP growth; Greater liberalization
4	Hutchison and McDill (1999)	44 OECD industrial countries, with primary focus on Japan.	1975–97	✗	**- Macro:** Sharp fall in asset prices; Decline in real GDP growth; Real credit growth **- Institutional:** Lower central bank independence; Increased explicit deposit insurance; Greater financial liberalization
5	Kaminsky and Reinhart (1999)	5 industrial and 15 developing countries.	Country-specific, broadly 1970s to 1995.	✓	**- Currency crisis:** Lagged banking crisis (predicts and aggravates); Contagion in capital outflow. **- Banking crisis:** Lagged currency crisis (aggravates, does not predict). **- Common factors (Twin crisis):** Lax financial supervision; Growth in credit/GDP; Growth in M2/foreign reserves; sharp decline in asset prices; Falling exports; Deterioration in terms of trade; Higher fiscal deficit/GDP.
6	Hardy and Pazarbaşioğlu (1999)	50 countries, with 38 experiencing crisis and 12 acting as controls.	1980–96	✓	**- Real sector:** Fall in real GDP growth; Private consumption boom. **- Banking sector:** Fall in deposit liabilities/GDP ratio; Boom-bust in private-sector credit/GDP; Boom-bust in the ratio of gross foreign liabilities of the banking system to GDP . **- Other factors:** Boom-bust in inflation; Rise in real interest rate; Appreciation in real effective exchange rate; Fall in real growth in imports.
7	Gourinchas, Valdes, and Landerretche (2001)	91 developing and developed countries.	1960–96	✓	**- Domestic macro factors:** Rise in private credit/GDP; Decline in potential (trend) GDP; Boom-bust in investment; Rising domestic real interest rate. **- Domestic policy factors:** Worsening of government deficit to GDP ratio; Decline in foreign reserves. **- International factors:** Boom-bust in current account; Appreciation in real exchange rate; Boom-bust in private capital inflows; Rising short-term debt. **- External factors:** Boom-bust in terms of trade.

continued . . .

...continued

#	Authors (Year)	No. of countries	Sample years	EME	Significant predictors
8	Eichengreen and Arteta (2002)	75 developing countries, based on Caprio & Klingebiel (1999).	1975–97	✓	High rate of domestic credit growth; Low reserves/M2 ratio; Rise in interest rates and fall in real GDP in advanced economies cause crisis in EMEs, but only in pre-1990s crisis; Financial liberalization
9	Borio and Lowe (2002)	34 countries, based on criteria detailed on page 12.	1970–99	✓	Boom-bust in asset price inflation.
10	Schularick and Taylor (2012)	14 developed countries.	1870–2008	✗	Past 5-year boom in bank credit growth; Higher financialization (higher credit/GDP or increased size of stock markets); High leverage and low capital/liquidity buffers.
11	Jordà, Schularick, and Taylor (2015b)	17	1870–2013	✗	Leveraged bubbles (interaction of asset price bubbles and credit booms), only housing bubbles (not equity bubbles) are significant.
12	Richter, Schularick, and Wachtel (2021)	17	1870–2016	✗	Credit growth; Higher capital-to-asset and loan-to-deposit ratios predict crisis. **Asset prices:** Only housing bubbles (not equity bubbles) are significant.
13	Greenwood, Hanson, Shleifer, and Sørensen (2020)	42	1950–2016	✓	**Credit expansion and asset price booms (red zone):** Nonfinancial business credit growth and stock market valuations have risen sharply; Household credit growth and home prices have risen sharply.

noted long ago by Díaz-Alejandro (1985) and re-emphaszied by McKinnon and Pill (1996).

We highlight three factors that emerged as central to the prediction of crises in such small-open economy cases: inflation, the terms of trade, and the real exchange rate. Kaminsky and Reinhart (1999) show the dynamics of both the real exchange rate and the terms of trade in the years around a banking crisis. Both show a similar pattern: the real exchange rate appreciates and terms of trade improve in the years prior to the crisis, but the crisis is associated with a rapid deterioration in both. This boom-bust pattern in real exchange rates and the terms of trade is a robust pattern shown in this earlier wave of research (e.g., Caprio and Klingebiel, 1996; Hardy and Pazarbaşioğlu, 1999; Gourinchas, Valdes, and Landerretche, 2001).

Post–Global Financial Crisis research The Global Financial Crisis of 2008 led to a new wave of research focused on the factors that predict financial crises. Overall, this body of research focuses more on advanced economies, and it has the advantage of data sets covering a much longer time period. Credit growth and asset price growth emerge as even stronger predictors once a longer time series is used for estimation.

Schularick and Taylor (2012) and Jordà, Schularick, and Taylor (2015b) introduce a novel long-run data base covering key macroeconomic variables for 17 advanced economies from 1870 onward (see also Jordà, Schularick, and Taylor, 2017). The key measure of private credit is bank loans to domestic households and non-financial corporations. Using this data set, Schularick and Taylor (2012) focuses on predictability, using a specification where the probability of a financial crisis event is related to lagged real private credit growth. They find robust statistical power of credit growth in predicting a financial crisis using ROC (receiver operating characteristic) criteria, an aggregate of Type 1 and Type 2 errors. The results hold in the pre- and post-WW2 subsamples, and with a battery of controls.

Later work confirms these findings with variant definitions of the credit boom variable, and to summarize these findings, a simple logit specification in this vein would be

$$\text{logit}\,(p_{ct}) \equiv \log\left(\frac{p_{ct}}{1-p_{ct}}\right) = \alpha + \beta\Delta_5 CREDGDP_{ct} + \gamma X_{ct} + \epsilon_{ct}\,,$$

where the probability $p_{ct} \equiv \mathbb{P}(Crisis_{ct} = 1)$ and the dependent variable is the log odds ratio of a financial crisis is estimated as a function of the 5-year lagged change in private credit to GDP, denoted $\Delta_5 CREDGDP$, and controls X, which would be estimated on annual data for the 17 countries since 1870.

Illustrative results showing the predictive margins within a roughly mean plus/minus 2 s.d. range of the credit variable are shown in Figure 6a, with no controls. The unconditional probability of a crisis is 2.5% (1 in 40 years), corresponding to the mean value of $\Delta_5 CREDGDP$. However, when the credit growth variable rises one s.d. above its mean, the expected crisis probability almost doubles to 5% (1 in 20 years), and at two s.d. above the mean the expected crisis probability is near 10% (1 in 10 years), four times its baseline level.

Illustrative results for the prediction of the type of recession peak, financial versus normal, produce similar results, as shown in Figure 6b. Now the outcome variable is an indicator equal to one when the peak is a financial crisis peak, rather than a normal peak, using the Jordà, Schularick, and Taylor (2013) peak classification. The unconditional probability of a peak being a financial crisis peak is about 0.2 but the probability is again increasing in lagged credit growth.

The main results in Schularick and Taylor (2012) use full in-sample information, but in an out-of-sample exercise they show that estimates of the model up to the 1980s would have yielded significant predictive success in subsequent years. Richter, Schularick, and Wachtel (2021) focus on a similar data set. They define credit booms as situations where log real private credit per capita rises by more than a standard deviation relative to the predicted trend using only past information. Consistent with Schularick and Taylor (2012), they find strong predictive power of credit booms out of sample. Jordà, Schularick, and Taylor (2016) distinguish the explanatory power of mortgage and non-mortgage credit. In the full sample, both mortgage credit and non-mortgage credit predict financial crises, with non-mortgage

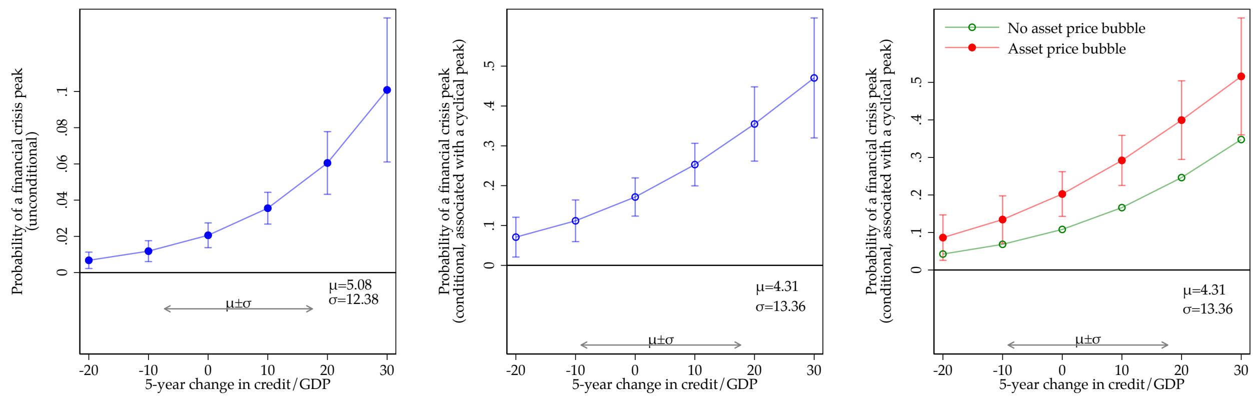
Figure 6: *Credit booms and elevated asset prices predict a financial crisis*

The figure shows logit predictive margins for financial crisis events, using lagged information, where the estimating equation takes the form $\text{logit}(p_{ct}) = \alpha + \beta\Delta_5 CREDGDP_{ct} + \gamma X_{ct} + \epsilon_{ct}$. and the sample mean (μ) $\pm$ 2 s.d (σ) range of the *CREDGDP* variable is shown. In these estimates there are no added controls. In the left panel, the data are all country-year *ct* observations and the outcome variable is a financial crisis using the JST classification in the advanced economy long panel. In the next two panels, the data are all country-year *ct* observations that correspond to cyclical peaks and the outcome variable is a financial crisis peak using the JST classification. The last panel includes an asset price bubble indicator. Authors' calculation. See text.

(a) *Baseline logit, credit growth only, predicting crisis years*

(b) *Baseline logit, credit growth only, predicting crisis recession peaks*

(c) *Expanded logit, credit growth and asset prices, predicting crisis recession peaks*



credit displaying stronger statistical power in pre-World War 2 sample. However, since World War 2, the strength of mortgage credit as a predictor has grown considerably.

To confront the issue of whether asset price booms also contribute meaningfully to elevated financial crisis risk, Jordà, Schularick, and Taylor (2015b) collate further data series on equity and housing prices for the long-panel of advanced economies. They develop a "bubble indicator" based on whether the asset price in a given year is more than one s.d. above its de-trended value (using a lowpass filter) and whether there is also a subsequent large correction. An illustration of this approach is in Figure 6c, where the sample is again restricted to recession peaks, and the logit estimation is augmented to include a bubble indicator for either asset price. When there is no bubble in either asset price, crisis risk is generally low. In contrast, when there is either kind of bubble, crisis risk is significantly elevated, by a factor of roughly 1.5 in the mid-range of credit growth.[8]

[8]The study by Richter, Schularick, and Wachtel (2021) takes a different approach but comes to a similar conclusion. After demonstrating the strong predictive power of credit expansion on the probability of a financial crisis, this article splits credit booms by whether they end in a financial crisis or not. It then compares the characteristics of the booms that do and do not end in a crisis. House price growth emerges as a central factor. In fact, the statistical power of the difference in house prices for booms and do and do not end in a bust is larger than for any other variable. House prices are closely linked to mortgage debt and construction booms, which helps connect this finding to the broader evidence that household and mortgage debt are the most powerful predictors of financial crises. For early studies recognizing the importance of house prices in explaining financial crises, see Reinhart and Rogoff (2008, 2009a).

This idea is taken further in a post-WW2 short-panel setting, which includes emerging economies, in an analysis by Greenwood, Hanson, Shleifer, and Sørensen (2020). Their sample includes 42 countries from 1950 to 2016, and they use the Baron, Verner, and Xiong (2021) financial crisis indicator as their outcome variable. Their data set also includes house price and business equity price growth, along with measures of both household and non-financial firm debt. Credit growth still predicts financial crises. However, asset price growth helps boost the predictive power, leading the authors to construct an indicator they call the "Red Zone" — denoting a country that finds itself in the top third of both the historical credit growth and asset price growth distribution, a particularly strong predictor of whether a financial crisis occurs within the next three years. The study demonstrates substantial out-of-sample predictive power of the Red Zone indicator variable on a subsequent crisis.

3.2. What causes the credit expansion?

Financial crises are systematically preceded by a large rise in the quantity of credit and a decline in its cost. As a result, exploring the causes of a financial crisis means exploring the reasons for the credit expansion that precedes it, with a focus on the supply side of credit.

One factor often cited as an important cause of credit expansion is financial liberalization, especially in an open economy setting. This theme emerges prominently in research written in the aftermath of the banking crises of the 1980s and 1990s, which were frequently preceded by deregulation of the financial sector. Demirgüç-Kunt and Detragiache (1998) presents one of the earliest attempts to systematically measure financial liberalization across many countries over time. Their review of policy changes leads them to conclude that "the a removal of interest rate controls was the centerpiece of the liberalization process." They show that such liberalization often precedes the banking crises of the 1980s and 1990s.[9]

The argument that financial liberalization is an important driver of credit boom is put forth in Kindleberger and Aliber (2005), who write that "a particular recent form of displacement that shocks the system has been financial liberalization or deregulation in Japan, the Scandinavian countries, some of the Asian countries, Mexico, and Russia. Deregulation has led to monetary expansion, foreign borrowing, and speculative investment." A large body of research focused on the Latin American experience in the 1970s and 1980s, and the Scandinavian experience of the 1980s and 1990s, emphasizes the importance of financial liberalization in explaining the boom-bust cycle in credit and the real economy.[10]

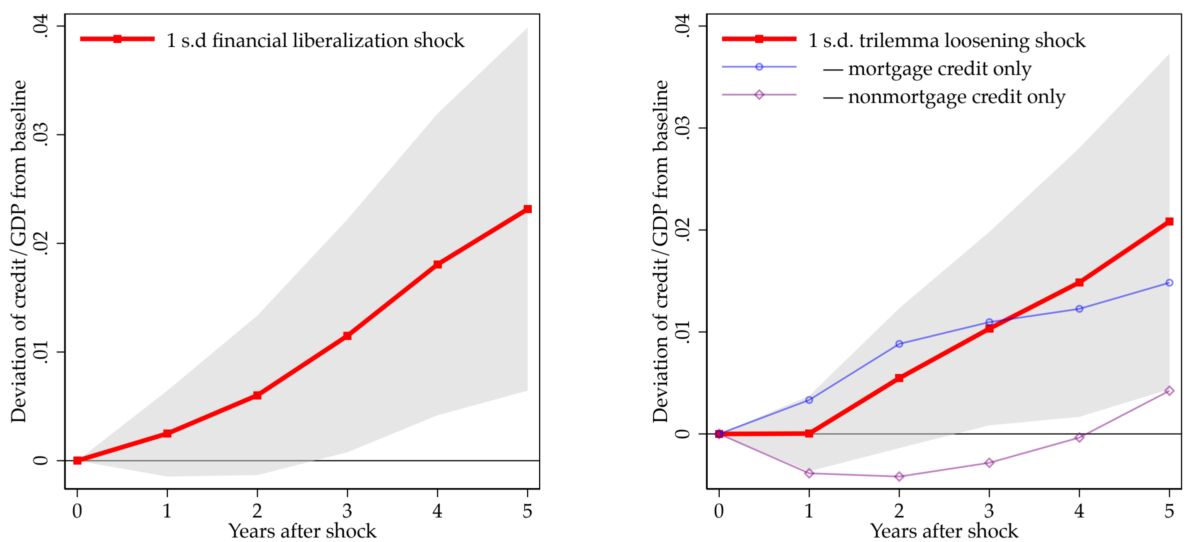
[9] Several articles follow the Demirgüç-Kunt and Detragiache (1998) argument that the removal of interest rate controls was a central piece of financial liberalization . These include Glick and Hutchison (2001) and Kaminsky and Reinhart (1999), among others. These studies consistently find that financial liberalization precedes banking crises.

[10] See Mian and Sufi (2018) for a summary of this literature. Key citations for Latin American include

Figure 7: *The response of credit to financial liberalization and monetary policy shocks*

The figure shows local projections of the deviation of the path of credit-to-GDP after a shock using the JST outcome measure in the advanced economy long panel. In the left panel, the shock is a change in the degree of financial liberalization using the dataset of Kaminsky and Schmukler (2008) for the period 1973–2005 In the right panel, the shock is a change in monetary policy proxied by the short-term local interest rate, identified using the Jordà, Schularick, and Taylor (2015a) trilemma instrument for the full sample since 1870. The latter also includes responses for both the mortgage and non-mortgage components of credit. Authors' calculation. See text. Authors' calculation. See text.

(a) *Financial liberalization shock* **(b)** *Monetary policy shock*



Some illustrative evidence is shown in Figure 7a using local projections. The outcome variable is private credit to GDP, denoted $CREDGDP_{ct}$, from the Jordà, Schularick, and Taylor (2017) bank loan measure, and the sample is the long-panel of advanced economies. The shock is a change in the degree of financial liberalization, treated as exogenous, according to a set of indices constructed by Kaminsky and Schmukler (2008) for the period 1973–2005, a range of dates which closely encompasses the great era of financial liberalization in both advanced and emerging economies. The index used here is the standardized sum of three measures of the domestic financial sector, the stock market, and the capital account. The figure clearly shows that in the 5 years after a financial liberalization event, changes in credit to GDP, which were on a positive long-run postwar trend anyway, had a tendency to accelerate even more rapidly.

Financial liberalization is one driver of credit expansions. And it may provide useful exogenous variation in some episodes. However, the fact that liberalizations are low frequency, occur in waves and in many countries at roughly the same time, casts doubt on the view that liberalization is the only or even the main primitive underlying shock that leads to the repeated credit booms of interest occurring at high-frequency throughout

Díaz-Alejandro (1985), and key citations for Scandinavia are Englund (1999) and Jonung and Hagberg (2005).

history. Furthermore, it is not obvious that financial liberalization in the absence of changes in credit supply should be associated with lower interest rates and a rise in asset prices (e.g., Justiniano, Primiceri, and Tambalotti, 2019). Instead, it is quite likely that liberalization, by opening a gate, enables other fundamental economic forces in the local or global economy to play out, creating the possibility of new or more elastic financial flows (intermediate claims, or leverage) relative to existing investment opportunities (real assets, actual or potential).

What are these broader forces driving flows of credit? One recent manifestation is the idea of a "global saving glut" proposed by Bernanke (2005) to explain the large capital inflows into many advanced economies from 1998 to 2006. An older version of this idea from the 1970s was the "petro-dollar" recycling argument that a rise in oil prices created an excess of dollar deposits in advanced economy banks, which were subsequently loaned to Latin American governments and corporations (e.g. Pettis, 2017; Devlin, 1989; Folkerts-Landau, 1985). In both of these narratives, some global change in savings leads to a large accumulation of deployable financial capital, which enters into certain liberalized countries and potentially drives a boom and bust cycle in credit.

A related idea has emerged recently with the rise in income inequality. There is plentiful evidence that the rich have a higher propensity to save out of lifetime income, therefore creating a "saving glut of the rich" when top income shares rise. Kumhof, Rancière, and Winant (2015) motivate their model with the observation that both the Great Depression and the Great Recession in the United States were preceded by a rise in income inequality and more borrowing by lower- and middle-income households.[11] Mian, Straub, and Sufi (2020b) focus on the United States from 1963 to 2016 and show that the rise in top income shares since the 1980s has been associated with a saving glut of the rich. Furthermore, this saving glut of the rich has financed a large rise in household and government debt.

In line with this evidence, Mian, Straub, and Sufi (2020a) build a model that incorporates the empirically-supported idea that the rich have a higher propensity to save out of lifetime income, so that a rise in the income share of the rich, in equilibrium, leads to a rise in borrowing by the non-rich. Such a buildup of debt eventually lowers aggregate demand in the future as low saving propensity individuals (the non-rich) make debt service payments to high saving propensity individuals (the rich). Going further, Klein and Pettis (2020) link the saving glut of the rich to the global saving glut by suggesting that rising current account surpluses in Germany and China since the 1980s have been due to the rise in inequality within those countries.

Of a more cyclical and high frequency nature, monetary policy may play an important

[11]See Eichengreen and Mitchener (2003) for a discussion of the U.S. credit boom of the 1920s.

role in explaining bursts of credit expansion, as lower interest rates may encourage banks to expand credit supply and/or take more risk. Jordà, Schularick, and Taylor (2015a) utilize an identification strategy based on the fact that countries with a fixed exchange rate regime experience fluctuations in short-term interest rates that are largely independent of local economic circumstances, a consequence of the trilemma of international macroeconomics. Using this empirical strategy with a data set covering 17 advanced economies over the past 140 years, they show that a loosening shock to local interest rates fuels an expansion in lending against real estate and growth in house prices. These are the conditions which heighten the risk of a financial crisis. Illustrative evidence is shown in Figure 7b using local projections, where the shock is a trilemma-identified 1 s.d. decline in local interest rates, and a significant credit growth response is seen, especially for mortgage credit.

Monetary policy by the U.S. Federal Reserve is shown to be a particularly important factor in explaining the global financial cycle according to Miranda-Agrippino and Rey (2020). Using a data set that begins in 1980, this study demonstrates that a single global factor explains a substantial amount of the variation in the price of risky financial assets around the world. Furthermore, this global factor reacts to changes in U.S. monetary policy, with a contraction in U.S. monetary policy leading to a tightening of global financial conditions. While Miranda-Agrippino and Rey (2020) do not focus specifically on the question of financial crises, it is likely that the patterns they uncover are related to the global boom and bust episodes seen over the past 40 years.

3.3. Behavioral biases, incentives, and predictability

The credit booms that predict financial crises are associated with a low cost of debt, and a low cost of risky debt in particular. An early study on such predictability by Greenwood and Hanson (2013) focuses on the United States and shows that a narrowing of credit spreads between high yield and investment grade corporations together with high issuance by low credit quality firms relative to high credit quality firms forecasts low excess returns to corporate bondholders. López-Salido, Stein, and Zakrajšek (2017) build on this empirical finding to show that these same measures of heightened credit market sentiment predict a reversal in credit market conditions and subsequently lower real GDP growth. Krishnamurthy and Muir (2017) collect novel data covering the interest spread between higher and lower grade bonds for 19 countries data going back 150 years. They confirm the relationship in the literature that crises are preceded by unusually high credit growth. They also show that crises are preceded by unusually low and falling credit spreads between higher and lower grade bonds. In other words, riskier firms are able to finance themselves at a relatively lower cost during the credit booms that precede financial crises.

These findings on spreads fit into the broader picture. It should be clear that a low spread between more risky and less risky debt is closely related to the idea that risky asset prices are high prior to financial crises. Holding expected cash flows fixed, a low interest spread between risky and less risky bonds would imply a relatively high risky asset price.

These complementary results in a large and growing body of work are important because they help narrow the set of theories that can plausibly explain why credit booms predict financial crises. Credit booms are periods in which the cost of financing risky debt is low and risky asset prices are bid up. The low cost of debt financing in combination with the rapid growth in debt is why many refer to these episodes as a "credit supply expansion," a "credit boom," or "frothy credit-market conditions." Creditors appear to become more willing to extend credit at a lower cost during the booms that precede financial crises.

The theoretical literature has advanced two broad paths to explain these results. In the first broad path, there are rational expectations models in which a financial crisis is particularly painful in the aftermath of credit expansion given incentive and information frictions that build up during the boom part of the boom-bust cycle. The second broad path argues that deviations from rational expectations are a crucial element in explaining the credit boom-crisis nexus.

The first class of models includes the studies by Gary Gorton and coauthors (e.g, Gorton and Ordoñez (2014, 2019); Dang, Gorton, Holmström, and Ordonez (2017); Dang, Gorton, and Holmström (2020)). The central idea in this research agenda is that the short-term debt securities that often fuel a credit boom and are at the heart of explaining the crisis are optimally structured to be "information-insensitive." Investors choose not to inform themselves on the quality of the underlying collateral, which can help fuel economic activity in the absence of any negative shock.

During the credit boom, the lack of information production leads to a depreciation of information about the quality of collateral backing the debt instruments. In such an environment, if there is an aggregate shock that reduces the value of the underlying collateral, there can be a "loss of confidence" in the collateral which triggers a panic. A key point of the framework is that a small shock can cause big problems if the underlying information on collateral value has deteriorated significantly during the credit boom. Gorton and Ordoñez (2019) argue that credit booms in which productivity falls substantially during the boom will be especially vulnerable to a small amount of negative information being suddenly revealed.

Diamond, Hu, and Rajan (2020) build a model in which frictions related to cash flow pledgeability lead creditors to rationally lend large amounts when there is a high probability of a high liquidity state in the future. They do so knowing that the realization of a low liquidity state in the future will be painful, as the amounts of debt taken on by expert managers of firms leads firms to be sold to less productive outsiders. The incentive to shift risk by financial intermediaries lies at the heart of models by both Acharya and Viswanathan (2011) and Coimbra and Rey (2017). Both models predict that financial fragility will rise during a credit boom, amplifying a decline in economic activity conditional on a negative shock.

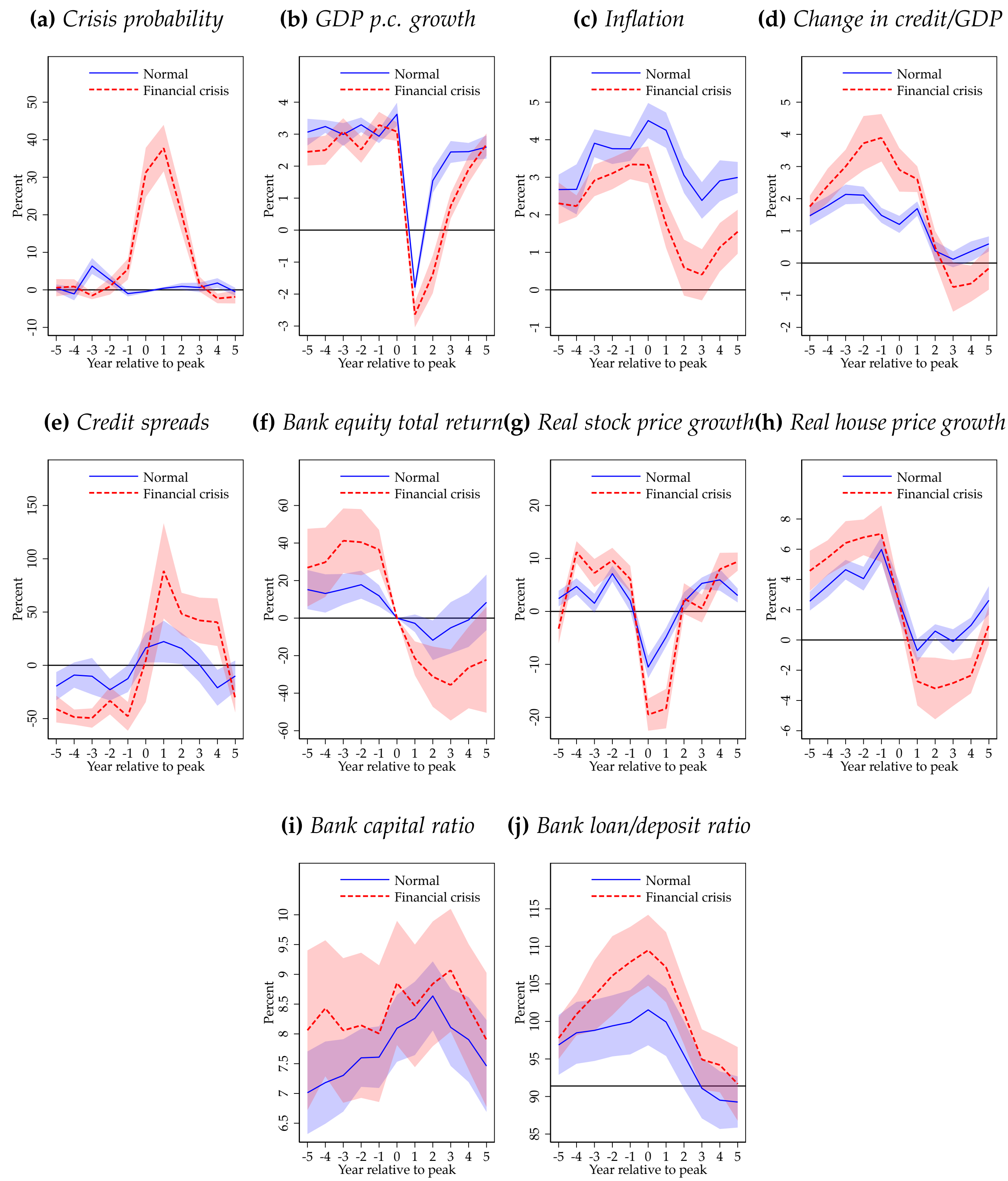
While incentive and information frictions can amplify the negative effects of a boom followed by a negative shock, these frictions do not generate systematic predictive power of credit booms on asset prices, in particular. Such predictability brings behavioral biases to the forefront when considering the boom-bust cycle associated with financial crises.

A particularly convincing study showing that flawed expectations are an important driver of credit expansions is the analysis of bank equity returns by Baron and Xiong (2017). This study builds on the evidence described above that a rise in the bank credit to GDP ratio predicts lower subsequent growth and a heightened probability of financial crises. The authors construct bank equity returns for 20 developed economies from 1920 to 2012. This allows for a detailed analysis of the returns realized to the holders of bank equity after an expansion in credit. They show that a rise in the bank credit to GDP ratio over the past three years that is above the 95th percentile of the historical distribution predicts an average return on bank equity over the next three years of −37.3%. Such a bank credit expansion predicts a heightened probability of a crash in bank equity prices, and yet bank credit expansion also predicts lower future returns. The ability of bank credit expansion known in year t to predict a large negative subsequent return on bank equity prices from years t to $t+3$ is difficult to reconcile with a framework built on rational expectations of bank equity holders.

Illustrative evidence on trends around financial crises are shown in Figure 8 for the JST long panel. Using an event-study approach, the average evolution of each variable is plotted relative to the peak year of the cycle. Averages are displayed separately for normal recessions (solid blue line) and financial crisis recessions (dashed red line). The first row of four charts shows the familiar timing of events and macro aggregates. Crisis probability is of course high in the ± 2 year window around a financial crisis recession, by construction, given the JST peak classification; it is negligible in normal recessions, although it is not exactly zero except in year zero, since nearby financial crisis events may be associated with a different nearby cyclical peak in JST. Real GDP per capita growth decelerates after a recession peak, but much more so in a financial crisis recession as expected. Likewise, a recession is associated with the onset of a disinflationary period of several years, but the trend is much more pronounced in a financial crisis recession. Finally, the fourth chart

Figure 8: *Key macro-financial trends in normal and financial crisis recessions from an event-study*

The figure shows macro-financial trends in normal and financial crisis recessions. The time axis is normalized to make year 0 coincide with the cyclical peak. The recessions classification follows Jordà, Schularick, and Taylor (2013), and updates thereto. All variables are from the JST Macrohistory dataset, except bank equity returns from Baron and Xiong (2017), credit spreads from Krishnamurthy and Muir (2017) and capital and loan/deposit ratios from Jordà, Richter, Schularick, and Taylor (2021). Growth rates, inflation, and total returns are expressed in log $\times 100$ units. Credit/GDP is expressed in percentage points. Credit spreads are normalized and expressed in percentage deviation from the country mean. Authors' calculation. See text.



shows that financial crisis recession peaks are preceded by credit booms and followed by credit crunches much more so than normal recessions.

The second row of charts in Figure 8 shows some interesting financial market covariates using selected asset prices. The first chart shows the Krishnamurthy and Muir (2017) *normalized* credit spread, which is the percent difference of the credit spread from its country mean (so 0% means the spread is equal to this average), and clearly spreads are tighter than average (50% lower) before a financial crisis recession peak, and much wider immediately after (50%–100% higher), compared to the minimal variation seen in normal recession events. The next chart shows the Baron and Xiong (2017) real total return on bank equities, which is a little high before a normal recession peak and indistinguishable from zero after; but near a financial crisis recession peak, bank equities experience a very large run up before, and a large crash afterwards, with significant negative real returns (note that these are log×100 units). Finally, we can see that distress clearly spills over into broader aggregate asset prices, where the onset of a financial crisis recession event similarly implies much larger and predictable reversals for investors exposed to the stock market or housing market, as shown in the last two charts.

The recent study by Richter and Zimmermann (2019) looks into the dynamics that occur at banks to uncover the specific biases that may help explain these results. In particular, the study points to the extrapolation of a sudden rise in bank profits as the origin of the bank credit expansion. A rise in profits predicts a rise in lending, and, ultimately, financial crises can emerge when profits further into the future eventually fall. Delving further into the rise in profits, the study finds that a key reason for the rise in the profits is a decline in loan loss provisions. All of these patterns are consistent with the idea that a reason behind the expansion of credit is the rise in optimism by bank managers that comes after the realization of high profits on lending. This rise in optimism can explain why the quantity of credit expands, why interest rates fall, and why bank equity profits are predictably negative once the credit expansion has become sufficiently large. In a related finding, Mian, Sufi, and Verner (2017) show that the decline in the mortgage interest rate relative to the sovereign bond interest rate is a powerful predictor of a rise in the household debt to GDP ratio.

Further insight into actors' motivations emerges from recent work on bank capital and its consequences by Jordà, Richter, Schularick, and Taylor (2021). They collect new data for the long panel of advanced economies on the liability side of the banking system, tracking the evolution over time of bank capital ratios, and well as other key ratios for the funding mix, such as loan to deposit ratios and the fraction of non-core funding. The standard assumption about governance, which has guided recent regulatory activity, is that if banks have more "skin in the game" they should engage in more prudent risk-management behavior and thereby reduce the probability that financial institutions will face large losses that put their existence at risk. However, the historical evidence goes against this argument. Banks have failed consistently across time, in times of high capital ratios like the late 1800s, and in times of low capital ratios like the last 30–40 years. Crisis prediction regressions show no association, or possibly an inverted one, between capital ratios and crisis risk. Jordà, Richter, Schularick, and Taylor (2021) also develop an instrument for changes in bank capital, giving their results a causal interpretation: higher bank capital ratios do not reduce the risk of crises. Thus, consistent with Baron and Xiong (2017), bank managers and owners seem unaware risks are rising, and capital levels seem to make no difference as one might assume if the incentives of rational agents were well aligned. In contrast, other balance sheet ratios such as the loan to deposit (LtD) ratio appear to have significant predictive power, and this remains even after controlling for lagged credit growth. Illustrative patterns for the capital and LtD ratios are shown in the third and final row of charts in Figure 8.

Systematic extrapolation errors may not be just confined to actors in the financial sector, such as lenders and borrowers. The expansion of credit is also associated with systematic forecast errors of GDP growth by leading world organizations such as the OECD and the IMF. This result is demonstrated in Mian, Sufi, and Verner (2017), who show that the expansion of the household debt to GDP ratio from year $t-4$ to year $t-1$ can systematically predict GDP growth forecast errors from year t to year $t+3$. The forecasts are made in year t, which implies that a factor known for sure at time t predicts forecast errors going forward. Forecasters appear to systematically miss the power of credit expansion in predicting lower subsequent growth.

All told, the emerging historical evidence supports the existence of systematic behavioral biases in explaining credit cycles, and such evidence has spurred a rise in theoretical research trying to model the evolution of beliefs in a framework departing from rational expectations (e.g., Bordalo, Gennaioli, and Shleifer, 2018; Greenwood, Hanson, and Jin, 2016; Krishnamurthy and Li, 2020; Maxted, 2020).

3.4. Triggers

Financial crises are predictable at the 3 to 5 year horizon, but that should not be seen as decreasing the importance of understanding the specific immediate factors that trigger the crisis itself. The seminal work by Diamond and Dybvig (1983) points to the importance of multiple equilibria with demandable debt financing, and the bank run equilibrium in this model is undoubtedly a powerful explanation for the events that triggered the Global Financial Crisis in 2008.

In terms of the specific factors that tip the scale from boom to bust, a rise in debt service payments is a likely culprit. Drehmann and Juselius (2014) and Drehmann, Juselius, and Korinek (2018) utilize a data set covering new borrowing and debt service flows for a panel of 16 countries from 1980 to 2015. They focus in particular on the debt service ratio (DSR), which represents the interest and principal payments made by borrowers scaled by disposable personal income. Like other researchers, they find that a rise in private credit is a strong predictor of a financial crisis. However, they also show that a rise in the DSR is a short-run factor that may explain how the crisis is actually triggered.

The dynamics they illustrate suggest that an innovation to new borrowing leads to a slow but steady rise in the DSR. By three to five years after the initial innovation, the DSR begins to rise substantially. A banking crisis becomes much more likely as these debt service payments peak. As Drehmann and Juselius (2014) write, "the DSR's [debt-service ratio] early warning properties are especially strong in the two years immediately preceding crisis. In the last four quarters before crises, the DSR is even a nearly perfect indicator."

It is well established that economic downturns often begin with banking sector distress, a tightening of credit conditions, and a widening of credit risk spreads (e.g., Lown and Morgan, 2006; Gilchrist and Zakrajšek, 2012). A recent literature focuses on higher frequency measures that predict a decline in economic growth at the one-year or less horizon (e.g., Gilchrist and Zakrajšek, 2012; Giglio, Kelly, and Pruitt, 2016; Adrian, Boyarchenko, and Giannone, 2019). A general finding of this literature is that deteriorating financial conditions are strong predictors of the lower quantiles of the economic growth distribution. There is also evidence that even if easy financial conditions are favorable to growth in the short term, they may lead to negative consequences at longer horizons a few years out, and all the more so if credit growth has been elevated (Adrian, Grinberg, Liang, and Malik, 2018).

This points to the idea that the ultimate trigger of the financial crises that lead to lower growth is an adverse shock in the financial sector, one which might well follow a period of easy financial conditions.

Summary The empirical evidence rejects the view that financial crises should be viewed as random events. Instead, they are predictable. Credit growth and asset price growth are key factors that predict financial crises, and these two factors have significant forecasting power even out of sample. The ability of credit expansions to predict asset price returns in particular raises important questions for the study of business cycles, and it suggests that deviations from rational expectations should be a central part of the discussion. In general, the evidence on financial crises comports with the view that the study of business cycles should indeed be a study of the entire cycle – both the boom and bust.[12]

[12] This conclusion is also reached by Beaudry, Galizia, and Portier (2020), who aptly entitled their study "Putting the Cycle Back into Business Cycle Analysis."

4. Explaining the painful consequences of a crisis

Financial crises are painful. But what exactly is the mechanism through which a financial crisis leads to recessions and unemployment? In this section we explore that question. Headline unconditional data on outcomes, as we saw in Table 1, and in other studies (Bordo, Eichengreen, Klingebiel, and Martínez-Pería, 2001; Cerra and Saxena, 2008; Reinhart and Rogoff, 2009b), provide important motivation, but ultimately it is only through the study of covariates that we can learn more about the underlying mechanisms that deliver unusually damaging economic outcomes after financial crisis events.

4.1. The crisis itself, or the boom that precedes it?

The power of credit and asset price booms in predicting financial crises raises an empirical conundrum that has been difficult to answer definitively in the literature: are the painful consequences of a crisis the result of imbalances that preceded the crisis or the effect of the crisis itself? Or put into the language of policy counterfactuals: suppose we could isolate two countries with the exact same conditions that generally precede the onset of a financial crisis, but we then could randomly intervene to switch off the crisis itself in one of the countries. How much less severe would the recession be with such an intervention?

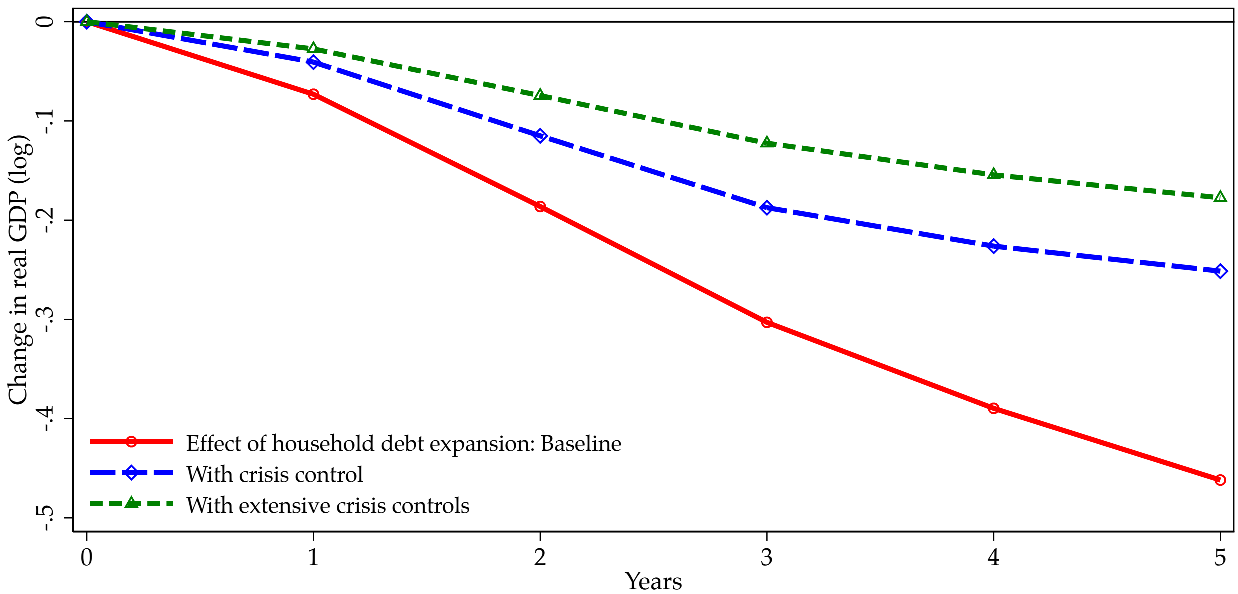
Such perfect randomized experiments are not available in macroeconomic episodes. As a result, the literature has approached this question with a number of techniques, all of which suggest a similar conclusion: the painful consequences of financial crises are a function of both the conditions that precede the crisis and the amplification effect of the crisis itself. There is less agreement on the relative strength of each channel, which is why it remains a fruitful avenue for future research.

The separation of the two channels is a central endeavor of Jordà, Schularick, and Taylor (2013), who focus on a sample of 14 countries from 1870 and 2008. In particular, the analysis in this study conditions on recessions and explores which recessions are the most severe. Recessions associated with a financial crisis are deeper and longer. Unconditionally, a financial crisis recession is associated with a 3.1% contraction in GDP per capita, and the recession lasts for four years. In contrast, a non-financial crisis recession is associated with a 2% contraction, but the recession is only 1 to 2 years and the recovery by year 3 is strong.

However, a key result that emerges in Jordà, Schularick, and Taylor (2013) is that both normal and financial crisis recessions are significantly worse if they are preceded by a large rise in credit. The magnitudes are large; for example, a financial crisis recession preceded by an expansion in credit that is 3 percentage points of GDP larger per year is characterized by a trough in GDP per capita that is up to 3 percentage points worse.

Figure 9: *Household Debt Expansion and Subsequent Growth: Controlling for a Financial Crisis*

The figure plots $\hat{\beta}^h_{HH}$ from the following specification estimated at each horizon h: $y_{it+h} - y_{it} = \alpha + \beta^h_{HH} \left[{}^{HHD_{it-1}}/_{Y_{it-1}} - {}^{HHD_{it-4}}/_{Y_{it-4}} \right] + \sum_{j=0}^{5} \gamma^j Crisis_{it+j} + \epsilon_{it}$. The sample follows Mian, Sufi, and Verner (2017), which includes 811 observations for 37 countries. The red line is from a specification excluding the financial crisis controls, the blue line includes a control for a crisis at any point in time from $t = 0$ to $t = 5$, and the green line includes individual indicator variables for a crisis at any point from $t = 0$ to $t = 5$. Authors' calculation. See text.



Normal recessions preceded by a similarly sized expansion in credit are prolonged by at least a year and per capita GDP after five years is 2 percentage points weaker compared to normal recessions with no expansion in credit. Jordà, Schularick, and Taylor (2016) explore the role of mortgage credit; the results are similar, and we return to this study in subsection 4.2. Jordà, Schularick, and Taylor (2015b) show that these responses are amplified in the presence of asset price bubbles, and especially so for housing price bubbles, which accords well with the similar findings on crisis probability we discussed earlier.

To help assess the relative importance of the crisis and the factors leading up to the crisis, we present an exercise in Figure 9 based on the results from Mian, Sufi, and Verner (2017). This study shows that a rise in household debt to GDP ratios predicts a subsequent slowdown in growth. The red line in Figure 9 replicates a central result from their study: a rise in the household debt to GDP ratio from four years ago to last year predicts a substantial decline in subsequent real GDP growth from the current year onward.

How much of the decline in subsequent GDP growth is due to the fact that a rise in household debt predicts a financial crisis (e.g., Schularick and Taylor, 2012; Greenwood, Hanson, Shleifer, and Sørensen, 2020)? To explore this question, the blue long-dashed and green dashed lines in Figure 9 plot the LP responses to prior household debt expansion after controlling for the presence of a financial crisis (using the BVX measure) up to horizon year 5. Given the results already discussed above, it should not be surprising that inclusion of such a financial crisis control adds significant explanatory power to the regression, and that inclusion will reduce the predictive power of prior household debt expansion.

The blue line plots coefficients after controlling for a single indicator variable if there is a crisis in the country at any point during the future horizon, and the green line plots coefficients after allowing for separate indicator variables for a financial crisis in any of the years in the future horizon. The inclusion of the flexible controls for a financial crisis in the latter specification is quite an extreme test that stacks the deck against finding any independent effect of household debt expansion on subsequent GDP growth.

Even with these extensive controls for a financial crisis from $t = 0$ to $t = 5$, the rise in household debt from $t-4$ to $t-1$ continues to have quantitatively large negative effects on subsequent GDP growth. In terms of magnitudes, the baseline coefficient on growth five years out is –0.46, and it is reduced to –0.18 with the most extensive financial crisis controls. This simple exercise suggests that as much as 40% of the negative effects of household debt expansion on subsequent growth is independent of its ability to predict a financial crisis. While this particular exercise is conducted using the expansion in household debt, we do not believe the results are unique to this predictor. It is likely that other predictors of financial crises such as asset price booms would also affect subsequent GDP even in the absence of a financial crisis.

Another approach to quantifying the relative importance of a crisis versus the factors that precede it is a close examination of the timing of economic output declines around the initiation of a crisis. Baron, Verner, and Xiong (2021) show the dynamics of real GDP around the initiation of a financial crisis as measured by a bank equity crash of 30%. There is a substantial decline in real GDP relative to trend in the year of the bank equity crash itself; however, the year after the crash is on average even worse in terms of GDP growth. Statistical analysis in Baron, Verner, and Xiong (2021) shows that a bank equity crash worse than 30% predicts a 2 to 4 percentage point decline in real GDP growth three years after the shock. While this evidence is not conclusive, it does point to a significant acceleration in the severity of a recession after a crash in bank equity values.[13]

An interesting study by Gertler and Gilchrist (2018) focuses on the Great Recession in the United States in an attempt to tease out the relative contribution to recession severity from vulnerabilities associated with elevated household debt, the collapse of the housing market, and disruption in the financial sector. The empirical strategy exploits both time series variation in financial market conditions along with cross-sectional variation across

[13]See also a related study by Bernanke (2018) that uses time series variation to argue that financial market disruption was a crucial driver of the severity of the Great Recession in the United States.

regions within the United States. The main finding is that about half of the decline in employment from 2007 to 2010 was due to issues related to housing and household balance sheets, and half due to financial market disruption. The use of both panel and time series variation is a promising avenue for future research in this area.

The bottom line from the existing empirical research is that the negative effects of a financial crisis are due both to financial crisis itself along with the credit booms that precede them. The next subsection turns to research focused on the reasons that a credit boom has long-lasting effects on the economy.

4.2. Not all credit booms are equal

A sudden rise in the private debt to GDP ratio predicts financial crises and lower subsequent growth. However, the cross-sectional variation across countries tends to show a positive correlation between measures of debt to GDP and per-capita GDP levels (e.g., King and Levine, 1993). The cross-sectional relationship suggests that not all increases in debt are bad for the economy, and in the long run a deeper credit market boosts living standards. Is there a way to distinguish whether a sudden rise in debt is good or bad for an economy?

Economic models reveal an important distinction between credit booms that tend to increase the productive capacity of the economy and those that tend to boost demand for final consumption goods (e.g., Schmitt-Grohé and Uribe, 2016; Kalantzis, 2015; Ozhan, 2020; Mian, Sufi, and Verner, 2020c). The models in this literature conclude that a credit boom that fuels the non-tradable sector can often have harmful effects on an economy such as real exchange rate appreciation, misallocation to lower productivity sectors, and a durables overhang in the housing sector.[14].

There is a growing body of evidence that supports these models. A rise in debt that boosts local demand portends worse economic outcomes and heightened risk of a financial crisis. Studies have used a variety of proxies for debt that tends to boost local demand, such as mortgage debt, debt issued to households, and debt raised by firms producing non-tradable goods. Jordà, Schularick, and Taylor (2016) examine the explanatory power of mortgage and non-mortgage credit for GDP growth after a normal of financial crisis recession peak in the long panel of 17 advanced economies back to 1870. An increase in either form of credit expansion is associated with an extra drag on growth in both normal and financial crisis recessions, but the drag from mortgage credit booms is especially strong after WW2 when this type of household debt became so dominant. A related study is Mian, Sufi, and Verner (2017). Using a sample of 30 countries from 1960 to 2012, the authors show

[14] A related but distinct argument is that a credit boom may lead to a misallocation of capital within the business sector, and therefore cause lower productivity. See, for example, Gopinath et al. (2017)

that the change in the household debt to GDP ratio consistently outperforms the change in the business debt to GDP ratio in predicting a subsequent decline GDP growth.

Jordà, Kornejew, Schularick, and Taylor (2020) expand the long panel to study both business and household credit and find similar results focusing on recession paths of GDP after a cyclical peak. They find that a household credit boom predicts a much deeper recession, but there is no noticeable drag from a business credit boom. The result holds in normal and financial recessions, and interestingly the only exception is when there is a business credit boom in circumstances where qualitative indicators suggest high bankruptcy and reorganization frictions.

Using a very different open-economy empirical design, Benguria and Taylor (2020) study the aftermath of crises in an expanded long panel of advanced and emerging economies since the 19th century. Crossing the macro dataset with trade data on exports and imports, including for bilateral pairs, they ask whether the aftermath of a crisis shows up in an export or import collapse. If financial crises typically damaged the real-economy supply side, via firms, then output including exports sold would be depressed, all else equal in the rest of the world. If financial crises typically damaged the real-economy demand side, via households, then demand including imports bought would be depressed, all else equal in the rest of the world. Simple benchmark models of deleveraging shocks confirm this, and the data strongly confirm the second narrative not the first: financial crises are followed by import compression, leaving exports little changed. This is the tell-tale sign of a demand-side deleveraging shock working through household credit supply channels.

The recent working paper by Muller and Verner (2020) introduces a novel data set splitting the sectoral composition of business credit for a sample of 116 countries going back to 1960. This shows that splitting business credit to firms producing non-tradable goods (e.g., construction, real estate, trade, accommodation, and services) versus tradable goods (e.g., manufacturing) leads to novel insights on the business cycle dynamics of credit booms. More specifically, a rise in business debt for non-tradable firms generates a boom and bust cycle in real GDP and a heightened probability of a financial crisis. In contrast, a rise in business credit for tradable firms is associated with a steady rise in real GDP, and no increase in the probability of a financial crisis or a recession. Muller and Verner (2020) also replicate the findings in the previous literature that household debt is associated with a large rise in the probability of a financial crisis and a subsequently lower GDP growth. Put together, these findings support the view that credit booms that fuel consumer demand are particularly dangerous for financial and macroeconomic outcomes.

Summary The economic upheaval brought about by financial crises garners a great deal of attention, and deservedly so. However, it is important to remember that financial crises come about due to rapid credit and asset price growth; these underlying imbalances are also important factors explaining the decline in economic activity associated with crises. We need more research aimed at quantifying the relative importance of crises versus the factors that precede crises. A growing area of research focuses on credit booms and suggests that these booms fuel the demand for consumption goods, notably via household debt, and are particularly dangerous for future economic activity.

5. Open economy considerations

Countries are connected through financial and goods markets, and as a result there is an important international dimension to the study of financial crises. As mentioned in section 3, the pre-GFC wave of research on financial crises found robust support to the idea that open economy considerations such as real exchange rate appreciation and the evolution of the terms of trade were important in the prediction of financial crises.

A closely related question is whether the dynamics of crises are different in emerging market economies in which open market issues tend to be more pronounced. One study that explores such differences is Gourinchas and Obstfeld (2012), who employ a sample including many emerging and advanced economies from 1973 to 2007. Their central conclusion is that "domestic credit expansion and real currency appreciation have been the most robust and significant predictors of financial crises, regardless of whether a country is emerging or advanced." Other studies typically include a robustness table that compares results across emerging markets and advanced countries (e.g., Table IV in Mian, Sufi, and Verner (2017); Table 6 in Muller and Verner (2020); and Table 5 in Greenwood, Hanson, Shleifer, and Sørensen (2020)). The general finding is that the power of credit growth in predicting financial crises and lower subsequent growth is similar across all types of countries.

There is no doubt that the features of financial crises in small open economies and emerging markets are distinct. Researchers have emphasized the importance of the interaction of banking crises with sovereign debt and currency crises in these countries (e.g., Kaminsky and Reinhart, 1999; Gourinchas and Obstfeld, 2012). However, despite these obvious differences, the power of credit growth in particular is remarkably robust across all countries independent of whether they are more open or closed, or more advanced versus developing. Recent studies in the literature tend to pool both advanced and emerging economies, and there is less emphasis on the differences between the two.

Since the Global Financial Crisis, two open economy issues have received a fair amount of attention in the literature: first, are the dynamics of financial crises different if credit expansion is fueled by borrowing from overseas? And second, does there exist a global financial cycle that can help understand why some crisis episodes are more severe than others?

5.1. Borrowing from abroad?

Credit booms lead to financial crises and painful macroeconomic consequences. But does it matter whether the credit is financed from domestic versus foreign savers? Jordà, Schularick, and Taylor (2011) uses a sample of 14 developed economies from 1870 to 2008 and examines whether an accumulated current account deficit helps predict financial crises. In these developed economies, the authors find that credit growth remains the best predictor. For example, using the area under the receiver operating characteristic curve (AUC) methodology of determining predictive power, the analysis finds that credit growth has more predictive power than current account deficits. However, the authors find evidence that the predictive ability of credit growth increases slightly if external factors are added to the regressions. Borrowing from abroad makes a financial crisis somewhat more likely than borrowing domestically.

Mian, Sufi, and Verner (2017) examine this question in a sample that includes 30 mostly advanced economies from 1960 to 2012. Their analysis focuses on the factors that predict GDP growth, and they find that the accumulation of current account deficits does not by itself explain lower subsequent economic growth. This is in contrast to the rise in household debt to GDP, which robustly predicts lower subsequent growth. However, the authors show that the interaction of a rise in household debt and an accumulated current account deficit is a significant predictor of lower subsequent growth. In terms of magnitudes, their analysis shows that a country with a one standard deviation increase in the rise in the household debt to GDP ratio over three years with no accumulated current account deficit experiences a statistically significant predicted decline in subsequent real GDP of 1.2%. If a country also experiences an accumulated current account deficit during the period of a rise in household debt, then the predicted decline in subsequent GDP is twice as large. A household debt boom financed by foreigners predicts lower growth than one financed domestically.

Perhaps the most direct answer to this question is the recent study by Richter and Diebold (2021). The analysis uses the "financial sector unveiling" technique introduced by Mian, Straub, and Sufi (2020b) to measure the ultimate funding source of credit booms in an unbalanced panel of almost 40 countries from 1970 to 2018. The core finding is that foreign-financed household credit expansion is associated with reallocation from the tradable to the non-tradable sector, and such credit expansions predict lower subsequent real GDP growth and a heightened probability of financial crises. In contrast, domestically-financed credit growth does not predict these outcomes.This study suggests that borrowing from abroad is a crucial aspect of the boom-bust dynamics associated with credit expansions.

5.2. Crises and the Global Financial Cycle

The idea that a global financial cycle is an important driver of financial crisis episodes is an old one; in the forward to an update of Kindleberger (1978), Robert M. Solow wrote that "any reader of this book will come away with the distinct notion that large quantities of liquid capital sloshing around the world should raise the possibility that they will overflow the container."[15] A central question for research on financial crises is whether this global financial cycle influences the probability and/or the severity of a financial crisis within a given country.

The existence and determinants of a global financial cycle are the subject of the research agenda by Silvia Miranda-Agrippino and Helene Rey (Rey, 2015; Miranda-Agrippino and Rey, 2020), and also the subject of a chapter included in this volume. We focus on research that takes this cycle as given and explores the consequences of it for real economic activity and financial crisis episodes.

The household debt cycle explored in Mian, Sufi, and Verner (2017) has a strong global component. In their sample covering the 1960 to 2012 period, there were two distinct global booms in household debt: from 1984 to 1990 and from 2000 to 2007. Both of these global household debt expansions were followed by a slowdown in global economic activity. Mian, Sufi, and Verner (2017) show that a time series regression collapsing all economies in their sample from 1960 to 2012 shows a statistically significant and large negative effect of a rise in global household debt on subsequent global real GDP growth. The negative effect of household debt expansion on a given country's subsequent growth is stronger for countries that have a household debt cycle more correlated with the global household debt cycle.

A recent study by Aldasoro, Avdjiev, Borio, and Disyatat (2020) measures a domestic financial cycle and a global financial cycle. The former is measured using non-financial private sector credit growth, the ratio of credit to GDP, and growth in residential property prices within a given country. The latter is measured at the global level using variables similar to the analysis in Miranda-Agrippino and Rey (2020). The authors show that the two types of cycles are distinct and in general "do not display a strong and obvious association." However, the relationship between the two cycles tightens around banking crises. Banking crises tend to be preceded by a boom in both the global and domestic financial cycle, and

[15] We discovered this quote in the introduction of Richter and Diebold (2021).

both turn downwards just before the banking crisis occurs. The timing patterns suggest that "unsustainable booms are driven predominantly by the [domestic financial cycle], with capital flows turbocharging them in the later stages."

6. Open questions and future research

Our survey focused on empirical evidence on financial crises, highlighting a wave of new research in the years since the 2008 crisis. We conclude with some discussion of fruitful directions for future research and connections to important debates about policy and theory.

Normative issues and policy implications The normative and policy issues can be framed in terms of the so-called "lean" versus "clean" debate. This concerns the question as to whether policymakers, and especially central banks, should lean against credit booms and asset bubbles to prevent or mitigate crises before they happen, or whether they should sit back and watch, as they largely did pre-2008, then wait for a crisis to happen, and do their best to clean up the mess afterwards.

Before 2008, some voices in the desert raised alarms about the financial stability risks of a purely "clean" regime (Borio and White, 2004; Borio and Shim, 2007). But the debate then took on much greater urgency after the crisis hit (White, 2009; Stein, 2012, 2013). Within this there is also the issue of what kind of leaning should be done, whether via the interest rate tool (with the risk of misses on other targets like inflation or employment) or via other additional macroprudential policy tools (which the central bank would need to be enabled and willing to use).[16]

From a research perspective, how to weight these choices is a difficult problem since predictive signals are imperfect, the benefit of mitigation might be offset by costs, and false positives and false negatives must be considered in dynamic general equilibrium. Such a consensus model, with a plausible parameterization is a distant goal. As a practical matter of policy, under imperfect knowledge and short memories, choices must be and have been made throughout history, with central bank mandates originally geared predominantly to financial stability with the gold standard rules (e.g., the Fed at its founding, and earlier still the Bank of England guided by Thornton and Bagehot). Over time mandates shifted to inflation and output objectives, with the former taking priority after 1973 as policymakers groped for a new nominal anchor. Risks and costs of crises faded from view as the Great Moderation period created a false sense of security. An operational focus on the interest

[16] Here, history, as well as the fundamental theorem of algebra, suggest that if the number of tools is greater than or equal to the number of targets, then standard and macroprudential policy goals can be simultaneously met (Aikman, Bush, and Taylor, 2016).

rate as the policy tool led, via the fundamental theorem of algebra, to the ability to hit only one target given one instrument. Financial stability took the back seat.

The pre-2008 view that the financial system could self-regulate was widely accepted, and some saw unsound or cyclical regulators as the problem. Or, government failure larger than market failure. In this view, if unhelpful rules are removed or non-binding, banks could be trusted to impose sensible self-restraints which would be sufficient to prevent credit booms, crises—and their own destruction. (If a city removes a guard-rail from a cliff, people don't suddenly jump off.) In 2008 this argument tripped, and Alan Greenspan told Congress it had been the "flaw" in his worldview. The costs of crises were now front and center, not easily brushed off as a minor side-effect of a more *laissez-faire* "clean" regime.

The macroprudential mix Still from a research standpoint, we seek GE models with appropriate friction and information assumptions, and with or without behavioral departures, to frame these new policy directions, a task which is underway, and which may be guided by some of the evidence we have surveyed here. And as an empirical matter, the potential costs of simply leaning via the interest rate alone may be prohibitive (Svensson, 2016), and may be far from optimal policy in models where realistic frictions or distortions lead to cycles of sub-optimal leveraging and deleveraging (Bianchi, 2011; Korinek and Simsek, 2016; Bianchi and Mendoza, 2018; Farhi and Werning, 2020; Bordalo, Gennaioli, Shleifer, and Terry, 2021), where these include, e.g., pecuniary externalities and extrapolative beliefs.

Today the question appears to be not whether but what macroprudential policies should exist, whether they should go beyond interest rate control, whether and how to implement time-variation, and how to understand and calibrate these choices. In practice, many policy toolkits have been augmented with new, higher, Basel-approved capital ratios, to put more skin-in-the-game for bankers, but the hope that higher capital alone will prevent crises is not supported by the historical evidence as argued by Jordà, Richter, Schularick, and Taylor (2021), although a better capitalized banking system seems to be associated with less severe recessions once a crisis hits, so the policy may not be without some merits.

So stronger, possibly time-varying measures and/or sectorally-targeted may be needed in addition to that Basel minimum, such as the use of maximum loan-to-value (LTV) ratios (e.g., Jeanne and Korinek, 2020; Acharya, Bergant, Crosignani, Eisert, and McCann, 2020; Peydró, Rodriguez Tous, Tripathy, and Uluc, 2020). For example, the 80% mortgage LTV cap is seen as having aided financial stability in crisis-free Canada, even when it was discarded in the country to the South. Such constraints on contracts may confront more stubborn political opposition, not to say ideological resistance, illustrated by the tensions over the time-varying mortgage LTV requirements in Israel (Fischer, 2014).

Objections to stronger macroprudential interventions like these often arise from distributional concerns, although that argument loses force as evidence mounts that even plain-vanilla interest rate policy actions of central banks also have pervasive distributional impacts too, so there may be no distributionally neutral tools at the policymaker's disposal anyway. That may be too bad. But, as with unchecked pandemics, if the high costs and negative externalities of crisis events are judged unacceptable then preventive measures are likely to be taken even if they have downsides of their own, requiring hard policy choices.

Also open for debate, and at least as controversial, are the roles for stricter policies, policies that target levels or debt or leverage, and policies that apply in aggregate or vary by sector or region. At an international level, we can also see how macroprudential policy bleeds into capital control policy, once cross-border debt flows are taken into account. In an open economy setting, we then might ask how macroprudential policy links with the optimal policy under the trilemma, and the choice of exchange rate regime and capital controls (Jeanne and Korinek, 2010; Devereux, Young, and Yu, 2019; Farhi and Werning, 2012). These issues are certainly central in emerging markets contending with "fear of floating" and in the Eurozone, both cases providing ample historical evidence of troublesome cross-border debt booms.

Policy space and public debt The above contrasts the choice of "lean" or "clean" regimes. But in reality there is also the more likely outcome, a "lean and clean" regime where both sets of tools are employed. This raises questions of its own, especially relating to public debt and fiscal space. Empirically, the predictive relationship between past public debt and financial crisis has been weak throughout history, in contrast to the strong predictive power seen for private debt (Jordà, Schularick, and Taylor, 2011). Furthermore, in the historical data, a cyclical rise in public debt to GDP ratios does not predict lower subsequent growth (Mian, Sufi, and Verner, 2017). However, with public debt levels rising around the world to high levels, the risk to an out-of-sample forecast rises and we make a few observations.

First, as noted by Jordà, Schularick, and Taylor (2011) and Romer and Romer (2018), even if high or rising public debt doesn't raise the probability of a crisis event, it may hamper the ability of policymakers to buffer any subsequent recession, either by limiting direct fiscal interventions or by limiting the state's capacity to backstop or repair the damaged financial sector. In extremis, its damage to the government's net revenues may even tip the sovereign into distress or default (Reinhart and Rogoff, 2011). So there may still be virtue in reserving fiscal space for rare disasters (as with COVID). Even so, this point is tempered by our current inability as economists to specify or estimate where the public debt limit binds, with many advanced economies now well past the proposed 90% of GDP limit about 10 years ago, with no sign of stress as yet.

Second, these issues likely matter for the "lean and clean" outcome we seem to be heading towards, since we have yet to ask whether the two are really substitutes or complements. The latter contrary view would say that as the authorities embrace more "clean" tools, like ex post bailouts, LOLR actions among broader ranges of institutions or asset classes, and other backstops, so will the force of moral hazard trigger even more risk taking ex ante. One option is then to forget time consistency, and let policy evolve to do ever more cleaning at greater fiscal cost, the so-called doom loop (Alessandri and Haldane, 2009). In this feedback loop, some ex post policies, via the socialization of risk, may pose a threat to, rather than giving assistance to, macro-prudential strategies. The alternative to more "clean" is more "lean" ex ante even just to hold keep risks and costs unchanged. This is a topic little studied but worthy of attention.

Third, if these risks are misjudged and the plan for stability fails, and we suppose either a lack of fiscal space or insufficient leaning materializes, any country can be at risk of an EM style or Eurozone-periphery style of feedback loop where the banks can't survive without help from the sovereign, and the sovereign can't survive if it helps the banks (Acharya, Drechsler, and Schnabl, 2014). And here, what constitutes fiscal space is very clearly endogenously determined by the potential balance sheet holes and GDP costs that could appear if banks enter a crisis state.

On this path perhaps the quiet and mostly-politically-isolated life of central banks—old school monetary policy and narrow financial regulation—is slowly disappearing. The links between the financial side and the real economy, and between financial risks and fiscal risks, have become strong. The future of macroprudential policy and the broader question of how to address financial crises is then more of a symptom than a cause of the blurring lines between monetary and fiscal policy, one element in a large and heated debate in academia as much as in the corridors of power.

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