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Leveraged bubbles ☆

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ABSTRACT

What risks do asset price bubbles pose for the economy? This paper studies bubbles in housing and equity markets in 17 countries over the past 140 years. History shows that not all bubbles are alike. Some have enormous costs for the economy, while others blow over. We demonstrate that what makes some bubbles more dangerous than others is credit. When fueled by credit booms, asset price bubbles increase financial crisis risks; upon collapse they tend to be followed by deeper recessions and slower recoveries. Credit-financed housing price bubbles have emerged as a particularly dangerous phenomenon.

> *[O]ver-investment and over-speculation are often important; but they would have far less serious results were they not conducted with borrowed money.*
> *– Irving Fisher, "The Debt-Deflation Theory of Great Depressions," 1933*

> *All of us knew there was a bubble. But a bubble in and of itself doesn't give you a crisis…. It's turning out to be bubbles with leverage.*
> *– Former Federal Reserve Chairman Alan Greenspan, CNBC Squawk Box, 2013*

What risk do asset price bubbles pose for an economy? Naturally, in the wake of the largest financial crisis since the Great Depression, the causes and consequences of extended mispricing of financial assets have climbed to the top of the agenda for macroeconomists and policymakers. It has become harder to dismiss such bubble episodes as rare aberrations and exclude them from macroeconomic thinking on axiomatic grounds.

In the pre-crisis consensus, to a large extent, policymakers and economists preferred to ignore bubbles, arguing that they could not exist, or could not be detected, or not reliably, or that nothing could or should be done, or there might be

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unintended consequences, and so on. Researchers and central bankers imagined that the problem of depressions had been solved and that the financial sector would be self-stabilizing. The financial stability role of central banks was mostly regarded as secondary, if not quaintly vestigial. The crisis exploded these and other myths which had taken hold based on very little firm empirical evidence, and with scant regard for the lessons of history. The Former Fed Chairman very publicly resiled from old beliefs: he stepped away from a benign neglect approach to markets' irrational exuberance, admitted the “flaw” in his worldview, and began to entertain, as above, the possibility that central banks might need to pay heed to bubbles, or at least some of them, rather more seriously than before.[1]

Yet how policymakers should deal with the potential risks emanating from asset price bubbles remains a hotly debated issue. In particular, the question as to whether central banks should use interest rates or macroprudential tools in response to such risks has attracted considerable attention. Recent influential contributions such as Svensson (2014) and Galí (2014) have cautioned against using interest rates to “lean against the wind”.

Where are we now? Among policymakers and economists a post-crisis consensus seems to be emerging, and this new view worries a lot about *leveraged bubbles*. Yet, the skeptic might well ask: Is not this new consensus just as detached from evidence-based macroeconomics as the last one? Is not more empirical work needed before we rush to embrace another approach? Sadly, as of now, if one seeks statistically powerful inference based on data from large samples, then one can find little empirical evidence about varieties of asset price bubbles and the damage they might wreak on the economy.

This paper aims to close this gap by studying the nexus between credit, asset prices, and economic outcomes in advanced economies since 1870. We use a dataset that spans the near universe of advanced economies in the era of modern economic growth and finance capitalism over the last 150 years. Financial crises and asset price boom–busts are relatively rare events. Thus, any empirical study must employ very long time series and the historical experience of more than one country to have any hope of conducting a reasonable statistical analysis, as our prior work has shown.

Our key result is that some bubbles matter more than others. What makes bubbles dangerous is the role of credit, as was belatedly suspected by Greenspan. This finding also fits with conjectures put forward by Mishkin (2008, 2009) and other policymakers after the crisis: the idea that there are two categories of bubbles. Pure, unleveraged “irrational exuberance” bubbles may pose a limited threat to financial stability or the macroeconomic outlook. “Credit boom bubbles,” on the other hand, may be a dangerous combination. In such bubbles, a positive feedback develops that involves credit growth, asset prices, and increasing leverage. When such credit boom bubbles go bust, in Mishkin's words, “the resulting deleveraging depresses business and household spending, which weakens economic activity and increases macroeconomic risk in credit markets.” Arguably, these deleveraging pressures have been a key reason for the slow recovery from the financial crisis (Mian and Sufi, 2014; Jordà et al., 2013).

This paper builds upon our previous research. In Jordà et al. (2013) we showed that the debt overhang from credit booms is an important feature of the business cycle and that it is associated with deeper and longer lasting recessions. Subsequently, we collected a more comprehensive dataset on credit than had been hitherto available in Jordà et al. (2015). This paper uses these new data together with novel long-run historical data on asset prices (both in equities and houses). These two datasets allow us to investigate the interaction between asset prices and debt overhangs.

The plan of the paper is as follows. First, we introduce the two historical datasets underlying this study. In the second part, we study the role of credit and asset price bubbles in the generation of financial crises. Using a comprehensive dataset, covering a wide range of macroeconomic and financial variables, we demonstrate that it is the interaction of asset price bubbles and credit growth that poses the gravest risk to financial stability. These results, based on long-rung historical data, offer the first sound statistical support based on large samples for the widely held view that the financial stability risks stemming from of an unleveraged equity market boom gone bust (such as the U.S. dotcom bubble) can differ substantially from a credit-financed housing boom gone bust (such as the U.S. 2000s housing market). Third, analyzing the consequences of bursting asset price bubbles for the macroeconomy, we show that the output costs in the depth of the financial crisis recession, and the speed of the subsequent recovery, are shaped by the interaction of asset price run-ups and the pace of credit growth in the prior boom phase.

Our conclusions align with an emerging post-crisis consensus, but with actual an evidentiary basis. Asset price bubbles and credit booms may be harmful, but the interaction of the two sows the seeds of severe economic distress. The risk of a financial crisis then rises substantially and the ensuing recessions are considerably more painful. Leveraged housing bubbles turn out to be the most harmful combination of all.

Our new discoveries also place a renewed and nuanced emphasis on our earlier work on the causes of financial instability (Schularick and Taylor, 2012; Jordà et al., 2015). It is not only credit growth, but the interaction of credit and asset prices that matters for financial stability risks and the economic costs of financial crises.

1. Data

Our study relies on the combination and extension of two new long-run macro-finance datasets that have recently become available. In Jordà et al. (2015) we presented the latest vintage of our long-run credit and macroeconomic dataset in

[1] For the CNBC interview see Matthew J. Belvedere, “Bubbles and leverage cause crises: Alan Greenspan,” October 23, 2013 ⟨http://www.cnbc.com/id/101135835⟩. For more depth see the interview with Gillian Tett (“An interview with Alan Greenspan,” *FT Magazine*, October 25, 2013).

Table 1
Data sources, period, and coverage details of the house price and equity price data. For each country, we show the period covered by the equity market index, the period covered by the house price index, and the period covered by the bank loans series.

Country	Equity prices	House prices	Bank loans
Australia	1870–2013	1870–2013	1870–2013
Belgium	1870–2013	1878–2013	1885–2013
Canada	1870–2013	1921–2013	1870–2013
Switzerland	1899–2013	1901–2013	1870–2013
Germany	1870–2013	1870–2013	1883–2013
Denmark	1914–2013	1875–2013	1870–2013
Spain	1870–2013	1971–2013	1900–2013
Finland	1912–2013	1905–2013	1870–2013
France	1870–2013	1870–2013	1900–2013
U.K.	1870–2013	1899–2013	1880–2013
Italy	1906–2013	1970–2013	1870–2013
Japan	1899–2013	1913–2013	1874–2013
Netherlands	1890–2013	1870–2013	1900–2013
Norway	1914–2013	1870–2013	1870–2013
Portugal	1929–2013	–	1870–1903/1920–2013
Sweden	1870–2013	1875–2013	1871–2013
U.S.	1870–2013	1890–2013	1880–2013

Notes: Equity prices are broad indices. House prices are quality adjusted where possible. For bank loans, the financial institutions covered include commercial banks (CB) and other financial institutions (OFI) such as savings banks, credit unions, and building societies. Data generally cover all monetary financial institutions.
Sources: Jordà et al. (2015) and Knoll et al. (2014). See appendix, Table 8.

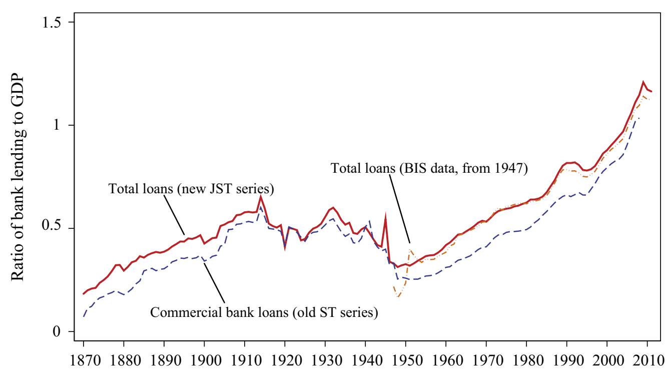

Fig. 1. Bank credit to the domestic economy, 1870–2013, with a comparison of data from three different sources: Average ratio to GDP by year for 17 countries. *Notes*: *Total Loans* (*new JST series*) refers to new data on total loans to the nonfinancial private sector (businesses and households) from the banking sector (broadly defined as explained in the text) and compiled by us for this paper. *Commercial bank loans* (*old ST series*) refers data on total loans to the nonfinancial private sector by commercial banks compiled by Schularick and Taylor (2012). *Total loans* (*BIS data*) refers to data on total loans by the banking sector compiled by the BIS (2013). All three series are reported as a fraction of GDP by year, based on a simple average across all 17 countries in the sample. See text.

the form of an annual panel of 17 countries since 1870.[2] To study asset price booms we have then added equity price data, as detailed below. The second dataset underlying the study by Knoll (2014) and Knoll et al. (2014) covers house prices since 1870 on an annual basis for the panel of 17 countries. Table 1 gives an overview of the underlying data we use for housing prices, stock market prices, and bank lending.

The combined data now include observations up to 2013, and therefore include the Global Financial Crisis and its aftermath. We have also stretched the coverage of equity prices, with data typically beginning in the late 19th or early 20th century for all countries.

Fig. 1 compares the new total bank credit series we have constructed with an older series from Schularick and Taylor (2012) which relied mainly on credit by commercial banks alone. After WW2, both series can be compared to the credit database maintained by the Bank for International Settlements (2013). The three series track each other closely, with the shift between the old Schularick and Taylor (2012) series and our new series reflecting the wider coverage of credit institutions.

The trends in long-run bank lending are well known by now: after an initial period of financial deepening in the late 19th century the average level of the credit-to-GDP ratio in advanced economies reached a plateau of about 50% on the eve of WW1. Subsequently, with the notable exception of the deep contraction seen in bank lending in the Great Depression and

[2] At the core of this dataset are credit aggregates series for bank lending for 17 countries, both for total and disaggregated credit. Data on macroeconomic control variables come from our previous work, where we relied on the efforts of other economic and financial historians and the secondary data collections by Maddison (2005), Barro and Ursúa (2008), and Mitchell (2008a,b,c). Data on financial crisis dates come from the now standard sources such as Bordo et al. (2001), Laeven and Valencia (2008, 2012), and Reinhart and Rogoff (2009).

WW2, the ratio broadly remained in this range until the 1970s. The trend then broke: the three decades that followed were marked by a sharp increase in the volume of bank credit relative to GDP. Bank lending on average roughly doubled relative to GDP between 1980 and 2010 as average bank credit to GDP increased from 61% to 114%. Put differently, the data dramatically underscore the expansion in credit that preceded the Global Financial Crisis of 2008. Even so, this is only a lower-bound estimate of the size of this recent credit boom; it excludes credit creation by the shadow banking system, which was significant in some countries, notably the U.S. and the U.K.

Turning to house prices, Knoll et al. (2014) combine data from more than 60 different sources. They construct house price indices reaching back to the early 1920s in the case of Canada; the early 1900s for Finland, Germany, Switzerland; the 1890s

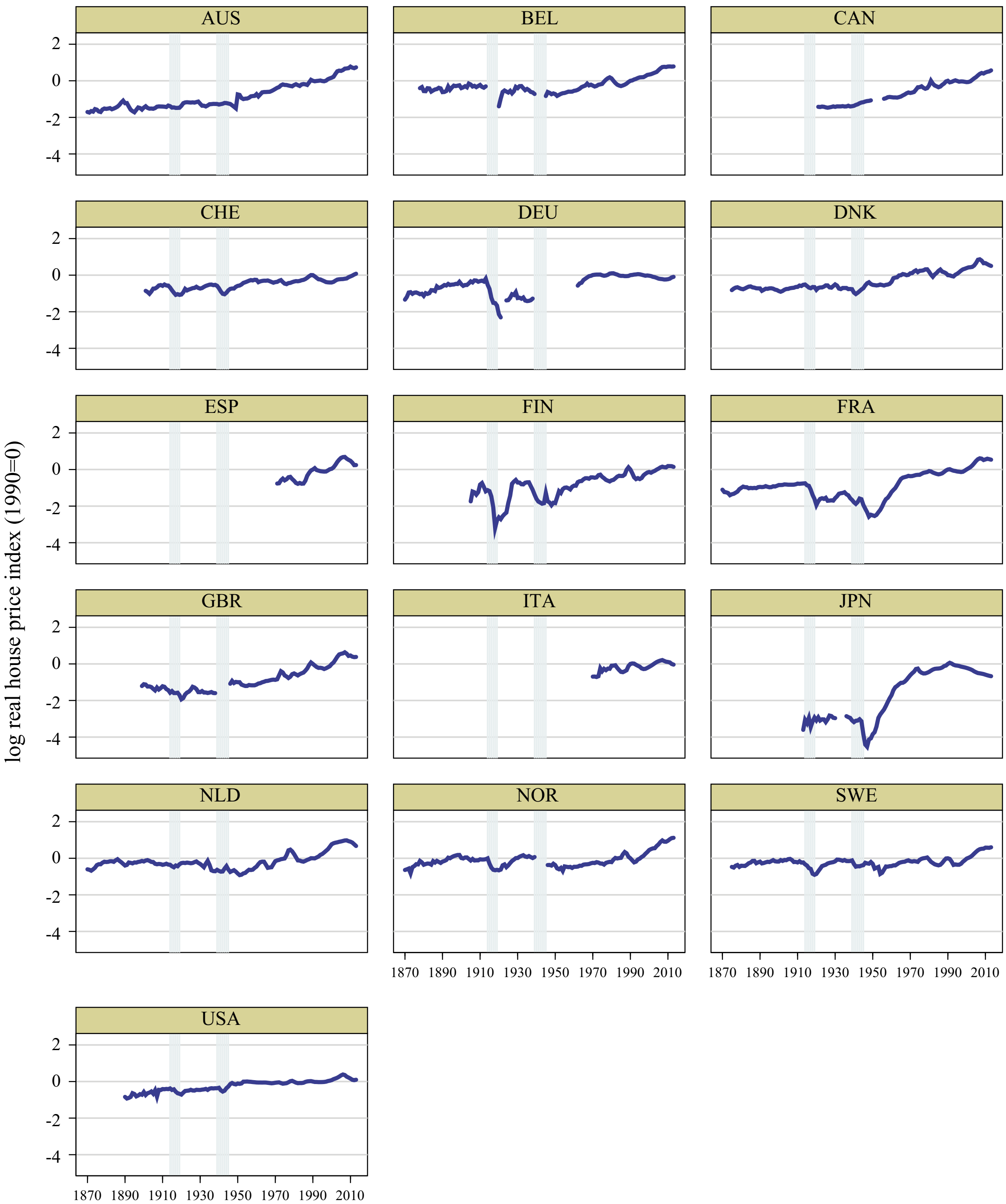

Fig. 2. Real house prices in the long run. *Notes*: Nominal house price index divided by consumer price index. See text. The years of the two World Wars are shown with shading.

for Japan, U.K., U.S.; and the 1870s for Australia, Belgium, Denmark, France, Netherlands, Norway. Compared to existing studies such as Bordo and Landon-Lane (2013), the dataset extends the series for the U.K. and Switzerland by more than 30 years, for Belgium by more than 40 years, and for Japan by more than 50 years. Overall, the new dataset doubles the number of country-year observations, allowing a more detailed study of long-run house price dynamics.

Constructing long-run house price data requires pragmatic choices between the ideal and reality. A house is the bundle of the structure and the underlying land. The price of the structure corresponds to its replacement value which is a function of construction costs. The best possible index would measure the appreciation of the price of a standard, unchanging house in each country. But houses are heterogeneous assets therefore posing particular challenges for the construction of price indices that are

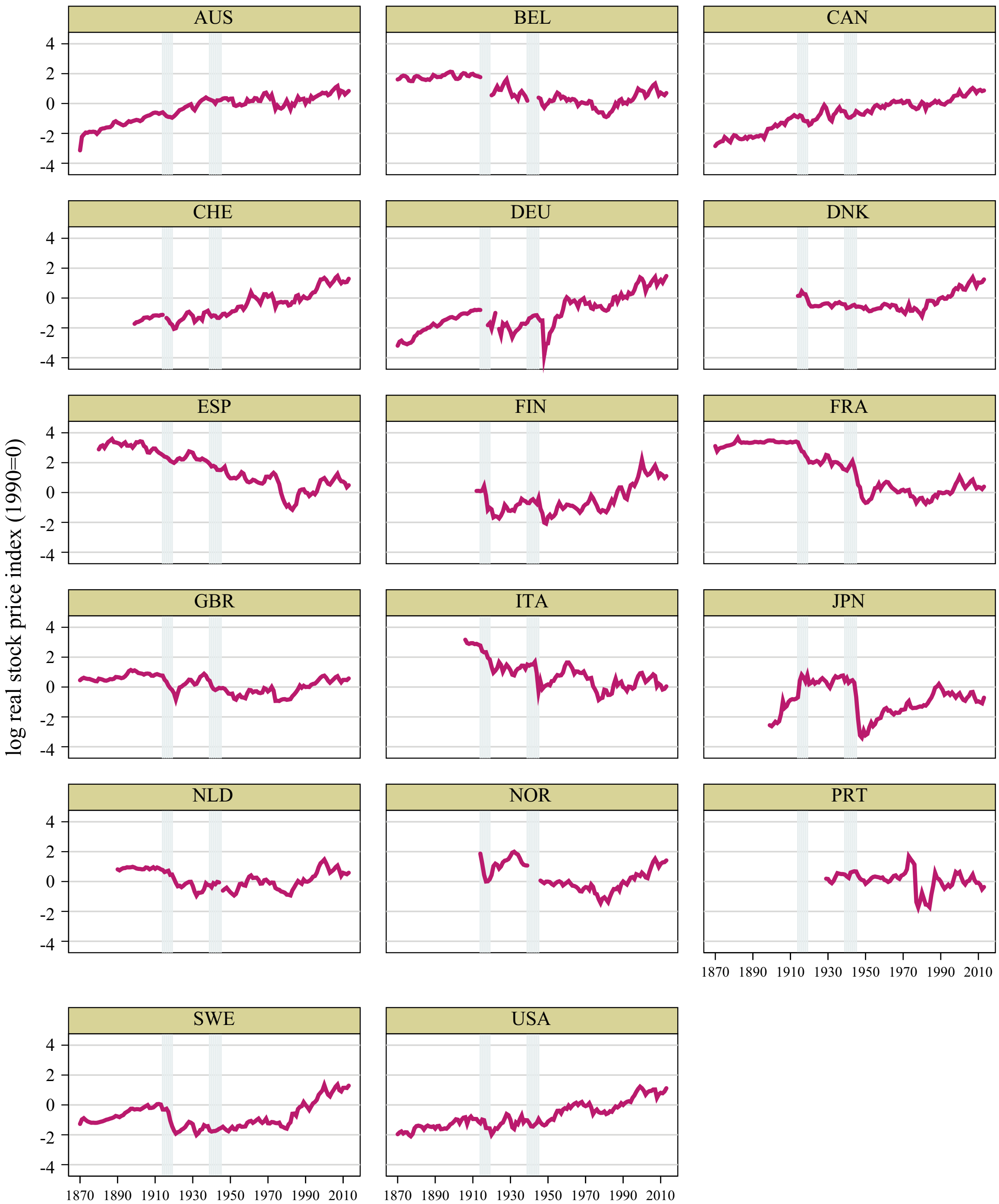

Fig. 3. Real equity prices in the long run. *Notes*: Nominal equity price index divided by consumer price index. See text. The years of the two World Wars are shown with shading.

comparable across countries. Moreover, house price data exist for shorter sample intervals and have to be spliced to construct at a long-run index. With these caveats in mind, the reconstructed series provide the best available basis for empirical analysis.

Knoll et al. (2014) show that the path of global house prices in the 20th century has not been continuous. Real house prices, deflated with the consumer price index (CPI), remained stable from 1870 until the middle of the 20th century after which they rose substantially, as Fig. 2 shows. Fig. 2 also demonstrates that there are large swings in real house prices. Periods of pronounced increases are often followed by abrupt corrections, as Knoll (2014) discusses. In addition, Fig. 2 demonstrates that there is considerable heterogeneity in house price trends across economies that otherwise have similar characteristics and comparable long-run growth performance.

Turning to equity prices, Fig. 3 displays the equity market data underlying our empirical analysis. Just like house prices, real equity prices exhibit considerable cross-country heterogeneity and volatility in the course of the 20th century. It is also noteworthy that, just as house prices, equity prices seem to share a general tendency to increase faster than CPI in recent decades.

In total, the asset price dataset assembled here—combining both equity and housing prices—is the largest of its kind to date. It rests on 2139 country-year equity price and 1855 house-price observations. On average, we have 126 years of equity prices and 109 years of housing prices per country. With sample size comes statistical power: using this large historical dataset, we can perform more formal benchmarking and statistical analysis for the near-universe of advanced-country macroeconomic and asset price dynamics, covering over 90% of advanced-economy output. In the next section, we briefly show how we identify asset price bubbles in the data before studying their economic consequences.

2. Empirical identification of asset price bubbles

The term "bubble" is typically used when asset prices deviate from their fundamental value in an asymmetric and explosive way, often in conjunction with a subsequent crash. Bubbles can occur even if investors have rational expectations and have identical information, so-called rational bubbles, but also under asymmetric information, in the presence of limits to arbitrage, and when investors hold heterogeneous beliefs (e.g., Brunnermeier, 2008).

Determining the presence of bubbles empirically, however, is no easy task. One option is to follow Borio and Lowe (2002), as well as Detken and Smets (2004) and Goodhart and Hofmann (2008), who have defined housing price booms as deviations of real house prices above some specified threshold relative to an HP filtered trend with a high smoothing parameter. We build upon this kind of definition, but it is not the only approach. Bordo and Jeanne (2002), by contrast, focus on the explosive growth dynamics instead of the level deviation from long-run assumed fair value. In their work, an asset price boom episode is detected when the 3-year moving average growth rate exceeds the series average by more than 1.3 times the series standard deviation. Other definitions of bubbles based on sustained peak-trough or trough-peak changes appear in works by Helbling (2005), Helbling and Terrones (2003), and Claessens et al. (2008) for the IMF.

As this brief survey makes clear, there is no accepted standard definition of bubble phenomena. Research has used both large deviations of price levels from some reference level and also large rates (or amplitudes) of increase/decrease as indicative of the rise and fall of bubble events.

In the following, we propose a combination of both approaches and apply two joint criteria for the detection of an asset price bubble episode. In essence, for our definition we require firstly that log real asset prices diverge significantly from their trend, becoming elevated by more than one standard deviation from a country-specific Hodrick–Prescott filtered trend ($\lambda = 100$, annual data). A discrete sequence of such years we now define as a price elevation *episode*. But, secondly, we also require for our definition that at some point during an episode of elevation thus defined, a large price correction occurs ("the bubble bursts"), with real asset prices falling by more than 15% (a change of -0.15 log points) over a 3-year window looking forwards from any year in the episode.

The precise signals we use in each country-year observation are defined as follows, where p_{it} is the log real asset price, whether equity or housing; z_{it} is the HP detrended log real asset price (for that country); and $I(.)$ is the indicator function:

$$\text{Price Elevation Signal}_{it} = I(z_{it} > \text{standard deviation of } z \text{ in country } i),$$

$$\text{Price Correction Signal}_{it} = I(p_{i,t+3} - p_{it} < -0.15),$$

$$\text{Bubble Signal}_{it} = (\text{Price Elevation Signal} = 1) \quad \text{and} \quad (\text{Price Correction Signal} = 1 \text{ at some point in the episode}).$$

We developed these joint criteria to avoid counting as bubbles cases where prices ran up quickly, but did not correct downwards sharply, e.g., because fundamentals improved sufficiently to give justification to the price rise, or prices rose from depressed levels and converged back to fundamentals. For robustness we also re-ran all of our analysis using only the first signal, with little change in the results. Furthermore, although the literature favors defining asset prices in real terms, we also experimented with asset prices normalized relative to nominal GDP and nominal GDP per capita. The main results reported in Section 6 did not change materially, and are not reported here, although they are available upon request.

To provide a more granular view of our bubble signal algorithm, Fig. 4 zooms in on several 10-year windows surrounding well-known asset price boom and bust cycles for several countries in our dataset. The line in each chart plots the log real asset price for that country in the specified period, with the ± 1 s.d. reference band centered on the HP trend, and the markers on the line with year labels pick out those years which our algorithm selects as "bubble" episodes. To the naked eye the algorithm seems to produce reasonable signals for all these cases.

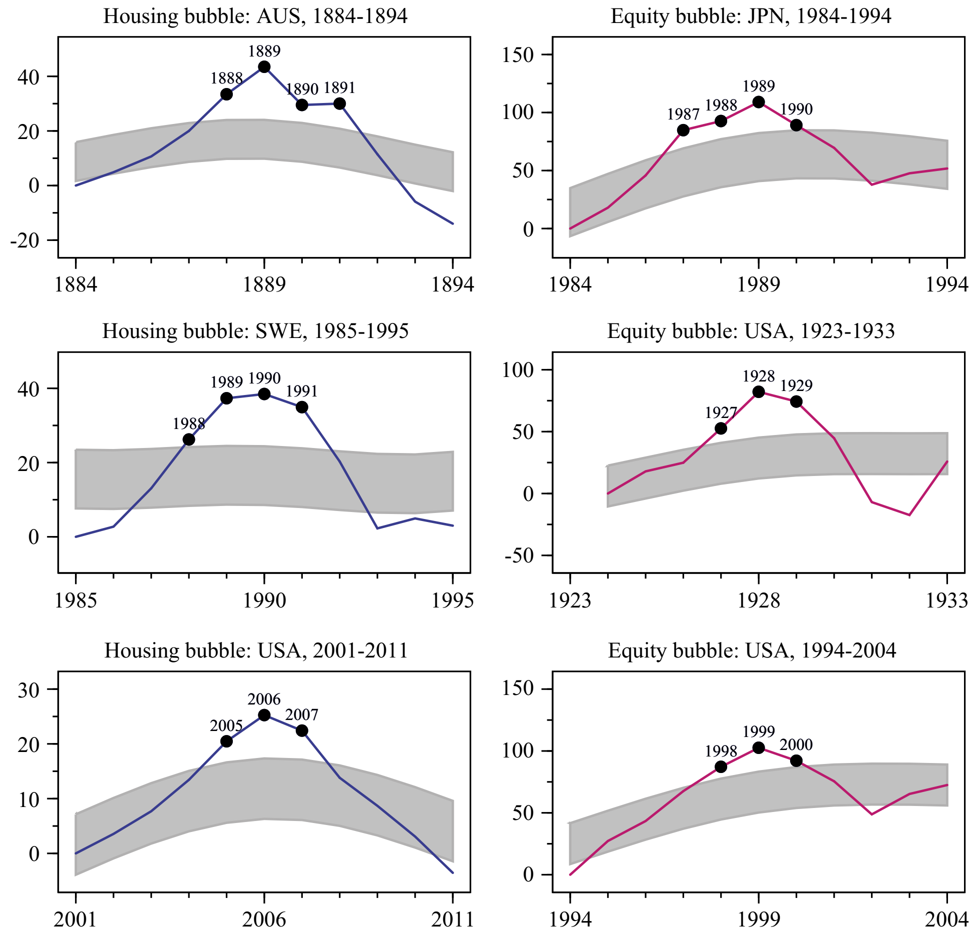

Fig. 4. Examples of the bubble indicator for six illustrative episodes. The figures show, for each 10-year window, the log real asset price (rebased to the start year), a band of ± 1 s.d. (for that country's detrended log real asset price), and the years for which the Bubble Signal is turned on using our algorithm. *Notes*: See text.

Table 2
Average amplitude, rate, and duration of bubbles.

	Full sample		Pre-WW2		Post-WW2	
	(1) Equity	(2) House	(3) Equity	(4) House	(5) Equity	(6) House
Amplitude	28.1 (24.3)	14.9 (13.8)	22.5 (17.9)	11.8 (17.0)	30.0 (25.9)	17.3 (10.5)
Rate	14.9 (11.0)	5.2 (3.7)	12.1 (10.7)	4.8 (4.7)	15.8 (11.1)	5.5 (2.7)
Duration	2.1 (1.0)	3.1 (1.3)	2.4 (1.1)	3.0 (1.7)	2.0 (1.0)	3.2 (0.8)
Observations	98	41	24	18	74	23

Notes: *Amplitude* refers to the percentage change in the price from the point in time where the asset price breaks the one standard deviation barrier with respect to the Hodrick–Prescott trend, and the collapse of the bubble. *Rate* refers to the annual rate of change in the price of the asset identified by the *amplitude* variable. *Duration* refers to the number of periods that the bubble lasts so that *amplitude* divided by *duration* equals *rate*. Standard errors in parenthesis. See text.

Finally, Table 2 provides a bird's-eye view of the main features of equity and housing bubbles from the point they start until they collapse. Start is defined as the moment when the price elevation signal switches on at $+1$ s.d. Comparing columns (1) and (2) based on the full sample, it is clear that fluctuations in equity prices are far more volatile, and on average, about twice the size of those in house prices. As a result, the average duration of equity bubbles is one-third shorter on average (2 versus 3 years). These differences are similar across eras, as the subsample analysis in columns (3)–(6) reveals.

Table 3
Relative frequency of asset price bubbles by type of recession.

Financial crisis recessions	Full sample (1)	Pre-WW2 (2)	Post-WW2 (3)
No bubble	15	13	2
Equity bubble	13	6	7
Housing bubble	5	2	3
Both bubbles	13	2	11
Total	46	23	23
Normal recessions	(4)	(5)	(6)
No bubble	70	46	24
Equity bubble	34	4	30
Housing bubble	7	3	4
Both bubbles	9	2	7
Total	120	55	65

Notes: The table entries show the number of events of each type in the relevant sample period. Recessions are the peaks of business cycles identified using Bry and Boschan (1971) algorithm. A recession is labeled *financial* if there is a financial crisis within a 2 year window of the peak. Otherwise it is labeled *normal*. Bubble episodes are associated with recessions by considering the expansion over which the bubble takes place and using the subsequent peak. See text.

Some of the most fabled historical episodes that our bubble signal picks up include the Australian real estate boom of the 1880s that crashed in the early 1890s leading to a prolonged period of economic adjustment. We also pick up a major speculative real estate boom that took hold in Copenhagen and spread to other Danish cities in the early 1900s. We also detect the 1920s real estate boom in the U.S. The parallels of this last event to the boom and bust of the 2000s have recently been analyzed by White (2014): housing starts surged and, with large regional variation, prices rose strongly, fueled by easy credit and financial innovations. The crash occurred in the mid-1920s, well in advance of the Great Depression. Yet it led to a surge in foreclosures that weakened the financial system.

The equity boom–bust of the late 1920s is arguably the most famous asset price boom and bust episode in modern economic history. From their trough in 1921, U.S. equity prices had increased 6-fold by 1929, but the Roaring Twenties ended for good that year on October 24, Black Thursday. The market fell 11% in the space of a few minutes of trading. The following week, Black Thursday was followed by Black Monday and Black Tuesday: on both days, shares posted double-digit losses. The Wall Street crash of October 1929 has ever since played a central role in historical accounts of the Great Depression.

Turning to the second half of the 20th century, our bubble signal picks up the Swiss housing boom in the 1980s as well as the Scandinavian boom and bust episodes of the late 1980s and early 1990s, often linked to the process of financial deregulation that swept the region at the beginning of the decade. The Japanese asset price bubble accelerated strongly after 1985 (Okina et al., 2001). Initially, equity prices posted the strongest gains. Land prices only followed the Nikkei index with a lag of a few years. Japanese urban land prices doubled over a few years, while the price of listed equities tripled. Equity prices peaked in 1989, while real estate peaked in 1991. While stock prices had fallen by 60% in 1992 already, land prices deflated more slowly and remained on a downward trajectory for almost two decades after their peak. By 2012, the nominal value of real estate was about half its 1991 value.

3. Bubbles and the business cycle

Are financial crisis recessions typically preceded by asset price booms? The Global Financial Crisis, the gravest crisis to engulf advanced economies since the Great Depression, is often linked to the bursting of a housing bubble in the U.S. The analysis going forward will switch to a recession-based calendar to study the after effects of leverage and asset price booms. We begin with Table 3 which provides a simple tally of this association in the context of our historical dataset.

The recession dates that we use henceforth refer to the just-preceding *peak* of the business cycle, that is, the year in which activity starts to decline. Recessions are dated using the Bry and Boschan (1971) algorithm. In annual data, this simply means that years in which output is below (above) its previous level are years of recession (expansion). Furthermore, we separate recessions into financial crisis recessions (those recessions where a financial crisis took place within a ± 2 year window) and normal recessions (for which we are unable to find a concomitant financial event). We split the sample before and after WW2 in addition to provide the full sample results. With this change of dating, bubble episodes are henceforth associated with each peak according to whether the bubble signal is equal to one in the preceding expansion phase. Therefore, the sample statistics reported in the previous section (computed over all years) will not apply to recession episodes in the remainder of the paper.[3]

An important reason to split the sample at WW2 is the dramatic break in the trend growth of lending following this turning point as seen in Fig. 1. This break was heavily driven by a surge in postwar mortgage lending (Jordà et al., 2015), often in concert with government programs to promote home ownership. Home ownership rates in the U.K. before WW2 stayed well below 30% and barely cracked 50% in the U.S., for example. On the eve of the Great Recession those numbers more than doubled for the U.K.

[3] For example, there could be bubble signals in a recession phase and there could be more than one bubble in an expansion phase.

and would top out at 65% in the U.S. The implication for the analysis is clear and well reflected in Table 3. As a larger portion of the population invested in real estate, fluctuations in the price of this asset class had more widespread economic implications.

The first noteworthy result in the top panel of Table 3 is that financial crisis recessions in the pre-WW2 era were just as likely to take place in association with a bubble episode in equities and/or housing than not: 10 out of 23 financial recessions have this feature. In part this likely reflects the observation that speculation took place in other asset classes, primarily commodities. For example, the panic of 1907 in the U.S. is often associated with speculation in copper by United Copper Co. When copper prices collapsed, so did United Copper and its main creditor, the Knickerbocker Trust Co., at the time the third largest financial institution in the U.S. The fall of Knickerbocker set off massive consolidation of the financial system (and subsequently the creation of the Federal Reserve System), as well as one of the largest waves of bank failures in U.S. history.

After WW2, however, we find that all but 2 financial crisis recessions (out of a total of 23) were associated with a collapse of equity and/or housing prices. The differences do not stop there. Whereas equity price booms play a prominent role in those financial recessions associated with a bubble episode before WW2 (6 out of 10 bubble-related financial crisis recessions involved equities alone), after WW2 it appears that most episodes involved bubbles in both equity and housing prices, with 11 out of 21 bubble-related financial crisis recessions linked to bubbles in both asset classes.

What about normal recessions? Is there a similar pattern pre- and post-WW2? Do bubbles always lead to recessions? The bottom panel of Table 3 contains the frequency tally of bubble episodes in normal recessions. And just as with financial crisis recessions, there are marked differences between the pre- and post-WW2 eras. Before WW2, the vast majority of normal recessions have no links to bubbles in either equities or housing, and 46 out of 55 normal recessions fit this mold. After WW2 only about one-third, or 24 out of 65 recessions, fall in this category. About half of the post-WW2 era recessions, 30 out of 65, are linked to bubbles only in equities, and a much smaller number is linked with a bubble in housing prices or both housing prices and equities (4 and 7 episodes, respectively, out of 65 total normal recessions).

It is useful to keep in mind that equity prices are far more volatile that housing prices. As a result, we find a larger proportion of equity price bubbles relative to housing price bubbles. For the full sample, there are 26 equity price bubble episodes versus only 18 housing price bubbles out of just 46 financial crisis recessions. The contrast is starker in normal recessions with 43 equity price bubble episodes relative to 16 housing price bubbles, out of a much larger total of 120 normal recessions.

Finally, financial crisis recessions happened regularly in the pre-WW2 era. Nearly one-third of all recessions (23 out of 78) are classified as a financial crisis recession. After WW2 the incidence of these disruptive episodes wanes somewhat: 23 out of 88 post-WW2 recessions are classified as being associated with a financial crisis.

Table 3 already reveals several important themes in the data that we will explore in more detail in the next few sections. Importantly, the post-WW2 era appears to have weathered numerous equity price bubbles that did not turn into financial crisis episodes. Housing price bubbles, although less frequent, are more disruptive and are more likely to be associated with a financial crisis episode.

In the next few sections we will elaborate further on this distinction. First, we will ask under what circumstances do bubbles lead to financial crises. Second, we will aim to quantify the economic consequences of asset price bubbles. We will show that credit growth plays a central role both for the likelihood that a bubble leads to a financial instability and for the costs of a bursting bubble on the economy as a whole.

4. Asset price bubbles and financial crises

One of the most striking features of the era of modern finance has been the surge in bank lending (as a ratio to GDP) in advanced economies following WW2 and first reported in Schularick and Taylor (2012). Subsequent research has further clarified the sources of this proliferation in bank lending. Building on the original data collected by Schularick and Taylor (2012), Jordà et al. (2015) break down bank lending into mortgage and nonmortgage lending. While both types of bank lending experienced rapid growth in the post-WW2 era, the share of mortgages relative to other types of lending grew from a low point of less than 20% in the 1920s to the nearly 60% in the Great Recession.

Rapid expansion of credit has subsequently been associated with a higher likelihood of experiencing a financial crisis recession (Jordà et al., 2013; Drehmann and Juselius, 2014). The goal of this section is to study the interaction of asset price bubbles and credit growth in generating financial crisis recessions.

In particular, we investigate how the pairing of credit and asset price bubbles affect the probability that a recession will be financial in nature. Define a binary variable $F_{i,t(p)} \in \{0, 1\}$ for $p = 1, \ldots, P$ and $i = 1, \ldots, 17$. For each country i, the $F_{i,t(p)}$ is defined only when calendar time t coincides with a peak p in economic activity—the start of a recession. Therefore the sample size is P, the total number of peaks in the sample. $F_{i,t(p)}$ takes the value of one if the pth peak corresponds to a financial crisis recession (defined as a recession where a financial crisis is recorded to have happened at any time in a two year window of the peak), and is zero if the recession was normal instead.

The data on peaks spans 1870–2013 in 17 advanced economies, as we described earlier, and are therefore best thought of as a panel. In order to accommodate the observation that some countries experience more financial crisis recessions than others, we include a set of fixed effects and estimate a simple panel logit model. We call this the *benchmark* model and the summary statistics of fit are reported in column (1) in Table 4 for the full sample analysis, and column (4) for the post-WW2 subsample. This fixed-effects only specification captures the heterogeneity in a sample of 17 countries. The specification

Table 4
Logit models for financial recessions. Full and post-WW2 samples.

	Full sample			Post-WW2 sample		
	(1) Benchmark	(2) Credit only	(3) Full model	(4) Benchmark	(5) Credit only	(6) Full model
Credit		0.40*** (0.11)			0.49*** (0.17)	
No bubble × credit			0.22 (0.18)			0.56 (0.35)
Equity bubble × credit			0.18 (0.18)			−0.07 (0.29)
Housing bubble × credit			0.54*** (0.20)			0.55* (0.30)
Both bubbles × credit			0.82*** (0.30)			1.20** (0.50)
Pseudo-R^2	0.03	0.13	0.16	0.08	0.20	0.295
AUC	0.61 (0.05)	0.71 (0.05)	0.71 (0.05)	0.69 (0.07)	0.76 (0.06)	0.82 (0.06)
Observations	142	142	142	81	81	81

Notes: Standard errors in parentheses. The dependent variable based on peaks of business cycles identified using Bry and Boschan (1971) algorithm. The dependent variable is one if the recession is associated with a financial crisis within a 2-year window of the peak, 0 otherwise. Bubble episodes are associated with recessions by considering the expansion over which the bubble takes place and using the subsequent peak. See text.

* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

simply models the probability of a financial crisis recession as

$$Pr\left[F_{i,t(p)}=1|\alpha_i\right]=\frac{\exp(\alpha_i)}{1+\exp(\alpha_i)}. \tag{1}$$

Next we consider a credit control. This variable is defined in similar fashion to the credit variable in Jordà et al. (2013). It measures the growth of credit over the expansion preceding the pth peak in deviations from a country mean (again, to soak up any cross-country variation that may unduly enhance the fit of the model). The results of extending the benchmark model are reported in column (2) of Table 4 for the full sample, and column (5) for the post-WW2 subsample. The specification of the logit model now becomes

$$Pr\left[F_{i,t(p)}=1|\alpha_i,(x_{i,t(p)}-\overline{x}_i)\right]=\frac{\exp(\alpha_i+\beta(x_{i,t(p)}-\overline{x}_i))}{1+\exp(\alpha_i+\beta(x_{i,t(p)}-\overline{x}_i))}. \tag{2}$$

The final specification interacts the credit variable with our bubble indicators. The objective is to capture the interaction of having a bubble and credit expansion during the expansion that precedes the recession in question. Here we consider a collection of different scenarios: (a) recessions preceded by a housing price bubble, $d^H_{i,t(p)}=1$; (b) recessions preceded by a bubble in equities, $d^E_{i,t(p)}=1$; (c) recessions preceded by normal asset price fluctuations, $d^N_{i,t(p)}=1$; and (d) recessions preceded by both a bubble in equities and a bubble in house prices, $d^B_{i,t(p)}=1$. The variables $d^j_{i,t(p)}$ for $j=H,E,N,B$ are dummy variables. The results of this exercise are reported in columns (3) and (6) in Table 4 for the full and post-WW2 samples, respectively. The specification of the logit in this case becomes

$$Pr\left[F_{i,t(p)}=1|\alpha_i,(x_{i,t(p)}-\overline{x}_i),d^j_{i,t(p)}\right]=\frac{\exp(\alpha_i+\beta(x_{i,t(p)}-\overline{x}_i)+\sum_j\gamma_j d^j_{i,t(p)}(x_{i,t(p)}-\overline{x}_i))}{1+\exp(\alpha_i+\beta(x_{i,t(p)}-\overline{x}_i)+\sum_j\gamma_j d^j_{i,t(p)}(x_{i,t(p)}-\overline{x}_i))}. \tag{3}$$

Before discussing the particulars of the estimation, we remark on how we measure the ability of the model to sort recessions into normal versus financial crisis recessions. We move away from metrics based on the likelihood (such as the reported pseudo-R^2) and focus instead on the AUC statistic, which stands for the *area under the curve*. This statistic takes on the value 0.5 in models where the covariates offer no ability to sort the data into each bin, and takes on the value of 1 in models with the ability to perfectly sort the data. The reason to use this type of statistic is that models with apparent low fit can nevertheless have considerable classification ability. The AUC statistic is a standard in biomedical research and is frequently reported when evaluating the properties of medical tests. It has the advantage that in large samples it is approximately distributed as a Gaussian random variable. In economics, Jordà and Taylor (2011) explain its properties and its applicability. We refer the interested reader to their paper.

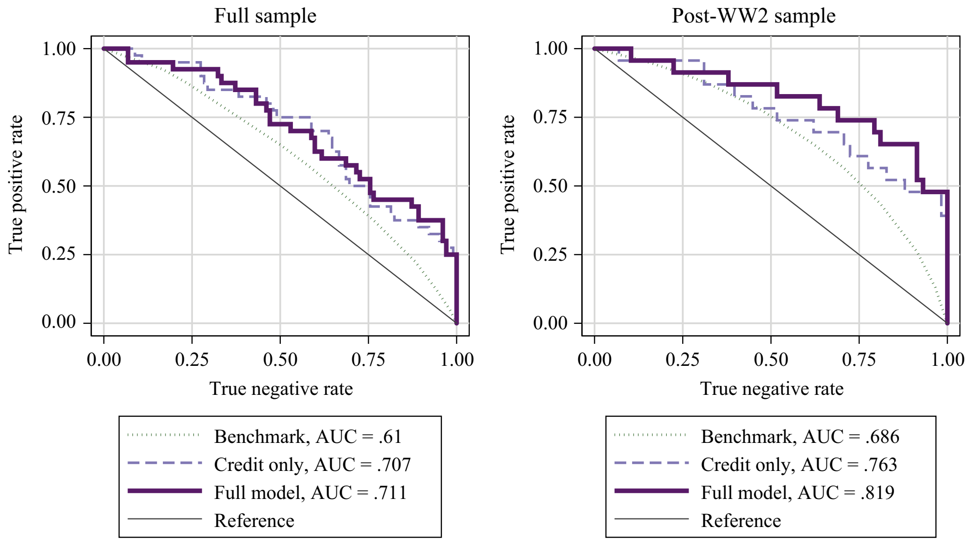

Fig. 5. Correct classification frontiers for financial recessions: the interaction of credit and asset price bubbles. *Notes*: The CCF for the post-WW2 corresponds to the estimates in columns (4)–(6) of Table 4 whereas the full sample CCF corresponds to the estimates reported in columns (1)–(3) of Table 4.

Turning our attention to Table 4 first, consider the benchmark model reported in column (1). This model has an AUC=0.61 indicating fairly low sorting ability, but different from the 0.50 null. The explanation is that knowing what country is under consideration is useful because some countries have experienced more financial crisis recessions than others in our sample. Next, column (2) extends the model with the credit variable. Here we are able to replicate the main result in Jordà et al. (2013): credit growth is associated with a higher likelihood of experiencing a financial crisis recession (notice that the coefficient estimate is positive). The AUC grows from 0.61 to 0.71 and is statistically significantly different from the benchmark null.

The more interesting set of results is reported in column (3). The interaction with the different bubble scenarios is quite revealing. The coefficient estimates all have the correct sign (they are positive). Moreover, the coefficients associated with the incidence of either a housing bubble or both bubbles at the same time have a statistically significant coefficient whereas the coefficient on credit when there is no bubble, or only an equity bubble, in the preceding expansion is not significant and close in value to zero. The AUC for this model is 0.71, hardly an improvement on the simpler model in column (2) based on the credit variable alone. However, the more revealing part of this exercise is to be found in the magnitudes and significance levels of the individual coefficients on the interaction terms in this model, as reported in column (3).

In order to assess the properties of these estimates before and after WW2 and in light of the trends in mortgage credit discussed earlier, we turn or attention to the results reported in columns (4)–(6) for the post-WW2 sample. The benchmark model is reported in column (4) and attains an AUC of 0.69. Knowing the country is still informative, more so given the smaller size of the sample. Next, column (5) confirms the Jordà et al. (2013) results reported in column (2). Credit remains an important factor in understanding financial crises. The AUC climbs to 0.76 in the post-WW2 sample, a very respectable value indicating high levels of sorting ability.

Finally, column (6) displays estimates for the full model in which the credit variable is interacted with each of the bubble scenarios. These results suffer from having a smaller sample, but by and large support the findings in columns (1)–(3) using the full sample. However, over this period the equity bubble scenario has a coefficient that is not statistically significant. This is consistent with the summary statistics reported in Table 3. In the post-WW2 era there are many instances of normal recessions preceded by equity bubbles that did not trigger a financial episode. The AUC climbs further from 0.76 to 0.82.

As a way to visualize the sorting ability of the different models we display in Fig. 5 the *correct classification frontiers* (or CCFs) of the full sample and post-WW2 models. The CCF plots the rate of true predictions of financial crisis recession on the vertical axis (true positive rate) against the rate of true predictions of normal recession (true negative rate). A perfect classification technology would generate a CCF that would hug the north-east corners of the unit square whereas a classifier no better than a coin toss would generate a classification technology on the diagonal of this same unit square. Jordà and Taylor (2011) provide a more careful and detailed explanation on how this curve can be constructed and its statistical properties.[4]

[4] Here, $F_{i,t(p)}$ is a binary outcome (0 or 1). Let $\hat{p}_{i,t(p)} = Pr[F_{i,t(p)} = 1|\hat{\theta}]$ be our binary classifier using the logit models, with estimated parameters collected in $\hat{\theta}$. The true positive rate is $TP(c) = P(\hat{p}_{i,t(p)} > c|F_{i,t(p)} = 1)$, and the specificity of the classifier as the true negative rate $TN(c) = P(\hat{p}_{i,t(p)} \le c|F_{i,t(p)} = 0)$.

We define the Correct Classification Frontier or CCF, a variant of the ROC curve, as the plot of the true positive rate $TP(c)$ against the true negative rate $TN(c)$, for all thresholds c on the real line. When the threshold c gets large and negative, the classifier is very aggressive in making crisis recession calls, almost all signals are above the threshold, and (TN,TP) converges to $(0,1)$ as $c \to \infty$; conversely, when c gets large and positive, the classifier is very conservative in making crisis recession calls, almost all signals are below the threshold, and (TN,TP) converges to $(1,0)$ as $c \to -\infty$.

The area under the CCF, known as the area under the curve (AUC) will be 0.5 for the null uninformative classifier and 1 for a perfect classifier. Concerning inference, testing whether a classifier is informative, or better than an alternative classifier, is simple with the AUC statistic since it is asymptotically normally distributed with a variance that can be easily estimated.

Both figures clearly show that there are considerable gains in classification ability from using the panel logit estimates based on the covariates considered, rather than the fixed effects null. More importantly, the results of this exercise support an important observation: credit booms in the expansion tend to be associated with a higher likelihood of a subsequent financial crisis recession, and the interaction with asset prices is especially important in the post-WW2 period. In the next section we explore the interaction between credit and asset bubbles over the business cycle in more detail.

5. The economic costs of bubbles

We have seen that credit fueled asset price bubbles, especially those in housing markets after WW2, are associated with a higher likelihood of financial crisis recession. Moreover, Cerra and Saxena (2008) and Jordà et al. (2013) show that financial crisis recessions tend to be deeper and more protracted. In this section, we ask whether the bursting of bubbles in asset markets are particularly associated with deeper recessions. To answer this question we turn to modern, semi-parametric time series methods.

The empirical approach we use is based on the local projections method pioneered by Jordà (2005). The particular setup we use here closely mirrors that in Jordà et al. (2013). Specifically, let $\Delta_h y_{i,t(p)+h} = y_{i,t(p)+h} - y_{i,t(p)}$ for $h = 1, \ldots, 5$ and where $y_{i,t(p)}$ refers to 100 times the log of output per capita in country i at the time of the pth peak or recession. In other words, $\Delta_h y_{i,t(p)+h}$ measures the cumulative growth rate of output per capita from period $t(p)$ to period $t(p)+h$ measured in percent. This is the left-hand side variable whose fluctuations we are interested in characterizing.

Because of sample size limitations, we are unable to pursue as ambitious a specification as we used in the previous section. Moreover, since the pre-WW2 sample contains too few instances of housing bubbles, in the analysis that follows we focus solely on full sample results and results based on the post-WW2 era only. Furthermore, we approach the problem more modestly by examining recessions and their recovery on average in the presence of bubbles in equities and house prices, but sorted depending on whether credit during the expansion grew above or below the historical mean rather than with an interaction term as we did in the previous section. Before we bring additional controls, we set up the benchmark specification.

Using similar definitions to those in the previous section, we define a bubble indicator variable, $d^j_{i,t(p)} = 1$ if the prior expansion has a bubble in $j = (E)quity, (H)ouse$ prices. Next, define the indicator variable $\delta_{i,t(p)} = \mathbf{1}[(x_{i,t(p)} - \overline{x}_i) > \overline{(x_{i,t(p)} - \overline{x}_i)}]$, which is meant to capture when credit grows above the historical mean ($\delta_{i,t(p)} = 1$) or below the mean ($\delta_{i,t(p)} = 0$). In order to account for country fixed effects but still estimate an overall average constant path, we define the fixed effects to add up to one and implicitly define them in reference to the U.S. as follows: $D_{i,t(p)} = \mathbf{1}[i]/I$ for $i = 1, \ldots, I-1$ where I denotes the U.S. Hence the benchmark local projection specification is

$$\Delta_h y_{i,t(p)} = \sum_{i=1}^{I-1} \alpha_{i,h} D_{i,t(p)} + \mu_h + \sum_j \gamma_h^{j,Hi} d^j_{i,t(p)} \times \delta_{i,t(p)} + \sum_j \gamma_h^{j,Lo} d^j_{i,t(p)} \times (1 - \delta_{i,t(p)}) + \epsilon_{i,t(p)} \quad \text{for } h = 1, \ldots, 5, \tag{4}$$

and the coefficients of interest are μ_h, which capture the average path of output in a recession and subsequent recovery, and the coefficients $\gamma_h^{j,k}$ for $j = E, H$ and $k = Hi, Lo$ with Hi indicating when credit grew above the mean in the preceding expansion, and Lo when it grew below the mean. The coefficients $\gamma_h^{j,k}$ capture how much worse the path of the recession is whenever there is a bubble in either equities or house prices and credit in the expansion grows above or below the historical mean. That is, the sum of μ_h and $\gamma_h^{H,Hi}$, for example, refers to the average path of the recession and recovery when the preceding expansion had above average growth in lending and a housing bubble.

Table 5 reports the estimates of expression (4) for the full sample that we consider. That is, yearly data over the following periods, 1870–1909, 1920–1935, and 1948–2013; basically, we exclude 5-year windows around the two World Wars. The entry labeled *Recession* shows the average path of real GDP per capita after a peak when there are no bubbles (in the prior expansion). In the first year of recession real GDP per capita declines by 1.9%. By year 2, the economy bounces back into positive territory and keeps growing so that by year 5 real GDP per capita is 6% above where it started. This pattern is consistent with Cerra and Saxena (2008) and Jordà et al. (2013). As a summary statistic of the post-recession path for each type of outcome, the final column labeled "Sum" presents a direct LP-estimate of the cumulated recession baseline path and the cumulated total of the GDP losses relative to that baseline in each of the bubble cases sustained over the five-year window.

How does the presence of an asset price bubble affect these paths? We start with bubbles in equity markets which, as we saw in Section 3, are more frequent events than bubbles in housing markets. When accompanied by below average credit growth, equity bubbles appear to have virtually no effect on the depth of the recession and the speed of the recovery. This is true in a statistical sense since as only one of the coefficient estimates is significant, but also quantitatively as the coefficient estimates themselves are small. When the equity bubble coincides with above average credit growth, the effect is stronger. In that case the recession lasts an extra year and the overall drag after five years is 3.6 percentage points of real GDP per capita relative to the peak of the cycle.

Turning to housing bubbles, it is immediately obvious that they are considerably more damaging events. The drag on the economy is more than twice as big as with equity bubbles in cases accompanied by higher than average credit growth. In terms of the path of the recession and recovery, we note that it can sink the economy for several years running so that even by year 5 real GDP per capita is still below the level at the start of the recession.

These results can be more easily visualized in Fig. 6. The left-hand side panel shows the average path of real GDP per capita of the no-bubble economy along with the average path when there is an equity bubble and below/above average

Table 5
LP recession/recovery path, no controls, full sample, 1870–2013. *Dependent variable:* cumulative percentage change in real GDP per capita (100 × Δ log).

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5	(6) Sum
Recession	−1.93***	0.75	3.49***	5.43***	6.10***	13.84***
	(0.27)	(0.48)	(0.70)	(0.90)	(0.89)	(2.97)
Equity bubble, low credit	−0.16	−2.12**	−2.27	−2.07	−1.26	−7.87
	(0.46)	(0.92)	(1.34)	(1.33)	(1.63)	(4.97)
House bubble, low credit	−0.17	−1.21	−2.89	−3.33	−1.95	−9.55
	(0.61)	(1.08)	(1.84)	(2.50)	(2.52)	(8.00)
Equity bubble, high credit	0.13	−1.87	−3.70**	−4.05**	−3.60*	−13.08*
	(0.51)	(1.17)	(1.66)	(1.81)	(1.99)	(6.32)
House bubble, high credit	−0.86	−5.34*	−7.09***	−8.27**	−8.03**	−29.60**
	(1.71)	(2.78)	(2.42)	(3.66)	(3.22)	(13.40)
Macroeconomic controls	No	No	No	No	No	No
Bubble terms = 0, *p*-value	0.98	0.01	0.01	0.03	0.02	0.02
R^2	0.522	0.235	0.220	0.253	0.309	0.211
Observations	140	140	140	140	140	140

Notes: Standard errors (clustered by country) in parentheses. The dependent variable is the cumulative change in real GDP per capita from the peak of the business cycle (the start of the recession). Peaks are identified using Bry and Boschan (1971) algorithm. Bubble episodes are associated with recessions by considering the expansion over which the bubble takes place and using the subsequent peak. The bubble indicators are binned depending on whether bank lending (credit in the table) grew above (high) or below (low) the historical mean. See text.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

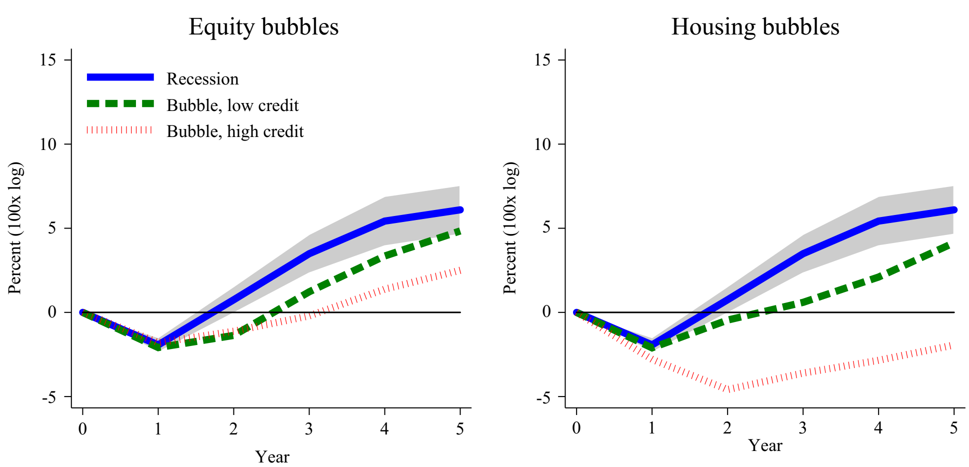

Fig. 6. Recession and recovery paths: the role of bubbles and credit, no controls, full sample. *Notes*: The figure displays the coefficients reported in Table 5. The solid blue line reports the average no-bubble path. The grey area represents the 90% confidence region around the average path. The green dashed line is the sum of the average no-bubble path and the bubble coefficient when credit is below the mean, whereas the dotted red line is the sum of the average no-bubble path and the bubble coefficient when credit is high. Full sample: 1870–2013, excludes the World Wars and a window of 5 years around them. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

credit growth, and the right-hand side panel shows a similar chart using the housing bubble indicator instead. Each panel displays the baseline no-bubble path with a 90% confidence region.

5.1. Adding controls

Table 5 and Fig. 6 provide the first of several interesting findings, and they accord well with the results discussed in Section 4. Briefly, it appears that equity bubbles are less harmful to the economy than housing bubbles are. However, regardless of the type, asset bubbles associated with rapid credit growth are especially damaging. These results could be manifestations of other economic phenomena happening at the same time and driving the bubbles and credit creation themselves. Consequently, we expand the control set as much as possible to try to account for macroeconomic conditions existing at the start of the recession.

In order to do this, we expand the specification of the benchmark local projection in expression (4). First, in order to account for whether higher than average credit growth has a negative effect on output beyond its interaction with the bubble indicators, we include $\delta_{i,t(p)}$ directly as a regressor. Note that we cannot enter $(1-\delta_{i,t(p)})$ simultaneously as a regressor since then we would have perfect colinearity with the constant term.

Next, we include the value at the peak and one lag of the following controls: (1) the growth rate of real GDP per capita; (2) the growth rate in investment per capita; (3) the CPI inflation rate; (4) the short-term interest rate (usually measured as the 3-month rate on government securities); (5) the long-term interest rate (usually measured as the 5-year rate on government securities); and (6) the current account to GDP ratio.

Suppose we let $X_{i,t(p)}$ denote the vector containing the seven controls observed at the peak and one lag. Expression (4) with the additional controls becomes a new specification

$$\Delta_h y_{i,t(p)} = \sum_{i=1}^{I-1} \alpha_{i,h} D_{i,t(p)} + \mu_h + \beta_h \delta_{i,t(p)} + \sum_j \gamma_h^{j,Hi} d_{i,t(p)}^j \times \delta_{i,t(p)} + \sum_j \gamma_h^{j,Lo} d_{i,t(p)}^j \times (1-\delta_{i,t(p)}) + X_{i,t(p)}\Phi + \epsilon_{i,t(p)} \quad \text{for } h=1,\ldots,5. \quad (5)$$

We now present estimates of this form, which are the central preferred results of this paper, and selected coefficient estimates of expression (5) are reported in Table 6 for the 1870–2013, excluding 5-year windows around the World Wars, whereas estimates based on shorter sample from the post-WW2 period (1948–2013) are reported in Table 7. Fig. 7 presents in graphical form the estimates from both tables by appropriately combining the coefficients in expression (5).

The basic lessons from the naïve analysis in expression (4) and Table 5 remain largely unchanged with the additional controls. Equity bubbles are damaging. They are associated with a worse recession and a slower recovery in the full sample. However, as we shall see, the damage from equity bubbles largely dissipates after WW2. The paths of real GDP per capita become largely indistinguishable from the typical path in recessions. Although equity bubbles have limited effect overall, they are clearly associated with more damage when accompanied by above average growth in credit regardless of the sample studied.

Meanwhile, bubbles in housing prices are associated with noticeably worse recessions and recovery paths of real GDP per capita, and even more so when credit expands above the historical mean during the preceding expansion. Panel (a) of Fig. 7 makes this difference readily apparent. The coefficient estimates are negative and statistically significant.

Table 7 repeats the estimation of expression (5) but restricting the sample to the post-WW2 period. As we discussed earlier, there are some differences in the incidence of bubble episodes before and after WW2. However, the pre-WW2 sample is too short to provide reliable estimates. Hence, the comparison between Tables 6 and 7 and panels (a) and (b) of Fig. 7 provide the best way to assess the stability of our findings across samples. By and large the differences are small, although there is perhaps one noticeable difference. Allowing for the decline in precision in the shorter sample, and focusing

Table 6
LP recession/recovery path, with controls, full sample, 1870–2013. *Dependent variable:* cumulative percentage change in real GDP per capita (100 × Δ log).

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5	(6) Sum
Recession	−1.83***	0.80	3.20***	5.92***	7.07***	15.16***
	(0.35)	(0.73)	(0.79)	(1.38)	(1.13)	(4.04)
Equity bubble, low credit	−0.49	−2.26*	−2.97**	−2.99**	−2.37	−11.08**
	(0.41)	(1.11)	(1.30)	(1.39)	(1.47)	(5.11)
House bubble, low credit	−0.18	−1.73	−3.69**	−5.13**	−4.01*	−14.74**
	(0.56)	(1.12)	(1.60)	(2.25)	(2.12)	(6.94)
Equity bubble, high credit	−0.07	−2.03	−4.49***	−4.22**	−3.69**	−14.50**
	(0.68)	(1.69)	(1.45)	(1.67)	(1.54)	(5.94)
House bubble, high credit	−0.29	−5.08*	−6.54**	−8.52**	−8.52***	−28.95**
	(1.79)	(2.80)	(2.35)	(3.74)	(2.87)	(12.84)
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Bubble terms=0, p-value	0.83	0.01	0.01	0.01	0.01	0.01
R^2	0.594	0.319	0.404	0.416	0.484	0.396
Observations	140	140	140	140	140	140

Notes: Standard errors (clustered by country) in parentheses. The dependent variable is the cumulative change in real GDP per capita from the peak of the business cycle (the start of the recession). Peaks are identified using Bry and Boschan (1971) algorithm. Bubble episodes are associated with recessions by considering the expansion over which the bubble takes place and using the subsequent peak. The bubble indicators are binned depending on whether bank lending (credit in the table) grew above (high) or below (low) the historical mean. See text.

* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 7
LP recession/recovery path, with controls, post-WW2 sample. *Dependent variable:* cumulative percentage change in real GDP per capita (100 × Δ log).

	(1) Year 1	(2) Year 2	(3) Year 3	(4) Year 4	(5) Year 5	(6) Sum
Recession	−0.99***	1.51**	3.77***	6.05***	8.15***	18.48***
	(0.26)	(0.54)	(0.84)	(1.13)	(1.38)	(3.76)
Equity bubble, low credit	−0.55	−1.58	−0.74	−0.64	−0.81	−4.32
	(0.45)	(1.02)	(1.35)	(1.69)	(1.94)	(6.04)
House bubble, low credit	−0.09	−1.78	−3.26*	−4.13*	−4.30*	−13.55
	(0.72)	(1.62)	(1.84)	(2.10)	(2.21)	(7.85)
Equity bubble, high credit	−0.35	−2.39*	−2.25	−1.97	−1.51	−8.46
	(0.69)	(1.32)	(1.41)	(1.74)	(1.77)	(5.99)
House bubble, high credit	0.98	−2.25*	−5.02***	−5.83***	−7.51***	−19.63***
	(0.89)	(1.09)	(1.29)	(1.75)	(1.99)	(5.68)
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Bubble terms=0, p-value	0.10	0.00	0.00	0.00	0.01	0.00
R^2	0.679	0.508	0.602	0.675	0.744	0.621
Observations	85	85	85	85	85	85

Notes: Standard errors (clustered by country) in parentheses. The dependent variable is the cumulative change in real GDP per capita from the peak of the business cycle (the start of the recession). Peaks are identified using Bry and Boschan (1971) algorithm. Bubble episodes are associated with recessions by considering the expansion over which the bubble takes place and using the subsequent peak. The bubble indicators are binned depending on whether bank lending (credit in the table) grew above (high) or below (low) the historical mean. See text.

* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

therefore on the point estimates, in the post-WW2 sample it makes a much bigger difference whether the bubble is in equities or houses: housing booms appear more damaging and equity booms less damaging than in the full sample, but both are still much worse when they are matched with a credit boom.

Before we examine the robustness of our results, we summarize the main findings so far. Recessions tend to last for one year and the average loss of output is just under 2% in real per capita terms. The recovery starts in year 2 by which time most of the loss in the first year is made up, and the economy continues to grow at about the same yearly rate for the next three years. If the economy experiences an asset price bubble (as we have defined it) during the preceding expansion, the recession tends to be deeper and the recovery slower. The detrimental effects of an asset price bubble depend on two factors: whether the bubble happens in equities or in houses, and whether the bubble happens to coincide with rapid growth in private credit as well. Our results clearly show that over the history of advanced economies, the worst outcomes are clearly when the bubble is in housing prices and there is a credit boom. In that case, even after five years, the economy typically has not yet quite recovered from the recession and is still struggling to regain its peak level of real GDP per capita.

Several factors could affect these preliminary conclusions and the next section conducts a number of robustness checks. In Section 4 we saw that credit fueled bubbles have classification ability for whether the recession is normal or associated with a financial crisis. Therefore, the next section evaluates whether allowing for a different average path depending on whether the recession is normal or not will undo our main results. The second important robustness check has to do with the differences we have reported all along between the pre- and post-WW2 periods. The pre-WW2 period is characterized by the preponderance of equity bubbles over housing bubbles and to a great extent, this result could be driven by the volatile period between the two World Wars. Thus, we check how sensitive are our results when we exclude this particularly tumultuous interwar era. Finally, many of the conclusions from this section are an almost too-perfect description of the Global Financial Crisis and Great Recession. Naturally, we ask to what extent the results on how the economy responds are driven by the recent experience. To that end, we cut off the sample in 2008 to examine whether the main results survive when we omit this potentially influential episode.

5.2. Robustness check 1: accounting for financial crises

The first of the robustness checks investigates whether the estimates we obtain for our bubble indicators may be proxying for the fact that financial crisis recessions are different from normal recessions and asset price bubbles are often associated with financial crises, as Section 4 showed. The simplest way to check for this effect is to expand the specification in expression (5). Let $F_{i,t(p)}=1$ if the recession at time $t(p)$ is a financial crisis recession, 0 otherwise. Including this indicator

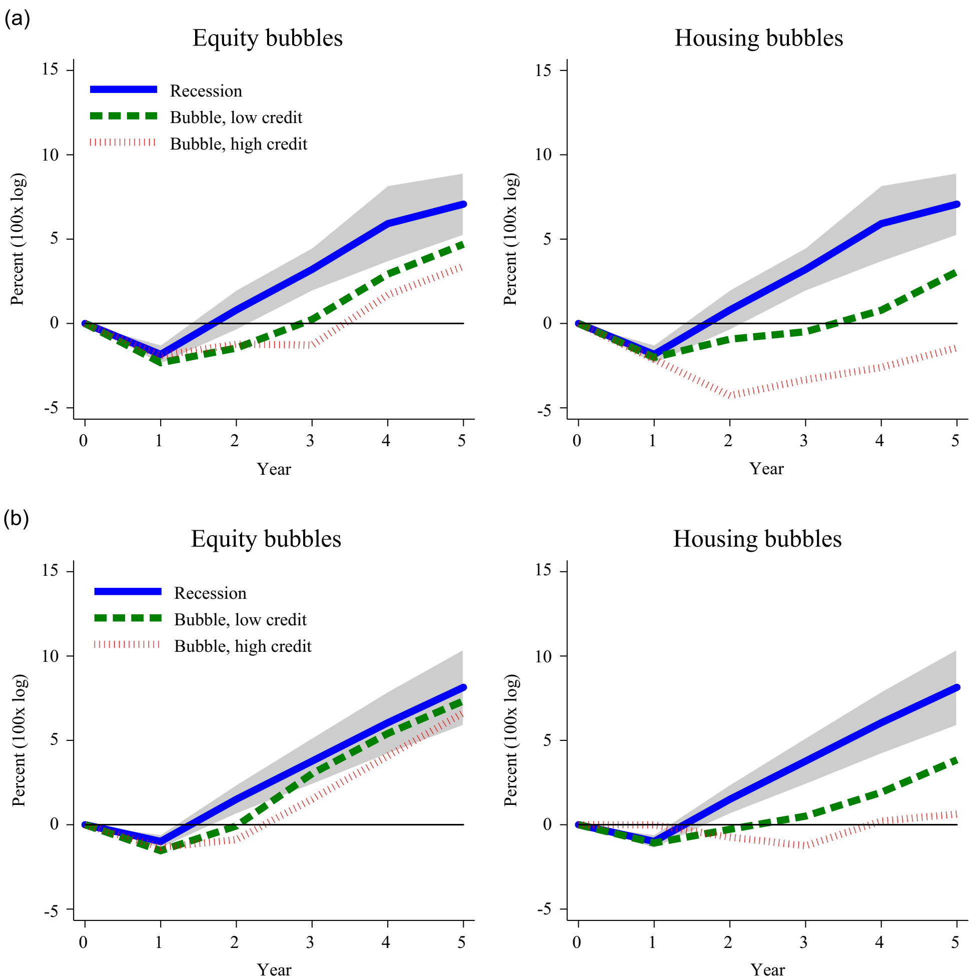

Fig. 7. Recession and recovery paths: the role of bubbles and credit, with controls. (a) Full sample, 1870–2013. (b) Post-WW2 sample, 1948–2013. *Notes*: Panel (a) in the figure displays the coefficients reported in Table 6, whereas panel (b) corresponds to the coefficients in Table 7. The solid blue line reports the average no-bubble path. The grey area represents the 90% confidence region around the average path. The green dashed line is the sum of the average no-bubble path and the bubble coefficient when credit is below the mean, whereas the dotted red line is the sum of the average no-bubble path and the bubble coefficient when credit is high. The full sample, 1870–2013, excludes the World Wars and a window of 5 years around them. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

in expression (5) we obtain a new specification

$$\Delta_h y_{i,t(p)} = \sum_{i=1}^{I-1} \alpha_{i,h} D_{i,t(p)} + \mu_h + \beta_h \delta_{i,t(p)} + \theta_h^{Hi} F_{i,t(p)} \delta_{i,t(p)} + \sum_j \gamma_h^{j,Hi} d_{i,t(p)}^j \times \delta_{i,t(p)} + \theta_h^{Lo} F_{i,t(p)} (1-\delta_{i,t(p)}) + \sum_j \gamma_h^{j,Lo} d_{i,t(p)}^j$$
$$\times (1-\delta_{i,t(p)}) + X_{i,t(p)} \Phi + \epsilon_{i,t(p)} \quad \text{for } h = 1, \ldots, 5. \tag{6}$$

That is, we interact the financial crisis recession indicator $F_{i,t(p)}$ with the indicator that determines whether credit grew above or below the historical mean, $\delta_{i,t(p)}$.

The results of this estimation are reported in Fig. 8(a). With this estimation strategy, the financial crisis recession indicator picks up on the fact that this type of recession tends to be worse than normal recessions, a fact already documented in Cerra and Saxena (2008), for example, as well as in our own earlier work. However, even though we are now soaking up this source of variation from the data directly, the coefficient estimates for the bubble–credit interaction indicators are qualitatively similar to the estimates reported in Table 6 and Fig. 7(a). The effects of bubble–credit interactions are somewhat attenuated, as one would expect, but they do not go to zero even with this harsh test. The difference between equity versus housing bubbles remains. The former are bad, the latter are worse.

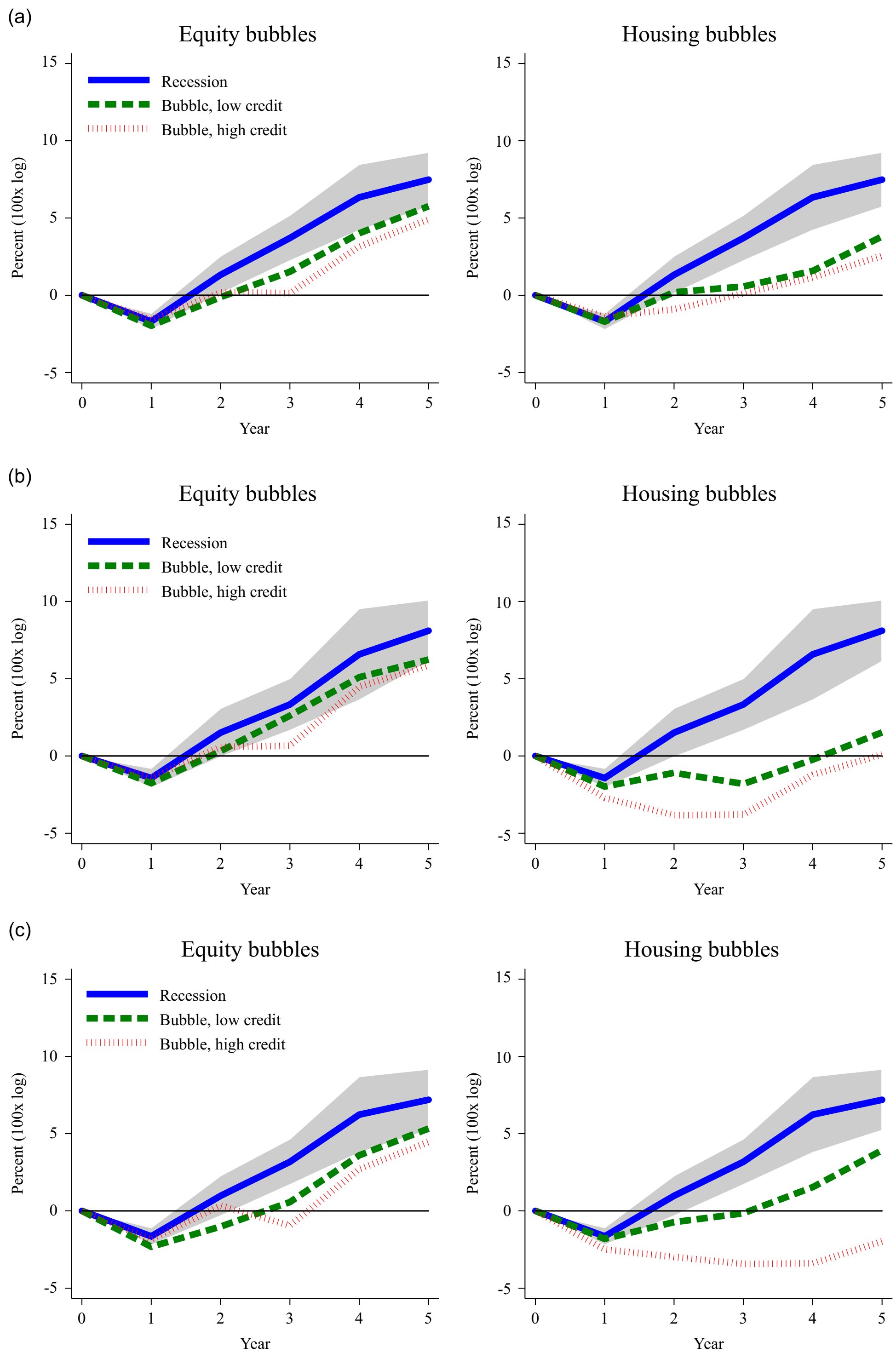

Fig. 8. Recession and recovery paths: robustness checks with controls. (a) Including indicators for normal/financial recessions, full sample 1870–2013. (b) Sample excluding the interwar years, 1870–1909 and 1948–2013. (c) Sample excluding the years since Global Financial Crisis, 1870–2006. *Notes*: The solid blue line reports the average no-bubble path. The grey area represents the 90% confidence region around the average path. The green dashed line is the sum of the average no-bubble path and the bubble coefficient when credit is below the mean, whereas the dotted red line is the sum of the average no-bubble path and the bubble coefficient when credit is high. All samples exclude the World Wars and a window of 5 years around them. See text. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

5.3. Robustness check 2: excluding the interwar period

The interwar period, which we define to be between 1909 and 1948, to include 5-year windows around the two world wars, was characterized by a volatile macroeconomic environment and considerable turmoil in international financial markets. Naturally, this period includes the Great Depression, and the Crash of 1929, which could be skewing some of the results we have been reporting so far about the changing importance of equity bubbles and the overall results we have reported in Table 6 and Fig. 7(a).

We therefore performed the experiment of re-estimating the results excluding the interwar years and this is reported in Fig. 8 (b). The broad picture remains largely unchanged. Equity bubbles become somewhat less relevant (not surprisingly, since we have eliminated from the sample the 1930s slump, which followed a massive equity run-up), and the dramatic effects of credit booms and housing price bubbles remain of about the same magnitude as in our main results.

5.4. Robustness check 3: excluding the global financial crisis

The last robustness check that we conduct examines whether the strong core results we find in our full sample estimation are driven by the recent Global Financial Crisis. In many countries, notoriously the U.S. and Spain, a deep slump followed an expansion which saw the coupling of a housing bubble and a rapid expansion of mortgage lending, including shadow banking activities such as mortgage backed securities, and other housing related derivatives. It was the collapse of house prices and the credit crunch that heralded the fall of the economic dominoes in 2007–2008.

Fig. 8(c) re-estimates the main results by truncating the sample to pre-2007 years, which limits the estimation sample to recession peaks and recoveries from years before the Global Financial Crisis had erupted. Again, the data indicate strongly that our core findings reported in Table 6 and Fig. 7(a) are not the result of this one global episode but rather an enduring characteristic in the historical record.

6. Conclusion

Do asset price bubbles and leverage pose a risk to macroeconomic and financial stability? And, setting aside the numerous competing theoretical explorations of this question, what does the evidence show? In light of recent events these are some of the most pressing questions for researchers and policymakers in macroeconomics and finance.

In recent years, central banks typically ignored credit and stayed on the sideline when asset price bubbles inflated. Their hands-off approach has been criticized, among others, by institutions such as the BIS that took a less sanguine view of the self-equilibrating tendencies of financial markets and warned of the potentially grave consequences of asset price busts. The critical assumption was that central banks would be in a position to manage the macroeconomic fall-out. They could clean-up after the mess. While the aftermath of the dotcom bubble seemed to offer support for this rosy view of central bank capabilities, the 2008 Global Financial Crisis dealt a severe blow to the assumption that the fall-out of asset price bubbles was always and everywhere a manageable phenomenon.

Although these observations are based on just two data points from recent history, they mesh well with the key finding of this paper: not all bubbles are created equal. In this paper, we turned to economic history for the first comprehensive assessment of the costs of asset price bubbles. We provide evidence on which types of bubbles matter and how their economic costs differ. From a monetary and macroprudential policy point of view, our findings may help us to understand the tradeoffs involved in the "leaning against the wind" and "mopping up after" strategies. We show that when credit growth fuels asset price bubbles, the dangers for the financial sector and the real economy are much more substantial. The damage done to the economy by the bursting of credit-boom bubbles is significant and long-lasting. These findings can inform ongoing efforts to devise better guides to macro-financial theory and its real-world application at a time when policymakers are searching for new approaches in the aftermath of the Great Recession.

Appendix A: House price data

This table shows the geographic coverage, method, and sources of the house price index used in this paper, based on Knoll (2014) and Knoll et al. (2014).

Table 8
House price data.

Country	Period	Geographic coverage	Type of real estate	Method
Australia	1870–1889	Urban (Melbourne)	Existing dwellings	Median price
	1900–2002	Urban (6 capital cities)	Existing dwellings	Median price
	2003–2013	Urban (8 capital cities)	New and existing dwellings	Mix adjustment
Belgium	1878–1950	Urban (Brussels area)	Existing dwellings	Median price
	1951–2003	Nationwide	Existing dwellings	Mean price
	2004–2013	Nationwide	Existing dwellings	Mix adjustment
Canada	1921–1949	Nationwide	Existing dwellings	Replacement value
	1956–1974	Nationwide	New and existing dwellings	Average prices
	1975–2013	Urban (5 Cities)	Existing dwellings	Average prices
Denmark	1875–1937	Rural	Existing dwellings	Average prices
	1938–1970	Countrywide	Existing dwellings	Average prices
	1971–2013	Countrywide	New and existing dwellings	SPAR method
Finland	1905–1946	Urban (Helsinki)	Building sites	Average sq. m. prices
	1947–1969	Urban (Helsinki)	Existing dwellings	Average prices
	1970–2013	Nationwide	Existing dwellings	Mix adj. hedonic
France	1870–1935	Urban (Paris)	Existing dwellings	Repeat sales
	1936–1995	Nationwide	Existing dwellings	Repeat sales
	1996–2013	Nationwide	Existing dwellings	Mix adj. hedonic
Germany	1870–1902	Urban (Berlin)	Developed and undeveloped	Average prices
	1903–1922	Urban (Hamburg)	Developed and undeveloped	Average prices
	1923–1938	Urban (10 cities)	Developed and undeveloped	Average prices
	1962–1969	Nationwide	Building sites	Average prices
	1970–2013	Urban	New and existing dwellings	Mix adjustment
Japan	1880–1913	Rural	Residential land	Average prices
	1913–1930	Urban	Residential land	
	1930–1936	Rural	Paddy fields	
	1936–1955	Urban	Residential land	
	1955–2013	Urban	Residential land	Mix adjustment
Netherlands	1870–1969	Urban (Amsterdam)	Existing dwellings	Repeat sales
	1970–1996	Nationwide	Existing dwellings	Repeat sales
	1997–2013	Nationwide	Existing dwellings	SPAR method
Norway	1870–2003	Urban (4 cities)	Existing	Hedonic, repeat sales
	2004–2013	Urban (4 cities)	Existing	Hedonic
Switzerland	1900–1929	Urban (Zurich)	Developed and undeveloped	Average price
	1930–1969	Nationwide	New and existing	Hedonic
	1970–2013	Nationwide	New and existing	Mix adjustment
Sweden	1870–2013	Stockholm, Gothenburg	Existing	Repeat sales
United Kingdom	1899–1929	Urban	Existing dwellings	Average prices
	1930–1938	Nationwide	New and existing dwellings	Average price
	1946–1952	Nationwide	Existing dwellings	Average prices
	1953–1967	Nationwide	New dwellings	Average prices
	1968–2013	Nationwide	Existing	Mix adjustment
United States	1890–1934	Urban (22 cities)	New and existing dwellings	Repeat sales
	1935–1952	Urban (5 cities)	Existing dwellings	Median prices
	1953–1974	Nationwide	New and existing dwellings	Mix adjustment
	1975–2013	Nationwide	Existing dwellings	Repeat sales

Source: Knoll (2014) and Knoll *et al.* (2014).

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