Housing finance

SUMMARY

This paper unveils a new resource for macroeconomic research: a long-run dataset covering disaggregated bank credit for 17 advanced economies since 1870. The new data show that the share of mortgages on banks' balance sheets doubled in the course of the twentieth century, driven by a sharp rise of mortgage lending to households. Household debt to asset ratios have risen substantially in many countries. Financial stability risks have been increasingly linked to real estate lending booms, which are typically followed by deeper recessions and slower recoveries. Housing finance has come to play a central role in the modern macroeconomy.

JEL codes: C14, C38, C52, E32, E37, E44, E51, G01, G21, N10, N20

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The great mortgaging: housing finance, crises and business cycles

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1. INTRODUCTION

The past three decades have seen an unprecedented surge in the scale and scope of financial activities in advanced economies – a process that is sometimes referred to as *financialization*. Its effects continue to be contentiously debated.

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Financialization shows up in the rising income share of finance (Greenwood and Scharfstein, 2013; Philippon and Resheff, 2013), the ascent of household debt (Mian and Sufi, 2014), as well as the growth of the volume of financial claims on the balance sheets of financial intermediaries (Schularick and Taylor, 2012; Jordà *et al.*, 2013). The increasing size and leverage of the financial sector has been interpreted as an indicator of excessive risk taking (Admati and Hellwig, 2013; Aikman *et al.*, 2015) and has been linked to the increase in income inequality in advanced economies (Godechot, 2012; Piketty, 2013), as well as to the growing political influence of the financial industry (Johnson and Kwak, 2013). Clearly, understanding the causes and consequences of the growth of finance is a first-order concern for macroeconomists and policy-makers. Yet surprisingly little is known about the driving forces of these important new trends in modern financial history.

This paper studies these issues through the lens of long-run macroeconomic history. Our first contribution is to unveil a new resource for macroeconomic research: a long-run dataset on disaggregated bank credit for 17 advanced economies since 1870. The dataset is the result of a large-scale investigative process and an extensive standardization effort to produce consistent time series. In addition to our new credit variables, the data-set also contains a rich set of macroeconomic controls. The new data allow us to delve much deeper into the driving forces of *financialization* than has been possible until now.

The database that we provide covers disaggregated bank balance sheet data at annual frequency for the near universe of industrial countries since 1870. In particular, we study the development of various subcomponents of loans on banks' balance sheets – secured and unsecured lending as well as lending to businesses and households – over a span of 140 years. We document the rising share of real estate lending (i.e., bank loans secured against real estate) in total bank credit and the declining share of unsecured credit to businesses and households. We also document long-run sectoral trends in lending to companies and households (albeit for a somewhat shorter time span), which suggest that the growth of finance has been closely linked to an explosion of mortgage lending to households in the last quarter of the twentieth century. The key facts that the new data allow us to establish can be summarized as follows.

First, we demonstrate that the sharp increase of credit-to-GDP ratios in advanced economies in the twentieth century has been first and foremost a result of the rapid growth of *loans secured on real estate*, i.e., *mortgage and hypothecary lending*.[1] The share of mortgage loans in banks' total lending portfolios has roughly doubled over the course of the past century – from about 30% in 1900 to about 60% today. To a large extent, the core business model of banks in advanced economies today resembles that of real estate funds: banks are borrowing (short) from the public and capital markets to invest (long) into assets linked to real estate.

[1] We will use the terms 'mortgage lending' and 'real estate lending' interchangeably in this paper.

Second, looking more deeply at the composition of bank credit, it becomes clear that the rapid growth of *mortgage lending to households* has been the driving force behind this remarkable change in the composition of banks' balance sheets. The intermediation of household savings for productive investment in the business sector – the standard textbook role of the financial sector – constitutes only a minor share of the business of banking today, even though it was a central part of that business in the nineteenth and early twentieth centuries. We also find that household mortgage debt has risen faster than asset values in many countries resulting in record-high leverage ratios that potentially increase the fragility of household balance sheets and the financial system itself. Complementing the recent influential work of Mian and Sufi (2014) for the United States, our work takes a longer and wider view to show that the blowing up and bursting of private credit booms centered on aggressive mortgage expansion reflects deep processes at work across *all* of the advanced countries, and building up persistently across the entire post-World War II period.

Third, we demonstrate that the shifts in the composition of banks' balance sheets have important consequences for our understanding of the source of financial instability. Mortgage lending booms were only loosely associated with financial crisis risks before World War II, but real estate credit has become a more important predictor of impeding financial fragility in the post-war era. From the perspective of policy-makers aiming to design new macro-prudential policies today, our work confirms the crucial role of mortgage credit in the build-up of financial fragility.

Fourth, by using our new disaggregated credit data we can robustly demonstrate that the magnitude and structure of credit booms have important consequences for business-cycle dynamics. Reinhart and Rogoff (2009, pp. 215–20) argued that financial crisis recessions may have a tendency to be long and painful, a conjecture based on simple path averages for a sample of 18 post-war bank-centered financial cases in advanced economies. Here, with our granular historical dataset, we perform more formal benchmarking and statistical analysis for the near-universe of advanced-country macroeconomic performance since 1870, covering over 90% of advanced economy output, and encompassing up to 200 recession episodes, with 1/4 of them linked to a financial crisis and 3/4 being normal cycles.[2]

[2] Note that we focus on advanced economies only, as in Reinhart and Rogoff (2009, Chapter 13). In their next chapter (p. 223), they explain that they exclude emerging economies from the sample so as 'not to appear to engage in hyperbole'. Their analysis including emerging economies shows similar but stronger patterns of deeper recessions. This echoes previous studies, e.g., Cerra and Saxena (2008), and several papers from the BIS, IMF and other organizations. Our view is that given the institutional and other differences between advanced and emerging economies which may create greater output volatility in the latter group (Acemoglu *et al.*, 2003), it is preferable to conduct analysis on a long-narrow panel of advanced economies rather than a short-wide panel which pools together both advanced and emerging economies which may be structurally different. With a smaller N, we need larger T in order to have statistical power, leading to the historical approach which we have followed here.

With sample size comes statistical power, and our hypothesis tests show that the typical output path during recession and recovery in financial-crisis recessions is significantly worse than in normal recessions, amounting to a cumulative loss of 20% of annual output over 5 years. But why is there such a negative effect due to a financial crisis? We use modern methods based on inverse propensity score weighting to argue that it is an effect and that cannot be fully explained away by other (observable) characteristics. Still, one key covariate, credit, is particularly influential in shaping business cycle dynamics. Recessions that follow larger credit booms tend to be significantly worse, all else equal. Furthermore, we can show that contemporary business cycles are predominantly influenced by trends in the mortgage component of credit. Since World War II, it is only the aftermaths of mortgage booms that are marked by deeper recessions and slower recoveries. This is true both in normal cycles and those associated with financial crises.

Our findings echo the developments witnessed in the aftermath of the global financial crisis and also underline the need for additional nuance in monitoring the build-up of financial instability: it is not just a matter of how loose credit is in the aggregate, but also for what kind of purpose it is used.

2. A NEW HISTORICAL CREDIT DATABASE

The data unveiled in this paper are the result of an extensive data collection effort over several years. It covers bank credit to the domestic non-financial private sector (business and households) on an annual basis from 1870 to 2013 for the near-universe of advanced economies. The dataset builds on and extends the long-run credit data compiled by Schularick and Taylor (2012), and the updated series in Jordà *et al.* (2013), in three important ways:

1. *Disaggregated credit data:* The new dataset tracks the development of various types of bank lending. For the first time, we can construct the share of mortgage lending in total bank lending for most countries back to the nineteenth century. In addition, we calculate the share of bank credit to business and households for most of countries for the decades after World War II and back to the nineteenth century for a handful of countries.
2. *Broader coverage of financial institutions:* In addition to commercial banks' balance sheets, our data now include credit extended by savings banks, credit unions, and building societies yielding a more accurate picture of total credit creation by financial intermediaries. Accordingly, we have calculated a new series of total bank lending to the private sector that replaces the older series from Schularick and Taylor (2012). Data constraints prevent us from including direct borrowing in capital markets and private credit contracts between individuals which have been sizable in some countries in the early nineteenth century as Hoffman *et al.* (2000) show for France. However, comparing our annual data to Goldsmith's (1969) decadal benchmark estimates for total credit indicates that our series capture the largest part of total credit for all countries across the sample period.

3. *Larger and longer sample:* We added bank credit as well macroeconomic control data for Belgium, Finland and Portugal bringing the total number of countries covered by our database to 17.

Where do these new data come from? We consulted a broad range of sources, from economic and financial history books and journal articles, publications of statistical offices and central banks, and archival sources at central and private banks. The scale of this data collection effort would not have been possible without the generous support of many colleagues at various research institutions, archives, central banks and statistical offices who shared their data or directed us to potential sources. We are also heavily indebted to a group of dedicated research assistants in various places who successfully chased often imprecise references through libraries and archives in various countries. Details of the data construction appear in an extensive (100 + pages) Supplementary Appendix which also acknowledges the support we received from many colleagues.

For some countries, we extended existing data series from previous statistical work of financial historians or statistical offices. Such was the case for Australia, Canada, Japan and the United States. For other countries, we relied on recent data collection efforts at central banks, such as for Denmark, Italy and Norway. Sometimes we combined information from a wide range sources and spliced series to create long-run datasets for the first time. Belgium provides a good illustration of the challenges involved. Data on mortgage lending by financial institutions before World War I come from a German-language dissertation published in 1918; data for the interwar credit market are taken from a recent (2005) reconstruction of Belgian national income accounts undertaken by a group of economic historians at the University of Leuven. Disaggregated data for bank credit in the two decades following World War II come from the Monthly Bulletin of the Belgian National Bank and a statistical publication of the Ministry of Economics respectively. Finally, we relied on unpublished data on mortgage credit for the years 1960–2013 that the Statistics Department of the Belgian National Bank shared with us.

Data on macroeconomic control variables come from our previous dataset, where we relied on the work of economic and financial historians and secondary data collections by Maddison (2005), Barro and Ursúa (2008), and Mitchell (2008*a*,*b*,*c*). As noted, we have now added macroeconomic data for three additional countries, bringing our total to 17 countries, covering most advanced economies.

Table 1 summarizes the coverage of our database by country and type of credit. Overall, we have found long-run data for most countries for total bank lending and mortgage lending. Disaggregated data for bank credit to companies and households are available for some countries over the entire sample period, and are available in the post-World War II period for the majority of countries.

Figure 1 provides a first comparison of our new bank credit series with the older series taken from our previous dataset, which covered predominantly credit by commercial banks. As a consistency check, we also plot alternative post-World War II data that have been recently made available by the Bank for International Settlements (2013).

Table 1. New credit data in this study: sample coverage by country

Country	Total loans	Real estate	Households	Business
Australia	1870–2013	1870–2013	1870–2013	1870–2013
Belgium	1885–2013	1885–2013	1950–2013	1950–2014
Canada	1870–2013	1874–2013	1956–2013	1961–2013
Switzerland	1870–2013	1870–2013	1870–2013	1870–2013
Germany	1883–2013	1883–2013	1950–2013	1950–2013
Denmark	1870–2013	1875–2013	1951–2013	1951–2013
Spain	1900–2013	1904–2013	1946–2013	1946–2013
Finland	1870–2013	1927–2013	1948–2013	1948–2013
France	1900–2013	1870–2013	1958–2013	1958–2013
United Kingdom	1880–2013	1880–2013	1880–2013	1880–2013
Italy	1870–2013	1870–2013	1950–2013	1950–2013
Japan	1874–2013	1893–2013	1948–2013	1948–2013
Netherlands	1900–2013	1900–2013	1990–2013	1990–2013
Norway	1870–2013	1870–2013	1978–2013	1978–2013
Portugal	1870–2013	1920–2013	1979–2013	1979–2013
Sweden	1871–2013	1871–2013	1871–2013	1975–2013
United States	1880–2013	1880–2013	1945–2013	1945–2013

Notes: The data cover commercial banks and other financial institutions such as savings banks, credit unions and building societies. Data generally cover all monetary financial institutions. The following exceptions apply. Australia: pre-World War II mortgage loans are savings banks only; Belgium: pre-World War II mortgage loans are other financial institutions (OFIs) only; Canada: mortgage loans before 1954 are OFIs only; Switzerland: pre-1906 loans are commercial banks (CBs) only; Germany: pre-1920 mortgage loans are OFIs only; Spain: until 1996 total loans are CBs only; Denmark: pre-World War II mortgage loans are OFIs only; Japan: pre-World War II mortgage loans are CBs only; Norway: pre-1900 mortgage loans are mortgage banks only; Portugal: 1870–1903 total loans are CBs only; Sweden: pre-1975 household lending is mortgage lending only; USA: pre-1896 real estate lending is savings banks only. Sources listed in a forthcoming Supplementary Data Appendix. See text.

Reassuringly, our new series and the BIS series track each other closely where they overlap. This is true both in aggregate and at the country level.

The new data confirm the long-run patterns that we uncovered in earlier work: after an initial period of financial deepening in the late nineteenth century the average level of the credit-to-GDP ratio in advanced economies reached a plateau of about 40% around 1900. Subsequently, with the notable exception of the deep contraction seen in bank lending in the Great Depression and World War II, 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 2013 as average bank credit to GDP increased from 62% in 1980 to 114% in 2013.

The data dramatically underscore the size of the credit boom prior to the global financial crisis of 2008. A substantial part of that boom occurred in a very short time span of little more than 10 years between the mid-1990s and 2008–9. For our 17 country sample, the average bank credit to GDP ratio rose from 78% of GDP in 1995 to 111% of GDP in 2007 – an unprecedented increase of more than 30 percentage points (p.p.) as a ratio to GDP in just 12 years, implying a rapid pace of change of around 2.5 percentage points per year (p.p.y.). Moreover, this is only a lower bound estimate as it excludes credit creation by the shadow banking system, which was significant in some countries, such as in the US and the UK.

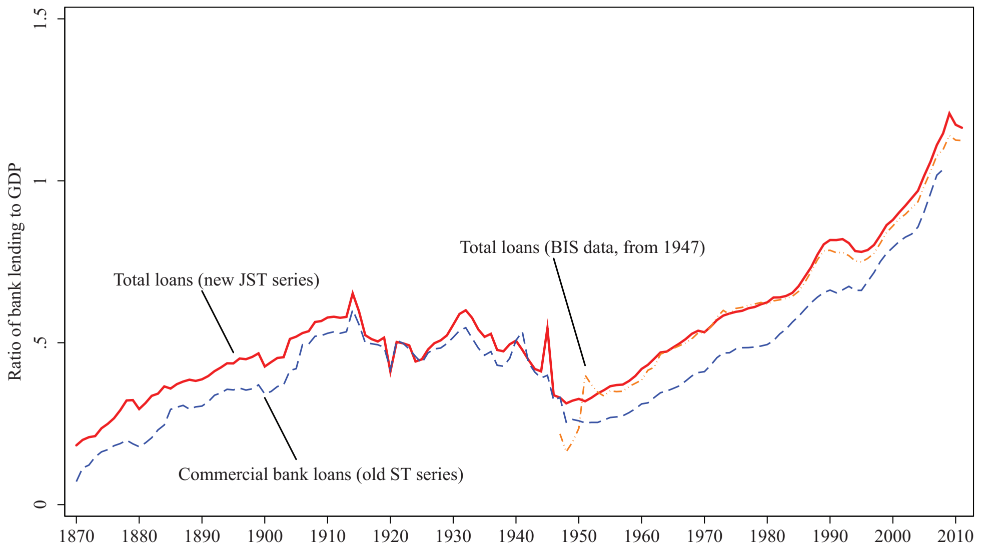

Figure 1. Bank credit to the domestic economy, 1870–2013, with a comparison of data from three different sources: average ratio to GDP by year for 17 countries

Notes: *Total Loans (new JST series)* refers to new data on total loans to the non-financial 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 non-financial 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 reported as a fraction to GDP and then averaged across all 17 countries in the sample. See text.

The next two sections explore the composition of this remarkable long-run leveraging of the advanced economies in more detail. We study the role of mortgage lending as well as changes in the sectoral composition of bank credit.

3. THE GREAT MORTGAGING

Figure 2 shows the long-run trends of mortgage credit and unsecured lending to business and household sectors since 1870. The visual impression is striking. Over a period of 140 years, the level of non-mortgage lending to GDP has risen by a factor of about 3, while mortgage lending to GDP has risen by a factor of 8, with a big surge in the last 40 years.

Virtually, the entire increase in the bank lending to GDP ratios in our sample of 17 advanced economies has been driven by the rapid rise in mortgage lending relative to output since the 1970s. Non-mortgage lending to business and consumers for purposes other than purchase of real estate has grown much more slowly and actually remained remarkably stable in the long run relative to output. On the eve of World War I, non-mortgage bank lending in the advanced economies was 41% as a ratio to GDP on average. In 2013 the corresponding ratio was 46%, only marginally higher. Bank lending to GDP ratios have risen so strongly on average because of a parallel

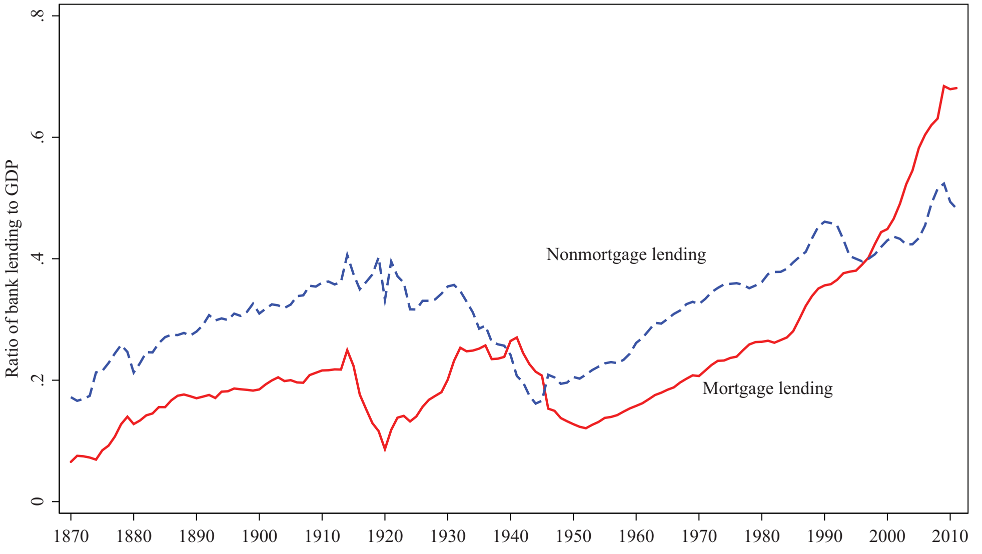

Figure 2. Bank mortgage and non-mortgage lending to GDP, 1870–2013: average ratio to GDP by year for 17 countries

Notes: Mortgage (residential and commercial) and non-mortgage lending to the business and household sectors. Average across 17 countries. See text.

increase in mortgage credit: from an average of about 20% as a ratio to GDP at the beginning of the twentieth century to 68% of GDP by 2013.

It is important to stress that a substantial share of mortgage debt was held privately outside the banking system in the nineteenth century. Exact numbers are hard to estimate. In France and the UK, privately held mortgage debt likely accounted for up to 10% of GDP around the year 1900; in the US and Germany an even higher share of farm and non-farm mortgages was probably held outside banks (Hoffman *et al.*, 2000). To some extent, the strong rise in mortgage lending relative to GDP evident in our data reflects the integration of these earlier forms of 'informal' private lending into the financial system in the course of the twentieth century.

Figure 3 gives a country-by-country snapshot of the composition of the loan books of the banking sector at three points in time: 1928, 1970 and 2007. This allows us to compare the business of banking on the eve of the Great Depression, right before the Bretton Woods System collapsed, and just before the global financial crisis of 2008. These three snapshots tell a consistent story. In most advanced countries, the share of mortgage lending relative to other lending has increased dramatically over the past century. With very few exceptions, the banks' primary business consisted of non-mortgage lending to companies both in 1928 and 1970. In 2007, banks in most countries had turned primarily into real estate lenders. On average, non-mortgage lending accounted for 72% of the total in 1928 and 62% in 1970. The share had fallen to less than 45% of total bank lending by 2007. In the US and Norway, about 70% of loans on bank balance sheets were mortgages in 2007, in the UK the corresponding figure was 52%.

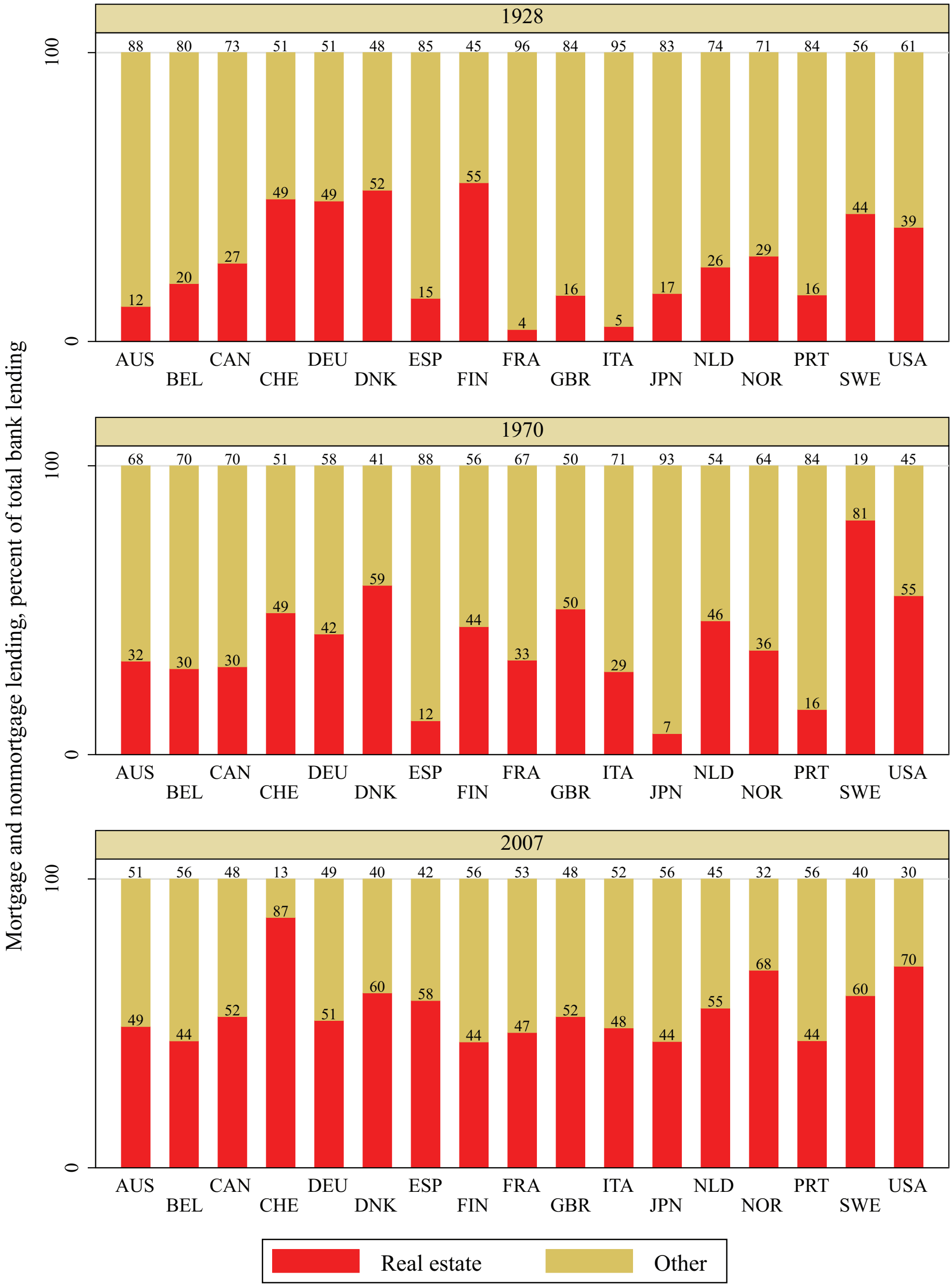

Figure 3. Three snapshots of the real estate share of bank lending: 1928, 1970 and 2007

Notes: Share of mortgage lending to total lending in 1928, 1970 and 2007 for each of the countries in the sample. See text.

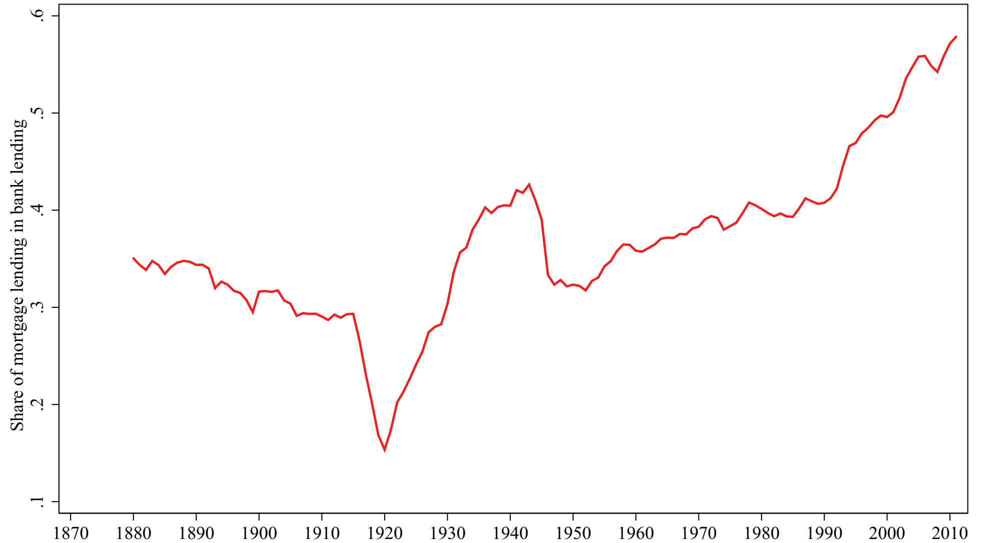

Figure 4. Aggregate share of real estate lending in total bank lending

Notes: Share of real estate lending to total lending averaged across 17 countries. Before 1880 the sample size is too small for use. See text.

Figure 4 shows the time profile of this astonishing change in the business of banking, and tracks the share of real estate loans on banks' balance sheets since 1870. We can clearly see the instability of credit in the interwar period when banks in many countries were forced to finance the war efforts of governments and cut back sharply on business lending in the 1930s. After World War II real estate credit increased as a share of total lending, driven in part by the reconstruction efforts in Europe and the boom in suburban housing in many countries, notably the United States. However, the overall share of real estate credit on banks' balance sheets remained around 40% until the mid-1980s, whereupon we see the start of a global real estate lending boom for the past 30 years leading to a large jump in the ratio. As a result, the shares of mortgage and non-mortgage lending are now approximately the inverse of what they were at the beginning of the twentieth century.

4. THE LEVERAGING OF HOUSEHOLDS

In this section, we examine sectoral trends in bank lending. Table 2 dissects the increase of total bank lending to GDP ratios over the past 50 years into growth of household debt and business debt. In the 50 years since 1960, we see that the increase in total lending to the private sector amounted to about 80 p.p. of GDP on average in the 17 advanced economies. At the country level, Spain tops the list with overall growth of the bank credit to GDP ratio of 135 p.p. followed closely by the Netherlands and Denmark. At the bottom of the list we find Japan, Belgium, and Germany. With regard to the sectoral composition, the picture could not be clearer. The increase in lending has been

Table 2. Change in bank lending to GDP ratios (multiple), 1960–2010

Country	Total lending	Mortgage	Non-mortgage	Households	Business
Spain	1.35	0.97	0.38	0.76	0.60
Netherlands	1.35	0.70	0.65	—	—
Denmark	1.26	0.97	0.3	0.75	0.51
Australia	1.13	0.70	0.42	0.77	0.36
Portugal	1.05	0.58	0.47	—	—
USA*	0.88	0.54	0.34	0.48	0.39
USA	0.22	0.20	0.02	0.15	0.07
Great Britain	0.82	0.55	0.27	0.67	0.16
Sweden	0.71	0.45	0.26	—	—
Canada	0.62	0.35	0.27	0.55	—
Norway	0.62	0.59	0.03	—	—
Finland	0.62	0.27	0.35	0.43	0.19
France	0.62	0.41	0.20	0.45	0.16
Italy	0.59	0.45	0.15	0.39	0.20
Switzerland	0.52	0.74	−0.21	0.52	0.01
Germany	0.51	0.29	0.20	0.21	0.29
Belgium	0.48	0.28	0.20	0.31	0.18
Japan	0.35	0.38	−0.03	0.27	0.08
Average	0.79	0.54	0.25	0.50	0.26
Fraction of average	1.00	0.68	0.32	0.64	0.33

Notes: Column (1) reports the change in the ratio of total lending to GDP expressed as a multiple of the initial value between 1960 and 2013 ordered from largest to smallest change. Columns (2) and (3) report the change due to real estate versus non-real estate lending. Columns (4) and (5) instead report the change due to lending to households versus lending to businesses. The USA entry with * includes credit market debt. *Average* reports the across country average for each column. *Fraction of average* reports the fraction of column (1) average explained by each category pair in columns (2) versus (3) and (4) versus (5). Notice that averages in columns (4) and (5) have been rescaled due to missing data so as to add up to total lending average reported in column (1). See text.

driven primarily by increased lending to the household sector. Household borrowing accounts for about 2/3 of the total increase in bank credit since 1960, predominantly driven by real estate lending. But there are important differences between individual countries: Belgian, German and Japanese households have increased their debt levels by 30 p.p. (or less) of GDP, while their Australian, Spanish and British counterparts have ramped up debt levels by about 75 p.p. of GDP over the same period.

A natural question to ask is whether this surge in household borrowing reflects rising asset values without substantial shifts in household leverage ratios (defined as the ratio of household mortgage debt to the value of residential real estate) or, on the contrary, whether households increased debt levels relative to asset values. The latter would potentially raise greater concerns about the macroeconomic stability risks stemming from more highly leveraged household portfolios.

We therefore gathered historical data for the total value of the residential housing stock (structures and land) for a number of benchmark years to relate household mortgage debt to asset values. We combine information from Goldsmith's (1985) seminal study of national balance sheets with the more recent and more precise estimates of historical wealth to income ratios by Piketty and Zucman (2013). There are considerable difficulties involved in the calculations so we restrict the analysis to a small subsample of

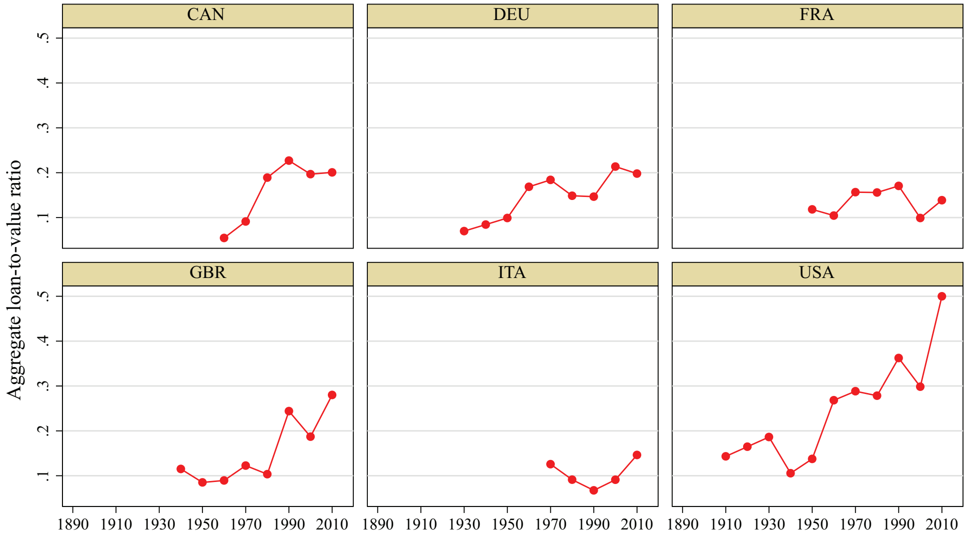

Figure 5. Ratio of household mortgage lending to the value of the housing stock

Sources: Piketty and Zucman (2013), Goldsmith (1985) and our data. Individual data points are rough approximations relying on reconstructed historical balance sheet data for benchmark years.

countries for which we have long-run data. Yet even here the margins of error are likely to be big and the numbers should be interpreted with caution.[3]

Figure 5 shows that the ratio of household mortgage debt to the value of real estate has risen strongly in the United States and the United Kingdom in the past three decades – despite the boom in house prices. In the United States, mortgage debt to housing value climbed from 28% in 1980 to over 40% in 2013, and in the United Kingdom from slightly more than 10% to 28%. A general upward trend in the second half of the twentieth century is also clearly discernible in a number of other countries.

5. THE RISE OF HOME OWNERSHIP

The boom in mortgage lending and borrowing in the post-World War II era is a major trend that emerges from our data. Table 3 demonstrates that this rise in mortgage credit has financed a substantial expansion of home ownership in the advanced economies.

Home ownership rates were on average slightly above 40% around 1950 in the countries for which we have long-run data. In the 2000s, about 60% of households owned the house that they lived in – an increase of 20 p.p. in the course of the past half century. Put differently, while the notion that home ownership is a constitutive part of the

[3] In particular, it was not always possible to clearly separate the value of residential land from overall land for the earlier years and therefore we made assumptions on the basis of available data for certain benchmark years.

Table 3. Home ownership rates in the twentieth century (%)

	Canada	Germany	France	Italy	Switzerland	UK	USA	Average
1900							47	
1910							46	
1920						23	46	
1930							48	
1940	57					32	44	
1950	66	39	38	40	37	32	47	43
1960	66	34	41	45	34	42	62	46
1970	60	36	45	50	29	50	63	48
1980	63	39	47	59	30	58	64	51
1990	63	39	55	67	31	68	64	55
2000	66	45	56	80	35	69	67	60
2013	69	45	58	82	37	64	65	60

Sources: Canada: Miron and Clayton (1987), 'Housing in Canada 1945–1986'; Statistics Canada (2013), 'Home ownership rates by age group, all households'; France: Friggit (2013), 'Les ménages et leur logements depuis 1955 et 1970'; Germany: Statistisches Bundesamt (2013), 'Statistisches Jahrbuch 2013'; Italy: Balchin (1996), 'Housing Policy in Europe'; Dolinga and Elsinga (2013), 'Demographic Change and Housing Wealth'; Switzerland: Werczberger (1997), 'Home Ownership and Rent Control in Switzerland', Bundesamt für Wohnungswesen (2013), 'Wohneigentums, 1950–2000'; United Kingdom: Office for National Statistics (2013), 'A Century of Home Ownership and Renting in England and Wales'; United States: Census Bureau (2013), 'Housing Characteristics'.

national identity may be a widely accepted idea in many countries, on closer inspection what is often described as a fundamental trait of national culture turns out to be a relatively recent phenomenon. In the UK, for instance, home ownership rates were as low as 23% in the first quarter of the twentieth century. In the US too, the majority of households did not own their homes until about 1960.

The rise of credit-financed home ownership in the second half of the twentieth century has clearly been aided by the growth in scale and scope of housing policy, albeit the exact contribution remains hard to quantify. Large-scale interventions into housing markets were largely a product of the Great Depression, but remained an important part of the post-World War II policy landscape in many countries.

In the United States, the National Housing Act of 1934 led to the creation of the Federal Housing Authority (FHA), whose primary purpose was to insure banks and other private lenders for home loans and to create a liquid secondary mortgage market. Two years before, in 1932, the Federal Home Loan Bank System had been established. Through its government backing, the System could borrow at favourable interest rates and pass them on to mortgage borrowers, an arrangement that became an enduring feature of the American housing finance system (Gaertner, 2012). President Roosevelt created the Federal National Mortgage Association (FNMA) in 1938 which quickly became known by its nickname Fannie Mae. The agency issued bonds in capital markets with implicit backing from the federal government and invested in FHA insured mortgage loans, thereby creating a more liquid secondary market for insured mortgages. As time went by, the standardization of loans using FHA criteria enabled nationwide banks and other financial institutions to move into geographically remote mortgage markets, and this translated into a rising share of mortgages on banks' balance sheets.

Government interventions in the US housing markets intensified after World War II mainly due to the activities of the Veterans Administration (VA), which was established as part of the G.I. Bill in 1944. VA guaranteed loans had median loan-to-value ratios of 91%, and a substantial proportion even passed the 100% bar (Fetter, 2013). The VA and FHA programs insured more than 6.5 million mortgages in the first 15 years after the war and the associated rise of suburbia transformed the American landscape. The share of federally subsidized mortgage credit relative to all mortgages reached 40% in the 1950s. On its own, the G.I. Bill likely accounted for up to 25% of the increase in home ownership for the cohorts affected by the VA programs (Fetter, 2013). Moreover, while the tax deduction of interest expenses had formed part of the US tax code since the introduction of the federal income tax in 1913, the sharp rise in mortgage debt and highly progressive income tax rates turned the mortgage interest deduction into a much more important subsidy for home buyers in the postwar decades. Aided by such policies, American home ownership increased from 40% in the 1930s to nearly 70% by 2005 before declining to 65% in the wake of the global financial crisis.

While the UK shares a similar experience, with home ownership rates rivaling those of the US, not all countries implemented changes in policies to boost private home ownership and mortgages. Germany and Switzerland provide good counterexamples. In Germany, loan-to-value ratios at savings and mortgage banks (the main providers of home loans) were often capped at 60%. At the same time, the comparatively high levels of rent protection that were put in place in the immediate postwar years were upheld in the following decades and the German tax code provided only limited incentives to take on debt. Switzerland even levied taxes on the imputed rents of house owners. As a consequence, the home ownership rate in Germany stood at 43% in 2013 and was hence only marginally higher than the 39% ratio reached in 1950. In a similar fashion, home ownership in Switzerland stagnated around 35% in the past half century.

In addition to country-specific housing policies, international banking regulation also contributed to the growing attractiveness of mortgage lending from the perspective of the banks. The Basel Committee on Bank Supervision (BCBS) was founded in 1974 in reaction to the collapse of Herstatt Bank in Germany. The Committee served as a forum to discuss international harmonization of international banking regulation. Its work led to the 1988 Basle Accord (Basel I) that introduced minimum capital requirements and, importantly, different risk weights for assets on banks' balance sheets. Loans secured by mortgages on residential properties only carried half the risk weight of loans to companies. This provided another incentive for banks to expand their mortgage business, which could be run with higher leverage. As Figure 1 shows, a significant share of the global growth of mortgage lending occurred in recent years following the first Basel Accord.

Summing up, rising homeownership, changing financial regulation and increasing leverage likely all contributed to the rapid run-up in mortgage credit in the second half of the twentieth century – as did rising house and especially land prices analysed by Knoll *et al.* (2014). However, a comprehensive quantitative analysis of the drivers must remain beyond the scope of the paper.

6. MORTGAGE CREDIT AND FINANCIAL INSTABILITY

We now turn from data description to formal statistical analysis, and our first hypothesis addresses a crucial question as to why one should care about the disaggregated credit measures that we have so laboriously collected. Namely, have changes in the structure of financial intermediation, highlighted by the growing importance of mortgages in total bank credit, made advanced economies more financially fragile?

In this section, we look at the classification ability of various credit-based measures in predictive models of financial stability. In particular, we are interested if and how the disaggregated credit data help improve the classification ability of crisis forecast models and whether housing credit today has become more closely associated with financial crisis risks as its share in total credit has grown. While our long-run perspective is novel, we are not the first to study the crisis potential of the different categories of lending. Büyükkarabacak *et al.* (2013) find that both household credit expansions and business credit booms are predictive of banking crises but the effect of business lending is less strong and robust. In related work, Beck *et al.* (2012) study disaggregate credit data and show that business credit, not household credit, is positively associated with economic growth.

Following Schularick and Taylor (2012), we start from a probabilistic model that specifies the log-odds ratio of a financial crisis occurring in country i in year t, denoted with the binary variable S_{it}, as a linear function of lagged credit ratios in year t,

$$\log \frac{P[S_{it} = 1 | X_{it}]}{P[S_{it} = 0 | X_{it}]} = \psi_{0i} + \psi_1 X_{it} + e_{it}, \tag{1}$$

where X_{it} refers to a vector of lagged changes of the credit ratios of interest. Here we use 5-year moving averages as a parsimonious way to summarize medium-term fluctuations. Notice that the model includes country fixed-effects. We report estimates based on a variety of specifications detailed below, essentially a horse-race among the various credit aggregates using the full sample, the pre-World War II era, and the post-World War II period. The error term e_{it} is assumed to be well behaved.

Dates of systemic financial crises are taken from Jordà *et al.* (2013) with updates, which in turn builds on Bordo *et al.* (2001) and Reinhart and Rogoff (2009). The Laeven and Valencia (2008, 2012) dataset of systemic banking crises is the main source for post-1970 crisis events.[4] Section A in the Appendix provides the country-specific dates of financial crises that we use.

[4] Following the definition of Laeven and Valencia (2012), a financial crisis is characterized as a situation in which there are significant signs of financial distress and losses in wide parts of the financial system

Table 4. Classifying financial crises: logit prediction models

(a) Full sample	(1)	(2)	(3)	(4)
Mortgage loans		23.06***		13.89*
		(7.65)		(8.22)
Non-mortgage loans			41.62***	37.96***
			(9.42)	(9.31)
AUC	0.61	0.66	0.72	0.72
	(0.03)	(0.03)	(0.03)	(0.03)
Observations	2040	1794	1764	1764
(b) Pre-World War II	(5)	(6)	(7)	(8)
Mortgage loans		17.31		28.48
		(12.13)		(18.08)
Non-mortgage loans			52.34**	54.87***
			(21.24)	(17.33)
AUC	0.63	0.68	0.76	0.76
	(0.04)	(0.04)	(0.04)	(0.04)
Observations	1003	734	704	704
(c) Post-World War II	(9)	(10)	(11)	(12)
Mortgage loans		45.57***		32.02**
		(14.26)		(14.24)
Non-mortgage loans			51.61***	37.24**
			(15.18)	(15.90)
AUC	0.60	0.71	0.72	0.74
	(0.05)	(0.06)	(0.06)	(0.05)
Observations	976	998	998	998

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. Robust standard errors for the regression coefficients are in parentheses. Country-fixed effects are not shown. The two world wars are excluded from the estimation sample. Panel (a) uses the full sample from 1870 to 2013 across the 17 countries. Panel (b) uses pre-World War II data only. Panel (c) uses post-World War II data only. The reference null model based on a specification with country-fixed effects only reported in columns (1), (5) and (9). Non-mortgage loans has an AUC significantly different from the null model in all three samples. Mortgage loans has an AUC that is not statistically different from the null model in the pre-World War II sample but is significant in the post-World War II and in the full samples. Standard errors for the AUC in parentheses. See text.

The key results are shown in Table 4. Column (1) reports the null model with country-fixed effects only. This serves as a benchmark or null to judge whether a more elaborate model is any better at explaining the data. Next we consider the models based on mortgage loans in column (2) and non-mortgage loans in column (3), as well as the combination of both (4). Panel (a) reports the results for the full sample from 1870 to 2013 (excluding world wars), panel (b) is based on a pre-World War II sample from 1870 to 1939 (excluding World War I) with corresponding results reported in columns (5) to (8),

that lead to widespread insolvencies or significant policy interventions. The important distinction here is between isolated bank failures, such as the collapse of the Herstatt Bank in Germany in 1975 or the demise of Baring Brothers in the UK in 1995, and system-wide distress as it occurred, for instance, in the crises of the 1890s and the 1930s, in the Japanese banking crises in the 1990s, or during the global financial crisis of 2008. It is clear that the lines are not always easy to draw, but the overall results appear robust to variations in the crisis definitions.

and panel (c) is based on a post-World War II sample from 1946 to 2013 with corresponding results reported in columns (9) to (12).

Earlier work by Schularick and Taylor (2012) showed that, in aggregate, credit helps predict financial crises. But with our new dataset we can ask a sharper question: does the type of credit that drives the expansion make a difference? We confirm that a high rate of credit extension over the previous 5 years is indicative of an increasing risk of a financial crisis. This is true for both mortgage lending and non-mortgage lending (columns 2–4). All forms of credit growth over GDP have highly significant coefficient estimates. Over the long run, there does not appear to be only one type of credit-boom driven financial instability. Financial fragility seems to have a variety of sources.

However, the type of credit does seem to matter, and we find evidence that the changing nature of financial intermediation has shifted the locus of crisis risks increasingly towards real estate lending cycles. Whereas in the pre-World War II period mortgage lending is not statistically significant, either individually or when used jointly with unsecured credit (columns 6 and 8), it becomes highly significant as a crisis predictor in the post-World War II period (see columns 10 and 12). Nevertheless, both types of credit appear to play an independent role as column (12) shows, and the coefficients are similar.

A different way to see this changing relationship is through the AUC statistic.[5] The AUC is a summary statistic of classification ability whose asymptotic distribution is Gaussian in large samples, making inference straightforward (see Jordà and Taylor, 2013). In the simplest models, the AUC takes on the value of 1 for perfect classification ability and 0.5 for an uninformative classifier or 'coin toss'. In our application, we replace the 0.5 null with the AUC from the model with fixed-effects only.[6] With the AUC we can then compare the classification ability of models using different subcategories of credit.

The AUC tests for predictive ability for the different models lend support to the view that over time mortgage credit has come to play a larger role in the genesis of financial instability. In panel (b) the predictive ability of the mortgage based model is far inferior to the non-mortgage or combined model before 1940: compare column (6) with columns (7) and (8). But in panel (c) for the post-World War II period the AUC is a solid 0.71, considerably higher than before and close to the AUC of 0.72 the non-mortgage based model: see columns (10) and (11). Here the mortgage credit-based crisis prediction model outperforms the null model by a good margin: the fixed effects null AUC is 0.60, as reported in column (9). Moreover, it is almost on par with the combined model in column (12) and performs similarly in terms of overall classification ability to the model

[5] AUC stands for *Area under the Curve*. The curve is usually the *receiver operating characteristic curve* or ROC. In Jordà and Taylor (2013) it refers to the *Correct Classification Frontier* or CCF. Jordà and Taylor (2013) provide an overview of this literature and the AUC, ROC and CCF.

[6] Some countries have been more prone to financial crises than others historically. We want to examine the marginal contribution of the credit variables beyond differences in country-average crisis incidence.

using non-mortgage loans only as reported in column (11), with these results contrasting with the findings for the pre-World War II era.

6.1. Robustness checks

We explore the robustness of our findings by expanding the analysis in two directions. First, global economic conditions could have spillover effects onto individual economies. Contagion of financial distress can cross borders unfettered: Would as many dominoes have fallen if not for the collapse of Lehman Brothers? Second, for the post-World War II era we have data on the split between residential and commercial real estate lending. Recall that in Table 4 we showed that mortgage lending increasingly became an important element of financial risk after World War II. It is natural to ask which of these categories of mortgage lending is the more relevant source of financial fragility.

The results of these two lines of inquiry are summarized in Table 5. First, we take the specification from column (4) in Table 4 and expand it by adding an additional classifier which we call *global factor*, which is common to all countries in any given year. The global factor is the share of PPP adjusted GDP of countries that are in a financial crisis. This variable has the virtue of giving relatively more weight to large countries in distress. Notice that this variable is contemporaneous and, hence, self-referential. Its purpose is to stack the odds against finding a spurious role for credit that could have been explained by a more careful investigation of potential international financial linkages and spillover effects. Such an investigation is outside the scope of our paper. Columns (1) to

Table 5. Classifying financial crises: robustness checks

	(1) *Full sample*	(2) *Pre-World War II*	(3) *Post-World War II*	(4) *Post-World War II*
Non-mortgage loans	38.61***	54.94***	40.92***	27.34
	(9.27)	(17.48)	(15.22)	(24.42)
Mortgage loans	11.57	28.50	24.47*	
	(8.42)	(17.98)	(14.49)	
Residential mortgages				28.16*
				(16.94)
Commercial mortgages				7.80
				(23.70)
Global factor	1.81***	−0.65	3.02***	2.77***
	(0.69)	(1.09)	(0.96)	(0.96)
AUC	0.73	0.76	0.77	0.76
	(0.03)	(0.04)	(0.05)	(0.06)
Observations	1764	704	998	860

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. Robust standard errors for the regression coefficients are in parentheses. Country-fixed effects are not shown. The two world wars are excluded from the estimation sample. Column (1) uses the full sample from 1870 to 2013 across the 17 countries. Column (2) uses pre-World War II data only. Columns (3) and (4) use post-World War II data only. Columns (1), (2) and (3) expand the results of Table 4 with the global factor classifier. The global factor is the share of the sum of PPP adjusted GDP for all the 17 countries in our sample in financial crisis. Differences in the number of observations between columns (3) and (4) reflect differences in data availability for some of the variables. Standard errors for the AUC in parentheses. See text.

(3) report the estimates for the full 1870–2013 sample, and the pre- and the post-World War II samples, respectively.

Next, we disaggregate the mortgage lending variable into residential and commercial mortgage lending. Due to data limitations, we are only able to report results based on the post-World War II sample. Even for this case, which is reported in column (4) of Table 5, we also include the global factor variable.

The global factor variable is highly significant but this is no surprise given our previous discussion. More importantly, we note that the coefficient estimates change little from those reported in Table 4. The main effect is on the standard errors, as we anticipated, and also due to differences in available samples, thus affecting overall statistical significance.

Importantly, as displayed in columns (1) and (3) in Table 5, the role of mortgage lending dissipates and does not appear to be a relevant factor in any of the samples. The more careful breakdown provided in column (4) of the same table reveals a more nuanced picture. Out of all categories of lending, residential mortgage lending appears to be the more relevant item explaining financial crises, although with a similar coefficient to non-mortgage lending. In contrast, the coefficient on commercial real estate lending is numerically and statistically nearly zero.

The robustness analysis relies on smaller samples, incomplete data and self-referential variables meant to purposefully diminish any role that lending may have had in explaining financial crises. We judge that the results in Table 4 have withstood these attacks well. Along the way, we have learned that residential mortgage lending can be a particularly important variable to monitor. In the analysis that follows, we revert to the variables used in Table 4 to exploit the larger sample available and to be able to contrast the pre- and post-World War II periods.

7. MORTGAGE BOOMS, FINANCIAL CRISES AND THEIR AFTERMATH

The second half of the twentieth century saw an unprecedented increase in aggregate credit volumes. As we saw in Figure 1, total bank lending as a ratio to GDP more than doubled relative to the first half of the twentieth century. Using our new dataset, we were able to show that this striking trend was in large part driven by the tripling of real estate lending, in particular mortgage lending to households, as shown in Figure 2. On the eve of the 2008 global financial crisis, real estate loans represented about two thirds of all bank lending in the US and most other advanced economies. As a close correlate of this trend, we saw that mortgage credit became a specific source of financial instability in advanced economies in the post-World War II era, as discussed in the previous section.

We now turn to the aftermath of lending booms and study their consequences for the real economy. The objective is to see if and how the important shifts in the structure of financial intermediation have implications for the role of credit over the business cycle: is there historical evidence that recessions are more severe if they are preceded by lending booms? Is the much-debated debt overhang phenomenon a regular feature of the modern business cycle? Our analysis will be based on the near-universe of business cycles in advanced economies since 1870.

Debt overhang and the consequences of deleveraging have been a central focus of recent work on macrofinancial linkages. Many studies have pointed to debt overhang as a potential cause for slow recoveries from financial crises (see for example Cerra and Saxena, 2008; Reinhart and Rogoff, 2009; Mian and Sufi, 2013, 2014; Jordà *et al*., 2013, 2013). Our analysis goes beyond previous attempts at measuring the effects of debt overhang in two important ways. First, we use the new disaggregated credit dataset to study potentially unknown linkages between specific forms of bank credit and the real economy as well as potential shifts in these relationships over time. Second, we apply novel econometric techniques that allow us to address concerns often raised about the endogeneity of financial crises, and hence quantify more precisely the effects of debt overhang using a potential outcomes approach based on the Neyman–Rubin causal model.

We begin with as brief an exposition of the novel econometric approach we use as is possible and then move quickly on to the analysis. The following section characterizes the typical path of economies through recessions and recoveries in the near-universe of business cycles in advanced economies since 1870 using the Bry–Boschan algorithm to demarcate peaks and troughs of economic activity. Having established the typical path of economies over the cycle, we ask if and how financial factors modulate this trajectory. We will look both at the (new) aggregate and the disaggregated credit series, thereby both corroborating and extending previous studies of debt overhang and deleveraging.

Table 6 synthesizes the salient features of the underlying data. Column (1) reports summary statistics for all cycles between 1870 and 2013, 204 in total; column (2) for cycles between 1870 and 1939, 110 in total; and column (3) for cycles between 1948 and

Table 6. Summary statistics for recession type indicators and credit measures

	(1) All Recessions		(2) Pre-World War II Recessions		(3) Post-World War II Recessions	
	Mean	SD	Mean	SD	Mean	SD
Normal recession (indicator)	0.75	(0.44)	0.74	(0.44)	0.76	(0.43)
Financial crisis recession (indicator)	0.25	(0.44)	0.26	(0.44)	0.24	(0.43)
Total credit (p.p.y.)	0.80	(2.34)	0.51	(2.47)	1.15	(2.13)
Mortgage credit (p.p.y.)	0.61	(1.22)	0.50	(1.15)	0.74	(1.29)
Non-mortgage credit (p.p.y.)	0.19	(1.91)	0.01	(2.28)	0.41	(1.34)
Observations	204		110		94	

Notes: Full sample: 1870–2013 for 17 countries. Excludes world wars. *Normal recession* refers to a binary indicator that is 1 for normal recession 0 otherwise. *Financial crisis recession* is a binary indicator that is the complement to the normal recession binary indicator just described. *Private credit* refers to the accumulated growth in total lending in the expansion as a fraction of GDP and reported as an annual rate in deviation from country specific means, in percentage points per year (p.p.y.). *Mortgage credit* and *Non-mortgage credit* are constructed in a similar way. Total lending is the sum of mortgage lending and non-mortgage lending. See text.

2013, 94 in total. Moreover, we differentiate between normal business cycles and those associated with financial crises. Recessions are hence sorted into *normal* recessions and *financial crisis* recessions. A financial crisis recession occurs when a financial crisis is observed within ± 2 years of the business cycle peak. Section B in the Appendix contains a table detailing the breakdown into these two cases for our dataset.

We will now use this classification of the types of recessions to study if and how debt overhang worsens the path of economies through recession and recovery in normal times and after financial crises. We will also pay due attention to the possible endogeneity of financial crisis cycles using propensity score weights in the following section.

7.1. Statistical design

The question that we ultimately want to answer is if and how financial factors influence the severity of normal and financial recessions. In this section, we describe in greater detail our statistical approach. Compared to previous literature the key methodological innovation will be to account for the possibility that financial crises are endogenous to the credit cycle. We will first establish that financial crisis recessions are indeed more severe than normal recessions and then move on to study if prior credit booms make either type of recession worse.

We are interested in the cumulative change in log real GDP per capita, y, from today to some future period h measured in percentage points. We denote this cumulative change as $\Delta_h y_{\tau+h}$. The notation $\tau = t(p)$ indicates the calendar period t associated with the p^{th} peak (or start of the recession).[7] In addition, let d_τ be an indicator variable that takes the value of one if the p^{th} recession is associated with a financial crisis, and is zero otherwise.

The average path of normal versus financial crisis recessions can then be characterized as follows:

$$\theta_n^h = \frac{1}{N_n}\sum_{d_\tau=0} \Delta_h y_{\tau+h}; \qquad \theta_f^h = \frac{1}{N_f}\sum_{d_\tau=1} \Delta_h y_{\tau+h} \qquad \text{for } h = 0, 1, \ldots, H, \tag{2}$$

where N_n and N_f refer to the appropriate number of observations in each case (n is for normal recessions, f is for financial crisis recessions). A plot of $\{\hat{\theta}_n^h\}_{h=0}^H$ represents the average path of the economy in normal recessions, whereas the plot of the $\{\hat{\theta}_f^h\}_{h=0}^H$ represents the average path of the economy in financial crisis recessions instead. This is the type of plot that often appears in the literature, for example in Cerra and Saxena (2008)

[7] The country index is omitted to facilitate the exposition although in the applications below we include fixed effects and use cluster robust standard errors. These are among the main considerations given to the panel-data structure of our problem.

and Reinhart and Rogoff (2009). Any differences between the two paths, $\hat{\theta}_n^h$ and $\hat{\theta}_f^h$, could be due to differences in observable characteristics between the two types, not necessarily because financial crises make the recession worse through an independent channel. The next step is therefore to ask whether financial crisis recessions are different from normal recessions, all else equal.

This is where synthetic control methods come in. Building on a large literature in biostatistics and more recently in econometrics, Angrist *et al.* (2013) propose an inverse probability weighted (IPW) estimator of expression (2). The estimator consists of two stages. In the first stage, a model is constructed to determine the probability that the recession is of a financial crisis type $p(d_\tau = 1|\{\Upsilon_{\tau-l}\}_{l=0}^L)$. Here Υ_τ denotes a vector of lagged observable macroeconomic controls observed up to L periods before the recession starts. This probability will be called the *propensity score* and we denote its estimate as $\hat{p}_\tau$. The propensity score model can be estimated using a logit or a probit estimator, for example.

The second stage consists of recalculating expression (2) using weights given by the inverse of the propensity score in each bin. Weighting by the inverse of the propensity score puts more weight on those observations that were difficult to predict. These observations come closest to the random allocation ideal and hence receive more weight than those instances in which the type of recession was endogenous due to the other factors. Because it compensates for unknown non-linearities, the inverse probability weighting can be seen as a more flexible mechanism to control for the role of observables compared to controlling only through the conditional mean. The difference between the path of the economy in financial crisis versus normal recessions then provides a measure of the average effect of the financial crisis on the path of the economy. It is calculated as

$$\Lambda^h = \sum_{d_\tau=1} \frac{\Delta_h y_{\tau+h}}{\hat{p}_\tau} - \sum_{d_\tau=0} \frac{\Delta_h y_{\tau+h}}{1-\hat{p}_\tau}. \qquad (3)$$

Alternatively, we know that expression (2) can be recast as a simple regression estimate

$$\Delta_h y_{\tau+h} = \theta_n^h + \Lambda^h d_\tau + \epsilon_{\tau+h}. \qquad (4)$$

Hence, the counterparts to $\hat{\theta}_n^h$ and $\hat{\theta}_f^h$ in expression (2) can be directly obtained by noting that $\hat{\theta}_f^h = \hat{\theta}_n^h + \hat{\Lambda}^h$. In order to implement IPW in expression (3) all that is needed is to estimate expression (4) using weighted least-squares (WLS) with weights defined by $w_\tau = d_\tau/\hat{p}_\tau + (1-d_\tau)/(1-\hat{p}_\tau)$.

A natural extension to expression (4) is to include controls $\{\Upsilon_{\tau-l}\}_{l=0}^L$ directly in the regression estimator as well, such as in Jordà and Taylor (2013). We call this estimator IPWRA for 'IPW regression adjusted' to follow the nomenclature used in this literature. The WLS estimation of this extended regression is an example of a 'doubly robust' method (e.g. Lunceford and Davidian, 2004; Glynn and Quinn, 2013; Wooldridge, 2013). The *doubly robust* moniker refers to the control for observables via two channels: directly in the regression mean and through the propensity score. Hence, only one of these two channels need be properly specified to produce consistent estimates.

Yet, our key objective is to determine how aggregate credit and its disaggregated components affect the path of the recession. The doubly robust version of expression (4) estimated by WLS provides a natural springboard from which to do this. For example, let $(x_\tau - \bar{x})$ denote a measure of credit accumulated in the expansion measured at annual rate in percentage points per year (p.p.y.) and in deviations from its historical mean (in the applications below, the mean is country specific). The effect of this variable on the path of the recovery can be measured using the following specification:

$$\Delta_h y_{\tau+h} = \theta_n^h + \Lambda^h d_\tau + \beta^h (x_\tau - \bar{x}) + \sum_{l=0}^{L} \Upsilon_{\tau-l} \Gamma_l^h + \epsilon_{\tau+h}. \tag{5}$$

Expression (5) is the standard specification of a local projection (Jordà, 2005) with the $\{\hat{\beta}^h \times \delta\}_{h=0}^{H}$ as the estimate of the response of $\Delta_h y_{\tau+h}$ due to a perturbation in x_τ away from its mean $\bar{x}$ by an amount δ. When expression (5) is estimated by WLS using the propensity score model for $\hat{p}_\tau$ and the associated weights w_τ we have a doubly robust estimate (given observable controls).

It is important to be clear about what the propensity score achieves here. The IPWRA ensures that endogeneity of financial crisis recessions is addressed as best as possible given the data that we have. Otherwise, estimates of the effects of experiments concerning $(x_\tau - \bar{x})$ could be polluted by this endogeneity. In the analysis that follows $(x_\tau - \bar{x})$ will refer to different measures of credit build-up during the expansion.

7.2. Normal and financial recessions

This section provides baseline estimates of the simple average paths in normal and financial recessions using WLS in expression (4) using IPW. In the subsequent sections, we gradually incorporate the effect of alternative definitions of credit accumulation during the expansion and its components based on expression (5) using IPWRA, that is, estimated by WLS using the propensity score weights w_τ. At each stage, we provide the details of how these expressions are specifically implemented.

The set of controls $\Upsilon_{\tau-l}$ includes several important macroeconomic indicators: (1) the growth rate of real GDP per capita; (2) the CPI inflation rate; (3) the growth rate of real investment per capita; (4) short-term interest rates on government securities (usually 3 months or less in maturity); (5) long-term interest rates on government securities (usually 5 years or more in maturity); and (6) the current account to GDP ratio.

The propensity score model is estimated over the sample of recession-year events where we predict the normal versus financial-crisis type of the recession d_τ using two lags of this set of controls $\Upsilon_{\tau-l}$, country-fixed effects and the credit buildup indicator $(x_\tau - \bar{x})$. This variable measures the annual change of total lending in the previous

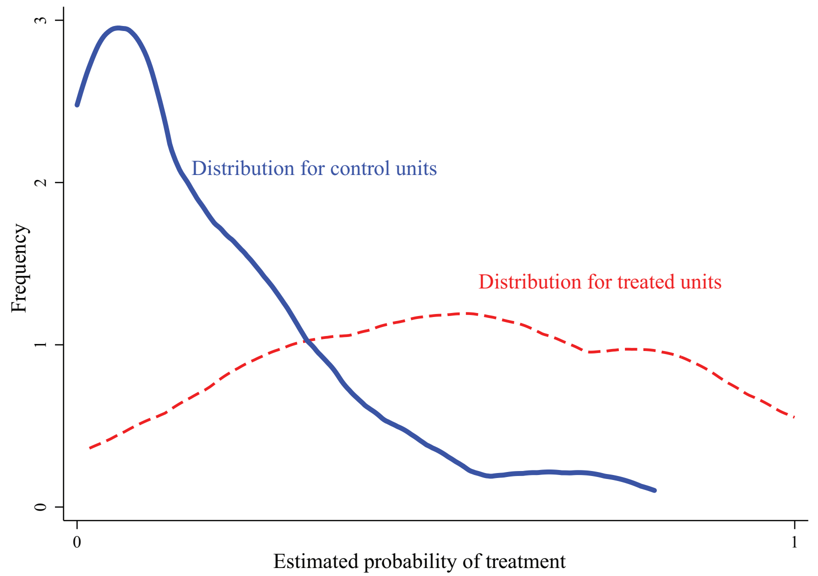

Figure 6. Checking for overlap in the propensity score

Notes: Propensity score logit models are estimated over the 1870–1939 (excluding World War I), and 1948–2013 samples. See text. The figure plots the empirical density of the predicted probabilities of financial-crisis type recessions from the logit model where $d_\tau = 1$ for financial-crisis recessions and $d_\tau = 0$ for normal recessions.

expansion as a ratio to GDP (in percentage points per year, or p.p.y.) to normalize differences in the duration of expansions. We estimate the propensity score using a logit model across the separate pre-World War II and post-World War II samples. World War II is a natural breakpoint given the trends in mortgage lending and overall credit discussed in previous sections.

Figure 6 displays the empirical density function of the predicted probabilities from the logit model of the propensity score. The figure shows that the logit model does not perfectly predict these binary outcomes and as a result there is a substantial region of overlap. Identification of the effects we seek comes from this overlap region.

Table 7 reports the results. Our initial estimates focused on three samples: all recessions (excluding world wars); recessions in the pre-World War II era; and recessions post-World War II. Since we found no qualitative differences across these regimes only the full sample results are reported (the subperiod results are shown in the Appendix). For each horizon denoted *Year 1* through *Year 5*, we report the estimates of the coefficients θ_n^h and θ_f^h using expression (4). In addition, the column labelled *Sum* reports the sum of the coefficients in years 1 through 5 as a measure of the cumulative loss/gain of welfare. We provide a test of the null that, at each horizon, the coefficients are statistically equal to each other. In addition to the p-value of this test we also report robust standard errors (clustered by country). The results show that the null is easily rejected except in Year 1. The effects are quantitatively large. Conditional on controls, the gap between normal and financial crisis recession paths is about 1% of per capita real GDP

Table 7. Local projections: path of real GDP per capita in normal versus financial recessions using inverse propensity-score weighting (IPW)

Deviation of log real GDP per capita, years 1–5, relative to Year 0, × 100						
Sample = All Recessions	Year 1	Year 2	Year 3	Year 4	Year 5	Sum
Normal recession	−1.59***	0.23	2.64***	4.10***	5.79***	11.17***
	(0.23)	(0.39)	(0.38)	(0.42)	(0.33)	(1.28)
Financial recession	−2.41***	−3.45***	−2.25***	−0.36	1.16**	−7.31***
	(0.35)	(0.54)	(0.55)	(0.53)	(0.46)	(1.88)
R^2	0.598	0.404	0.421	0.381	0.482	0.380
H_0 : *Normal* = *Financial*; p-value	0.18	0.00	0.00	0.00	0.00	0.00
Observations	171	171	171	171	171	171

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. Robust standard errors are in parentheses. Country fixed effects are not shown. Full sample: 1870–2013. Excludes world wars. The table compares the conditional average path of a normal recession against that of a financial crisis recession. Each panel tests equality of the conditional mean in normal and financial crisis recessions by reporting the p-value of the test. The variables are weighted by the inverse propensity score for the probability of observing a financial crisis recession instead of a normal recession. See text.

(relative to the start of the recession) in Year 1, which then rises to 3.5% in Year 2, and persists at about 4–5% in Years 3, 4 and 5. The cumulated gap therefore amounts to about 18% of annual output over the 5 years. The typical paths of economies in normal versus financial crisis recessions are clearly not the same.

7.3. The aftermath of credit booms

Financial crises are different from normal recessions and this difference cannot be explained by a large set of observable macroeconomic aggregates. The IPW estimates reported in the previous section ensure that the conditioning set is entered in as flexible yet parsimonious a manner as possible. The question we ask in this section is whether the differences documented in the previous section are due to credit buildups in the prior expansion phase of the business cycle. Because we have shown that credit buildups are predictive of financial crises, we want to avoid the problem of having our measures of the response to credit reflect simply an endogenous response to the selection of recession events into the normal or financial type. We employ the IPWRA estimator introduced earlier for this reason.

Using the IPWRA estimator in expression (5) we build on Table 7 and extend the specification to include credit dynamics. Recall the credit variable $(x_\tau - \bar{x})$ in expression (5) measures the annual change of total lending in the previous expansion as a ratio to GDP (in percentage points per year, or p.p.y.). We remove country-specific means to normalize differences across countries.

As an illustration, the scatter plot of Figure 7 shows the effect of the inverse probability weighting in the calculation of the β^h that we report in Table 8. Figure 7 plots a partial scatter of the accumulated change in real GDP per capita in year 5 after the recession starts, against the credit variable $(x_\tau - \bar{x})$ that we just described and which is observed at the start of the recession.

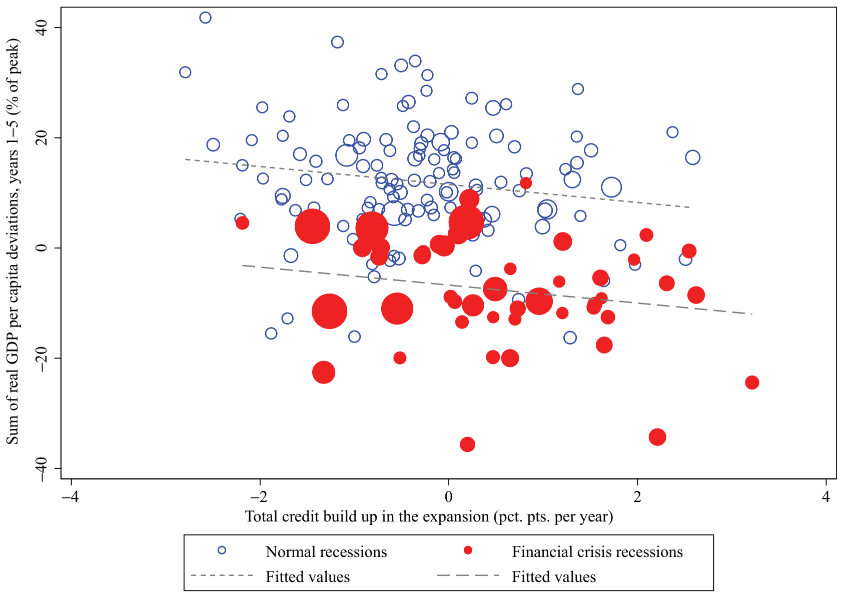

Figure 7. Inverse probability weighted scatter plot of the accumulated deviations in real GDP per capita over 1–5 years into the recession against the credit measure

Notes: Full sample 1870–2013 (excluding world wars). The size of the circle indicates the weight of that observation based on the inverse propensity score weight from the logit models estimated over 1870–1939 (excluding World War I), and 1948–2013. The slope estimates for each subpopulation (normal versus financial crisis recessions) indicate the effect of credit buildups in the expansions on real GDP per capita 5 years after the recession starts.

Table 8. Local projections: path of real GDP per capita in normal versus financial recessions and the role of credit using inverse propensity-score weighting regression adjustment (IPWRA)

Deviation of log real GDP per capita, years 1–5, relative to Year 0, × 100						
Sample = All Recessions	Year 1	Year 2	Year 3	Year 4	Year 5	Sum
Normal recession	−1.56***	0.33	2.76***	4.27***	5.95***	11.74***
	(0.23)	(0.38)	(0.37)	(0.39)	(0.37)	(1.26)
Financial recession	−2.35***	−3.14***	−1.91***	0.17	1.66***	−5.57***
	(0.34)	(0.48)	(0.45)	(0.52)	(0.48)	(1.42)
Private credit	−0.02	−0.35**	−0.30	−0.54**	−0.59**	−1.80**
	(0.06)	(0.14)	(0.26)	(0.25)	(0.24)	(0.77)
R^2	0.602	0.459	0.455	0.441	0.522	0.441
H_0 : *Normal* = *Financial*; p-value	0.18	0.00	0.00	0.00	0.00	0.00
Observations	171	171	171	171	171	171

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. Robust standard errors are in parentheses. Country fixed effects are not shown. Full sample: 1870–2013. Excludes world wars. The table compares the conditional average path of a normal recession against that of a financial crisis recession. Each panel tests equality of the conditional mean in normal and financial crisis recessions by reporting the p-value of the test. The variables are weighted by the inverse propensity score for the probability of observing a financial crisis recession instead of a normal recession. See text.

Table 9. Local projections: path of real GDP p.c. in normal versus financial recessions and the role of mortgage and non-mortgage credit using inverse propensity-score weighting regression adjustment (IPWRA)

Deviation of log real GDP per capita, years 1–5, relative to Year 0, × 100						
(a) All recessions	Year 1	Year 2	Year 3	Year 4	Year 5	Sum
Normal recession	−1.61***	0.24	2.62***	4.17***	5.74***	11.15***
	(0.20)	(0.42)	(0.43)	(0.43)	(0.47)	(1.50)
Financial recession	−2.35***	−2.87***	−1.86***	0.26	1.61**	−5.20**
	(0.35)	(0.56)	(0.57)	(0.69)	(0.60)	(1.93)
Mortgage credit	0.31**	−0.43*	−0.56	−1.18**	−1.00	−2.87
	(0.14)	(0.21)	(0.49)	(0.49)	(0.70)	(1.77)
Non-mortgage credit	−0.12	−0.35	−0.22	−0.30	−0.46	−1.45
	(0.08)	(0.20)	(0.42)	(0.38)	(0.49)	(1.38)
R^2	0.613	0.476	0.469	0.453	0.526	0.447
H_0 : *Normal* = *Financial*; *p*-value	0.20	0.01	0.00	0.00	0.00	0.00
H_0 : *Mortg* = *NonMortg*; *p*-value	0.04	0.80	0.65	0.25	0.63	0.62
Observations	161	161	161	161	161	161
(b) Pre-World War II recessions	Year 1	Year 2	Year 3	Year 4	Year 5	Sum
Normal recession	−2.45***	−1.15	2.34**	1.36	3.21***	3.32
	(0.56)	(0.82)	(0.78)	(1.22)	(0.98)	(3.20)
Financial recession	−2.79***	−4.17***	−3.31**	−2.59**	−1.02	−13.88***
	(0.45)	(1.07)	(1.16)	(1.05)	(1.44)	(4.19)
Mortgage credit	0.50	−0.78	−0.12	−2.00	−2.02	−4.42
	(0.39)	(1.04)	(1.31)	(1.24)	(2.01)	(5.47)
Non-mortgage credit	0.08	−0.18	−0.19	−0.38	−0.87	−1.53
	(0.19)	(0.41)	(0.58)	(0.55)	(0.68)	(1.85)
R^2	0.787	0.640	0.595	0.537	0.535	0.564
H_0 : *Normal* = *Financial*; *p*-value	0.72	0.06	0.01	0.03	0.07	0.02
H_0 : *Mortg* = *NonMortg*; *p*-value	0.32	0.59	0.96	0.26	0.65	0.66
Observations	73	73	73	73	73	73
(c) Post-World War II recessions	Year 1	Year 2	Year 3	Year 4	Year 5	Sum
Normal recession	−1.05***	0.36	2.75***	5.00***	6.93***	13.99***
	(0.20)	(0.22)	(0.28)	(0.35)	(0.29)	(0.99)
Financial recession	−1.88***	−2.31***	−0.33	1.18	2.68***	−0.67
	(0.38)	(0.36)	(0.53)	(0.72)	(0.67)	(2.12)
Mortgage credit	0.15	−0.70*	−1.40***	−1.80***	−1.94***	−5.69***
	(0.23)	(0.33)	(0.37)	(0.41)	(0.54)	(1.38)
Non-mortgage credit	−0.13	−0.22	−0.15	−0.35	−0.56	−1.41
	(0.23)	(0.33)	(0.47)	(0.49)	(0.64)	(1.59)
R^2	0.713	0.542	0.638	0.731	0.769	0.668
H_0 : *Normal* = *Financial*; *p*-value	0.17	0.00	0.00	0.00	0.00	0.00
H_0 : *Mortg* = *NonMortg*; *p*-value	0.50	0.33	0.11	0.11	0.22	0.13
Observations	88	88	88	88	88	88

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. Robust standard errors are in parentheses. Country-fixed effects and controls are not shown. Pre-World War I sample: 1870–1939 across 17 countries. Excludes World War I. Post-World War II sample: 1948–2013 across 17 countries. Each panel compares the conditional average path of a normal recession with the path in a financial crisis recession. In addition, it considers the effect of mortgage and non-mortgage credit buildups during the expansion as separate controls. The table provides two formal tests. First, it tests the equality of the conditional mean in normal and financial crisis recessions. Second, it tests that excess mortgage and non-mortgage credit have the same effect. The local projections are weighted by the inverse propensity score for the probability of observing a financial crisis recession instead of a normal recession. See text.

The inverse probability weighting, shown by the differences in the size of the points in the scatter plot, is an attempt to re-randomize the allocation of economies into the normal versus financial crisis recession bins. The largest weights of the subpopulation of economies that experienced a financial crisis recession (shown in solid red) are associated with smaller credit booms. These are the financial crisis recessions that look more similar to the normal recessions. Conversely, economies that experienced a normal recession and a large credit build-up also receive larger weights because they are the closest counterpoint to economies that experienced a financial crisis. The weighting is somewhat more sophisticated than this simple explanation would indicate since there are cases in which macroeconomic fundamentals clearly predict that a financial crisis is likely even when credit buildups are relatively small (e.g., the two observations at the bottom of the figure).

The negative slope coefficients for the weighted subsamples imply that the larger the credit buildup in the expansion the weaker is the subsequent recovery after the recession. The large and statistically significant intercept difference between the two regression lines for the subsamples measures the average difference between the aftermath of financial crisis and normal recessions, controlling for all measurable economic factors. This summary effect is consistent with the annual paths in Tables 7 and 8, and qualitatively large: it again adds up to about 20% for the sum of log real GDP per capita deviations over 5 years, i.e., a loss of 4% of output per year in that window.

Table 8 builds on the intuition in Figure 7 and shows that debt overhang is a regular phenomenon of the modern business cycle. Estimates of the credit buildup indicator are sometimes estimated inaccurately even though the economic effects are quite sizable. The coefficient estimates on the credit buildup indicator are statistically significant at conventional levels in Years 2, 4 and 5. At its peak effect in Year 5, every additional 1 p.p.y. of credit accumulation above the country specific mean is associated with about 0.6% lower real per capita GDP relative to the start of the recession.[8] Moreover, the summary statistics reported in Table 6 suggest that the experiment based on 1 p.p.y. of credit buildup is rather conservative since the sample standard deviation of this variable is about 2 p.p.

These results confirm the findings in Jordà *et al.* (2013) using new data and more sophisticated techniques. On an aggregate level, credit booms are associated with deeper recessions and slower recoveries. Put differently, credit bites back. However, even controlling for these effects financial crisis recessions are still dramatically more costly than normal recessions, with losses mounting to 1/5 of annual real GDP over 5 years. In the next section, we turn to a more granular analysis and examine if and how the composition of credit has an effect on the dynamics of the business cycle.

[8] That effect is larger in the pre-World War II sample at over 1% (but more volatile), and about the same post-World War II. See the Appendix for the analysis in Table 7 broken down by pre- and post-World War II samples.

7.4. The aftermath of mortgage booms

Up to now we have estimated recession paths based on total credit – but is all credit the same? Are overhangs from mortgage booms particularly severe?

In this section, we maintain the baseline IPWRA specification in expression (5) but split the credit variable into two components: mortgage lending versus non-mortgage lending. Mortgage lending includes residential and commercial real estate lending. Non-mortgage lending is a less homogeneous category that includes business lending and other unsecured lending such as consumer finance. As before, both enter the regressions as the rate of change of each type of lending in the previous expansion (as a ratio to GDP and in percentage points per year) to normalize differences in the duration of expansions. Each variable is measured in deviation from country-specific means.

Table 9 extends the analysis in Table 8 using each credit component separately. In addition, it reports how in this case we find somewhat differentiated results when the full sample is broken down by two subsamples separated by World War II.

First, as in Tables 7 and 8, the null hypothesis that the average paths conditional on controls and country-fixed effects in normal and financial crisis recessions are the same is comfortably rejected, except as before in Year 1. Over the five-year window, the output gap between the two paths cumulates to about 1/6 of annual output which still cannot be explained by the observable macroeconomic controls. Second, and in contrast with the results above, the regressions show that the dynamics of credit changed substantially after World War II so we report results for the full sample and two subperiods. The results from the full sample reported in panel (a) of Table 9 show scant evidence of a role for mortgage or non-mortgage credit. The reason why can be found in the subsample analysis.

Mortgage lending has economically important effects relative to non-mortgage lending, although both are imprecisely estimated. Still, the effect goes in the same direction for both types of lending. The faster the pace of lending during the expansion, the worse the subsequent recession. However, mirroring the long-run structural shift towards mortgage lending, a different picture emerges for the post-World War II sample: mortgage lending effects are now estimated precisely, whereas the effects of non-mortgage lending remain economically and statistically insignificant. After World War II the overhang from mortgage booms is severe and long-lasting, in line with the growing importance of mortgage lending in overall credit discussed above.

Based on the results in Table 9, in Figure 8 we present cumulated responses for real GDP per capita, the ratio of investment to GDP and the ratio of total lending to GDP. The solid lines in the figure refer to the average conditional path in normal recessions (displayed in solid blue along with a grey shaded 95% confidence region) and in financial crisis recessions (displayed in solid red). For each type of recession, we also modify the average path by considering model predictions under an alternative (above average) level of the credit buildup in the preceding expansion. The dotted lines correspond to the responses associated with a +1 s.d. acceleration of non-mortgage credit growth, whereas the dashed line corresponds to a +1 s.d. boom of mortgage credit.

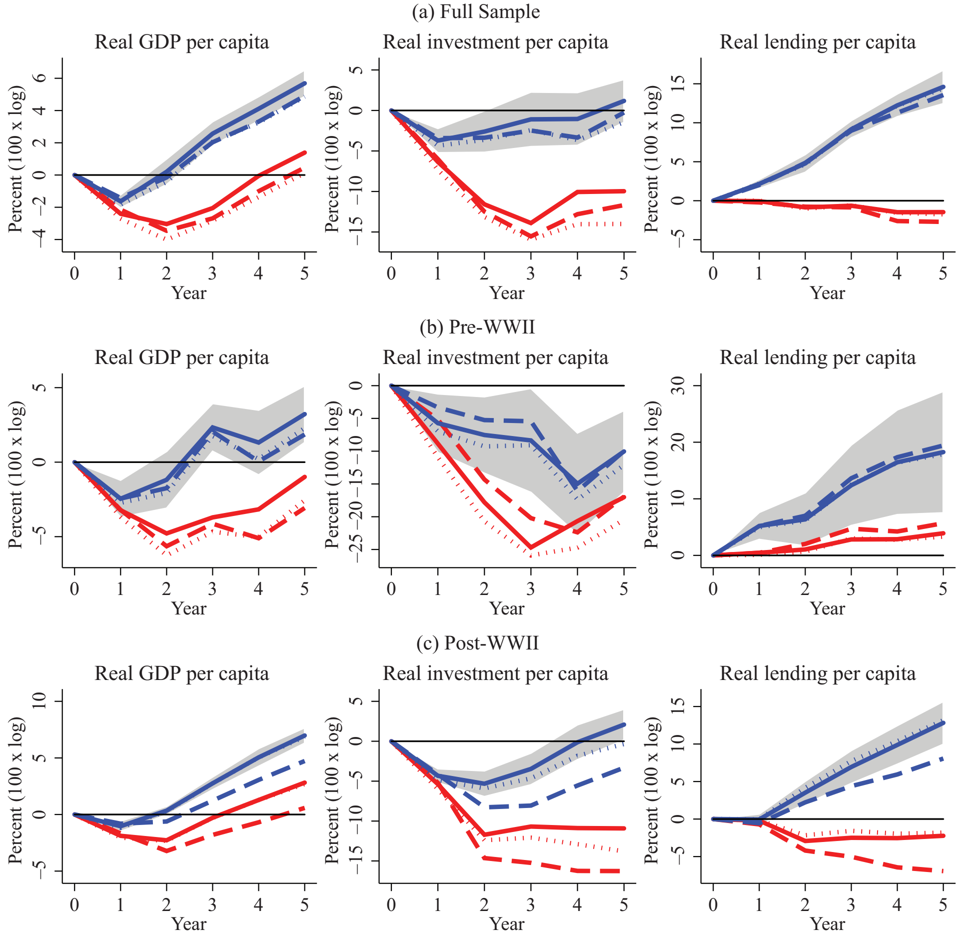

Figure 8. Conditional cumulated responses for real GDP per capita, the ratio of investment to GDP and the ratio of total lending to GDP from the start of the recession as a function of the type of recession and mortgage and non-mortgage credit

Notes: Samples: 1870–2013 (excluding world wars), 1870–1939 (excluding World War I) and 1948–2013. Scales matched by column but allowed to vary across variables. Each path shows IPWRA estimates of the cumulative change relative to peak for years 1–5 of the recession/recovery period under different experiments. The solid line with shaded region refers to the average path in normal recessions. The solid line without shaded region refers to financial crisis recessions. The shaded region is a 95% confidence interval. The dotted lines refer to the path in a normal/financial crisis recession when non-mortgage credit during the expansion grew at the mean plus one standard deviation. The dashed lines refer to the path in a normal/financial crisis recession when mortgage credit during the expansion grew at the mean plus one standard deviation. The IPWRA estimates are conditional on the full set of macroeconomic aggregates and their lags, with paths evaluated at the means. See text.

The first row of Figure 8 corresponds to the full 1870–2013 sample, the second row to the pre-World War II sample and the third row to the post-World War II sample. Notice that the pre-World War II sample includes the Great Depression which helps explain the slower trends in general and the particularly severe paths of GDP and investment. Overall, the responses for each type of recession and for each variable are nicely aligned with economic intuition. It is evident that in financial crisis recessions output, investment and credit are much more strongly affected than in normal recessions. It typically takes longer for economies to regain their previous peak output after a systemic financial crisis and even longer for investment.

Importantly, the figures also underscore the main lesson from Table 9: mortgage debt plays a key role in explaining the drag from debt overhang in the post-World War II decades. Comparing the responses for the post-World War II sample (bottom row) with either the full sample (top row) or the pre-World War II sample (middle row) reveals that mortgage booms lead to greater post-crisis drag on growth. These negative effects on the pace of the recovery are present both in normal recessions and in financial crisis recessions. Since World War II both normal and financial recessions tend to be considerably deeper and the recovery much slower when the preceding boom saw a strong expansion of mortgage debt.

Non-mortgage credit booms, in contrast, have virtually no effect on the path of the recession nowadays as shown in the bottom row of Figure 8. The dotted lines almost always lie on top of the solid lines. Yet matters are strikingly different for real estate credit booms. By Year 5, real GDP per capita is about 2.5% lower than it would otherwise be – regardless of the type of recession. The effects are even more dramatic when considering real investment per capita. The difference between the average path and the post-mortgage credit boom path are close to 7% after Year 5, potentially driven by a collapse in housing investment.

The estimates reported in Figure 8 are based on our IPWRA estimates and are the closest we can come to showing how the accumulation of credit (mortgage and otherwise) affects the path of the recession and recovery, even after controlling for crisis endogeneity. Although a financial crisis still makes the recession worse beyond other observable factors, comparing the results reported across Tables 7–9 we note that this effect becomes increasingly more attenuated even if it never completely disappears.

Summing up, the local projections demonstrate that the aftermath of credit booms is characterized by recessions that are deeper and recoveries that are slower than normal. However, our new disaggregated credit data adds important nuances to the debt overhang story. Since World War II, it was in particular the overhang from mortgage booms that was associated with more painful recessions and protracted recoveries.

8. CONCLUSIONS

This paper presented three new important insights into long-run credit dynamics in advanced economies. These insights are the result of combining modern methods of statistical analysis with the painstaking construction of a new dataset. We expect that the value of this dataset will transcend the present paper and that it will become an important resource for macroeconomic research going forward. The new insights also have important implications for macroeconomics researchers and policy-makers alike and they can be summarized as follows.

First, we found that in the second half of the twentieth century, banks and households have been heavily leveraging up through mortgages. Mortgage credit on the balance sheets of banks has been the driving force behind the increasing *financialization* of advanced economies. In relation to GDP, non-mortgage bank lending to companies and households has remained stable, with virtually all of the increase in the size of the financial sector stemming from a boom in mortgage lending to households. Household leverage ratios (mortgage debt divided by the value of the housing stock) have increased substantially in many economies over the twentieth century. About two thirds of the business of banking today consists of the intermediation of savings to the household sector for the purchase of real estate. At the beginning of the twentieth century, mortgage lending accounted for less than a third of the typical bank's loan book.

Second, we showed that the growth of mortgage credit has important implications for the sources of financial fragility in advanced economies, and hence for macroeconomic policies. Mortgage booms are an important source of financial instability in the post-World War II era, and mortgages have growing weight in total financial sector activity. We present evidence that the changing nature of financial intermediation has shifted the locus of crisis risk towards mortgage lending booms. This is an important new fact to be considered in the design of macro-prudential policies.

Third, we demonstrated that mortgage credit has also increasingly left its mark on business cycle dynamics. In the post-World War II period, the aftermath of mortgage booms gone bust is marked by considerably slower growth rates, irrespective of whether a financial crisis occurred or not. Non-mortgage credit no longer appears to have such an effect. Contemporary business cycles seem to be increasingly shaped by the dynamics of mortgage credit, with non-mortgage lending playing only a minor role. These findings mesh nicely with the growing importance of housing and housing finance for the overall economy (Leamer, 2015).

Overall, the findings of this paper call for a differentiated perspective on credit growth and on the implications that this differentiation has for financial stability, macroeconomic policies and financial regulation. Important insights into the sources of financial fragility and the role of credit in the business cycle would be missed without a disaggregated perspective on the various types of credit and their development over the course of modern macroeconomic history.

Discussion

Martin Ellison

University of Oxford

This is a 'great' paper, adding the Great Mortgaging to the Great Depression and the Great Recession in the list of defining macroeconomic events of modern times. The finding that housing finance is becoming increasingly important will come as little surprise to many economists, for example see the 2004 report of the Miles Commission into the UK mortgage market, but the magnitude of the shift in bank balance sheets is still surprising. Housing finance is also of interest because of its intimate link to house prices. Those of us in the United Kingdom on 19th October 2015 watched while the BBC headlined with the news that Oxford is currently the most unaffordable place to live in the United Kingdom, with average property prices in the city 16 times higher than average incomes. Having just bought a house in the centre of Oxford, is my timing of the market spectacularly bad? Should I worry that the Great Mortgaging is setting the UK economy up for a fall? How do we attract faculty to the University of Oxford if houses are unaffordable? Reading this paper helps answer these questions.

The new historical dataset in the paper shows that mortgage loans now account for a large proportion of bank balance sheets in 17 advanced economies, that banks have become primarily real estate lenders, and that this has changed both the dynamics of recessions and the frequency of financial crises. On the dynamics of recessions, a recession has always tended to be longer and more severe if it is accompanied by a financial crisis. However, mortgage financing plays an additional role after World War II. In short, if a post-war recession is preceded by a period of expanding mortgage credit then it tends to be longer and cause greater output losses than a recession that starts with more stable mortgage credit. The results apply whether or not the recession is accompanied by a financial crisis. On the frequency of financial crises, an expansion in mortgage credit increases the probability of a financial crisis post World War II but not before.

It is the luxury of a commentator to speculate freely on what may or may not be driving the Great Mortgaging. One possibility is developments in the relative price of durable goods and land. According to the US Bureau of Economic Analysis, the nominal price of US durables has fallen by more than 30% since 1994. In contrast, data from the Lincoln Institute of Land Policy show an almost 200% increase in nominal US land prices over the same period. Thinking of banks in their traditional role as maturity transformers, the Great Mortgaging would then be in line with expectations. The need to borrow to purchase durable goods has been dwarfed by a much greater need to borrow to purchase land. The argument that land has returned as a constraint to growth has been termed the 'Paradox of Soil' by *The Economist*.

Any attempt to understand why housing finance is having a greater impact on the economy is hampered by the small number of financial crises since World War II. The estimation results are based on only 11 financial crises occurring across 7 distinct years (Great Britain 1973 and 1990, Spain 1978, Denmark 1987, Norway 1987, Australia 1989, Finland 1989, Switzerland 1990, Sweden 1990, Italy 1992, Japan 1997). While the small number of observations makes formal econometrics challenging, it does offer the possibility of a deep narrative analysis. Using the econometric results as a lens to examine the stories behind each financial crisis is likely to be informative.

An alternative way to look at the estimation results is in terms of their out-of-sample predictive power. The sample period is already 1870–2011, so the only way to go out of sample is to look beyond the 17 advanced economies currently in the dataset. There is scope for interesting further work here. For example, Hale and Kennedy (2012) look at the Asian crisis and state that 'The overall effect of the global financial crisis on emerging Asia was limited and short-lived. However, the crisis affected some countries in the region more than others'. They have their own take as to why different countries were affected in different ways, but I would be curious to see if growth in mortgage credit plays a role in reconciling why Hong-Kong, Malaysia, Thailand, Korea and Singapore were 'Storm-tossed' countries while China, Philippines, India, Indonesia and Vietnam were 'Smooth-sailing' through the crisis.

Evi Pappa

EUI, UAB, and CEPR

During the last few decades, there has been a vast expansion of the role of financial markets and financial institutions in the operation of domestic and international economies. Financialization is thought to operate through three different channels: changes in the structure and operation of financial markets, changes in the behavior of non-financial corporations and changes in economic policy. Obviously, understanding the sources and effects of the growth of finance is a top concern for economists and policy-makers.

However, how does financialization work from a historical perspective? The data availability so far was scarce for studying the causes and consequences of these new trends in modern financial history. Hence, the first and very important contribution of Jordà, Schularick and Taylor's paper is to provide the profession with a new long-run standardized dataset covering disaggregated bank credit for 17 advanced economies since 1870. With the dataset of Jordà, Schularick and Taylor, economists are provided with important data sources to analyse one of the channels through which financialization works, the one of changes in financial markets. The authors construct important financial measures using the new data, such as the share of mortgage loans in total bank lending for most countries back to the nineteenth century, the share of bank credit to business and households for most countries for the decades after World War II, and back to the nineteenth century for a handful of countries. They then proceed by establishing stylized facts based on the new dataset. They document (1) a sharp rise of credit-to-GDP ratios between 1980 and 2013; (2) the doubling of the share of mortgages on banks' balance sheets in the course of the twentieth century, and (3) the substantial rise of household mortgage debt to asset ratios in many countries.

The most striking fact in their dataset, which gives the paper its title is what they call the 'Great Mortgaging'. In the second half of the twentieth century, banks and households have been heavily leveraging up through mortgages. Banks in this second half of the century behave more like 'real estate funds'. The analysis reveals that mortgage credit on the balance sheets of banks has been the driving force behind the increasing financialization of advanced economies. The authors finally show that this great mortgaging has been a major factor of financial fragility in advanced economies, and that it has also affected considerably the business cycle dynamics of the economies in the sample. In particular, mortgage booms are shown to be an important source of financial instability after World War II and credit booms to be associated with deeper recessions and slower recoveries.

On the specifics, the authors in the first part of the analysis show that the changes in the structure of financial intermediation, underlined by the growing importance of mortgages in total bank credit, made advanced economies more financially fragile. The disaggregated credit data help improve the classification ability of crisis forecast models and the authors show that housing credit has become more closely associated with financial crisis risks as its share in total credit has grown. These results are based on a probabilistic model that specifies the log-odds ratio of a financial crisis employing as predictors the various credit aggregates using the full sample, the pre-World War II era, and the post- World War II period. Yet the authors fail to report how credit booms compare to other crisis predictors. For example, Herrera *et al.* (2014) highlight the importance of political booms, measured by the rise in governments' popularity, in predicting financial crises above and beyond credit booms. On the other hand, Catão and Milesi-Ferretti (2013), using a shorter dataset, show that the ratio of net foreign liabilities (NFL) to GDP is a significant crisis predictor. Finally, financial contagion, and financial liberalization (see, e.g., Glick and Hutchison (1999), Tornell and Westerman (2002), Kaminsky and Reinhart (1999), and Kaminsky and Schmukler (2003)). The authors try to control for contagion in their robustness checks by including in their regressions a global factor, yet little is done in the analysis to control for financial liberalization that occurred in many countries in the long sample available.

On a more general note, the great mortgaging in the analysis is appearing as something that occurred by itself with no connection to other important financial trends of the twentieth century. The reader would gain perspective to think that this newly uncovered trend occurred at the same time as what Rajan (2005) calls the 'Disintermediation'. Financial markets have expanded and become deeper. The broad participation has allowed risks to be more widely spread throughout the economy. Technical change has reduced the cost of communication and computation, as well as the cost of acquiring, processing and storing information. Techniques ranging from financial engineering to portfolio optimization, from securitization to credit scoring, are now widely used. Deregulation has removed artificial barriers preventing entry, or competition between products, institutions, markets and jurisdictions. Finally, the process of institutional change has created new entities within the financial sector such as private equity firms and hedge funds, as well as new political, legal and regulatory arrangements. These changes might have affected the behaviour of banks and could be behind the shift in the supply of mortgages. In other words, the great mortgaging could be a consequence of financial developments and reflect increasing risk taking from other intermediaries. Along the same lines, another change of the last century worth mentioning is globalization (see, e.g., Lane and Milesi-Ferretti (2007)). The rapid integration of the international financial system during the past decade might have played an important role in limiting banks' capacity to perform their standard intermediation activities and border their role to real estate funds.

Finally, the increase in the price of houses is an important factor to take into account when analysing the great mortgaging phenomenon. House prices have increased significantly in the twentieth century. Moritz Schularick documents that in a recent paper of his coauthored with Katharina Knoll and Thomas Steger. Knoll *et al.* (2014) present new house price indices for 14 advanced economies since 1870. They show that real house prices stayed constant from the nineteenth to the mid-twentieth century, but rose strongly in the second half of the twentieth century. The data attribute the sharp increase to the rise of land prices and not construction costs. On the demand side, past trends can influence both the level of household investment in housing and the risk characteristics of the applicant pool. First, expectations of positive future home price growth based on past trends renders housing a more attractive asset, suggesting that a household will increase allocation to housing over the near term. Applicants borrow to finance this allocation, which makes them riskier from a lender's perspective. Second, because the after-tax financial benefits of mortgaged home ownership are increasing in income, higher forecast returns may also bring more low-income loan applicants into the market. On the supply side, mortgage lenders may interpret greater past price increases as evidence of lower default risk because the loan to value ratio is expected to fall with future house price increases. Consequently, lenders may accommodate the increased demand for mortgages because the expected future recovery from foreclosure is expected to exceed the outstanding mortgage principal. The supply of mortgage loans thus increases for all types of mortgages, but the effect may be most pronounced for borrowers with poor credit quality because of the participation effect. It is important to establish how the causation works. Is the great mortgaging a result of increase in the demand for mortgage loans, or in their supply? Definitely, government intervention, in the United States and the United Kingdom, as the authors highlight, and international banking regulations, such as Basel I, made loans secured by mortgages half as risky as corporate loans and this might have increased the supply of mortgages on the part of the banks. On the other hand, increasing leverage, increasing homeownership and increased stability (absence of wars, conflicts, etc.) might have increased the demand for mortgage loans. Yet, the current paper does not provide the reader with a definite answer. The relation presented is the reduced form. We really need to understand further the causation.

The above analysis suggests that a lot of future work can follow the current article in order to investigate further the sources of the great mortgaging. That said, this is an excellent piece of work that will inspire a lot of future research trying to understand further the dynamics of the great mortgaging. On top of that the dataset put forward by Jorda *et al.* will provide researchers with an important source of information for performing empirical work on related issues. Summing up this is a 'great' paper. It is very interesting and well-crafted and is very relevant for both academics and policy-makers. The amount and quality of data provided is precious for economic historians, macroeconomists and econometricians alike. I see the current paper as the benchmark of a new literature to come!

Panel discussion

Zoja Razmusa said that synchronization of cycles became important in the last crisis. She also said that the distribution and concentration of financial market participants are features that can be found in the data but is very difficult to do so. Ray Rees pointed out that when prices are rising, people start using equity, on the one hand to finance consumption and on the other hand to finance further investment in housing. That leads to speculative leveraging of ordinary households. When the bubble bursts, there is negative equity and that has real effects. He asked whether that phenomenon could be tested with cross-country data. Secondly, he wondered whether or not building societies should be defined as banks in the United Kingdom.

Ethan Ilzetzki said that the facts are interesting but asserting that banks have become real estate hedge funds is using charged language. There is no certainty in that direction. Secondly, he asked why mortgage shocks are not more damaging given that mortgage lending is larger compared to other forms of lending. Luigi Guiso had a remark on the timing. He said that most of the action on the change in the specialization of banks took place after 1990. Thus, to provide an explanation for why there is a change in the specialization, one should look at the last 20 years. He also said that if one can securitize then giving mortgages today, from an economic point of view, is not exactly the same as giving mortgages in 1920. From a statistical point of view, he asked whether securitization impacts the data or not. That is, when securitized mortgages are reported, he wondered if they still appear in the balance sheet of banks or not.

Tim Hatton said that there is almost no correlation between the rate of owner occupation and the share of bank lending going to mortgages in the cross-section, which suggests that some part of mortgages is used for purchase to rent rather than by owner-occupiers. Given that the share of mortgage lending going to owner-occupiers is increasing over time, he said that owner occupation is magnifying the effects of the housing price crisis. Leonardo Gambacorta also focused on the role of securitization and said that due to the originate-to-distribute model, banks could have reduced incentives to screen and monitor their clients so this also reduces the role of collateral. He pointed out the increase in the loan-to-value ratio in the United States where securitization was widely used, relative to the ratio in other countries where securitization was not as heavily employed.

Peter Egger criticized the regression part of the paper. He said that the inverse probability weighting method relies on two fundamental assumptions. One is that the independent variables used to explain probabilities are all the same for the same propensities and the other is that the scores are independent. He said that these two assumptions are violated for two reasons. The first is the presence of country fixed effects. These fixed effects are constant over time, meaning that the propensity scores are time-wise correlated by construction. The second is related to Evi Pappa's comment asking for time fixed effects due to a lot of overlap in the timing of the crises. He said that if time fixed effects are included along with country fixed effects, the method would only be applicable when comparing a country to itself when having a financial crisis and having none, which is impossible. The only way of achieving some independence in the data is to compare a country having a crisis to another time when the same country did not have a crisis.

Ester Faia focused on secular trends. She wondered whether big factors such as industrialization and migration could explain the significance of mortgage. Secondly, she discussed securitization and said that it was very important in the last 20 years but it is not a completely new phenomenon. She said that securitization happened between 1890 and 1907 because of competitive banking and the absence of a central bank. She also added that the 1907 crisis was much more similar to the 2008 crisis than the 1929 crisis, in terms of network externalities.

Jay Shambaugh asked whether cross-country heterogeneity in the timing of mortgage-to-bank lending changes can be used to determine causality. George de Menil asked for more information about the supply side of mortgage lending. He wondered about the degree to which changes in government regulations and the relaxation of limits on household indebtedness in granting mortgages have affected the increase in mortgage lending.

SUPPLEMENTARY DATA

Supplementary data are available at *Economic Policy* online.

APPENDIX

A. Dates of systemic financial crises, 1870–2013

The crisis prediction classification models in the paper employ data on all systemic financial crises from 1870 to 2013. Dates of systemic financial crises based on Jordà *et al*. (2013) and Schularick and Taylor (2012), sources therein, and updates. See text. AUS stands for Australia, BEL for Belgium, CAN for Canada, CHE for Switzerland, DEU for Germany, DNK for Denmark, ESP for Spain, FIN for Finland, FRA for France, GBR for the UK, ITA for Italy, JPN for Japan, NLD for The Netherlands, NOR for Norway, PRT for Portugal, SWE for Sweden, USA for the United States.

B. Dates of normal and financial crisis recessions, 1870–2008

The local projection analysis in the paper employs business cycle peaks from 1870 to 2008, excludes windows around the two world wars, reports projections out to 5 years

Table A1. Dates of systemic financial crises, 1870–2013

AUS	1893, 1989
BEL	1870, 1885, 1925, 1931, 1939, 2008
CAN	1873, 1907, 1923
CHE	1870, 1910, 1931, 1991, 2008
DEU	1873, 1891, 1901, 1907, 1931, 2008
DNK	1877, 1885, 1908, 1921, 1987, 2008
ESP	1883, 1890, 1913, 1920, 1924, 1931, 1978, 2008
FIN	1878, 1900, 1921, 1931, 1991
FRA	1882, 1889, 1930, 2008
GBR	1873, 1890, 1974, 1991, 2007
ITA	1873, 1887, 1893, 1907, 1921, 1930, 1935, 1990, 2008
JPN	1882, 1900, 1904, 1907, 1913, 1927, 1997
NLD	1893, 1907, 1921, 1939, 2008
NOR	1899, 1922, 1931, 1988
PRT	1890, 1920, 1923, 1931, 2008
SWE	1878, 1907, 1922, 1931, 1991, 2008
USA	1873, 1884, 1893, 1907, 1929, 1984, 2007

ahead, and uses the annual panel sample data where the last year's projections from 2008 end in 2013. As a result, peaks from the 2009 to 2013 period are not used in the sample, meaning that the empirical work does not include the global financial crisis as an in-sample event. The peak dates which we use are as shown in the table below where 'N' denotes a normal business cycle peak and 'F' denotes a peak associated with a systemic financial crisis, that is, a crisis within ±2 years of the peak. The peak-trough dating method follows Jordà *et al.* (2013) and uses the Bry and Boschan (1971) algorithm.

C. Subsample results for regressions in tables 6 and 7

We report results when the regressions in Tables 6 and 7 are estimated separately for Pre-World War II and Post-World War II Recessions. The subsample regressions in Table 8 appear in the main text since there are significant differences in the impact of different credit measures across periods. In these two tables, however, such differences are not present. Table A3 reports the simple normal versus financial path differences with no other control variables as in Table 6. The only qualitative difference between the Pre-World War II and Post-World War II Recessions arises from the lower average trend growth (plus the incidence of The Great Depression) in the earlier Pre-World War II sample, which lowers the intercept by about 5 p.p. over 5 years. But with respect to the normal versus financial coefficient differences, the findings from the full sample remain intact. Table A4 reports the normal versus financial path differences and the effect of the total credit control variable as in Table 7. The same normal versus financial differences remain, but the small sample size leads to

Table A2. Dates of normal and financial crisis recession peaks, 1870–2008

AUS	N	1875, 1878, 1881, 1883, 1885, 1887, 1889, 1896, 1898, 1900, 1904, 1910, 1913, 1926, 1938, 1943, 1951, 1956, 1961, 1973, 1976, 1981, 2008
	F	1891, 1894, 1989
BEL	N	1872, 1874, 1887, 1890, 1900, 1913, 1916, 1942, 1951, 1957, 1974, 1980, 1992
	F	1870, 1883, 1926, 1930, 1937, 2008
CAN	N	1871, 1877, 1882, 1884, 1888, 1891, 1894, 1903, 1913, 1917, 1928, 1944, 1947, 1953, 1956, 1981, 1989, 2007
	F	1874, 1907
CHE	N	1875, 1880, 1886, 1890, 1893, 1899, 1902, 1906, 1912, 1916, 1920, 1933, 1939, 1947, 1951, 1957, 1974, 1981, 1994, 2001
	F	1871, 1929, 1990, 2008
DEU	N	1879, 1898, 1905, 1913, 1922, 1943, 1966, 1974, 1980, 1992, 2001
	F	1875, 1890, 1908, 1928, 2008
DNK	N	1870, 1880, 1887, 1911, 1914, 1916, 1923, 1939, 1944, 1950, 1962, 1973, 1979, 1992
	F	1872, 1876, 1883, 1920, 1931, 1987, 2007
ESP	N	1873, 1877, 1892, 1894, 1901, 1909, 1911, 1916, 1927, 1932, 1935, 1940, 1944, 1947, 1952, 1958, 1974, 1980, 1992
	F	1883, 1889, 1913, 1925, 1929, 1978, 2007
FIN	N	1870, 1883, 1890, 1898, 1907, 1913, 1916, 1938, 1941, 1943, 1952, 1957, 1975, 2008
	F	1876, 1900, 1929, 1989
FRA	N	1872, 1874, 1892, 1894, 1896, 1900, 1905, 1907, 1909, 1912, 1916, 1920, 1926, 1933, 1937, 1939, 1942, 1974, 1992
	F	1882, 1929, 2007
GBR	N	1871, 1875, 1877, 1883, 1896, 1899, 1902, 1907, 1918, 1925, 1929, 1938, 1943, 1951, 1957, 1979
	F	1873, 1889, 1973, 1990, 2007
ITA	N	1870, 1883, 1897, 1918, 1923, 1925, 1932, 1939, 1974, 2002, 2004
	F	1874, 1887, 1891, 1929, 1992, 2007
JPN	N	1875, 1877, 1880, 1887, 1890, 1892, 1895, 1898, 1903, 1919, 1921, 1929, 1933, 1940, 1973, 2001, 2007
	F	1882, 1901, 1907, 1913, 1925, 1997
NLD	N	1870, 1873, 1877, 1889, 1894, 1899, 1902, 1913, 1929, 1957, 1974, 1980, 2001
	F	1892, 1906, 1937, 1939, 2008
NOR	N	1876, 1881, 1885, 1893, 1902, 1916, 1923, 1939, 1941, 1957, 1981, 2007
	F	1897, 1920, 1930, 1987
PRT	N	1870, 1873, 1877, 1888, 1893, 1900, 1904, 1907, 1912, 1914, 1916, 1925, 1927, 1934, 1937, 1939, 1941, 1944, 1947, 1951, 1973, 1982, 1992, 2002, 2004
	F	1890, 1923, 1929, 2007
SWE	N	1873, 1876, 1881, 1883, 1885, 1888, 1890, 1899, 1901, 1904, 1913, 1916, 1924, 1939, 1976, 1980
	F	1879, 1907, 1920, 1930, 1990, 2007
USA	N	1875, 1887, 1889, 1895, 1901, 1909, 1913, 1916, 1918, 1926, 1937, 1944, 1948, 1953, 1957, 1969 1973, 1979, 1981, 1990, 2000
	F	1873, 1882, 1892, 1906, 1929, 2007

Table A3. Local projections: path of real GDP per capita in normal v. financial recessions using inverse propensity-score weighting (IPW), subsample analysis for pre-World War II and post-World War II periods

Deviation of log real GDP per capita, years 1–5, relative to Year 0, × 100

(a) Sample = Pre-World War II Recessions	Year 1	Year 2	Year 3	Year 4	Year 5	Sum
Normal recession	−2.67***	−1.75***	1.67**	0.36	2.52**	0.13
	(0.51)	(0.47)	(0.56)	(1.10)	(0.95)	(2.33)
Financial recession	−3.36***	−5.72***	−4.40***	−3.98**	−1.52	−18.98***
	(0.47)	(0.99)	(0.93)	(1.37)	(1.29)	(4.59)
R^2	0.727	0.522	0.551	0.431	0.483	0.478
H_0 : *Normal* = *Financial*; p-value	0.46	0.01	0.00	0.01	0.02	0.00
Observations	82	82	82	82	82	82
(b) Sample = Post-World War II Recessions	Year 1	Year 2	Year 3	Year 4	Year 5	Sum
Normal recession	−1.03***	0.45	2.94***	5.28***	7.25***	14.91***
	(0.22)	(0.26)	(0.37)	(0.51)	(0.47)	(1.48)
Financial recession	−1.89***	−2.42***	−0.49	1.03	2.52***	−1.24
	(0.36)	(0.47)	(0.63)	(0.83)	(0.78)	(2.47)
R^2	0.698	0.459	0.552	0.658	0.711	0.587
H_0 : *Normal* = *Financial*; p-value	0.15	0.00	0.00	0.01	0.00	0.00
Observations	89	89	89	89	89	89

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. Robust standard errors are in parentheses. Country-fixed effects are not shown. Panel (a): 1870–1939 sample. Panel (b) 1948–2013 sample. Each panel tests equality of the conditional mean in normal and financial crisis recessions by reporting the p-value of the test. The variables are weighted by the inverse propensity score for the probability of observing a financial crisis recession instead of a normal recession. See text.

imprecise estimates of the total credit coefficient. With no significant differences here in the total credit coefficient for the Pre-World War II and Post-World War II Recessions, the findings of Table 7 are not overturned, and the tighter confidence intervals obtained from the full sample estimates are to be preferred.

Table A4. Local projections: path of real GDP per capita in normal versus financial recessions and the role of credit using inverse propensity-score weighting regression adjustment (IPWRA), subsample analysis for pre-World War II and post-World War II periods

Deviation of log real GDP per capita, years 1–5, relative to Year 0, × 100

(a) Sample = Pre-World War II Recessions	Year 1	Year 2	Year 3	Year 4	Year 5	Sum
Normal recession	−2.42***	−1.12	2.15***	1.35	3.40***	3.36
	(0.57)	(0.73)	(0.66)	(1.09)	(0.93)	(2.66)
Financial recession	−2.78***	−4.64***	−3.61***	−2.46**	−0.46	−13.94***
	(0.32)	(0.77)	(0.58)	(0.94)	(1.17)	(2.89)
Private credit	0.09	−0.30	−0.27	−0.71	−1.00*	−2.19
	(0.16)	(0.32)	(0.42)	(0.44)	(0.48)	(1.37)
R^2	0.776	0.608	0.577	0.511	0.527	0.555
H_0 : *Normal* = *Financial*; p-value	0.63	0.00	0.00	0.01	0.03	0.00
Observations	82	82	82	82	82	82

(b) Sample = Post-World War II Recessions	Year 1	Year 2	Year 3	Year 4	Year 5	Sum
Normal recession	−1.04***	0.41	2.84***	5.10***	7.05***	14.36***
	(0.20)	(0.30)	(0.36)	(0.45)	(0.41)	(1.39)
Financial recession	−1.91***	−2.27***	−0.31	1.24	2.78***	−0.48
	(0.40)	(0.49)	(0.70)	(0.90)	(0.82)	(2.68)
Private credit	0.01	−0.43	−0.72**	−1.01***	−1.19***	−3.33***
	(0.13)	(0.27)	(0.25)	(0.24)	(0.33)	(0.91)
R^2	0.700	0.503	0.601	0.699	0.746	0.636
H_0 : *Normal* = *Financial*; p-value	0.16	0.00	0.01	0.01	0.00	0.00
Observations	89	89	89	89	89	89

Notes: ***$p < 0.01$, ** < 0.05, * < 0.10. Robust standard errors are in parentheses. Country-fixed effects are not shown. Panel (a): 1870–1939 sample. Panel (b) 1948–2013 sample. Each panel tests equality of the conditional mean in normal and financial crisis recessions by reporting the p-value of the test. The variables are weighted by the inverse propensity score for the probability of observing a financial crisis recession instead of a normal recession. See text.

REFERENCES

Acemoglu, D., S. Johnson, J. Robinson and Y. Thaicharoen (2003). 'Institutional causes, macroeconomic symptoms: volatility, crises and growth', *Journal of Monetary Economics*, 50(1), 49–123.

Admati, A. and M. Hellwig (2013). *The Bankers' New Clothes: What's Wrong with Banking and What to Do about It*, Princeton University Press, Princeton, NJ.

Aikman, D., A.G. Haldane and B.D. Nelson (2015). 'Curbing the credit cycle', *Economic Journal*, 125(585), 1072–109.

Angrist, J.D., Ò. Jordà and G. Kuersteiner (2013). 'Semiparametric estimates of monetary policy effects: string theory revisited', NBER Working Paper 19355.

Bank for International Settlements (2013). *Long Series on Credit to Private Non-financial Sectors*. https://www.bis.org/statistics/credtopriv.htm.

Barro, R.J. and J.F. Ursúa (2008). 'Macroeconomic Crises since 1870', *Brookings Papers on Economic Activity*, 39(1), 255–335.

Beck, T., B. Büyükkarabacak, F.K. Rioja and N.T. Valev (2012). 'Who gets the credit? And does it matter? Household vs. firm lending across countries', *The B.E. Journal of Macroeconomics*, 12(1), 1–46.

Bordo, M.D., B. Eichengreen, D. Klingebiel and M.S. Martínez-Pería (2001). 'Is the crisis problem growing more severe?' *Economic Policy*, 16(32), 53–83.

Büyükkarabacak, B. and N.T. Valev (2013). 'The role of household and business credit in banking crises', *Journal of Banking & Finance*, 34(6), 1247–56.
Catão, L.A.V. and G.M. Milesi-Ferretti (2013). 'External Liabilities and Crises', IMF Working Paper Series No.113.
Cerra, V. and S.C. Saxena (2008). 'Growth dynamics: the myth of economic recovery', *American Economic Review*, 98(1), 439–57.
Economist, The (2015). 'Land-shackled economies: the paradox of soil', 4/4/2015.
Fetter, D.K. (2013). 'How do mortgage subsidies affect home ownership? Evidence from the mid-century GI Bills', *American Economic Journal: Economic Policy*, 5(2), 111–47.
Gaertner, K. (2012). 'White picket finance: the making of the U.S. mortgage market, 1932–1960', in H. Bonin, A. Gigliobianco, N.-V. Haueter and H. James (eds.), *Public Policies and the Direction of Financial Flows*, European Association for Banking and Financial History and National Bank of Romania, Bucharest, pp. 227–70.
Glick, R. and M. Hutchison (1999). 'Banking and currency crises: how common are twins?' in R. Glick, R. Moreno, and M. Spiegel (eds.), *Financial Crises in Emerging Markets*, Cambridge University Press.
Glynn, A.N. and K.M. Quinn. (2013). 'An introduction to the augmented inverse propensity weighted estimator', *Political Analysis*, 18(1), 36–56.
Godechot, O. (2012). 'Is finance responsible for the rise in wage inequality in France?' *Socio-Economic Review*, 10(3), 447–70.
Goldsmith, R.W. (1985). *Comparative National Balance Sheets: A Study of Twenty Countries, 1688–1979*, University of Chicago Press, Chicago.
Greenwood, R. and D. Scharfstein (2013). 'The growth of modern finance', *Journal of Economic Perspectives*, 27(2), 3–28.
Hale, G. and A. Kennedy (2012). 'Emerging Asia: two paths through the storm', FRBSF Economic Letter, 2012–9.
Herrera, H., G. Ordonez and C. Trebesch (2014). 'Political booms, financial crises', NBER Working Paper Series No. 20346. National Bureau of Economic Research, Cambridge.
Hoffman, P.T., G. Postel-Vinay and J.-L. Rosenthal (2000). *Priceless Markets: The Political Economy of Credit in Paris, 1660–1870*, University of Chicago Press, Chicago.
Johnson, S. and J. Kwak (2013). *13 Bankers: The Wall Street Take Over and the Next Financial Meltdown*, Vintage Books, New York.
Jordà, Ò. and A.M. Taylor (2013). 'Performance evaluation of zero net-investment strategies', NBER Working Paper 17150.
——. (2013). 'The time for austerity: estimating the average treatment effect of fiscal policy', NBER Working Paper 19414.
Jordà, Ò., M. Schularick and A.M. Taylor (2013). 'When credit bites back'. *Journal of Money, Credit and Banking*, 45(s2), 3–28.
Kaminsky, G. and C. Reinhart (1999). 'The twin crises: causes of banking and balance of payments problems', *American Economic Review*, 89, 473–500.
Kaminsky, G. and S. Schmukler (2003). 'Short-run pain, long-run gain: the effects of financial liberalization', NBER Working Paper 9787, June.
Knoll, K., M. Schularick and T. Steger (2014). 'No price like home: global house prices, 1870–2012', CEPR Discussion Paper 10166.
Laeven, L. and F. Valencia (2008). 'Systemic banking crises: a new database', IMF Working Paper 08/224.
——. (2012). 'Systemic banking crises database: an update', IMF Working Paper 12/163.
Lane, P.R. and G.M. Milesi-Ferretti (2007). 'The external wealth of nations mark II: revised and extended estimates of foreign assets and liabilities, 1970–2004', *Journal of International Economics* 73, 223–50.
Leamer, E. (2015). 'Housing really is the business cycle: what survives the lessons of 2008–09?' *Journal of Money, Credit and Banking*, 47(s1), 43–50.
Lunceford, J.K. and M. Davidian (2004). 'Stratification and weighting via the propensity score in estimation of causal treatment effects: a comparative study', *Statistics in Medicine*, 23(19), 2937–60.
Maddison, A. (2005). 'Measuring and interpreting world economic performance, 1500–2001', *Review of Income and Wealth*, 51(1), 1–35.
Mian, A. and A. Sufi (2014). *House of Debt*, University of Chicago Press, Chicago.

——. (2013). 'Household leverage and the recession of 2007–09', *IMF Economic Review*, 58(1), 74–117.
Miles, D. (2004). 'The UK mortgage market: taking a longer-term view', HM Treasury.
Mitchell, B.R. (2008a). *International Historical Statistics: Africa, Asia, and Oceania, 1750–2005*, 5th edn, Macmillan, New York.
——. (2008b). *International Historical Statistics: Europe, 1750–2005*, 6th edn, Macmillan, New York.
——. (2008c). *International Historical Statistics: The Americas, 1750–2005*, 6th edn, Macmillan, New York.
Phillipon, T. and A. Reshef (2013). 'An international look at the growth of modern finance', *Journal of Economic Perspectives*, 27(2), 73–96.
Piketty, T. (2013). 'On the long-run evolution of inheritance: France, 1820–2050', *Quarterly Journal of Economics*, 126(3), 1071–131.
Piketty, T. and G. Zucman (2013). 'Capital is back: wealth-income ratios in rich countries, 1700–2013', CEPR Discussion Paper 9588.
Rajan, R. (2005). 'Has financial development made the world riskier', NBER Working Papers Series no. 11728; National Bureau of Economic Research, Cambridge.
Reinhart, C.M. and K.S. Rogoff (2009). *This Time is Different: Eight Centuries of Financial Folly*, Princeton University Press, Princeton, NJ.
Schularick, M. and A.M. Taylor (2012). 'Credit booms gone bust: monetary policy, leverage cycles, and financial crises, 1870–2008', *American Economic Review,* 102(2), 1029–61.
Tornell, A. and F. Westerman (2002). 'Boom-bust cycles in middle income countries: facts and explanation', NBER Working Paper 9219, September.
Turner, A. (2013). 'What do banks do? Why do credit booms and busts occur and what can public policy do about it?' in A. Turner et al. (eds), *The Future of Finance: The LSE Report*, London School of Economics and Political Science, London, pp. 5–86.
Wooldridge, J.M. (2013). *Econometric Analysis of Cross Section and Panel Data*, 2nd edn, MIT Press, Cambridge, MA.