Survival of the Biggest: Large Banks and Financial Crises*

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Abstract

This paper studies a newly compiled data set of annual balance sheets of more than 11,000 commercial banks across 17 advanced economies since 1870. The new data allow us to investigate banking industry structure and bank-level dynamics before, during, and after banking crises. We show that a country's largest banks (i.e., the top-5 by assets) typically gain market share in crises, as small banks fail more often or are absorbed, making the largest banks even more dominant after crises. This is despite the fact that the largest banks tend to take more risk before crises, suffer greater equity losses in crises, and contract their lending more. Instead, the survival and expansion of the largest banks appear linked both to substantially higher rates of government rescues and to the fact that their deposit flows are more insensitive to bank losses, compared to smaller banks. We find no evidence that large-bank-dominated systems have lower crisis frequency; in fact, conditional on crises, large-bank-dominated systems see more severe economic outcomes.

Keywords: banking crises, large banks, banking sector organization, banking interventions
JEL classification codes:

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1. Introduction

The collapse of Silicon Valley Bank in March 2023 and subsequent events were a powerful reminder that banking crises are recurring phenomena in modern economic history. Understanding their causes and consequences remains an urgent priority for economists. While recent work combining macro-finance and financial history has made important inroads (e.g., Schularick and Taylor, 2012; Mian, Sufi and Verner, 2017; Baron, Verner and Xiong, 2021), the existing literature on financial instability has typically worked either with aggregate data over longer time spans (covering many crises) or with bank-level data but only over short windows (focused on a single crisis episode). In this paper we can, for the first time, combine both approaches.

Our paper is centered around a new data set of the annual balance sheets and stock returns of individual commercial banks since 1870 across 17 advanced economies, comprising more than 11,000 individual banks and more than 216,000 bank-year observations. At a broad level, the data reveal a rapid expansion of the largest-5 banks in each country, which accounts for nearly the entire rise in financial sector size across all 17 economies over the last 150 years. Throughout this paper, we define a "large" bank to mean a top-5 bank by assets as ranked within each country. All countries in our sample see a convergence to large-bank dominated financial systems, including countries like the United States that started with highly fragmented banking systems.[1] At the same time, the persistence of large banks across history is very high, both relative to smaller banks and to large nonfinancial firms. For example, 50% of large banks in 1910 remain a top-5 bank over one hundred years later, despite numerous banking crises in between.

Why are large banks so persistent across history? And what accounts for the emergence of a financial sector dominated by a few large banks? While there are likely many factors that have led the financial sector to converge to a system dominated by a few large banks, we argue that banking crises have played a key role. Using our new bank-level dataset, we study the two-way feedback loops across history between banking crises and banking sector structure: the role that large banks play in driving banking crises and, conversely, how banking crises reshape banking sector structure.

We have four main findings. First, we find that large banks are substantially less likely to fail in banking crises than smaller banks. Smaller banks also tend to be absorbed at high rates by large banks in the aftermath of crises. As a consequence, the market share of large banks

[1] These results generalize prior research showing a dramatic rise in US banking sector consolidation over the last 30 years (Berger, Demsetz and Strahan, 1999; Janicki and Prescott, 2006; Fohlin and Jaremski, 2020).

tends to grow in crises, making them even more dominant going forward. We call this repeated pattern during crises the "survival of the biggest." We show that the aftermath of banking crises can account for ∼40% of the total increase in top-5 banks' asset share across history.

One may ask whether "survival of the biggest" is due to more prudent behavior of the large banks in the run-up to crises. Our second finding is that the opposite is true. Large banks typically take more, not less, risk than smaller banks in the run-up to crises, and large banks suffer bigger equity losses and contract their lending more in the aftermath of crises. Specifically, large banks take increased risk (relative to smaller banks) along a number of dimensions in the run-up to crises: a) increase their loans growth at a faster rate, b) decrease their capital ratios more, c) increase the ratio of wholesale funding to total assets more, and d) decrease the ratio of "safe assets" to total assets more. Large banks also disproportionately contribute in the aggregate to the credit booms preceding banking crises—especially after 1945, where the top-5 banks account on average for about 75% of credit growth during the run-up to banking crises and nearly all of the credit contraction after crises. Greater ex-ante risk-taking by large banks is also reflected in higher average ex-post equity losses during crises. To show this, we collect data on total stock returns of the top-20 banks by country-year (specifically, the subset of those 20 banks that is publicly traded) and demonstrate that the average total stock returns of large banks fall more in crisis episodes. The contraction of their loan portfolios after crises is also more pronounced. Interestingly, large banks' risk-taking measures and subsequent losses are magnified when large banks' size relative to the financial system is higher to begin with. In short, large banks tend to be more pro-cyclical, engage in more risk-taking, and have greater equity losses relative to smaller banks. Yet, they survive at a substantially higher rate and even increase their asset share after crises.

Our next, and third, set of results helps to explain why large banks paradoxically tend to survive at a substantially higher rate, even though they have higher equity losses. We show two (potentially interconnected) results: first, policymakers are substantially more likely to rescue top-5 banks on the verge of failure, and, second, large banks have more stable funding dynamics in crises, despite greater equity losses. To show the first of these results, we systematically examine top-20 banks across all historical banking crises and create a database of government rescues at the individual bank level—specifically, for all banks that exit or have stock returns less than -90% (which we interpret as being "on the verge of failure"). We find that, among banks "on the verge of failure", interventions explicitly intended to prevent failure and preserve the original banking institution are very common for top-5 banks but a lot less common for banks 6-20 (which instead tend to be merged away or wound down). This differential can account for most of the differences historically in failure and exit rates between top-5 and 6-20 banks. This analysis relies on a new database of rescues (or lack thereof) of all individual top-20 banks "on the verge of failure" in each historical crisis, which we document with detailed narrative historical sources specific to each bank. This result reject the hypothesis that "survival of the biggest" is mainly due to "market forces" (e.g., economies of scale for the largest banks, natural advantages of large banks during crises) and suggests a key role of government interventions.

The other reason large banks tend to survive more often, despite their higher risk-taking and worse asset-side performance, is that large banks have more stable funding dynamics in crises. We build on the methodology from Calomiris and Wilson (2004) and show that the relationship between stock returns (as a proxy for solvency) and deposit outflows is materially different for large and small banks in crises. For small banks, declines in stock returns correlate closely with deposit flight. For large banks, this link between stock declines and deposit outflows is muted. For instance, if a large bank's stock falls by 90% or more, the bank's deposit outflows tend to be modest with a higher chance the bank will survive, even though smaller banks see large deposit outflows and tend not to survive. We conclude that another key reason why large banks are special is that their financing is largely unresponsive to asset side risks. In other words, large banks' funding dynamics remain more stable, even if the equity market perceives deep solvency issues that would typically trigger creditor flight at smaller banks. One potential reason could be implicit government guarantees for creditors of too-big-to-fail banks (as discussed above). However, it is also possible that large banks have a more diversified deposit base or a more valuable deposit franchise, or that there exists a self-fulfilling "flight-to-safety" from small to large banks during crises, as theorized by He, Krishnamurthy and Milbradt (2019), if depositors believe that other depositors will similarly shift funds from small to large banks. Regardless of the reason, this result suggest that the "survival of the biggest" is a function of more stability on the funding side of the balance sheet, despite evidence for greater asset-side risks.

Fourth and finally, history shows that, contrary to widely held beliefs, banking systems dominated by a few large banks are not measurably safer than more fragmented banking systems. The frequency of banking crises is not lower in large-bank-dominated banking systems. In fact, conditional on experiencing a crisis, real economic outcomes are more severe in banking systems dominated by a few big banks.

Our analysis addresses the question of whether the dominance of the banking system by a few large banks is beneficial for financial stability. Economic theory offers competing channels for how large bank size can affect financial stability. Proponents of large banks argue that they are a source of stability by diversifying risks and better absorbing shocks. Large banks can tap into a big pool of funds, and their size and scale can allow them to spread risks across different markets, reducing the potential for a single market or industry shock to bring the bank in danger. A large-bank-dominated system may be better diversified with lower idiosyncratic risks (Demsetz and Strahan, 1997; Fernholz and Koch, 2017) and might be accompanied by higher charter values that reduce incentives for excessive risk taking (Keeley, 1990). Moreover, a small number of entities might be easier for regulators to focus on. In support of these arguments, financial historians have often argued (e.g., Bordo, Redish and Rockoff, 2015; Calomiris and Haber, 2015) that the US's highly fragmented financial system was historically less stable and experienced more frequent depositor panics than Canada's concentrated banking system.[2]

However, there are also counterarguments that suggest that large banks may actually be a source of instability. One of the primary concerns is that large banks might be perceived as "too-big-to-fail" by regulators and creditors, allowing these banks to take excessive risks. Additionally, their size and complexity as organizations can make them more difficult to regulate or harder to implement effective risk management and corporate governance. Their greater number of interconnections with other financial institutions adds to risk and amplifies contagion effects. And they may have greater access to risk-taking opportunities, such as access to risky trading activities and to greater international opportunities for risk taking, than small banks. Some prior research shows that larger banks tend to take more risk than smaller banks (Boyd and Runkle, 1993; Boyd and Gertler, 1994; Gropp et al., 2011; Huber, 2021). Laeven, Ratnovski and Tong (2016) study large global banks around the 2007-08 financial crisis and find that the largest banks around this crisis have higher leverage, less deposit funding, are organizationally more complex, and create more systemic risk. We similarly find that risk taking during credit booms in the run up to systemic banking crises is higher for large banks across history.

Our work builds on and adds to a large literature investigating the causes and consequences of banking crises across history. Aggregate credit cycles have been identified as a key driver of financial instability. Schularick and Taylor (2012) show that an acceleration of credit growth is the single best predictor of future financial instability. The credit build-up before a banking crisis is also significant indicator of the depth of the subsequent recession (Jordà, Schularick

[2]Claims of Canada's historical banking stability may be overstated. While it is true that Canada's banking system was only minimally affected in 2008, there have been many periods of financial instability in Canada since 1870. See Kryzanowski and Roberts (1993) and Baron, Verner and Xiong (2021). The stability claim is likely due to defining a banking crisis narrowly in terms of numbers of bank failures or depositor runs. In terms of other measures, such as aggregate credit-to-GDP contractions and bank equity losses, Canada performed near the bottom in our sample of 17 countries during the Great Depression period. Kryzanowski and Roberts (1993) explain the low bank failure rate during the Canadian Great Depression as due to implicit government guarantees and regulatory forbearance. Canada also experienced banking crises in the 1870s, 1920s, and, most recently, 1980s when many of its "Western" banks and trust companies failed (Baron, Verner and Xiong, 2021).

and Taylor, 2013; Krishnamurthy and Muir, 2017; Mian, Sufi and Verner, 2017; Mian and Sufi, 2010; Rajan and Ramcharan, 2015; Richter and Zimmermann, 2019). High banking sector leverage has also amplifying characteristics in the downturn (Jordà et al., 2021). Our results highlight that aggregate credit booms and busts are, most of the time, credit booms and bust by a handful of large banks (with some notable exceptions throughout history, like the U.S. Great Depression, in which the failures of many small banks are macroeconomically important). The main policy consequence is that macro-prudential policy objectives focused on restraining risk-taking and excessive credit growth should primarily target the very largest banks.

The paper proceeds as follows. Section 2 presents the new dataset. Section 3 outlines long-run trends in banking sector size and persistence. Section 4 presents our results on the survival of the biggest. Section 5 presents our analytical results on pre-crisis risk taking and ex-ante performance. Section 6 analyzes government rescues of banks and the funding dynamics of the largest banks in crises. Section 7 discusses the macroeconomic consequences of large-bank dominated financial systems. Section 8 concludes.

2. Data

At the core of our paper stands new data set that contains bank-level annual balance sheet information for nearly all commercial banks across 17 advanced economies since 1870. Most of the data is newly transcribed from a wide range of archival sources. The data set also includes information on entries, exits, mergers and acquisitions (M&As), and other events (e.g., name changes, spinoffs, nationalizations) needed to trace the lineage of each bank. Finally, we also collect stock total returns for the 20 largest banks around each banking crisis. We combine this new data set with macroeconomic data from Jordà, Schularick and Taylor (2017) (JST henceforth) and Baron, Verner and Xiong (2021) (BVX henceforth), along with prior data on the aggregate bank balance sheets of each country from Jordà, Richter, Schularick and Taylor (2021) (JRST henceforth).

In this section, we provide an overview of the sample coverage, data sources, definitions, and accounting conventions used in the construction of our new data set. The section is accompanied by an extensive Data Appendix that provides additional country-by-country information on the data.

2.1. Coverage and sources

We gather bank balance sheet data for individual banks in 17 advanced economies since 1870, thus covering the same sample of countries as in the JST Macrohistory Database. Keeping the JST country coverage provides us with a rich set of existing aggregate macroeconomic data that we can combine with the new bank-level data set. The 17 countries are Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

Most of the bank balance sheet data is newly transcribed, translated, and harmonized from a range of archival sources. While there have been recent efforts by government archivists to make scans of these sources accessible online, most sources are only available in print at specific research libraries or at central bank or government archives for each of the countries. Digitizing these historical sources required an eight-year process that involved the mass-scanning and transcription of ten-thousands of pages of historical documents and records from around the world. We employed several dozen data-entry contractors and research assistants involved in building the dataset, which was all done by manual data entry, followed by extensive quality-control checks.

The Appendix systematically documents all the sources used for each country and time period. In many countries and time periods, data on individual banks come from records held by central banks, statistical offices, banking associations, and bank regulators. For other countries and time period, data come from periodicals, stock market manuals, and other compendia with annual reports of traded companies that were historically published for many countries. We are also able to draw from a rich set of previous country-specific projects (e.g., Baubeau et al. (2021) on French banks prior to WWII, Natoli et al. (2016) on Italian banks from 1890 to 1973, and Carlson et al. (2022) on US national banks from 1870 to 1904). From the 1990s onward, data is often sourced from commercial data providers. Whenever no other systematic sources for all banks in a given country are available, we turn to information published in individual banks' annual reports, which we gathered from Harvard Business School's Historical Collections and the archives of several central banks around the world. To give the reader a taste of the original sources, Appendix Figure B.1 provides two examples of typical archival sources used in the construction of the dataset. The top panel shows a tabulation of all Canadian joint stock banks in 1900 published each month in the Gazette of the Canadian government. The bottom panel shows pictures from the annual report of Credit Lyonnais in 1905, one of the largest French banks at the time.

The focus of our dataset is on commercial banks. As most of our data comes from supervisory institutions, we therefore follow the regulators' designations in each country and time of which institutions are commercial banks. In terms of coverage, we have complete coverage of the entire commercial banking system in several countries, though we fall short of 100% for some countries and historical periods in other cases (as described in more detail below) due to the incompleteness of some historical sources. For some countries, we also have systematic balance sheet data for savings banks, mortgage banks, cooperative banks, building societies, investment banks, or private banks, which we also use in our analysis when available. However, this individual balance sheet data on other depository institutions besides commercial banks is only available for several but not all countries (see Appendix for details). Ideally, we aim to capture the private domestic banking system for each country. The reason is that we want our individual bank data to be able to aggregate to established country-level credit cycle datasets (e.g., from the JST Macrohistory Database or the BIS long credit series) that also cover the private domestic banking system in each country. Thus, our sample also includes domestic commercial bank subsidiaries of foreign banks. For domestically headquartered banks, we always use the highest level of aggregation available and thus use their consolidated balance sheets, which include foreign subsidiaries, since there is often no systematic way to exclude them.

Table 1 lists the average number of banks in each country, in addition to summary statistics of key variables used in the paper. The dataset includes more than 11,608 unique bank IDs and 214,671 observations. On average, our dataset includes 92 banks (median 39 banks) per country-year with the average bank remaining in the sample for 48 years (median 41 years). The number of banks differs considerably by country, with some of this variation explained by different banking system structures and some of it due to differences in coverage at the bottom of the size distribution. Our data covers on average 77% of banking sector assets (benchmarked against total assets from JRST). For a country-by-country comparison of the coverage of the bank-level data relative to the banking system as a whole (from JRST), see Figure B.4.

We define a "large" bank to mean a top-5 bank by assets, as ranked within each country and year. Our choice of five banks as the cutoff is motivated by the fact that the size distribution of banks in a country typically falls off after bank #5. See Figure A.1, which plots the asset size distribution by descending rank. While our results are not sensitive to the exact cutoff, the top-5 institutions generally capture banks that each individually comprise between 5% and 25% of the assets of the total banking system and play a central role in the structure of the financial system (e.g., as clearing banks and depository institutions for other banks,

Table 1: Summary statistics

This table reports summary statistics of key variables. All statistics are computed based on country-year observations. Asset growth and loan growth are winsorized at the 1 percent level.

	Median	Mean	S.D.	Min	Max
Number of banks per country-year	39.00	92.46	176.19	1.00	1988.00
Top-5 asset share	0.44	0.47	0.24	0.02	0.99
Ratio of total assets to JRST (2021)	0.77	0.76	0.36	0.01	2.16
Number years by bank	41.00	48.34	33.41	1.00	147.00
Bank age	41.00	54.10	46.44	0.00	423.00
One-year asset growth (unadjusted)	0.07	0.11	0.20	-0.33	1.13
One-year organic asset growth	0.07	0.10	0.19	-0.34	1.10
One-year loan growth (unadjusted)	0.08	0.13	0.30	-0.49	1.82
Number of banks by year					
Australia	24.00	24.62	7.96	3.00	45.00
Belgium	54.50	59.51	30.35	6.00	144.00
Canada	29.00	29.89	18.79	10.00	76.00
Denmark	159.50	140.62	64.24	18.00	272.00
Finland	10.00	10.66	4.62	2.00	23.00
France	8.00	17.61	16.85	5.00	62.00
Germany	85.00	292.43	538.18	3.00	1988.00
Italy	203.00	202.77	129.53	8.00	529.00
Japan	19.00	25.38	21.05	1.00	89.00
Netherlands	49.00	48.90	21.10	5.00	88.00
Norway	82.00	80.75	47.45	13.00	195.00
Portugal	27.00	30.33	13.44	5.00	61.00
Spain	92.00	82.04	51.80	2.00	213.00
Sweden	30.00	37.49	24.08	9.00	99.00
Switzerland	360.00	257.78	191.63	8.00	476.00
UK	43.00	59.81	50.08	8.00	157.00
USA	48.00	188.42	257.29	34.00	878.00

key intermediaries in money markets and capital market, foreign exchange clearing banks for international payments, and key counterparties of the central bank), making them distinct in many ways from large banks ranked #6-20, which typically lack these roles. For this reason, many countries at various points in history have called their largest financial institutions the "Big 4" or "Big 5".[3]

We have placed particular emphasis in the data collection to make sure that, at the very minimum, the largest 30 banks in each country-year are covered whenever possible; as Table 1 shows, the number of banks is substantially higher than this most of the time. We can nevertheless quantify the aggregate contribution of the smaller missing banks by computing the residual between the aggregate banking sector statistics and the sum of all the individual banks in our sample. The aggregate banking statistics include all depository institutions (including savings banks, cooperative banks, etc.), so most of our coverage gaps can be attributed to missing data on savings banks and cooperatives.[4] In some country-years, the sum of individual bank assets even exceeds country asset totals from JRST. These deviations are usually due to multinational bank groups with insufficient data to cleanly separate domestic and foreign activity. We redefine total banking sector assets as $max(\sum_i assets_i,\ total\ assets^{JRST})$ with $\sum_i assets_i$ equal to the sum of individual bank assets whenever appropriate, so that the sum of market share does not exceed 100 percent.

2.2. Balance sheets, bank stock returns, and banking sector structure

The main bank balance sheet categories are shown in Table 2. Harmonizing historical balance sheets across countries and time is an inherently difficult exercise. Numerous changes in accounting and reporting standards and level of detail complicate the construction of consistent data series. We therefore restrict our stylized balance sheet to a few items to guarantee relatively well-defined concepts. The balance sheet structure shown in Table 2 aligns with the aggregate

[3]For the use of this term in banking across a large number of countries, see: `https://en.wikipedia.org/wiki/Big_Four_(banking).`

[4]In the US, for example, our coverage of all commercial banks is far from complete. Due to the time-consuming nature of the data collection, over the period 1870-1965 we restrict our analysis to the national banks and largest New York state-chartered banks, using sources such as Carlson et al. (2022) (digitized balance sheets of all national banks, 1870-1904), the Annual Report of the Comptroller of the Currency (national banks, 1905-1935), and Moody's Bank and Finance Manuals (editions from 1928 onward). Complete data of state-chartered banks would have required obtaining and digitizing records for all 50 states individually, which was not practically possible for us and has previously been transcribed and studied by others (Calomiris and Mason, 2003; Fohlin and Jaremski, 2020), though not yet publicly released. Our priority, instead, has been obtaining and transcribing the data for the other 16 countries in the sample besides the US, for which digitized bank-level historical data has previously been very limited.

Table 2: Stylized bank balance sheet

Total assets	Total liabilities
= "Safe assets" (e.g., cash, govt bonds)	= Equity
+ Loans	+ Deposits
+ Other assets	+ Noncore short-term liabilities
	+ Other liabilities

balance sheet compositions of JRST. This allowed us to use their aggregate ratios as benchmark estimates and their underlying sources to guide us through the harmonization of the bank level balance sheet data.

We combine the main balance sheet dataset with information on the annual (as of December 31) total stock return, defined as the price return plus dividend return, of each listed bank among the top-20 by country in the ±5-years around banking crisis episodes (as defined below). The rightmost column of Table A.1 documents banking crisis episodes for which we were able to find bank stock prices and dividends.

For all banks in the dataset, we also collect information on entries, exits, M&As, and other events needed to trace the lineage of each bank, link it to predecessor and successor banks, and map the organization of the banking sector over time. To do this, we systematically examine all bank-level entry and exit events from the database, categorizing all such events into M&As, entries, failures, name changes, or other events, based on historical research of each individual bank, which we then document in the database. For each M&A transaction, the names of the targets and acquirers of M&As are coded, which allows us link the pre- and post-merger entities in the database.[5] We also collect other meta information for each bank, such as each bank's establishment year, its year when it ceased doing business as a bank, and other information to link predecessor and successor banks.

This database is substantially more detailed for events over the period 1946-2016, where we able to comprehensively categorize the "other events" into the following categories: spinoffs, nationalizations, acquisitions of or by foreign institutions, change of charter type, or missing data. Doing so allows us, in our subsequent analysis, to account for and correct all apparent discontinuities in the balance sheet data, which can be due to these "other events" listed above.

[5]Each bank is assigned a unique ID, and we adopt the convention to keep the ID of the acquiring entity in case of an "acquisition" (defined as when the name of one of the predecessor entities is preserved) and assign a new bank ID after a "merger" (when the combined entity has a new name). However, our analysis otherwise treats "mergers" and "acquisitions" as the same. Figure B.2 shows a schematic example to illustrate the ID assignment in the database. In 1892 the Union Bank of Australasia *acquired* the Bank of South Australia, preserving its previous ID. In contrast, in 1951 it *merged* with the Bank of Australasia to form the Australia and New Zealand Bank; in this case, the Australia and New Zealand Bank is assigned a new ID.

Given that we systematically start from all bank-level entry and exit events from the database, we can be assured that this database comprehensively delineates all possible discontinuities due to bank entry and exit.[6] However, for the period 1870-1945, our data is more limited, due to the painstaking research needed to be done on each bank to classify these "other events"; as a result, we are only able to collect comprehensive data on M&As (i.e., the year of each M&A transaction and the identities of the targets and acquirers), entries, failures, and name changes during this period.

2.3. Organic loan growth vs. loan growth due to M&As, entries, and failures

Using the above information, we then decompose total loan growth of each bank into "organic loan growth" (the component due to intrinsic net-origination of loans) versus the components of loan growth due bank entry, bank exit, having acquired another bank, and the "other events" discussed above (e.g., spinoffs). By calculating organic loan growth for each bank, we thus adjust for discontinuities in the aggregate credit growth of bank-size groups, which would otherwise lead to large inaccurate estimates of aggregate credit growth by bank-size groups.[7] We also adjust for a variety of other data quality and accounting issues, which are all systematically documented in our entries/exits database.[8]

2.4. Defining banking crises

In this paper, we define "banking crises" as country-year observations that are the first years of aggregate credit crunches, based on aggregate JST data–specifically when the past three-year

[6] To make sure we are not missing other unusual types of events, we also investigate all one-year changes in loan growth in excess of $\pm 10\%$ at the bank level, which may indicate potential discontinuities. While, in theory, all entries and exits into the database would reveal all M&As, entries, and failures, this may not be true in practice—for example, if an acquired entity (or spunoff entity) is missing from the database or if either the target or acquirer is a foreign firm or domestic nonbank firm. We therefore also investigate all bank-level one-year changes in loan growth of more than $\pm 10\%$ and, for each such observation, read historical annual reports of the company, Moody's Bank and Finance Manuals, and other historical documents for each of these observations to code any other M&As, entries, failures, and spinoffs that may have been missed.

[7] For example, if two medium banks merge to form a large bank, then it would naively appears as if medium banks collectively see an aggregate reduction in their loan portfolios (because two medium banks appear to "exit" from the sample), while large banks collectively would see an aggregate increase in their lending (because of the apparent entry of a "new" large bank). Alternatively, if a large bank acquires a small bank, it would naively look like a jump in loans at the large bank and an aggregate reduction in the loans of small banks.

[8] For example, we adjust for changes in accounting standards (e.g., country-level switches from GAAP to IFRS), switches of accounting unit (e.g., bank-level switches of the accounting unit from parent to consolidated company), and other accounting issues that arise in specific circumstances. We also adjust for data gaps and timing issues related to M&As (e.g., if two banks that merge exit the sample in year t, the new combined entity should enter the sample in year t+1). In rare cases, we substitute data from alternative sources, when there appears to be corrupted data (e.g., due to transcription errors or inconsistencies between various sources).

change in the ratio of bank credit-to-GDP is less than -1 s.d. relative to that country's history. Table A.1 reports the list of banking crises defined using this definition.

We define banking crises this way, as opposed to using previous banking crisis chronologies like JST or BVX, for two reasons. First, previous chronologies of banking crises likely have a bias in which they are more likely to call an episode a banking crisis if it involves distress of one or several of the largest banks in a country. Using one of these definition, our result that banking crises predominately center around problems at the biggest banks might therefore be circular. In contrast, aggregate "credit crunches" do not have this potential bias, given that an aggregate credit crunch of magnitude X could theoretically be due to a lending contraction either among a few large banks or among many small banks. Second, a "credit crunch" is, economically, a fundamental outcome for study, given the well-known macroeconomic consequences of credit crunches. The goal of this paper is, in some sense, to understand which types of banks' distress tend to lead to these large aggregate credit crunches.

In practice, the set of "credit crunches" is very similar to the set of JST or BVX banking crises (see Table A.1), and the main results of the paper are robust to these alternative crisis definitions.

3. The long-run evolution of the banking sector

We start by presenting two long-run trends in banking sector structure that emerge from our data. First, the asset share of top-5 banks and their absolute size relative to GDP have increased substantially over time, with the top-5 banks in each country accounting for most of the rise in financial sector size across time. Nearly all this increase in the top-5 asset share can be accounted for by M&As activity. Second, top-5 banks are highly persistent across history, in the sense that large banks are likely to continue to be a top-5 bank fifty, or even one hundred years, later. The persistence of large banks is high, both relative to smaller banks and to the largest nonfinancial firms in each country.

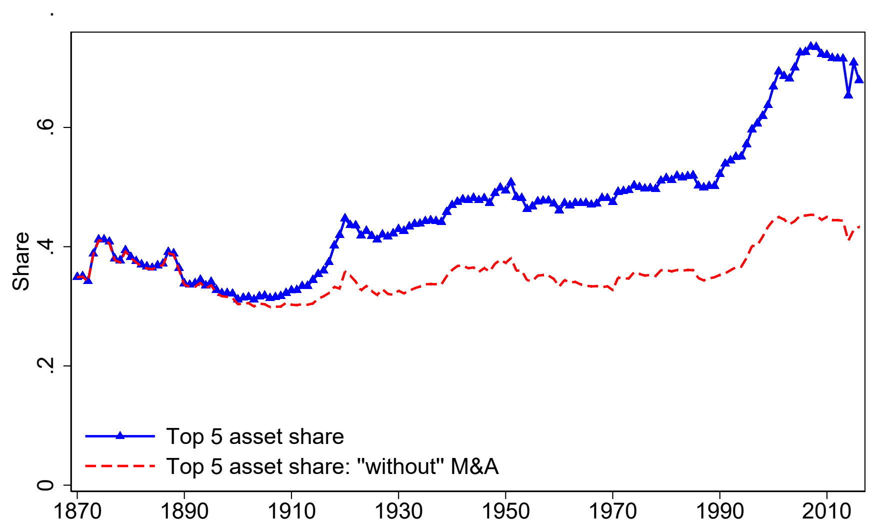
3.1. Asset shares and asset size of large banks over time

We first show that the asset share of the top-5 largest banks has increased from around 0.35 in 1870 to around 0.70 today. This is shown in Figure 1 Panel A, in which the solid blue line plots the asset share of the top-5 banks over time solid, averaged across the 17 economies in our sample. Panel A also shows that nearly all the increase in the share of the largest banks

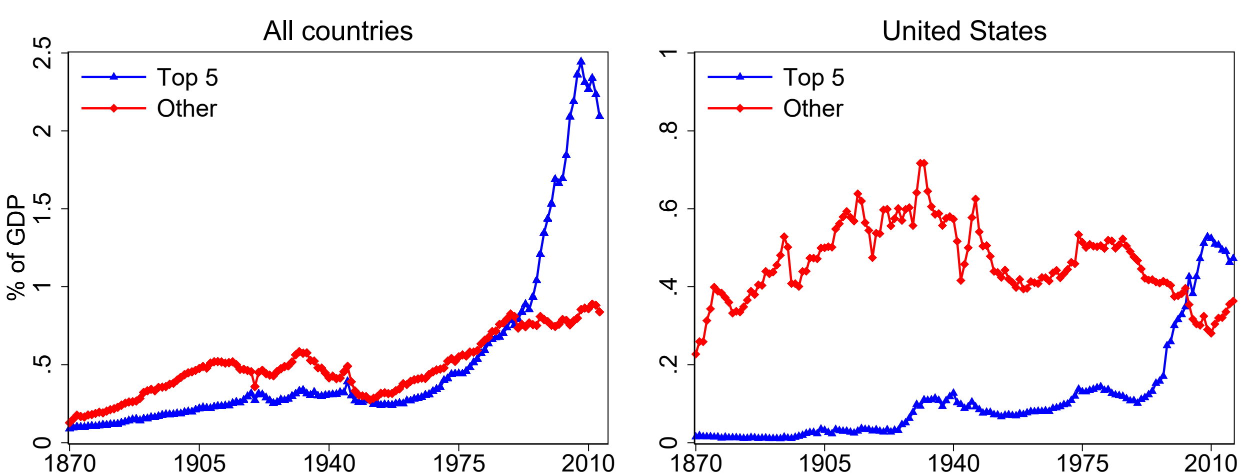
Figure 1: Increasing asset share of the top-5 largest banks

In Panel A, the solid blue line plots the asset share of the top-5 banks over time solid, averaged across the 17 economies in our sample. The dashed red line provides an estimate of the role that M&A activity played in the evolution of the top-5 asset share: specifically, how it would have evolved "without" M&A activity (see details in main text on the construction of this hypothetical). Panel B plots the size of banking system assets relative to GDP broken down into the top-5 banks and all other banks. The left plot in panel B shows averages across 17 advanced economies and the right plot shows data for the United States. We calculate the size of the "other banks" as the difference between top-5 bank assets and aggregate banking system assets from JRST to deal with missing data at the bottom of the distribution in some countries. Panel C shows how the increase in the top-5 share is nearly all explained by the rise in the asset size of top-5 banks relative to GDP (left plot) while the asset size of rest of the banking sector (non-top-5) relative to GDP is relatively constant over time (right plot). It is a binscatter with observations collapsed into 20 bins, in which each point represents the group specific means of the top-5 share and top-5 assets-to-GDP (or non-top-5 share and assets-to-GDP). Panel D shows that the top-5 banks account for a large and rising share of aggregate credit fluctuations. The left panel illustrates how the contribution of the top-5 banks to the cyclicality of credit is calculated for the US as an example country; the methodology is presented in detail in Appendix A. Panel B shows how the cyclicality contribution of the top-5 banks, averaged across countries, has changed over time.

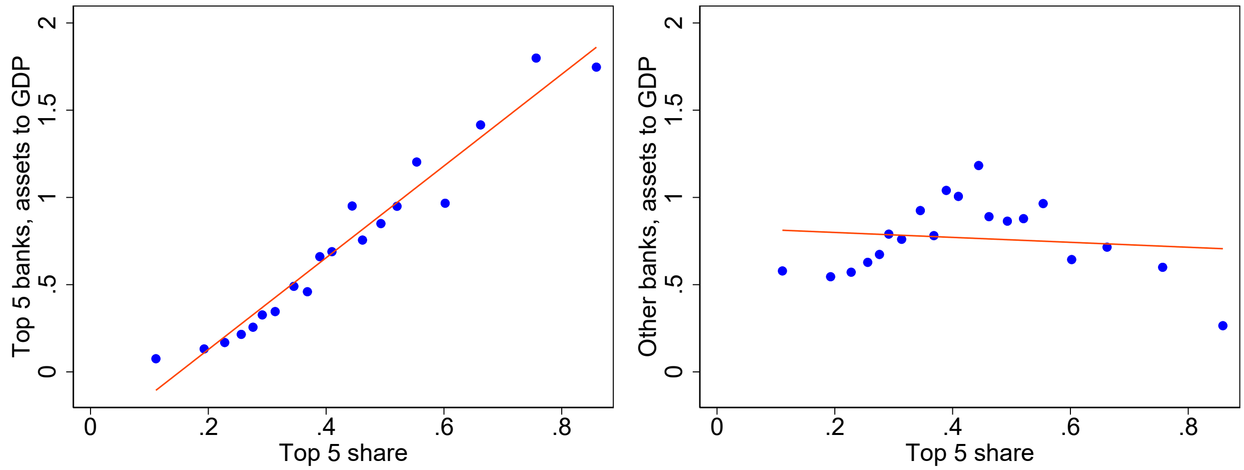
Panel A: Top-5 banks' asset share over time



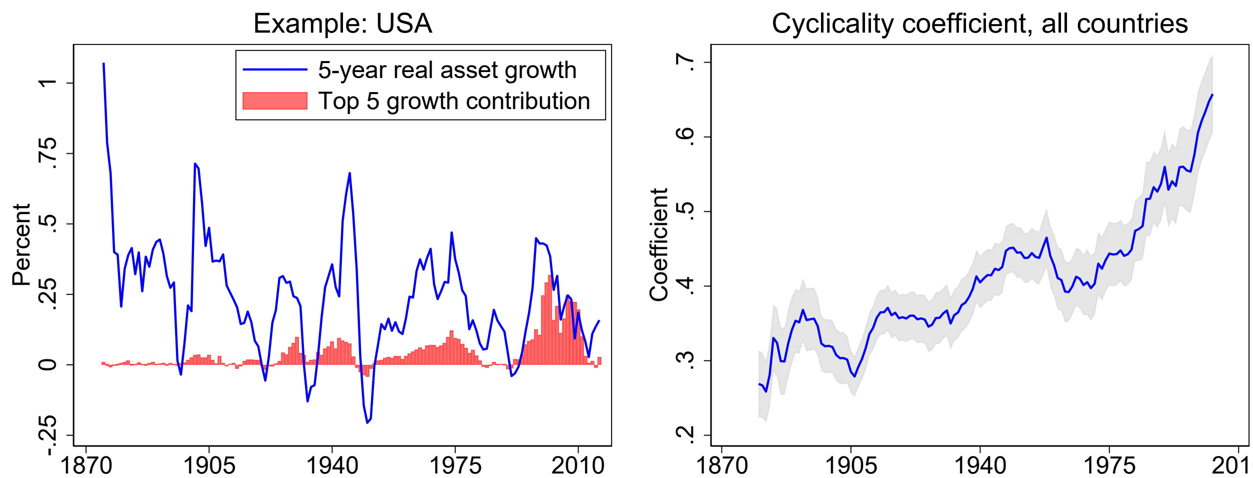
Panel B: Bank assets-to-GDP over time: Top-5 vs. all other banks



Panel C: Correlation between top-5 asset share and top-5 asset size



Panel D: Cyclicality: contribution of top-5 banks over time



can be accounted for almost entirely by M&As (rather than organic asset growth, bank entries, or failures); specifically, the dashed red line provides an estimate of the role that M&A activity played in the evolution of the top-5 asset share: specifically, how it would have evolved "without" M&A activity.[9] One can see that "without" M&As, the asset share of the top-5 banks would have remained relatively constant at around 0.35 across the entire sample, in contrast to the actual increase (blue line) in top-5 asset share from around 0.35 in 1870 to around 0.70 today.

Panel B shows that the asset size of top-5 banks relative to GDP has also increased substantially over time. Panel B plots the size of banking system assets relative to GDP broken

[9]To do this, we subtract out the increase in asset share of top-5 banks contributed by bank-year observations with M&As.

down into the top-5 banks and all other banks. The left plot in panel B shows averages across 17 advanced economies and the right plot shows data for the United States. In both panels A and B, we calculate the size of the "other" (i.e., non-top-5) banks as the difference between top-5 bank assets and aggregate banking system assets from JRST, as we do not want missing data for small banks in some countries to bias our results. Thus, we use the aggregate statistics just for these two plots to ensure that we are capturing the entire banking system's assets in each country. From panel B, one can see that for all countries (left plot), the assets-to-GDP of the top-5 banks and other banks has increased over time, diverging sharply after around 1990. Even for the United States (right plot), which is the country in our sample in which the top-5 banks historically have had the least asset share, we see a large increase starting around 1990, in which the top-5 banks overtake the asset share of all the other banks.[10]

Panel C shows how the increase in the top-5 share is nearly all explained by the rise in the asset size of top-5 banks relative to GDP (left plot) while the asset size of rest of the banking sector (non-top-5) relative to GDP is relatively constant over time (right plot). Specifically, Panel C plots a binscatter with observations collapsed into 20 bins, in which each point represents the group specific means of the top-5 share and top-5 assets-to-GDP (or non-top-5 share and assets-to-GDP).

Panel D shows that the top-5 banks account for a large and rising share of aggregate credit fluctuations. The left panel illustrates how the contribution of the top-5 banks to the cyclicality of credit is calculated for the US as an example country; the methodology is presented in detail in Appendix A. Panel B shows how the cyclicality contribution of the top-5 banks, averaged across countries, has changed over time; in particular, the share of variation in aggregate credit that can be explained by credit growth of the top-5 banks has increased from around 25% in the late nineteenth century to around 70% since the 1990s. As further discussed in Appendix A, the main reason for top-5 banks' large contribution to credit growth is simply that they are large to begin with; that is, they make up a large and increasing loan share of the banking system. However, in Section 5, we will also find an addition reason for their large contribution to the cycle is also that large banks tend to grow faster than the rest of the banking system during booms, further contributing to their procyclicality; and during the credit busts after banking crises, large banks account for nearly all the aggregate credit contraction. From these

[10]Figure A.3 plots Panel A country by country, showing that the asset share has increased over time (though not always monotonically) in each of the 17 countries. Figure A.4 plots Panel B country by country, similarly showing that the asset size of the top-5 banks relative to GDP has increased over time and accounts for most of the rise in banking sector size in all countries (except Germany). Figure A.2 provides a breakdown into more detailed bank-size groups of asset shares over time.

results, we conclude that the top-5 banks have come to comprise most of the aggregate cycle.[11]

3.2. The persistence of large banks

The second key trend is that top-5 banks are highly persistent in our sample, in the sense that they are likely to continue to be a large bank decades later and are substantially less likely to exit, compared to smaller banks and to top-5 nonfinancial firms in each country.

To see this, Figure 2 shows transition probabilities between bank size ranks over future one-year (left plot) and ten-year intervals (right plot). We code a transition to exit if an observation is the last for a bank in the database and if the bank's recorded final year when it ceased doing business as a bank is within the next three years. For banks with unknown final years, we treat the end of data as their exit year. Note that banks can exit the dataset for several reasons: failure, being acquired (by far the most common reason, see Appendix Figure A.8), or other reasons (e.g., incompleteness of our dataset, change of regulatory classification).

Panel A shows that banks in the top-5 have a 94% likelihood of remaining in the top 5 after one year and a 73% likelihood after ten years. Even if they fall in ranking to outside the top 5, the likelihood of top-5 banks remaining in the top-10 banks is 98% after one year and 84% after ten years. The likelihood of exiting increases sharply, as one goes down the size ranking, increasing monotonically to 4% and 36% for banks outside the top 100.

To see this another way, Figure 2 Panel B shows persistence over longer horizons. To generate this plot, the names of the top-5 banks and top-5 nonfinancial firms in each country were recorded in three years (1880, 1910, and 1970). Panel B then reports the percent of these banks and nonfinancial firms that remain in the top 5 (left) and in the top 20 (right) in 2020.[12,13] About 50% of the largest banks in 1910, and even 37% of the largest banks in 1880, are still among the largest 5 banks today. Panel B also shows that top-5 banks' persistence in a

[11] Our results are related to, but somewhat different from, those of Crouzet and Mehrotra (2020), who study nonfinancial firms and find that while smaller firms are more procyclical, in aggregate they are too small to contribute substantially in magnitude to the cycle.

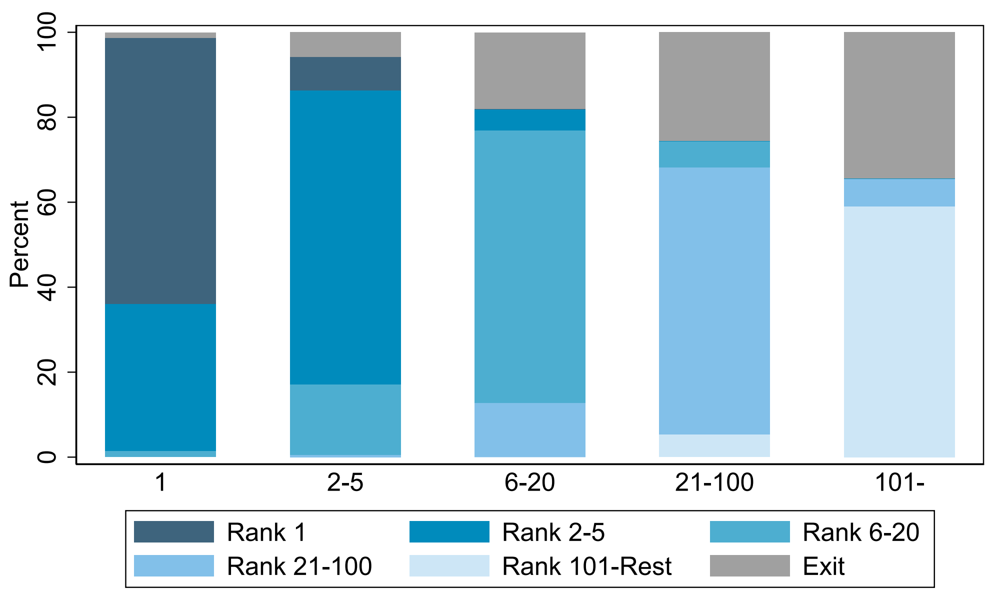
[12] For this analysis, we compile a dataset of the largest banks and nonfinancial corporations in each country at benchmark years, which are reported in Appendix Table A.2. Some examples of top-5 banks from 1910 that are still top-5 in 2020 (or represent the same principal institution after a merger or name change): Bank of New South Wales in Australia (which changed its name to Westpac in 1982); Bank of Montreal and Royal Bank of Canada in Canada; Den Danske Landmandsbank in Denmark (which changed its name to Den Danske Bank in 1976); Société Générale in France; Deutsche Bank in Germany, Credit Suisse and UBS in Switzerland; Barclays and Lloyds Bank in the UK, and National City Bank (Citigroup) in the US.

[13] The year 1910 was chosen as a benchmark year due to data availability for nonfinancial firms, as many economic history sources (e.g., Cassis et al., 2016) use around 1910 as a benchmark year for studying large businesses in the twentieth century. The year 1880 was chosen, rather than 1870, since our bank data is not available for several countries until 1880.

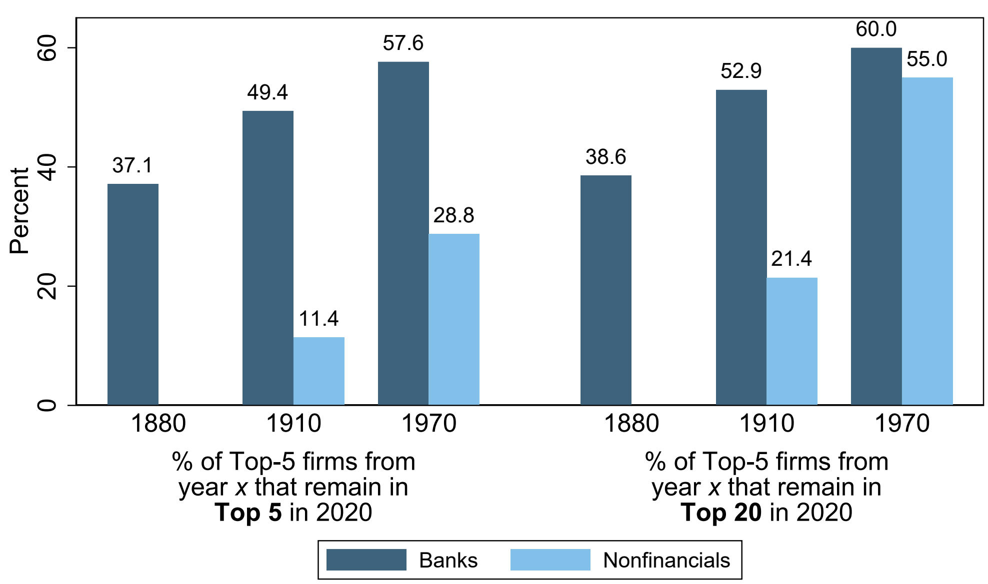
Figure 2: Large banks are highly persistent

Panel A shows transition probabilities between bank size ranks from year to year (left plot) and for ten year intervals (right plot). We code a transition to exit if an observation is the last for a bank in the database and if the banks recorded resolution year is within the next three years. For banks with unknown resolution years we treat the end of data as their exit year.

Panel A: Transition matrix between bank size groups over ten years



Panel B: Persistence of banks versus nonfinancials



country is significantly higher than that of nonfinancial firms. For example, only 11.4% (21.4%) of the largest 5 (20) nonfinancials by country in 1910 are still among the largest 5 (20) firms by country in 2020. Appendix Table A.3 provides additional detail on the persistence of banks and nonfinancials including statistics on their relative exits by bankruptcies and acquisitions for these benchmark years. Overall, the main takeaway from both Panel A and Panel B of Figure 2 is that large banks are likely to stay large banks and are substantially less likely to fail or be absorbed, compared to smaller banks and to top-5 nonfinancial firms in each country.

4. The "survival of the biggest"

In this section, we show that the asset share of large banks tends to grow in crises, due to the low exit probability of large banks during crises and the large number of acquisitions of smaller banks by top-5 banks. We call this repeated pattern during crises the "survival of the biggest."

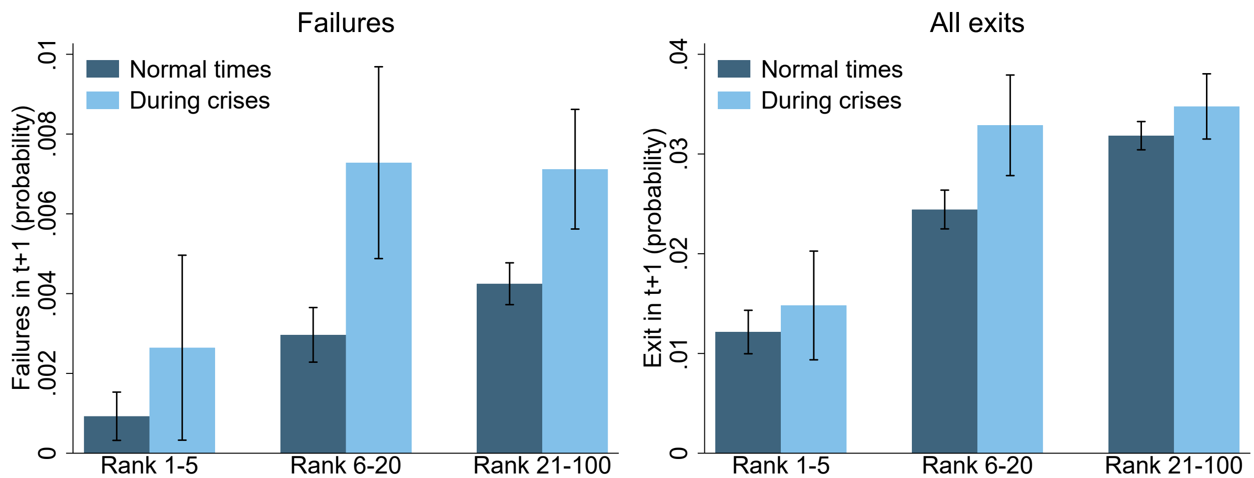
4.1. Failure and exit rates by bank size

We begin our discussion by showing that the exit or failure probability of large banks is very low, even during crises. Figure 3 plots bank failure probabilities (left plot) and bank exit probabilities (right plot) by bank size in normal times and during banking crises. Figure 3 also distinguishes between failures "during crises" (exits in the three years after the start of a banking crisis) and "normal times" (all other times). We define a bank-year observation as a bank exit if the observation is the last for a bank in the database and if the bank's recorded resolution year is within the next three years; we then normalize this value by total bank-year observations within each bank size category to generate a probability metric. Exits that are due to outright bankruptcies, liquidations, ceased banking operations, and revoked licenses are classified as failures. "During crises" includes all exits in the three years after the start of a banking crisis.

Figure 3 shows that the exit probability or failure probability of large banks is very low, even during crises. Figure 3 shows that the probability of a failure during banking crises (left plot) is around 0.4% for top-5 banks and rising to 0.9% and 0.8% for banks 6-20 and 21-100, respectively. The right plot looks at all exits and finds that the probability of a failure during banking crises is around 2% for top-5 banks and rises to around 4% for banks in both the 6-20 and 21-100 size categories. Figure 3 also demonstrates that failure rates for smaller banks are considerably higher than those for the top-5 banks. As shown by the figure, a similar result is

Figure 3: Failures and exit rates by bank size

The figure shows bank failure probabilities (left plot) and bank exit probabilities (right plot) by bank size in normal times and during banking crises. We define a bank-year observation as a bank exit if the observation is the last for a bank in the database and if the bank's recorded resolution year is within the next three years; we then normalize this value by total bank-year observations within each bank size category to generate a probability metric. Exits that are due to outright bankruptcies, liquidations, ceased banking operations, and revoked licenses are classified as failures. "During crises" includes all exits in the three years after the start of a banking crisis.



true during "normal times" also.

Note that bank exits of non-top-5 banks during crises are mostly due to acquisitions, not outright failures (4% for bank exits in 6-20 and 21-100 size categories, compared to 0.8%-0.9% for outright failures). Even among small banks and around crises, outright failures are relatively rare in our database, as being absorbed before failing is substantially more common after banking crises.[14]

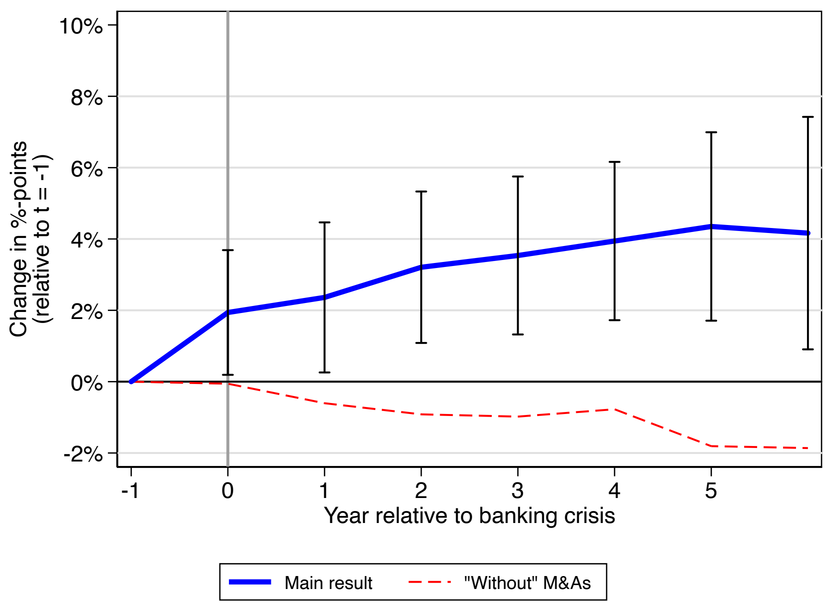
4.2. Change in asset share of top-5 banks around crises

Not only do top-5 banks have a substantially higher survival probabilities, as shown in the previous subsection, but the asset share of large banks also grows substantially during crises, mainly due to the large number of acquisitions of smaller banks by top-5 banks during crises, as we now show. Figure 4 plots the average percentage point increase in the asset share of top-5 banks in each year around banking crises. Specifically, the figure shows an event study

[14] See Figure A.8 for further descriptive statistics on the types of bank exits across the entire sample.

Figure 4: Increase in the top-5 asset share around banking crises

This figure plots the average percentage point increase (relative to the long-run trend) in the asset share of top-5 banks in each year around banking crises. The asset share is defined as the ratio of total assets of top-5 banks to total assets of all banks in the dataset within a given country. The solid blue plot is the unadjusted result, and the long-dashed plot corresponds to the result excluding changes due to bank M&As, using the same methodology as in Figure 1. Specifically, the figure shows an event study created by averaging across banking crises the cumulative increase (relative to t = -1) in the asset share of the top-5 banks, subtracting out the average increase in each country from 1870 to 2016 outside of crises. 95% confidence bands are computed using a simple standard error of the mean across banking crisis observations.



created by averaging across banking crises. The asset share is defined as the ratio of total assets of top-5 banks to total assets of all banks in the dataset within a given country. The solid blue plot is the unadjusted result, and the long-dashed plot corresponds to the result excluding changes due to bank M&As, using the same methodology as in Figure 1.

Figure 4 shows that the asset share of the top-5 banks (blue line) is cumulatively increasing by about three percentage points during the credit boom preceding the banking crisis (from t=-5 to t=-1). Almost all of that is due to M&As (the difference between the solid and dashed lines). In the years of the banking crises (from t=-1 to t=1), the asset share of the top-5 banks jumps about another two percentage points. And after the banking crisis (from t=1 to t=5), the asset share of top-5 banks jumps again about another two percentage points. Without M&A, their assets share appears to be slightly decreasing (the dashed red lines) and not significantly different from zero.

Note that the increase in asset share of top-5 banks around crises is not due, at least on average, to flows from small banks to top-5 banks (e.g., due to deposit flight-to-safety), as the asset share change "without" M&As is actually decreasing (the dashed red lines).[15] As we'll see in Section 5, the organic contraction is actually greater in magnitude for top-5 banks after crises due to their worse performance. Taking the US as an example, for every top-5 bank like JPMorgan Chase that emerged stronger from the 2008 banking crisis, there were other top-5 banks like Citigroup or Wachovia that nearly failed and saw large balance sheet contractions.

The overall result is that the large banks fail or exit less often than other banks and even gain asset share, despite their worse performance during the crisis, as we will see in the following section.

5. Pre-crisis risk-taking and performance during the crisis

To what extent does the "survival of the biggest" reflect more prudent behavior of the largest banks before the crisis? We show in this section that large banks typically take more, not less, risk than smaller banks in the run-up to crises and disproportionately contribute to pre-crisis credit booms. In the crisis, they face higher equity losses and contract their lending more.

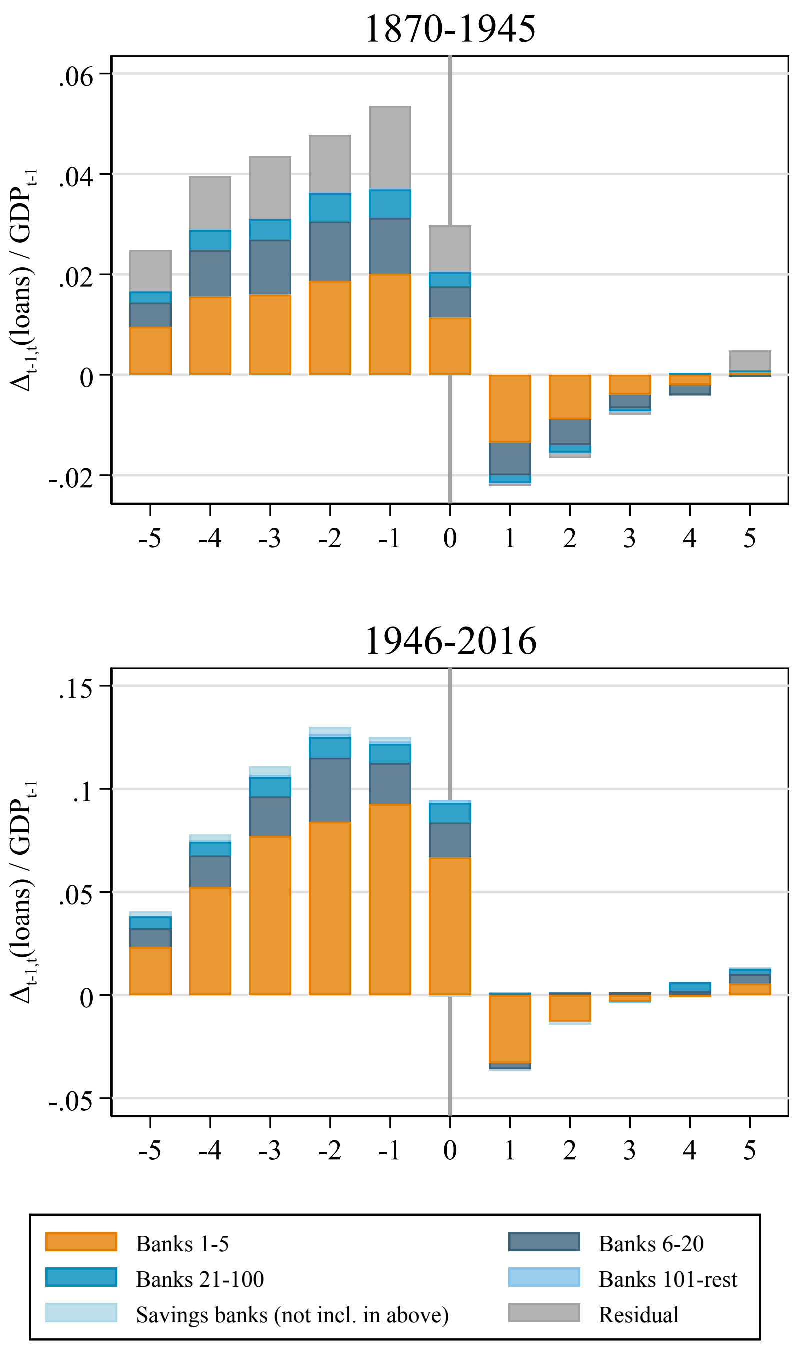
5.1. Risk-taking pre-crisis

In this subsection, we show two results on the risk-contribution of large banks in the run-up to crises. First, we show that the top-5 banks disproportionately contribute in the aggregate to the credit booms preceding banking crises—especially after 1945, where the top-5 banks account on average for about 75% of loan growth during the run-up to banking crises and nearly all of the loan contraction after crises. Second, we show that large banks take increased risk (relative to smaller banks) along a number of dimensions in the run-up to crises: a) increase their loans growth at a faster rate, b) decrease their capital ratios more, c) increase the ratio of wholesale funding to total assets more, and d) decrease the ratio of "safe assets" to total assets more. Interestingly, large banks' risk-taking measures and subsequent losses are magnified when large banks' size relative to the financial system is higher to begin with. Greater ex-ante risk-taking by large banks is also reflected in higher average ex-post equity losses during crises, as shown

[15] The increase in asset share of top-5 banks around crises is also not due new entries or failures (of either small or top-5 banks), as entries and failures contribute very minimally to the asset share change (unreported results).

Figure 5: Large banks' contribution to credit booms preceding banking crises

This figure plots the contribution, by banks of different sizes, to the credit booms and busts around banking crises. Specifically, the figure shows an event study created by averaging across banking crisis episodes (within the 1870-1945 subsample, top, and the 1946-2020, bottom). Within each episode, banks are ranked by asset size by asset size at t = -5; then, the change in total loans (from *t-1* to *t*) is aggregated across all banks within each bank-size category and normalized by GDP_{t-1}. See the text for the definition of loan growth used, which removes the contribution due to M&As (and spinoffs and similar transactions). Missing banks from our sample are captured by the gray "residual" component, defined as JRST aggregate bank loans minus the sum of all banks in our sample for each country and year.



in the next subsection.

We start by showing that the top-5 banks disproportionately contribute in the aggregate to the credit booms preceding banking crises. Figure 5 plots the aggregate contribution, by banks of different sizes, to the credit booms and busts around banking crises. Specifically, the figure shows an event study created by averaging across banking crisis episodes (within the 1870-1945 subsample, top, and the 1946-2020, bottom). To create this plot, we first create similar individual plots for each banking crisis: within each banking crisis, banks are ranked by asset size at t = -5 (as usual, to prevent the results from being driven by compositional changes in the size groups); then, $\Delta_{t-1,t}(Loans)/GDP_{t-1}$ (i.e. the annual change in loans, aggregated across all banks within each bank-size category and normalized by GDP_{t-1}) is plotted for each bank-size category.[16] See Figure A.10 for the plots for each individual banking crisis. We then take a simple across episodes to form the event study plotted in Figure 5. (We adjust t = 0 for each of the episodes so that the peak of the credit boom occurs at t = 0, see Table A.1, thus aligning the timing of the credit boom-to-bust across the events that we average.)

Note that Figure 5 plots loan growth as *organic loan growth* plus loan growth due to new entries and outright failures. The reason for doing this is to remove the loan growth contribution due to M&As (and spinoffs and similar transactions), which do not represent net-originations of new loans and can lead to extreme or inaccurate estimates of credit growth by individual banks. (For example, if bank A in our database is absorbed by bank B, it may naively look like a surge in loan growth at bank B and a -100% reduction in loan growth at bank A.) Note that this adjusted measure of loan growth (organic loan growth plus loan growth due to new entries and outright failures) is conceptually justified as a way to decompose loan growth into size categories, as this measure aggregates to total banking sector loan growth: M&As just transfer loans from one entity to another but do not increase or decrease the aggregate quantity. See Section 2.3 for methodology behind computing organic loan growth.

Figure 5 shows that, in the post-1945 period, the top-5 banks contribute roughly 75% of total loan growth during credit booms. After banking crises, large banks account for nearly all the aggregate credit contraction. The latter result about credit contractions is potentially related to the fact that the top-5 banks see worse equity losses during crises, as demonstrated in the next subsection. As further discussed in Appendix A, where we perform a more careful decomposition, top-5 banks' large contribution to loan growth is both because: a) they make

[16] In all the analyses in this section, we always rank banks by asset size at t = -5 before the crisis and hold the ranking constant through the end of the event study to avoid composition changes in the size categories from driving the results.

up a large and increasing loan share of the banking system, as shown in Figure 1; but, b) more importantly, their organic loans growth rates are *disproportionately procyclical*, increasing more than other banks during credit booms preceding banking crises and decreasing more during credit busts, as we also show below in Table 3. Thus, we conclude that the top-5 banks dominate the credit cycle, especially in the post-1945 period.[17]

We next turn to our second set of results showing that large banks take increased risk (relative to smaller banks) in the run-up to crises along the following dimensions: a) they increase their loans growth at a faster rate, b) decrease their capital ratios more, c) increase the ratio of wholesale funding to total assets more, and d) decrease the ratio of "safe assets" to total assets more. Interestingly, large banks' risk-taking measures and subsequent losses are magnified when large banks' size relative to the financial system is higher to begin with. While this last result does not implicate a particular theory (see below) of why large banks take more risk, it does suggests that asset size itself predicts risk-taking and that this problem is magnified when top-5 banks get larger.

[17]Note that our result on the large contribution of top-5 banks is not due to missing smaller banks in the sample, since any missing banks from our sample are captured in the gray "residual" component of Figure 5, defined as JRST aggregate bank loans minus the sum of all banks in our sample for each country and year.

Table 3: Increased risk-taking during the boom

Panel A: Loan growth during the boom

	Organic loan growth (t = -4 to -1) ×100%		Acquisition loan growth (t = -4 to -1) ×100%		Organic plus Acquisition (t = -4 to -1) ×100%		Raw loan growth (t = -4 to -1) ×100%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Large	0.28		2.53***		2.81***		0.98*	
	(0.53)		(0.45)		(0.69)		(0.54)	
Large x LBDom		1.39**		3.24***		4.63***		2.27***
		(0.60)		(0.50)		(0.78)		(0.61)
Large x NonLBDom		-3.64***		-0.00		-3.65**		-3.59***
		(1.12)		(0.95)		(1.48)		(1.16)
Constant	7.90***	7.90***	0.22***	0.22***	8.11***	8.11***	7.82***	7.82***
	(0.09)	(0.09)	(0.07)	(0.07)	(0.11)	(0.11)	(0.09)	(0.09)
Difference		5.03***		3.24***		8.28***		5.86***
		(1.27)		(1.08)		(1.67)		(1.31)
Episode FEs	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.23	0.23	0.01	0.01	0.15	0.15	0.21	0.22
Observations	15838	15838	15838	15838	15838	15838	15838	15838

Panel B: Capital ratios and noncore funding during the boom

	Change (Equity/assets) (t = -4 to -1) ×100%		Level (Equity/assets) (t = -4 to -1) ×100%		Change (Noncore/assets) (t = -4 to -1) ×100%		Level (Noncore/assets) (t = -4 to -1) ×100%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Large	-0.19***		-3.06***		1.02***		12.88***	
	(0.04)		(0.24)		(0.15)		(0.92)	
Large x LBDom		-0.22***		-3.70***		1.22***		17.98***
		(0.04)		(0.27)		(0.17)		(1.05)
Large x NonLBDom		-0.05		-0.78		0.31		-3.57*
		(0.09)		(0.51)		(0.33)		(1.88)
Constant	0.10***	0.10***	9.23***	9.23***	0.21***	0.21***	21.61***	21.62***
	(0.01)	(0.01)	(0.04)	(0.04)	(0.03)	(0.03)	(0.15)	(0.15)
Difference		-0.17*		-2.92***		0.91**		21.54***
		(0.10)		(0.58)		(0.37)		(2.15)
Episode FEs	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.05	0.05	0.29	0.29	0.07	0.07	0.21	0.22
Observations	14429	14429	15840	15840	13001	13001	14360	14360

Panel C: Safe asset ratios during the boom

	Change (Safe assets/assets) (t = -4 to -1) ×100%		Level (Safe assets/assets) (t = -4 to -1) ×100%	
	(1)	(2)	(3)	(4)
Large	0.19		-2.22***	
	(0.18)		(0.71)	
Large x LBDom		0.04		-2.24***
		(0.20)		(0.79)
Large x NonLBDom		0.94**		-2.13
		(0.45)		(1.65)
Constant	-0.32***	-0.32***	15.89***	15.89***
	(0.03)	(0.03)	(0.11)	(0.11)
Difference		-0.90*		-0.10
		(0.49)		(1.82)
Episode FEs	✓	✓	✓	✓
R^2	0.05	0.05	0.18	0.18
Observations	13522	13522	14895	14895

Why might large banks take more risk in the run-up to crises? One classic argument is that implicit government guarantees to creditors can reduce their incentives to monitor risk-taking or demand an appropriate risk premium in lending to the bank (Flannery, 1998; Gropp et al., 2006; Sironi, 2003). Alternatively, the size and complexity of top-5 banks can make them more difficult to regulate or harder to implement effective risk management and corporate governance. Their interconnections with other financial institutions and markets adds to risk and amplifies contagion effects. And large banks may have greater access to risk-taking opportunities than small banks (e.g., risky investment banking or capital markets activities, access to greater international opportunities).

While our results cannot disentangle which of these channels is most responsible to the increased risk-taking of large banks, our results are inconsistent with the hypothesis that large banks, on net, tend to be associated with greater financial stability. While it might still be the case that large banks could be better diversified with lower idiosyncratic risks (Demsetz and Strahan, 1997; Fernholz and Koch, 2017) or have higher higher charter values that reduce incentives for excessive risk taking (Keeley, 1990), other offsetting factors tend to negate these forces in the run-up to historical crises, leading large banks to take more risk on average (as we show here) and large-bank-dominated banking systems to have deeper macroeconomic crises (as we show in Section 7).

We now examine bank risk-taking in the run-up to banking crises. Table 3 estimates the following two bank-level regressions that analyze various dimensions of bank-level risk taking in the run-up to crises.

$$
\begin{aligned}
y_{i,t} &= a_{ep} + b_1 \cdot \text{Large}_i + \epsilon_{i,t} \\
y_{i,t} &= a_{ep} + b_2 \cdot \text{Large}_i \times \text{LBDom}_{ep} + b_3 \cdot \text{Large}_i \times \text{NonLBDom}_{ep} + \epsilon_{i,t}
\end{aligned} \tag{1}
$$

The regression is estimated for all banks i from year $t = -4$ to -1 around all banking crisis episodes (where $t = 0$ is the first year of each banking crisis, according to Table A.1). The regression is estimated with banking-crisis-episode fixed effects, a_{ep}. The outcome variable $y_{i,t}$ is one of a variety of bank-level risk-taking measures, discussed below. $Large_i$ is an indicator variable if bank i is a top-5 bank. $LBDom_{ep}$ stands for "Large-bank dominated" and is an indicator variable that equals one for a banking crisis episode if the combined asset share of top-5 banks at *t-5* is $\geq 50\%$. $NonLBDom_{ep}$ stands for "Non-large-bank dominated" and equals one for a banking crisis episode if the combined asset share of top-5 banks at *t-5* is $< 50\%$.

Intuitively, Equation (1) analyze various dimensions of bank-level risk taking in the run-up to crises comparing large versus small banks (within banking crisis episodes), also asking whether this difference between large and small banks increases in more large-bank dominated systems. These results are estimated in Table 3 (and also visualized in Figure A.11). Differences between the "large bank" coefficients for large-bank-dominated and non-large-bank-dominated systems, $b_2 - b_3$, are also tested in the table.

Four results emerge from Table 3. First, in the run-up to banking crises, large banks increase their loan growth at a faster rate than smaller banks (measured as the % annual growth rate in loans). In Panel A, the coefficient is not significant for organic loan growth (column 1) but positive and significant for loan growth due to acquisitions (column 3) and two measures of total loan growth (columns 5 and 7). When looking at large-bank-dominated systems (even columns), the coefficients on $\text{Large}_i \times \text{LBDom}_{ep}$ are positive and significant (row 2) for all types of loan growth, including organic loan growth, implying that large banks have much relatively faster growth rates of credit expansion on a %-change basis. Note that in these situations, large banks account for most of the aggregate credit growth, as we saw in the previous subsection, both because they are a large share of the banking system to start with, but also because they are even more procyclical than smaller banks, as these results show, disproportionately contributing to the boom. In contrast, in non-large-bank-dominated systems (row 3), the coefficients are negative and mostly significant, showing that these results actually flip, and large banks are now less-then-proportionately contributing to aggregate credit booms, in more dispersed banking systems.

The next three results are roughly analogous. The second result from Table 3 is that large banks decrease their capital ratios (common equity to assets) more than smaller banks in the runup to crises. In Panel B, column 1 shows that large banks decrease their equity more, as measured in the change in the ratio relative to $t = -5$, while column 3 shows that the level of equity-to-assets is lower for large banks than small banks. This result is consistent with evidence for the U.S. from Baron (2020), who shows that government guarantees to creditors lead to inefficiently large credit expansions, accompanied by decreases in their equity ratios. Columns 2 and 4 show that these relative differences between large and small banks are amplified before crises in large-bank-dominated banking systems.

The third and fourth results are that large banks increase the ratio of wholesale (i.e. non-deposit) funding to total assets more (Panel B, columns 5-8) and decrease the ratio of "safe assets" to total assets more, both as measured in the change in the ratio relative to $t = -5$ and in the level. Again, these relative differences between large and small banks are amplified before crises in large-bank-dominated banking systems.

5.2. Financial performance in the crisis

Greater ex-ante risk-taking by large banks is also reflected in higher average ex-post equity losses during crises. To show this, we collect data on total stock returns of the top-20 banks by country-year (specifically, the subset of those 20 banks that is publicly traded) and demonstrate that the average total stock returns of large banks fall more in crisis episodes. The contraction of their loan portfolios after crises is also more pronounced. Again, the relative losses between large and small banks are magnified in large-bank-dominated banking systems.

To analyze and compare the performance of top-5 banks and smaller banks during banking crises, we turn to Table 5, which summarizes three key performance metrics for banking crisis episodes. Again, we estimate Equation (1), but this time with three new outcome variables (bank stock returns, organic credit contraction, and failure rates) corresponding to *during and after the crisis* (i.e., $t = 0$ to 3).

Table 5 shows that the average returns of top-5 banks are significantly lower after banking crises than banks 6-20 (columns 1 and 2).

To estimate this regression of bank stock performance after the crisis, banks are ranked as usual by assets at $t = -5$ in each episode; then, real total returns, cumulated from $t = 0$ to 3, are computed group for the 954 banks in our sample around crises that are publicly traded and report returns. As column 1 shows, the returns of non-top-5 banks on average is -19.19% but more negative by -2.67 percentage points for top-5 banks. Column 2 shows that this difference is magnified in large-bank-dominated systems but insignificantly different from zero is non-large-bank-dominated systems, where large-bank-dominated is defined as banking crises where the top-5 asset share at *t-5* is $\geq 50\%$. These results are also visualized in Figure A.13.

We find similar evidence when comparing loan growth (column 3 and 4) of large and small banks during banking crises. However, columns 5 and 6 show that large banks fail less often in crises, and this lower failure rate is magnified in large-bank-dominated systems. At the same time, however, the other columns cast substantial doubt on the idea that the lower failure rate has to do with better fundamentals. Large banks have higher equity losses during the crisis. The contraction of their loan portfolios is also more pronounced. In short, large banks appear to engage more in risk-taking, and have greater losses. Yet they survive at a substantially higher rate.

Table 5: Bank performance during the banking crisis

	Bank stock total return (t = 0 to 3) ×100%		Credit contraction (t = 0 to 3) ×100%		Failure rate (t = 0 to 3) ×100%	
	(1)	(2)	(3)	(4)	(5)	(6)
Large	-3.67*		-2.68***		-2.00*	
	(2.10)		(0.76)		(1.05)	
Large x LBDom		-7.74**		-2.91***		-2.29*
		(3.01)		(0.88)		(1.21)
Large x NonLBDom		0.14		-1.98		-1.12
		(2.91)		(1.53)		(2.09)
Constant	-19.19***	-19.01***	0.65***	0.65***	3.43***	3.43***
	(1.28)	(1.28)	(0.12)	(0.12)	(0.17)	(0.17)
Difference		-7.88*		-0.92		-1.17
		(4.19)		(1.76)		(2.42)
Episode FEs	✓	✓	✓	✓	✓	✓
R^2	0.61	0.61	0.04	0.04	0.02	0.02
Observations	954	954	11561	11561	11561	11561

6. Explanations for top-5 banks' higher survival rate

In this section, we provide evidence to help explain why large banks tend to survive at a substantially higher rate during banking crises, even though they have higher equity losses. We show two (potentially interconnected) results: first, regulators are substantially more likely to rescue top-5 banks on the verge of failure, and, second, large banks have more stable funding dynamics in crises.

6.1. Government interventions

We systematically examine top-20 banks across all historical banking crises and create a database of interventions at the individual bank level. We find that, among banks "on the verge of failure", rescues explicitly intended to prevent failure and preserve the original banking institution are very common for top-5 banks but a lot less common for banks 6-20, which instead tend to be merged away or wound down. We argue the differential rate of such rescues can account for most of the difference across history between top-5 and 6-20 banks in failures and exit rates.

This analysis relies on a new systematic database of bank-level rescues (or lack thereof) of all individual top-20 banks "on the verge of failure" in each historical crisis. We document interventions bank-by-bank with detailed narrative historical sources specific to each bank. In contrast to prior research (e.g., Laeven and Valencia (2020), Metrick and Schmelzing (2021)) that documents interventions at the country level, this novel historical database of interventions covers 934 individual top-20 banks across 17 countries and almost 150 years of history. As discussed in further detail below, we focus on a specific type of government intervention that we show is quantitatively important for explaining "survival of the biggest": emergency rescues done for the explicit purpose of not letting a specific bank fail. We find that such policies of not letting banks on the verge of failure fail are extremely common for top-5 banks but a lot less common for banks 6-20—and that this differential can account for most of the differences in failure and exit between top-5 and 6-20 banks across history that we show in Figure 3.

We build this database in the following steps. First, we identify the top-20 banks by assets, ranked at t = -5 before each banking crisis (as usual, to hold the composition constant across the banking crisis). Second, we identify the subset of those top-20 banks which are on the "verge of failure," defined as a bank that, within a ±5-year window of the crisis, either fails, exits via a "distressed acquisition", or has a peak-to-trough stock decline of more than 90% (based on annual data of real total returns).[18] Third, emergency rescues (or lack thereof) of each individual bank are identified and documented using narrative historical sources specific to that bank.[19] We focus on identifying and documenting interventions explicitly intended to prevent failure and preserve the original banking institution (as opposed to arranging a merger to another institution). To make sure we're not missing interventions for some banks, which might potentially bias our comparison of top-5 versus 6-20 banks, we explicitly document why no intervention was given, if such was the case, and why regulators decided to let a bank fail (or arrange for a merger, etc.).

We emphasize that this analysis is purposely limited to just one particular type of intervention: *emergency rescues performed for the explicit purpose of preventing a specific bank from failing*—and only for the subset of top-20 publicly-traded banks that reach the verge of failure. Our database is not meant to include other important types of government interventions: for example, system-wide interventions, such as blanket guarantees of all system liabilities, that might potentially help smaller banks more than large banks or earlier interventions implemented before banks are on the verge of failure. However, we show that this one type of intervention is

[18]An exit by acquisition is categorized as "distressed" (rather than "voluntary") if the historical narrative in any way suggests that the bank was distressed or that regulators encouraged the acquisition, or if the bank's acquisition stock price was less than 50% from its peak.

[19]We limit ourselves to documenting interventions only in the subset of top-20 banks on the verge of failure because of the considerable time to perform historical research and document government interventions across all historical banking crises.

itself quantitatively important and accounts for much of the failure differential between large and small banks.

Before turning to the main results on interventions and survival rates in crises, we provide two examples of severe banking crises, the US in 2008 and the Netherlands in 1921, to discuss the type of interventions that we capture. In each of these cases, we select a top-5 bank and a 6-20 bank on the verge of failure:

- **U.S. in 2008**:
  - **Citigroup (Rank #1)**: In Nov. 2008, to prevent an outright collapse, policymakers went to extraordinary length, providing Citigroup with (among many other forms of assistance) a "Systemic Risk Exception," $300 billion in troubled asset guarantees, and $20 billion equity injection (in addition to $30B already from TARP). According to the TARP Inspector General's later report, "The essential purpose of the deal, as Paulson and Geithner later confirmed... was to assure the world that the Government was not going to let Citigroup fail."
  - **Washington Mutual (Rank #6)**: In contrast to Citigroup, Washington Mutual went into FDIC receivership on Sept 25, 2008 and was sold to JPMorgan Chase for a price of $1.9 billion (paid to the FDIC) and the assumption of most debt. However, unsecured senior debt obligations of the bank were wiped out, so not all creditors were protected.
- **Netherlands in 1921**:
  - **Rotterdamsche Bankvereeniging: (Rank #2)**: To prevent an imminent failure of the bank, due to defaults of several major industrial borrowers, policymakers provided the bank with 35 million guilder special emergency overdraft facility from central bank, 25 million guilder in equity injections and asset purchases, and a state guarantee of 60 million guilder in liabilities. The finance minister, Hendrik Colijn, declared that it was "in the interest of the nation to avoid a catastrophe" and that he was "therefore willing to support the [bank] with a substantial sum."
  - **Marx & Co's Bank (Rank #9)**: This bank was exposed to many of the same underlying borrower defaults, but policymakers did not prevent its failure. Nevertheless, it was given 27 million guilders in liquidity support to prevent a disruptive failure and to allow for the bank to be slowly unwound.

In both cases, the top-5 bank is preserved, while the 6-20 bank is resolved. Our database contains many other similar examples across history from the nineteenth century to the present. One broader takeaway from these examples and from our database as a whole is that "too-big-to-fail" rescues are not new (i.e., they did not start with the rescue of Continental Illinois in 1984) but have been common in crises in all countries and historical time periods. Policymakers are reluctant to let any top-5 bank fail, perhaps because they fear the macroeconomic consequences of an outright failure or because there is no other large enough and well-capitalized bank to acquire it. (In fact, there are only four examples of outright failures of top-5 banks in all our database across 17 countries and 150 years of history.)

Table 6 reports the results from our analysis of rescues. Results are reported as bank frequencies, tabulated among the sample of all banks being on the "verge of failure" during a crisis. Row 1 starts by reports the survival rates and confirms many of the results from before on the persistence and higher survival rates of top-5 banks: Top-5 banks on the verge of failure end up surviving (i.e. not failing or being acquired) 78% of the time (column 1), compared to 26% for 6-20 banks (column 2), a difference of 52 percentage points that is statistically significant (column 3). Row 2 then turns to rescues: Top-5 banks on the verge of failure receive an intervention that prevents failure or acquisition 64% of the time (column 1), while 6-20 banks receive one 13% of the time (column 2), a large and significant difference of 51% (column 3).

Table 6: Regulatory rescues of Top-5 banks

	Top-5 banks (N=88) (1)	Top 6-20 banks (N=174) (2)	Difference (3)
Bank did not failure or exit	78%	26%	52%***
Saved by regulators from failing or exiting	64%	13%	51%***
All creditors protected from losses	90%	59%	31%***

These results imply that if, hypothetically, regulators never did any of these interventions, and all else remained constant with regard to failure dynamics (a strong assumption), then the survival rates between large vs. small would be similar: (78% - 64%) = 14% for top-5 banks versus (26% - 13%) = 13% for 6-20 banks. This speculative back-of-the-envelope calculation nevertheless illustrates the magnitudes of how important these types of interventions seem to be in explaining the differential survival rates of top-5 versus other banks.

Finally, row 3 looks at another dimension of government interventions, whether all creditors are protected from losses. (We assume that creditors are protected from losses if: a) the bank does not fail, suspend convertibility, or impose a haircut on creditors; b) the bank is merged away and the acquirer assumes all liabilities in full; or c) the government announces that it is insuring all bank liabilities.) Top-5 banks on the verge of failure have their creditors fully protected from losses 90% of the time (column 1), compared to 59% for 6-20 banks (column 2), a statistically significant difference of 31 percentage points (column 3).

Overall, the results from Table 6 reject the hypothesis that "survival of the biggest" is mainly due to "market forces" (e.g., economies of scale for the largest banks, natural advantages of the largest banks during crises) and suggests a key role of government interventions.

6.2. Funding dynamics

Next we show that the relationship between stock returns (as a proxy for solvency) and deposit outflows is materially different for large and small banks in crises. For small banks, declines in stock returns correlate closely with deposit flight. For large banks, this link between stock declines and deposit outflows is broken. For instance, we show here that if a large bank's stock falls by 90% or more, there's a good chance the bank will have only small deposit outflows and survive, even though smaller banks would tend to see large deposit outflows and likely fail. As a result, we argue that a key reason why large banks are special is that their financing is largely unresponsive to asset side risks.

Table 7 estimates bank-level regressions around crises that analyzes the sensitivity of deposits to bank stock declines. We estimate the following equation:

$$\begin{aligned} y_{i,t=0,3} = a_{episode} &+ b_1 \cdot \text{Return}_{i,t=0,3}(range) \times \text{Large}_i \\ &+ b_2 \cdot \text{Return}_{i,t=0,3}(range) \times \text{Small}_i \\ &+ \gamma \cdot \text{Small}_i + \epsilon \end{aligned} \tag{2}$$

$Return_{i,t=0,3}(range)$ is an indicator variable that equals one when bank i's total cumulative stock returns from $t = 0$ to 3 are within the given *range* (e.g., from -60% to -30%). $Large_i$ is an indicator variable if bank i is a top-5 bank, and $Small_i$ is an indicator variable if bank i is not a top-5 bank. The outcome variables $y_{i,t=0,3}$ are bank-level changes (e.g., in total deposits) from $t = 0$ to 3. Intuitively, Equation (2) estimates the sensitivity in the outcome variable (e.g., change in total deposits) during crises to the bank stock return of bank i, comparing large versus small banks.

Table 7 reports the results. Column 1 reports estimates with the dependent variable being the percent change in total deposits. Conditional on a -30% to -60% bank stock decline, large banks do not see significant deposit outflows (row 1), while smaller banks see an average cumulative 6.60% deposit outflow. The deposit outflows are larger when the bank stock return is larger: when the cumulative bank return is $\leq$ -90%, the cumulative deposit outflow is -12.61% for large banks (row 5) but even larger at -23.99% for smaller banks (row 6). Subsequent rows test the difference between these coefficients for larger versus smaller banks, finding it statistically significant when the bank stock return is $\leq$ -90%. All regressions in Table 7 are estimated with episode fixed effects (an "episode" is a country crisis, e.g., France around 2008), so the estimates reflect differences between large and small banks with similar bank stock returns within the same country crisis.

Column 2 reports similar results but now with interbank liability growth as the dependent variable. A variety of papers implicate interbank lending as highly-informed lending about banks' conditions and highly runnable during a banking panic. Consistent with this literature, we find sizeable differences in interbank liability outflows between large and small banks—qualitatively similar to the results for deposit outflows but larger in magnitude.[20] Similarly, Column 3 reports results for the outcome variable being the change in banks' cash holdings on the asset side (which includes all forms of cash-like assets, such as specie, central bank reserves, and deposits at other banks) and shows that small banks see a sharper contraction in cash-like assets conditional on large bank stock declines.

One potential worry with this analysis is that the bank stock decline may not simply reflect solvency concerns but also liquidity concerns. However, this issue would likely bias the results in the *opposite* direction, so that the actual difference between the deposit sensitivity of large and small banks would be larger than the coefficients would seem to suggest. To see this, consider a large and small bank that have otherwise identical equity losses (defined theoretically as asset-side losses times leverage). If the small bank suffers greater liquidity issues as a result of these solvency issues, then its stock price will decline more than the large bank's. By this reasoning, if a large and small bank have equal stock price decline, the large bank must have greater underlying solvency losses, which would make the actual difference between the deposit sensitivities larger than the coefficients would seem to suggest.

[20] Ideally, one would want to decompose total deposit growth into demand deposits, time deposits, etc., given that the literature has similarly implicated time deposits as highly-informed and runnable. In contrast, demand deposits tend to be "sticky". However, for most countries in our sample, a consistent decomposition of deposit types is not available, making this analysis not possible.

Column 4 estimates the sensitivity of the probability of bank failure to changes in bank stock prices. The results show that large banks fail substantially less often than small banks do during crises, conditional on similar magnitude of bank stock declines. For example, conditional on a cumulative bank decline of $\leq$ -90%, large banks are no less likely to fail than if they didn't see a stock decline, but small banks' probability of failure is elevated by 8.13%. Here, "failure" is defined as an exit between years $t = 0$ to 3: either an outright failure or an acquisition by another bank.

Summing up, even though top-5 banks tend to have more pronounced solvency issues during crises, they are less likely (for a given magnitude of bank stock declines) to see deposit outflows or to fail than their smaller competitors.

Table 7: Deposit sensitivity to bank stock declines

	Deposit growth$_{0,3}$	Interbank liab. growth$_{0,3}$	Cash holdings growth$_{0,3}$	Failure prob.$_{0,3}$
	(1)	(2)	(3)	(4)
Return$_{-30\%,-60\%}$ × Large	0.03	1.00	0.56	-1.40
	(3.85)	(3.48)	(4.29)	(2.83)
× Small	-6.60*	-6.23*	-11.13***	2.18
	(3.87)	(3.52)	(4.16)	(2.36)
Return$_{-60\%,-90\%}$ × Large	-8.31**	-5.32	-8.72**	3.55
	(3.81)	(3.32)	(4.24)	(2.80)
× Small	-16.61***	-15.11***	-17.71***	3.85
	(3.84)	(3.46)	(4.07)	(2.40)
Return$_{-90\%,-100\%}$ × Large	-12.61**	-7.44	-11.80**	1.69
	(5.14)	(4.56)	(5.73)	(3.85)
× Small	-23.99***	-21.69***	-23.74***	8.13***
	(4.20)	(3.70)	(4.46)	(2.78)
Small	-9.58**	-10.49**	-10.15**	3.02
	(4.42)	(4.22)	(4.81)	(2.99)
Constant	8.97***	7.85***	9.58***	-2.75
	(3.17)	(2.97)	(3.30)	(1.72)
Difference (Large minus Small):				
Return$_{-30\%,-60\%}$	-6.63	-7.23	-11.69*	3.58
	(5.58)	(5.19)	(6.13)	(3.80)
Return$_{-60\%,-90\%}$	-8.30	-9.78**	-9.00	0.31
	(5.08)	(4.64)	(5.56)	(3.58)
Return$_{-90\%,-100\%}$	-11.38*	-14.24**	-11.94*	6.44
	(6.26)	(5.71)	(6.85)	(4.44)
Episode FEs	✓	✓	✓	✓
R^2	0.35	0.38	0.30	0.08
# Banks	222	214	224	270

7. Large-bank-dominated systems and financial instability

The question of whether large bank dominated banking systems are more stable than those with a more fragmented structure ones has long been a major concern in discussions about banking system stability. We present evidence here that not only challenges the hypothesis that a banking system dominated by large banks is more stable, but also suggests that a greater presence of large banks may actually lead to less macroeconomic stability.

As we saw in previous sections, large banks tend to take more risks and have worse equity performance, but they maintain a more stable funding base and fail less often, so it is unclear from these two opposing effects what the resulting macroeconomic consequence is. Thus we ask, conditional on a crisis, are the macroeconomic consequences on average worse for large-bank-dominated financial systems? Our analysis suggests that this is indeed the case. However, even if the macroeconomic consequences of crises are worse *conditional on a crisis* in large-bank-dominated financial systems, perhaps crises occur less frequently? Our analysis suggest that the likelihood of a crises occurring is a large-bank- versus non-large-bank-dominated financial system is no different.

To be clear, our analysis is not a full welfare comparison of the benefits and costs of large-bank systems, since large banks may provide important benefits to the economy outside of crises (e.g., economies of scale in deposit taking, lending, financial services and capital markets activities) that we do not measure. However, our analysis does suggest that large bank systems do have one important downside on the financial stability dimension, which is that crises tend to be more macroeconomically severe (while still happening at similar frequency), compared to in non-large-bank-dominated systems.

7.1. Large banks and crisis probability

Are crises more or less frequent in large-bank-dominated financial systems? We investigate the predictive power of the top-5 asset share and crisis probability using two banking crisis definitions (the credit crunch definition from Section 2.4 and the JST crisis chronology). Results are reported in Table 8. Despite trying a battery of various regression specifications, subsamples, and different crisis definitions, the results are uniformly null results with marginal effects very close to zero in magnitude. Thus, we do not find evidence that crises are more or less likely in large bank dominated banking systems.

Table 8: Probit models for banking crises.

The table shows probit classification models where the dependent variable is a banking crisis dummy and the regressors are lagged by one period. BSZ crisis (columns 1 and 2) is a dummy variable that indicates the start of a major credit crunch (see data section for more detail). Columns (3) and (4) use the crisis definition by JST and columns (5) and (6) the crisis definition by BVX.

	BSZ crisis					JST crisis				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Top 5 asset share$_{t-1}$	-0.01	-0.00	-0.02	-0.03	0.20	-0.02	-0.00	0.01	0.02	0.05
	(0.01)	(0.02)	(0.03)	(0.03)	(0.14)	(0.01)	(0.02)	(0.03)	(0.04)	(0.07)
$\Delta_{t-6,t-1}$Loans/GDP$_{t-1}$				0.15**	0.24***				0.16***	0.21***
				(0.05)	(0.08)				(0.04)	(0.06)
Country fixed effect		✓	✓	✓	✓		✓	✓	✓	✓
Decade fixed effect			✓	✓	✓			✓	✓	✓
Post 1980					✓					✓
Observations	2177	2177	2177	1976	596	2177	2177	2177	1976	596

7.2. Large banks and crisis severity

Next we show that crises in banking systems with a higher top-5 share tend to be deeper. We estimate the following local projection (Jordà, 2005) regressions to characterize the dynamics of output during banking crises:

$$\begin{aligned}\Delta_h y_{i,t} = {} & a_i^h + b_1^h Crisis_{i,t} \times LBDom_{i,t} + b_2^h Crisis_{i,t} \times NonLBDom_{i,t} \\ & + \Phi^h X_{i,t} + \epsilon_{i,t+h}\end{aligned} \tag{3}$$

for $h = 1, ..., 5$, where $\Delta_h y_{i,t}$ is the growth of real GDP per capita between time $t-1$ and $t+h-1$. Similar to before, $LBDom_{i,t}$ is an indicator variable that equals one when Top-5-share ≥ 0.5. The control vector $X_{i,t}$ includes country fixed effects, two lags of GDP growth and inflation, the lagged top-5 asset share and a post-1945 dummy. We define a banking crises as the beginning of a major credit contraction as in the rest of the paper and split crises into two groups depending on the asset share of the top-5 banks in our dataset prior to the crisis. The coefficients of interest are b_1^h and b_2^h and capture the relationship between crises and cumulative GDP growth over a h-year horizon for crises in large bank dominated versus non-large bank dominated systems (i.e., asset share above or below 50%).

Figure 6 shows the path of real GDP during banking crises in large bank dominated versus

Figure 6: Real GDP consequences of banking crises in large-bank-dominated systems

This figure displays local projection regression coefficients of equation 3 to study the evolution of real GDP in banking systems with a high and a low top-5 asset share. Full sample results, excluding world wars. 90% confidence bands are computed using the standard deviation of the difference between crises in large-bank-dominated and non-large-bank-dominated banking systems (see Table 9).

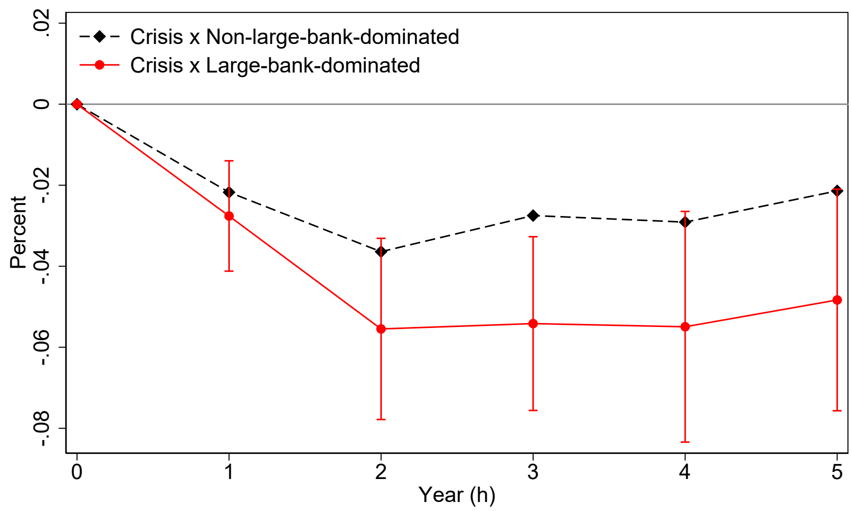


Table 9: Real GDP consequences of banking crises in large-bank-dominated systems

This table displays local projection regression coefficients of equation 3 to study the evolution of real GDP in banking systems with a high and a low top-5 asset share. Full sample results, excluding world wars.

	Year 1	Year 2	Year 3	Year 4	Year 5
Crisis_t x Large-bank-dominated$_{t-1}$	-0.03***	-0.06***	-0.05***	-0.05***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Crisis_t x Non-large-bank-dominated$_{t-1}$	-0.02***	-0.04***	-0.03*	-0.03	-0.02
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Difference	-0.01	-0.02	-0.03**	-0.03	-0.03*
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
R^2	0.143	0.165	0.162	0.184	0.188
Country fixed effects	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓
Observations	1956	1935	1915	1897	1878

non-large bank dominated systems. Table 9 shows analagous results in tabular form. We find that banking crises in large-bank-dominated systems are deeper than crises in non-large-bank-dominated banking systems.

8. Conclusion

This paper introduces a new long-run, bank-level, cross-country dataset to study the behavior and performance of large and small banks over the credit cycle. We show that large banks account for a rising share of the aggregate financial cycle, take more risk during pre-crisis credit booms and have higher losses during the crisis. We also show that large banks grow their market shares over the boom-bust cycle due to lower failure rates and by acquiring smaller banks. Our results are consistent with theories of excessive risk taking of large banks and implicit bailout guarantees and shows that large banks have been at the epicenter of financial instability and risk taking throughout history.

Appendix A: Large banks' contribution to the credit cycle

We discuss here additional methodology, used in the construction of Figure 1 Panel D, to show that the top-5 banks account for a large and rising share of aggregate credit fluctuation.

Appendix Figure A.6 shows the top-5 banks' contribution to the credit cycle in our full-sample analysis. We can decompose aggregate growth as follows:

$$g^{aggregate} = g^{large} * MShare^{large}_{t-1} + g^{small} * MShare^{small}_{t-1},$$

here g^{large} and g^{small} are the weighted average asset growth rates of large and small banks and $MShare^{large}_{t-1}$ and $MShare^{small}_{t-1}$ are their corresponding lagged market shares. This decomposition allows us to decompose aggregate asset growth into the share that can be accounted for by large banks and treat the remainder as a small bank residual. We use M&A adjusted growth rates when constructing the large bank contribution to separate organic from inorganic growth (see section 2 for more detail) .

Figure A.6, panel A, illustrates how the growth contribution of the top-5 banks is calculated in two countries - Canada (left-hand plot) and the United States (right-hand plot). The solid navy blue lines show aggregate 5-year real asset growth and the light blue bars show the share of the overall growth accounted for by top-5 banks. Large banks have always accounted for a large share of the aggregate growth dynamics in Canada, while their role in the United States was negligible early on. However, the plot for the United States also shows that the contribution of the largest 5 banks has risen over the last decades.

Panel B quantifies the growth contribution of the top-5 banks over time (left plot), across countries (right plot) and over time and across countries (bottom plot). To collapse annual growth contributions into one average, we regress the top-5 growth contribution on aggregate asset growth using centered ±10-year rolling windows (left plot), country level data (right plot) and three sample periods within each country (bottom plot).

The main result from the left plot of panel B is that the growth contribution of the top-5 banks to credit cycles has increased from around 25% in the late nineteenth century to around 60% since the 2000s. The right plot of Panel B displays the growth contribution of the top-5 banks by country, showing that there is a large variation in the average growth contribution across countries. While the average growth contribution is around 0.4, results differ across countries. Some countries (like Canada and Sweden) have historically been "large bank countries" with the average growth contribution over time of almost 0.7. On the other extreme, other countries (like Germany and the U.S.) are "small bank countries" and have historically had growth contributions around 0.05. Finally, Panel C shows that the increase in the growth contribution of the top-5 banks is a cross-country phenomenon. Across countries the contribution of large banks has risen when comparing the three sample periods, with some of the largest increases observed in countries starting from a low base.

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Appendix

Figure A.1: Asset shares by bank rank

This figure shows the distribution of bank assets across different ranks, averaged across countries and time. Each bank's rank is determined by its total assets in each respective year. The bank asset share is calculated using total banking system assets from aggregate data. Large-bank-dominated banking systems are country-years where the top 5 banks account for 50% or more of banking system assets. Non-large-bank-dominated systems are country-years where the top 5 banks account for less than 50% of of banking system assets.

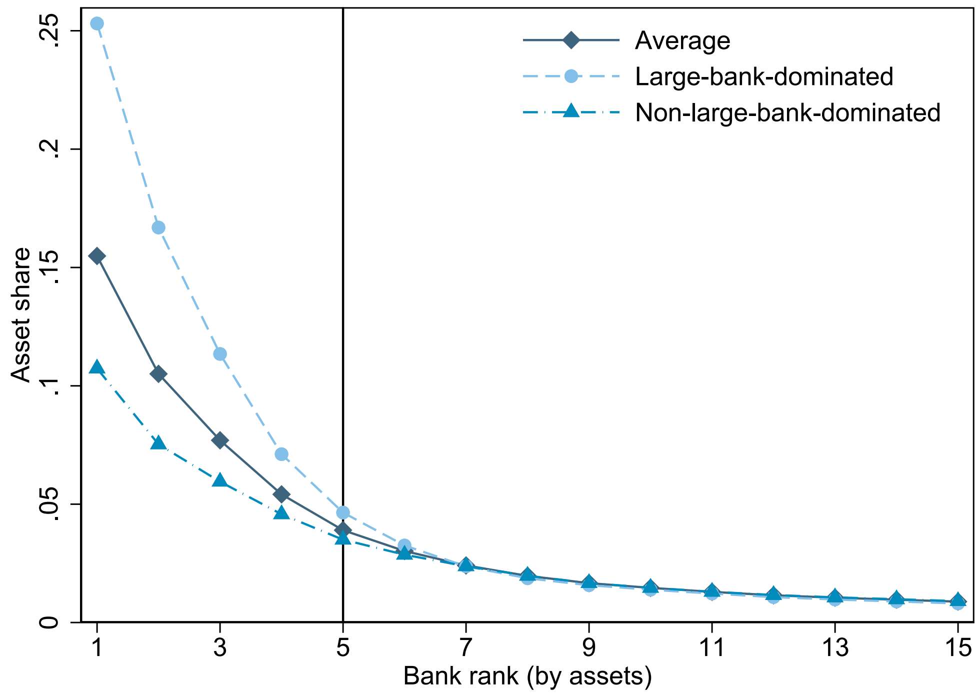


Figure A.2: Market shares by bank size groups

This figure plots the share of bank assets by size group over time. Banks are ranked by assets in each year. The share of bank assets is normalized by the total assets of the banking system in each country from aggregate data of Jordà et al. (2021), not by summing all the banks in the database–hence the white space in the plot.

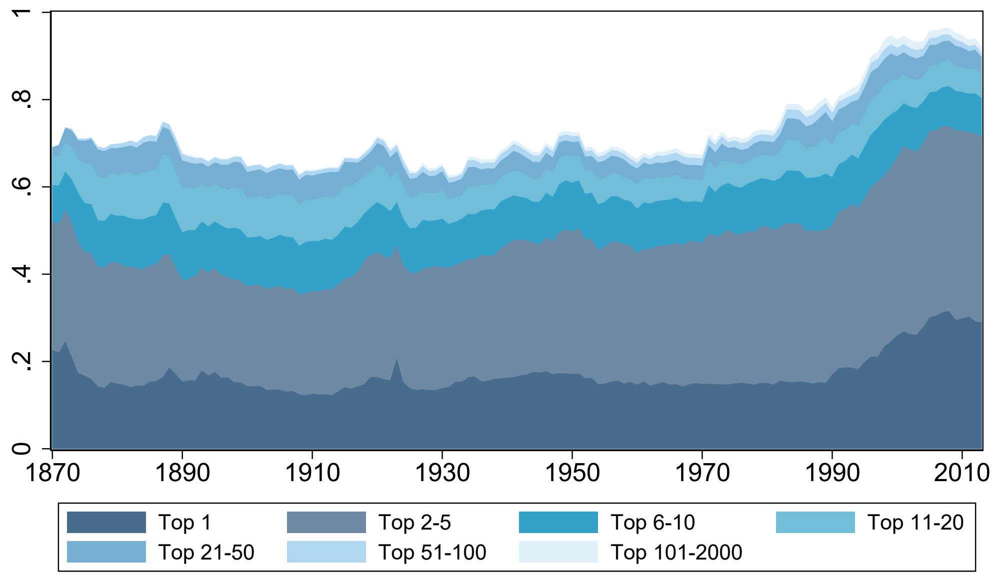


Figure A.3: Top-5 banks' asset share by country

This figure shows the asset share of the top-5 banks over time (solid blue line). The dashed red line provides an estimate of the role that M&A activity played in the evolution of the top-5 asset share: specifically, how it would have evolved "without" M&A activity (see details in main text on the construction of this hypothetical).

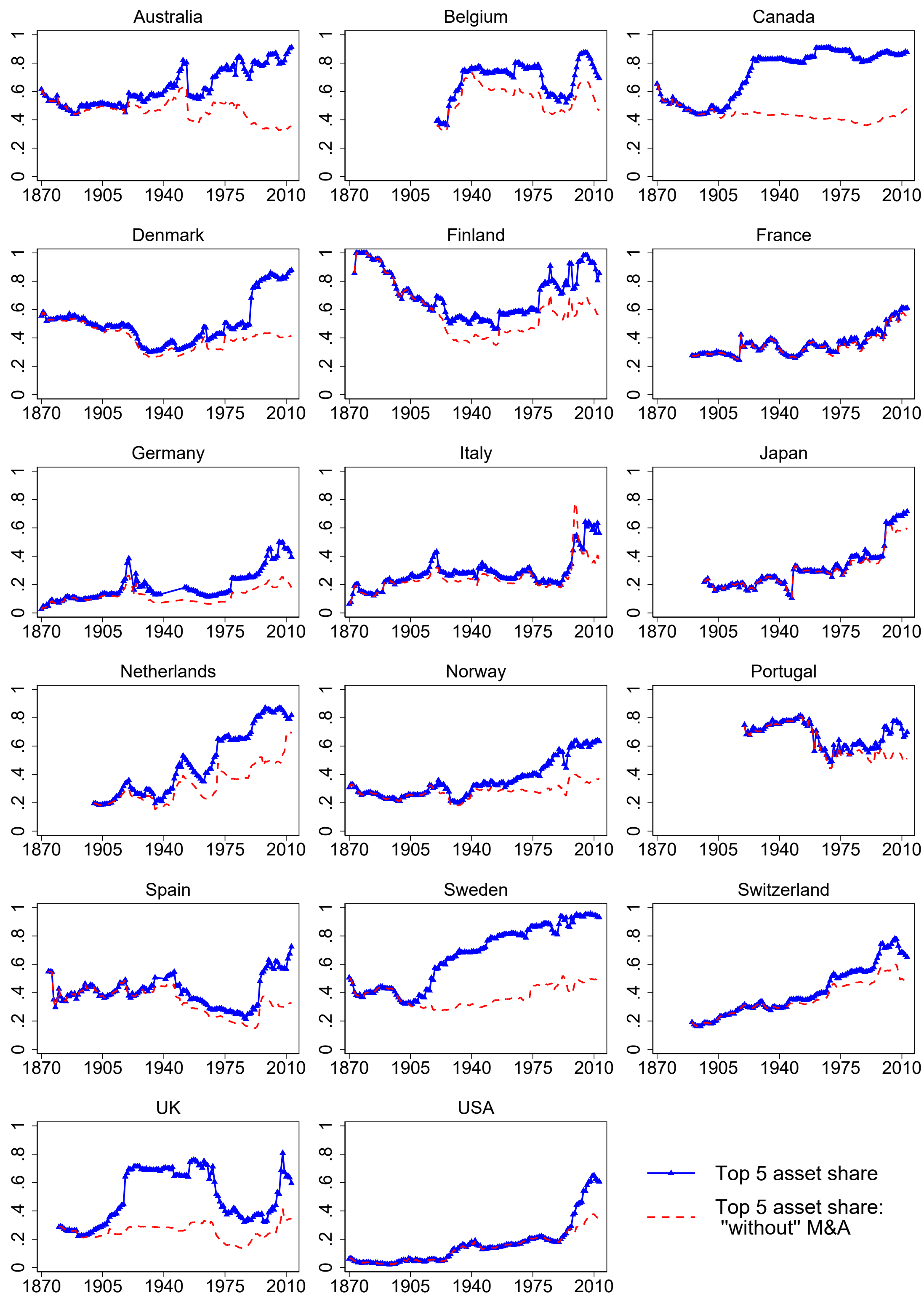


Figure A.4: Bank assets-to-GDP ratio of the top-5 banks versus all other banks by country

This figure shows the size of banking system assets relative to GDP broken down into the top-5 banks and all other banks. We calculate the size of the "other banks" as the difference between top-5 bank assets and aggregate banking system assets to deal with missing data at the bottom of the distribution in some countries.

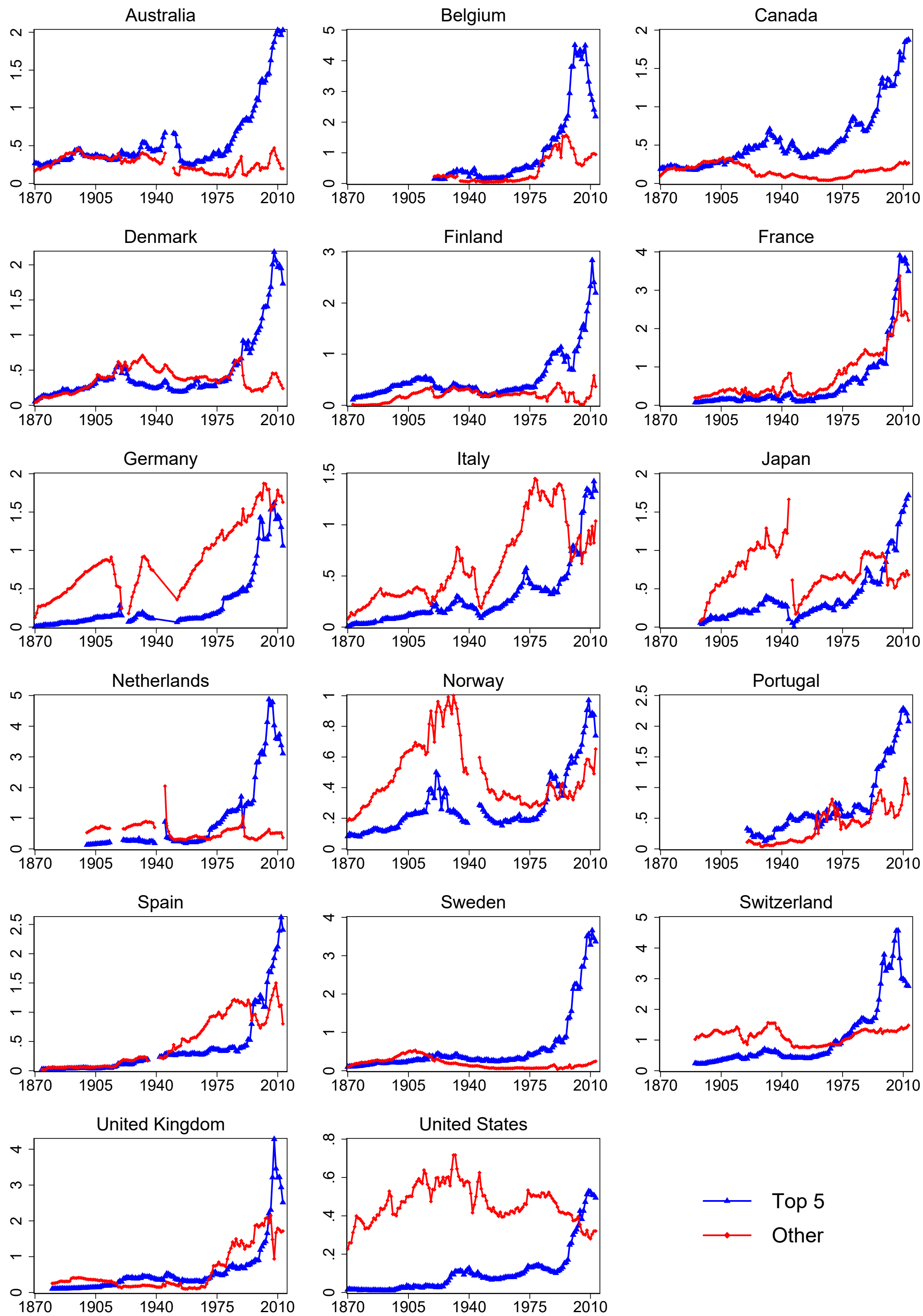
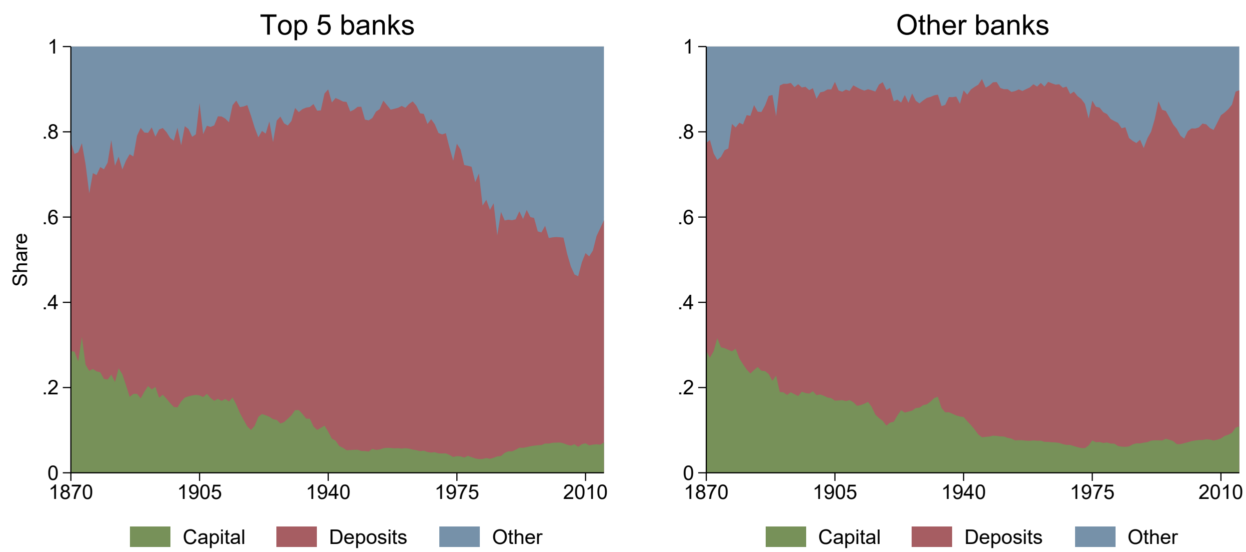


Figure A.5: Balance sheet composition of large and small banks

The top panel shows the liability composition of top-5 banks and all other banks. The bottom panel shows the asset composition of top-5 banks and all other banks. Median across banks in the two groups.

Panel A: Liabilities of the median top-5 and other banks



Panel B: Assets of the median top-5 and other banks

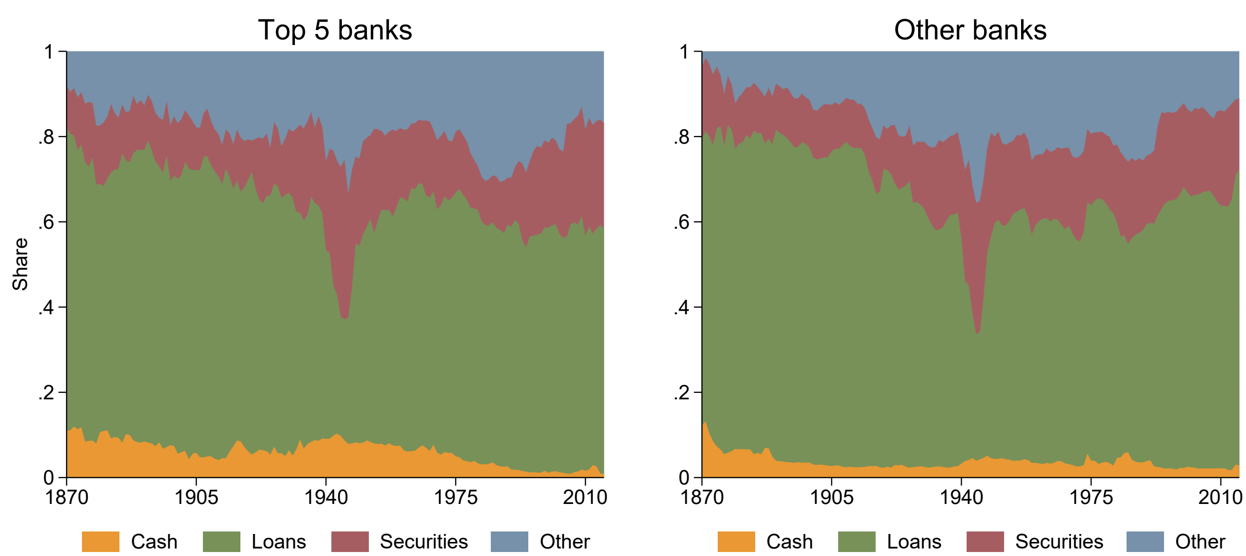
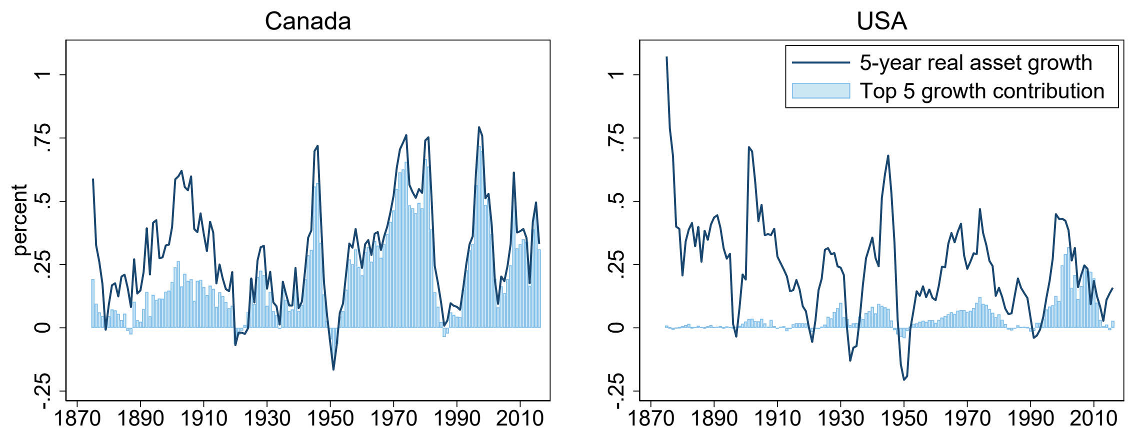


Figure A.6: Top-5 banks' contribution to the credit cycle

Panel A illustrates how the growth contribution of the top-5 banks is calculated for two countries. Panel B shows how the growth contribution of the top-5 banks changes over time (left plot) and across countries (right plot), as measured by the asset share of the top-5 banks. The Top 5 growth contribution is calculated as the M&A adjusted weighted growth rate of the top 5 banks times their lagged market share. Panel A is based on 5-year growth rates for illustrative purposes and the right hand panel of panel B is calculated using centered ±10-year rolling window regressions of the top-5 growth contribution on the aggregate growth rate.

Panel A: Growth contribution example for the United States and Canada



Panel B: Growth contribution by country and period

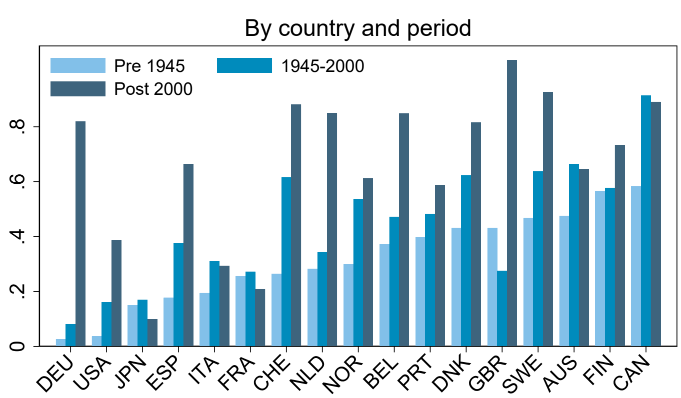
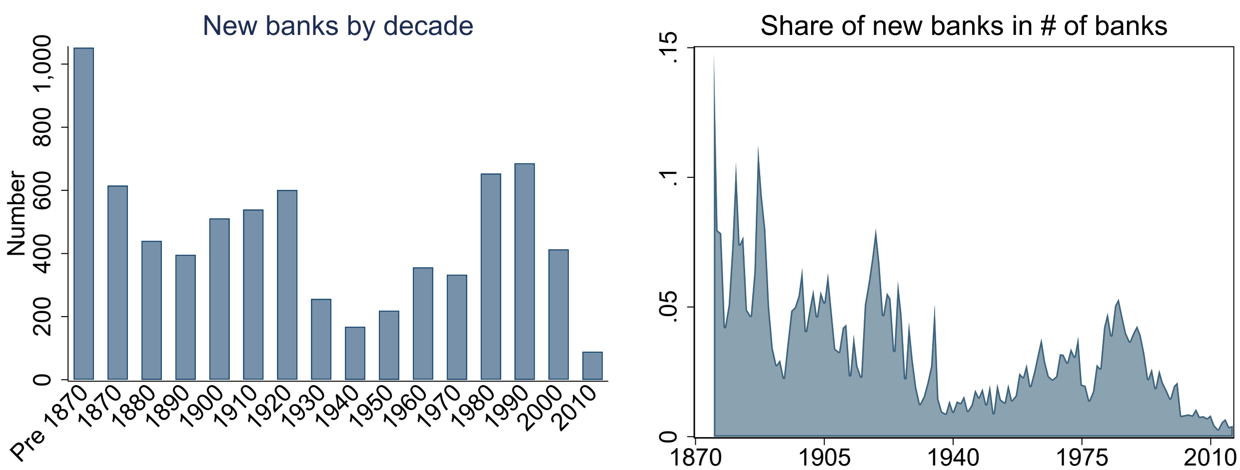


Figure A.7: Bank entry

Panel A plots the number of new banks by decade (left) and the fraction of new banks to total banks (right) across all the countries. Panel B plots the average bank age over time (left) and the distribution of banking sector assets by bank age groups over time (right), where "young" is defined as banks established within the last 10 years, "middle" is defined as banks 10 to 50 years old, and "old" is defined as banks older than 50 years. Figure only includes banks with non-missing establishment years.

Panel A: Bank entry over time



Panel B: Age structure of the banking system

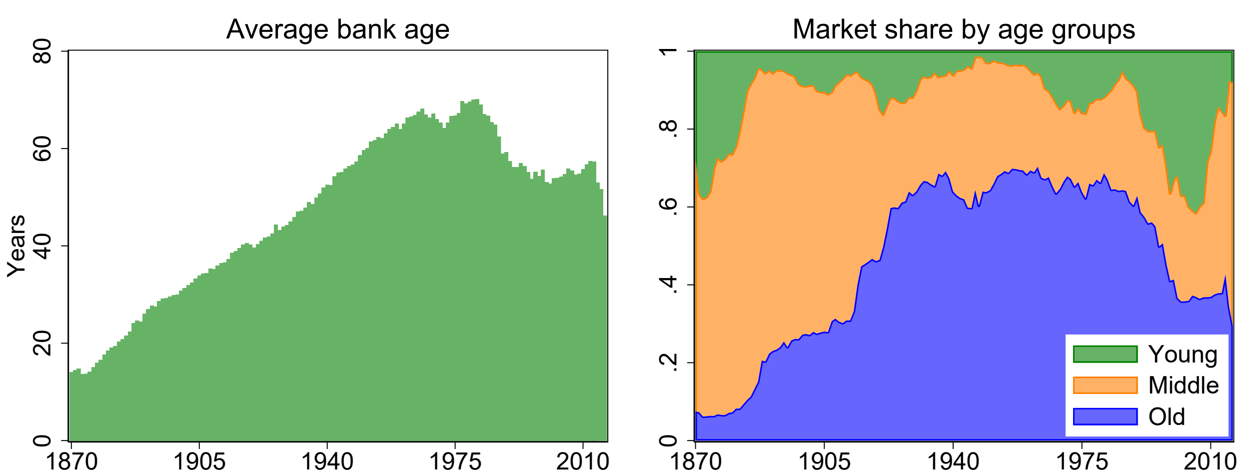
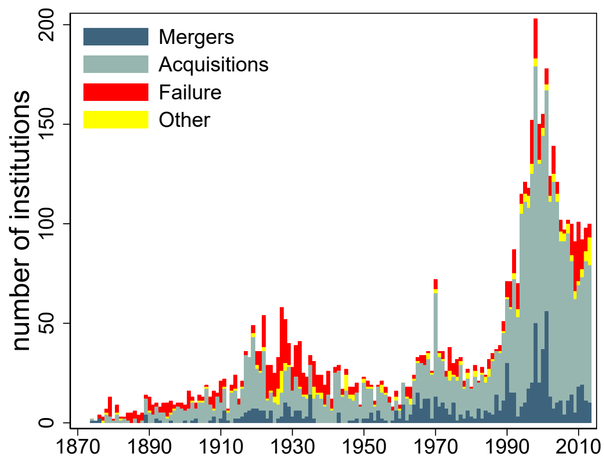
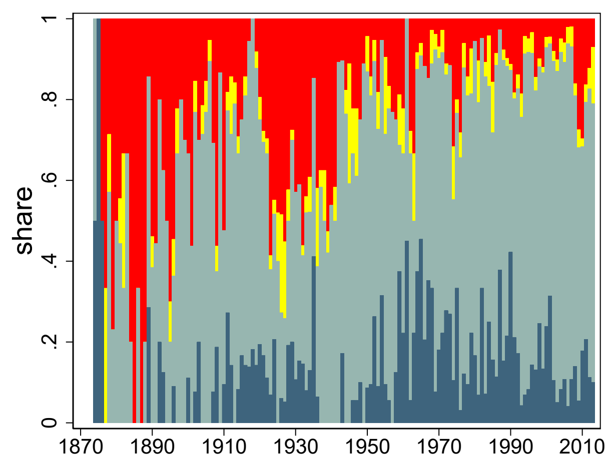


Figure A.8: Bank exit

Panel A shows the absolute (left) and relative (right) frequency of types of bank exits over time. Panel B shows the relative frequency of types of bank exits by bank size. Panel A only includes banks with known exit reason, while panel B also shows unclassified bank exits (grey bars).

Panel A: Number and type of bank exits over time





Panel B: Type of exit by bank size groups

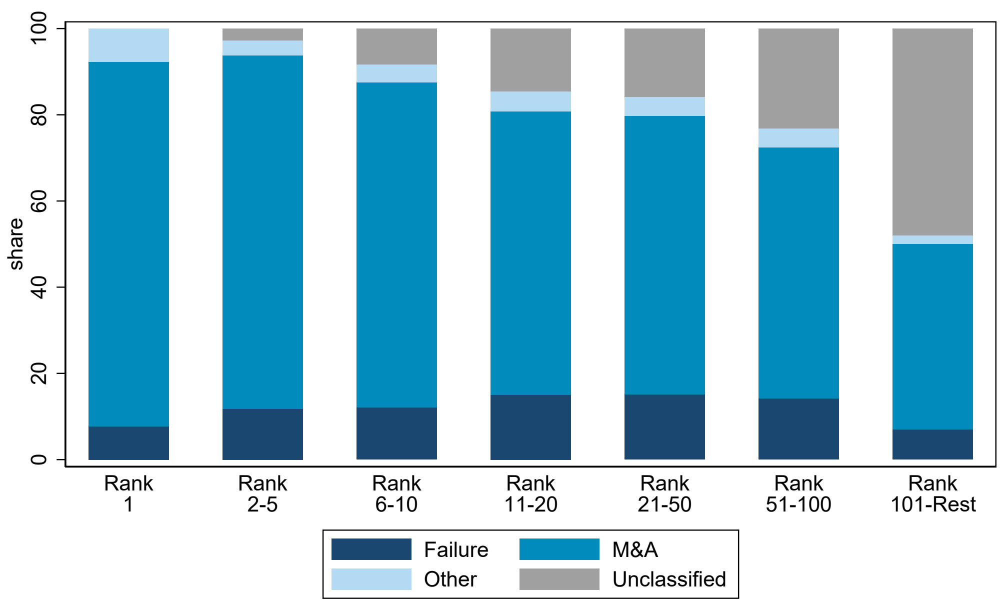


Figure A.9: M&A trends

The figure shows trends in M&A activity in our database. The left-hand plot shows the share of banking sector assets acquired or involved in a merger in a given year averaged across the 17 countries in our sample. The right-hand plot shows the number of individual Mergers and Acquisitions with target assets exceeding 10% of banking sector assets.

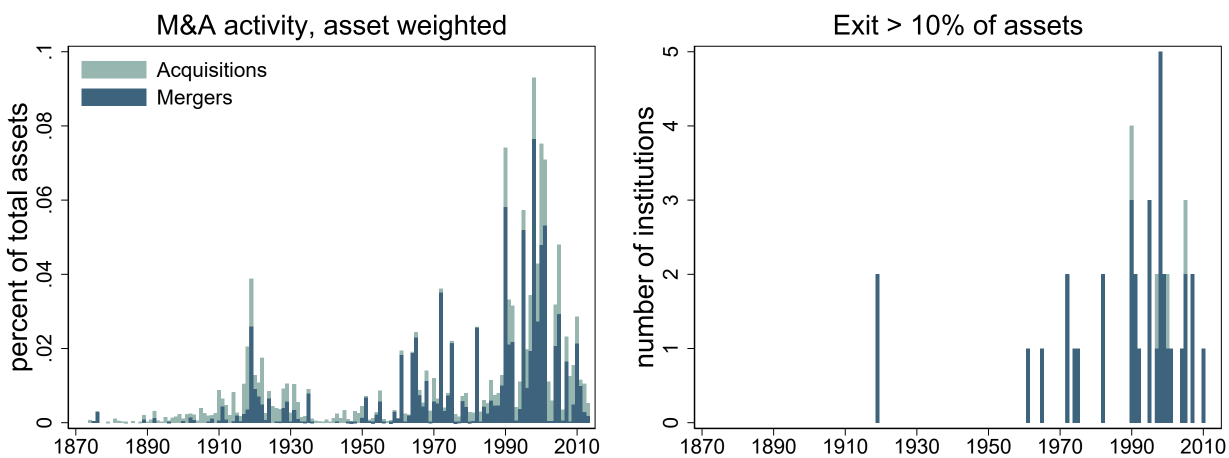
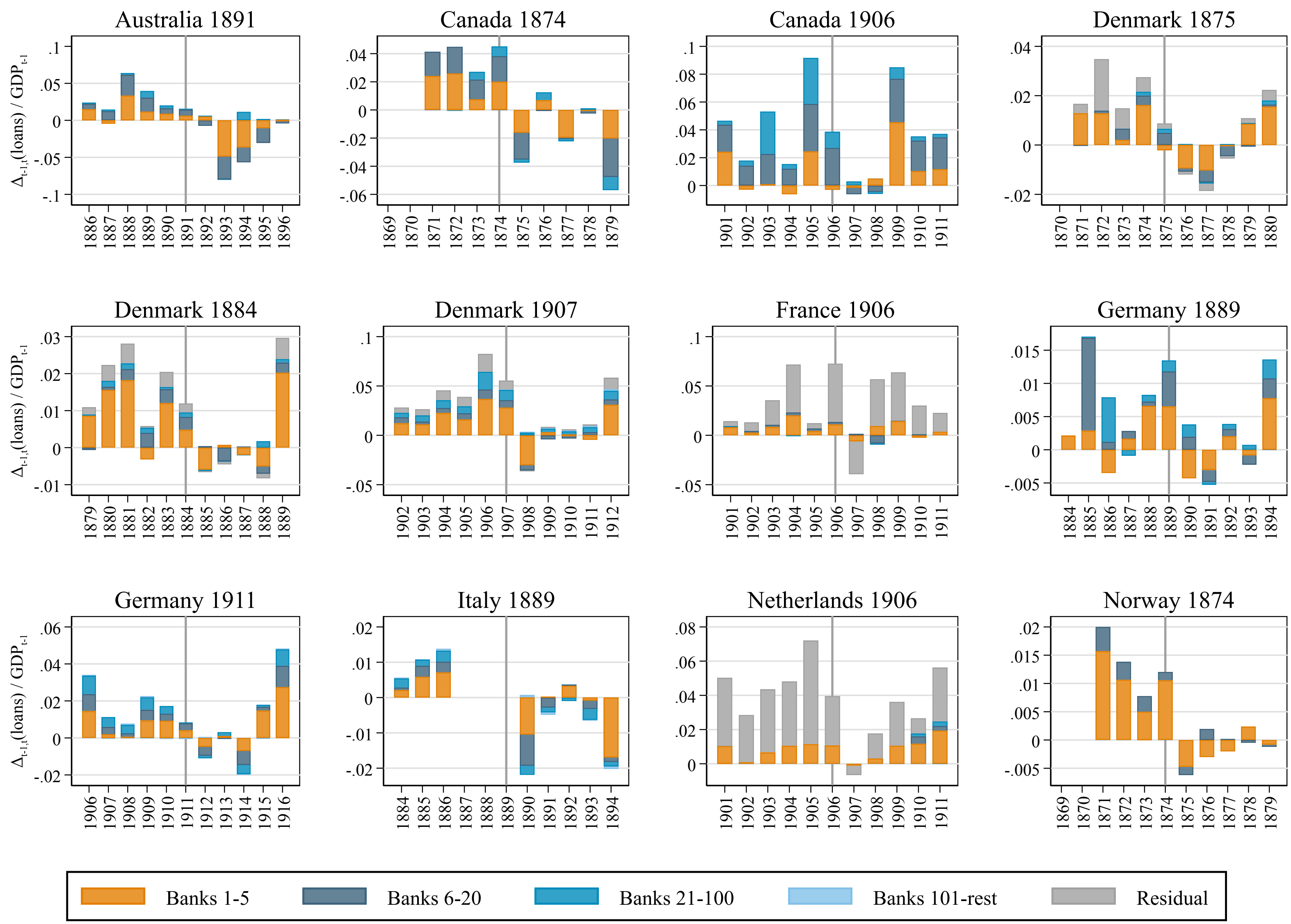
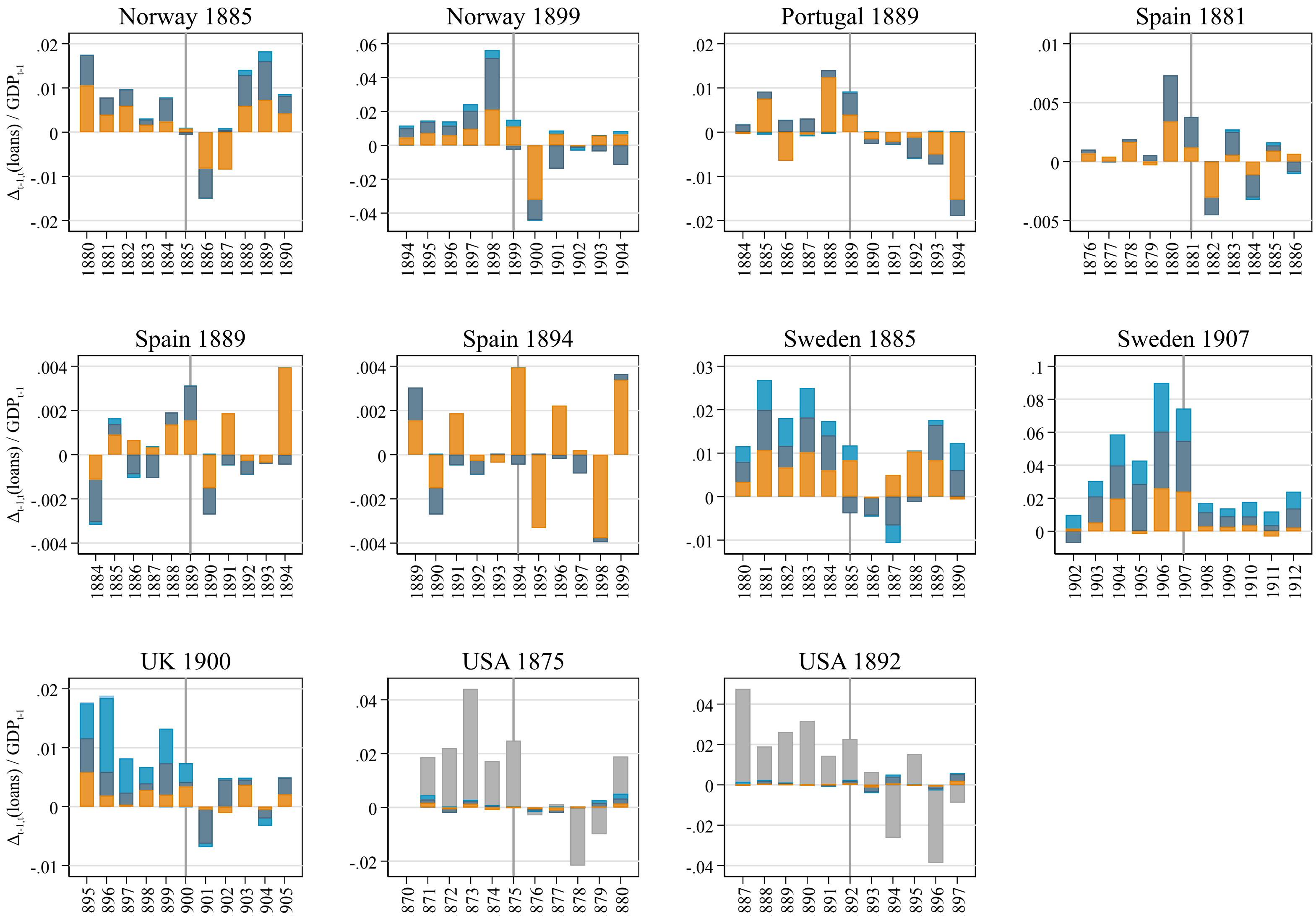


Figure A.10: Credit growth around individual banking crises

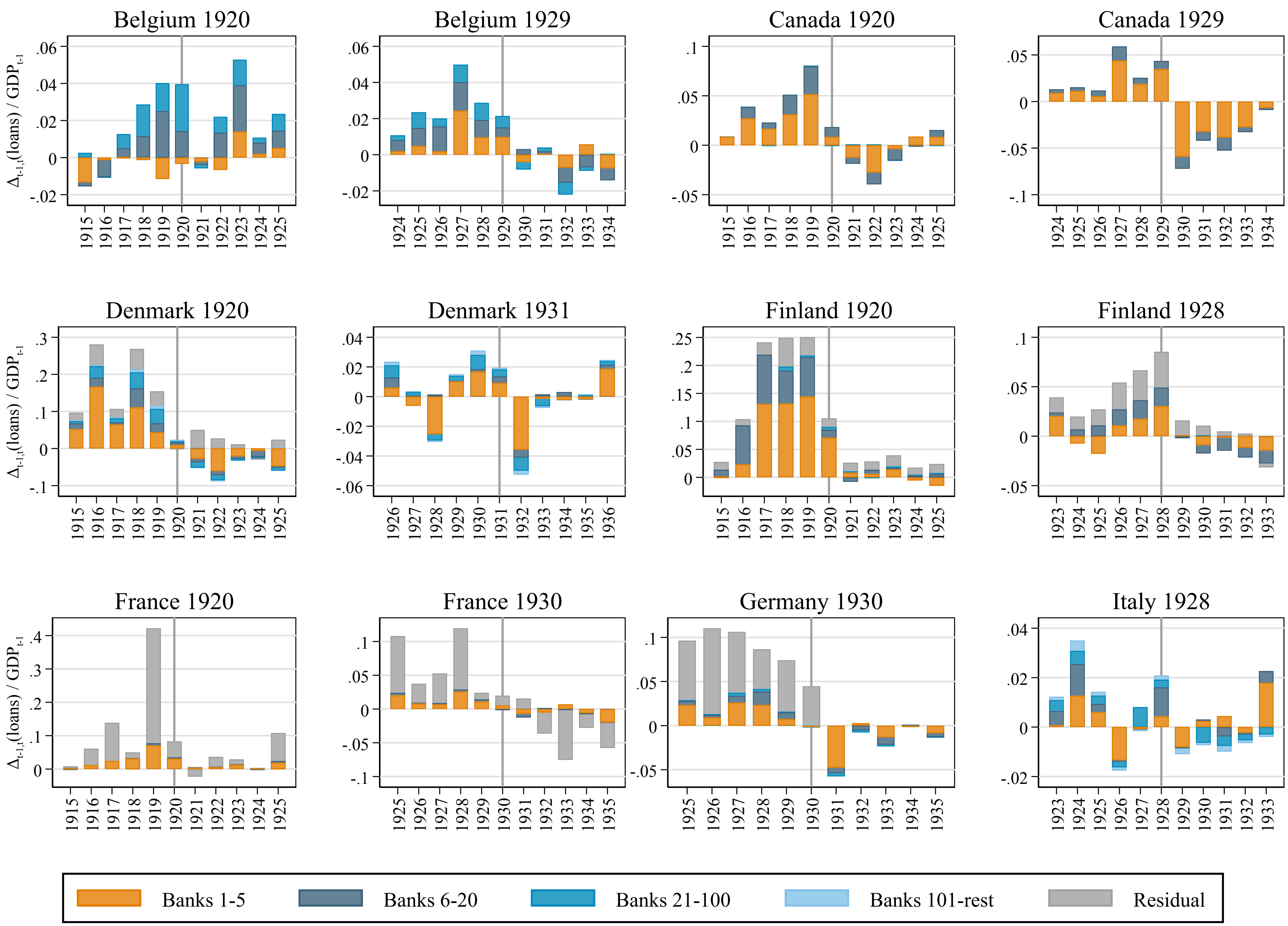
These plots are similar to Figure 5 but for each individual episode on the BSZ list.

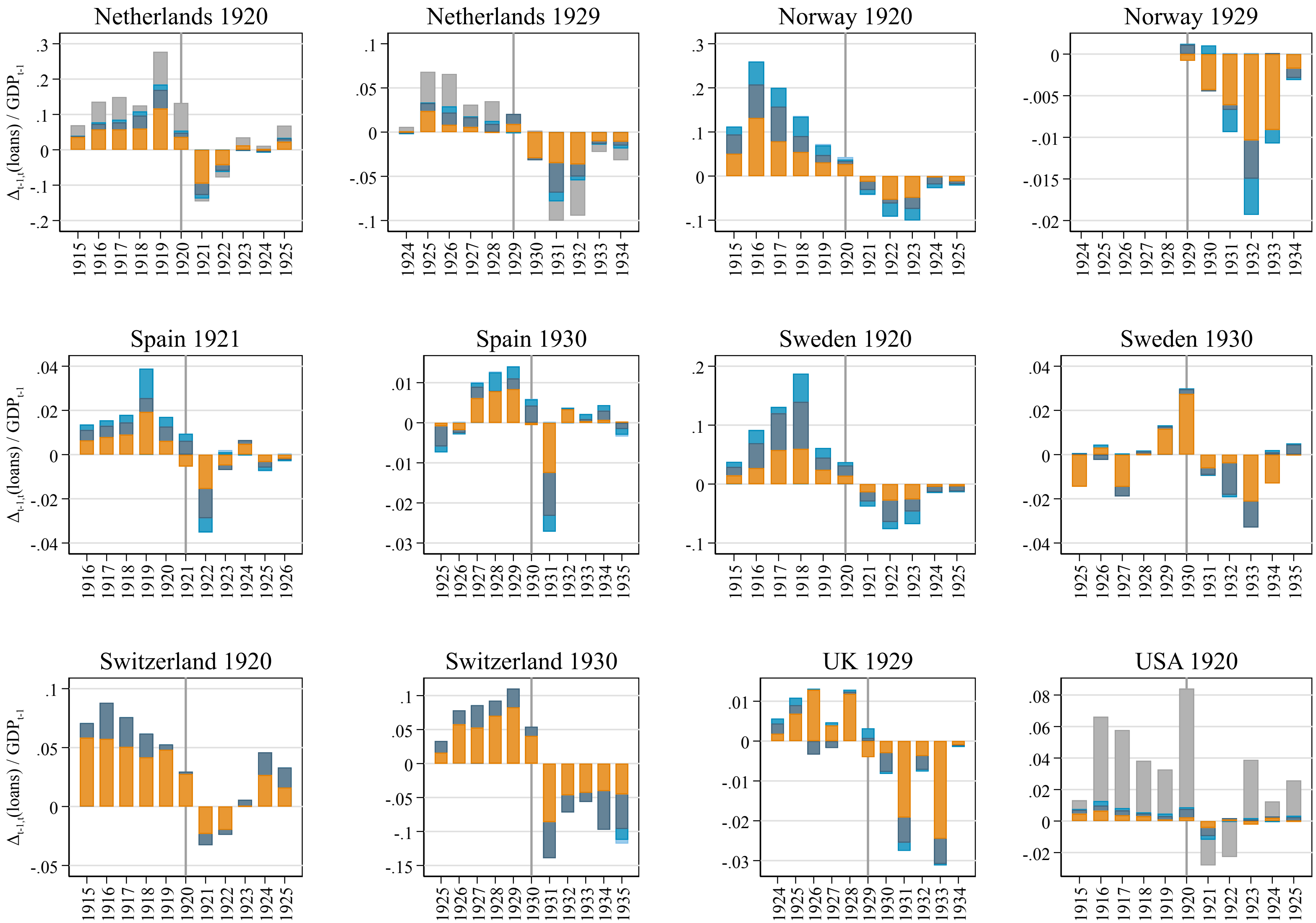
Panel A: 1870-1914 banking crises

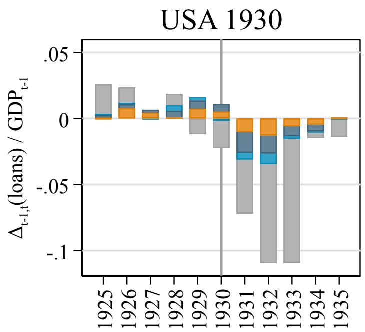



Norway 1885
Norway 1899
Portugal 1889
Spain 1881
Spain 1889
Spain 1894
Sweden 1885
Sweden 1907
UK 1900
USA 1875
USA 1892
$\Delta_{t-1,t}$(loans) / GDP_{t-1}

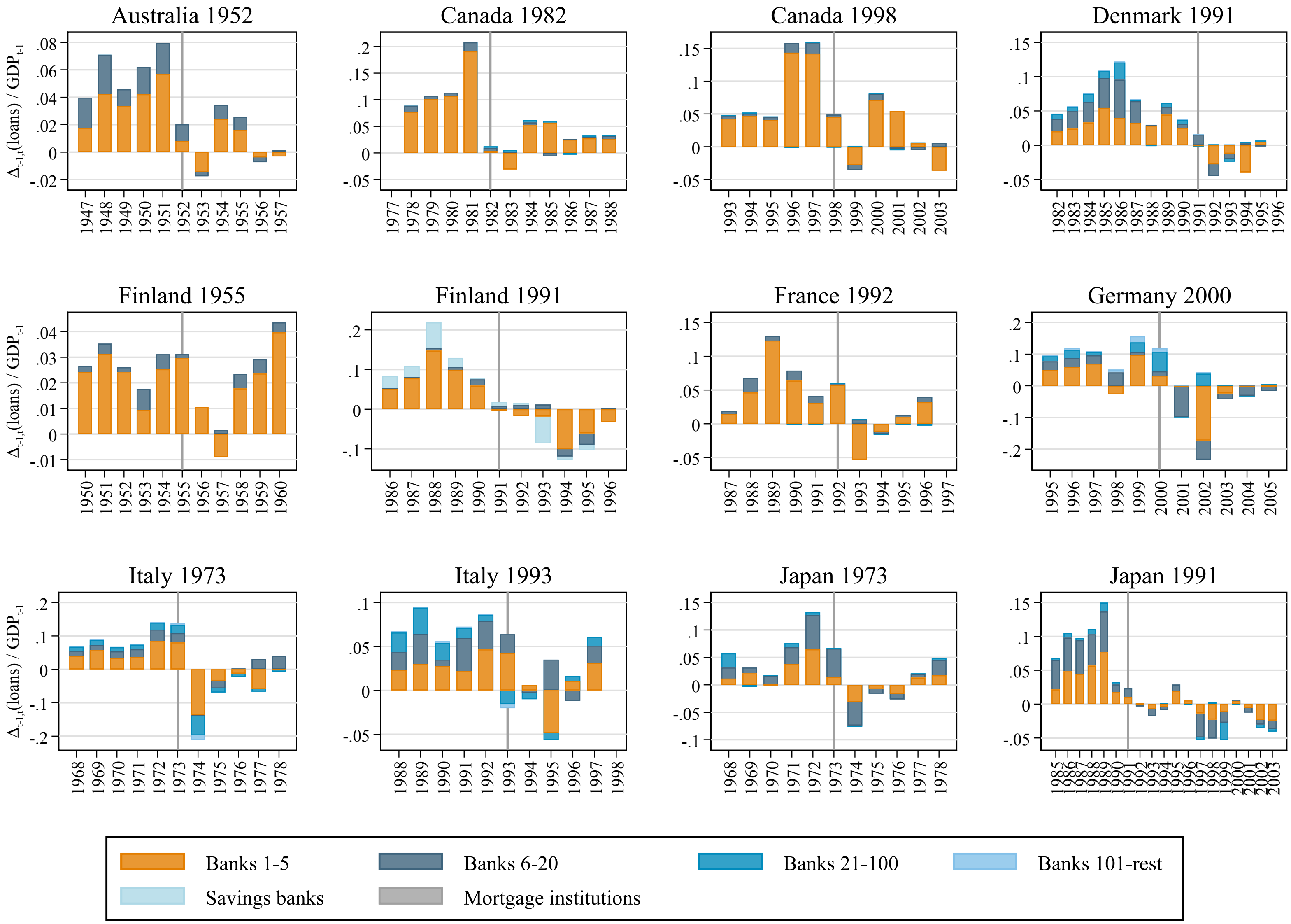
Panel B: 1915-1945 banking crises

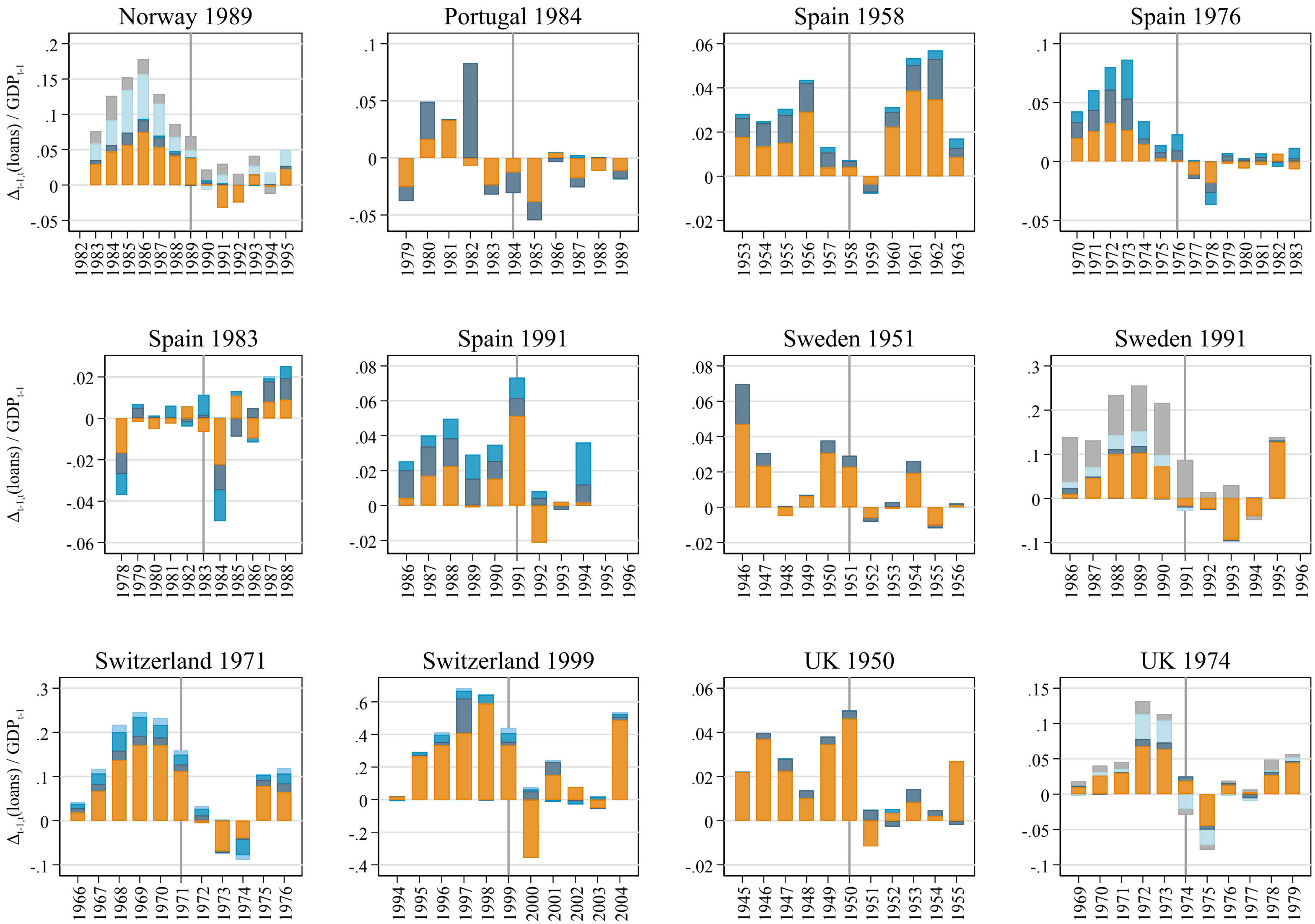



Netherlands 1920
Netherlands 1929
Norway 1920
Norway 1929
Spain 1921
Spain 1930
Sweden 1920
Sweden 1930
Switzerland 1920
Switzerland 1930
UK 1929
USA 1920
$\Delta_{t-1,t}$(loans) / GDP_{t-1}


USA 1930
.05
0
-.05
-.1
$\Delta_{t-1,t}$(loans) / GDP$_{t-1}$
1925
1926
1927
1928
1929
1930
1931
1932
1933
1934
1935

Panel C: 1946-2006 banking crises



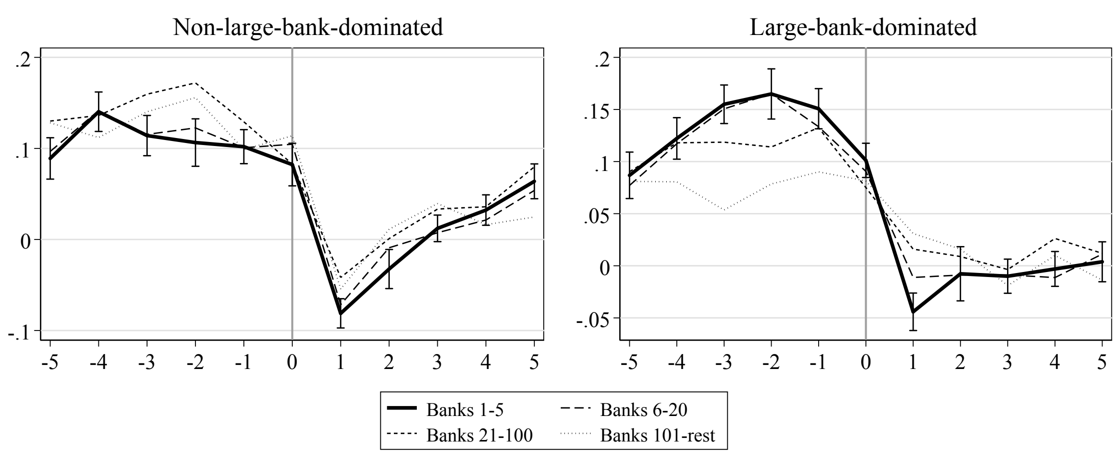

Norway 1989
Portugal 1984
Spain 1958
Spain 1976
Spain 1983
Spain 1991
Sweden 1951
Sweden 1991
Switzerland 1971
Switzerland 1999
UK 1950
UK 1974
$\Delta_{t-1,t}$(loans) / GDP_{t-1}

Panel D: 2007-2020 banking crises

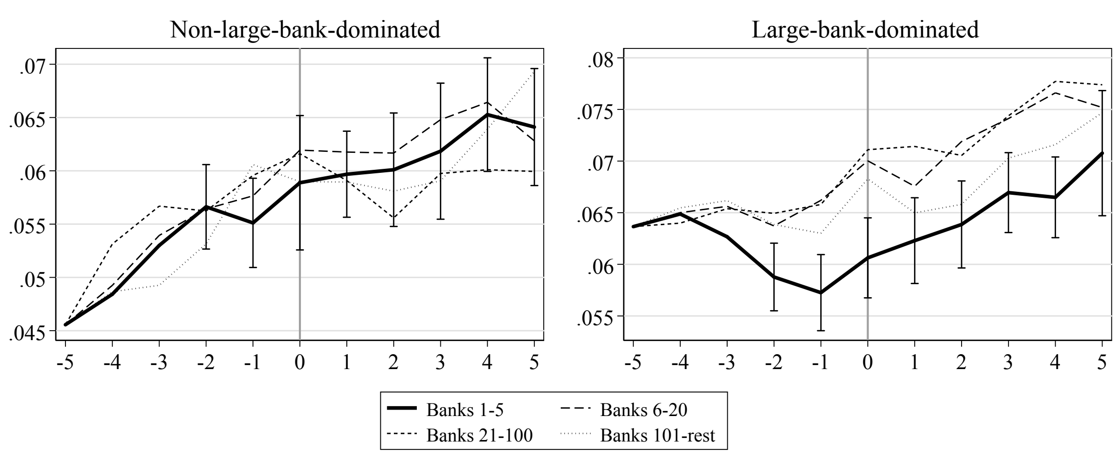
Figure A.11: Organic credit growth, capital ratios, noncore liability ratios, and safe asset ratios around banking crises

Panel A plots the organic growth rate of bank credit, by banks of different sizes, around banking crises. Panel B similarly plots the ratio of equity to assets, Panel C the ratio of noncore liabilities to assets, and Panel D the ratio of safe assets to total assets. Each event study is created by averaging across banking crises over the period 1870-2016. The left side of each panel averages across banking crises in "non-large-bank dominated" banking systems, and the right side average across banking crises in "large-bank dominated" banking systems, where "large-bank dominated" is defined as episodes when the combined asset share of top-5 banks at *t-5* is $\geq 50\%$. Size groups are determined by ranking banks by assets (within country) at *t-5* before each banking crisis. Average ratios in Panels B-D are computed by first aggregating numerators (e.g., noncore liabilities) and denominators (total assets) across all banks in each size group and within each banking crisis episode; then, the aggregate ratio for each size group is computed for each banking crisis; then, the ratio is averaged for each size group across all banking crises. Finally, the ratio levels in Panels B-D are then aligned at $t = -5$ (i.e. the non-top-5 categories are shifted by an additive factor so that they start at the same level as top-5 banks at *t-5*), in order to compare how the ratios change over time relative to the top-5 size group. 90% confidence bands are computed using a simple standard error of the mean across episodes of the difference between the Top 5 versus all other size groups.

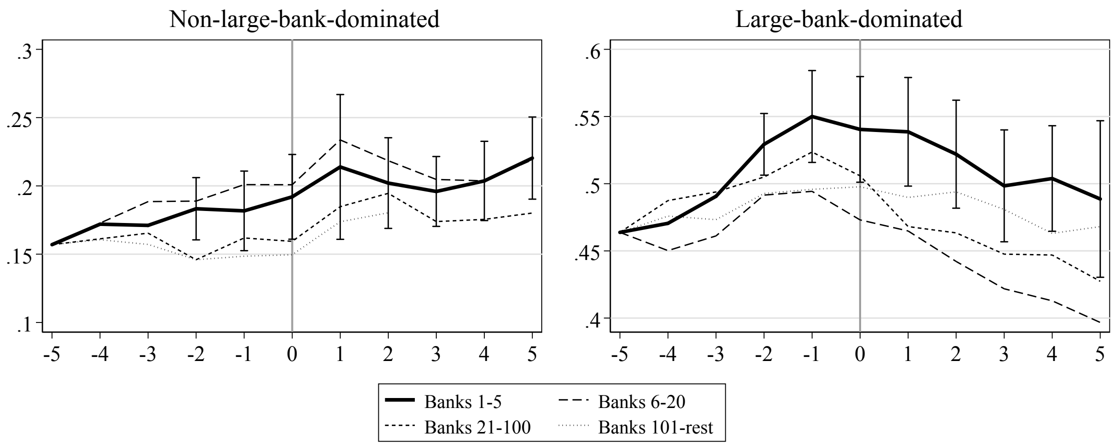
Panel A: Organic credit growth



Panel B: Equity-to-assets (aligned at $t = -5$)



Panel C: Noncore liabilities-to-assets (aligned at $t = -5$)



Panel D: Safe assets-to-assets (aligned at $t = -5$)

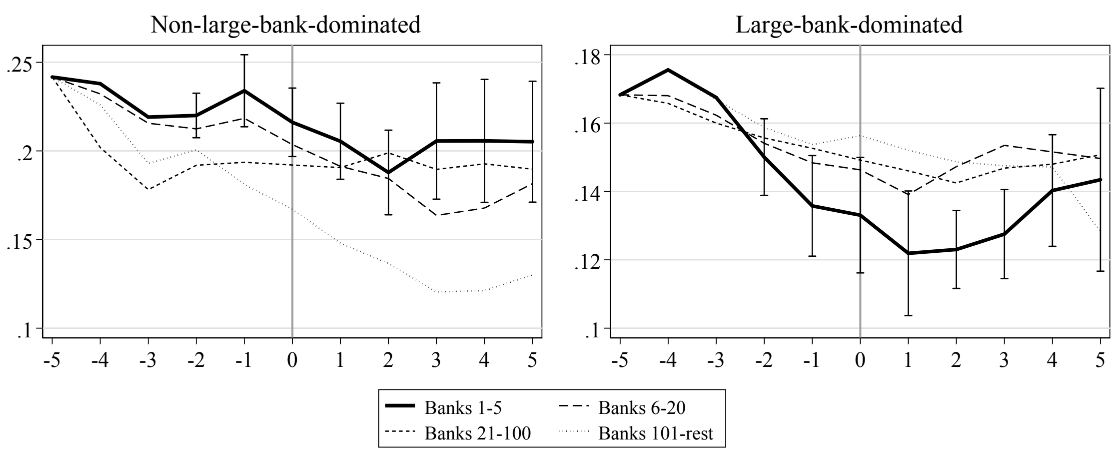


Figure A.13: Stock returns of top-5 and non-top-5 banks around banking crises

This figure plots event studies of average real total returns of bank stocks around banking crises, comparing top-5 banks (solid line) versus banks ranked 6-20 (dashed line). The left plot averages across "low" banking sector concentration episodes, and the right plot average across "high" banking sector concentration episodes, where "low" is defined as episodes where the top-5 asset share at *t-5* is $< 50\%$ and "high" as $\geq 50\%$). To generate the event studies, banks are first ranked by assets (within country) at *t-5* before each banking crisis. An equal-weighted average of cumulative real total returns (normalized relative to *t-1*) for all banks that are publicly traded is first taken within each episode for size groups 1-5 and 6-20, respectively; then, a simple average is taken across episodes. 90% confidence bands are computed using a simple standard error of the mean across episodes of the difference between the two size groups.

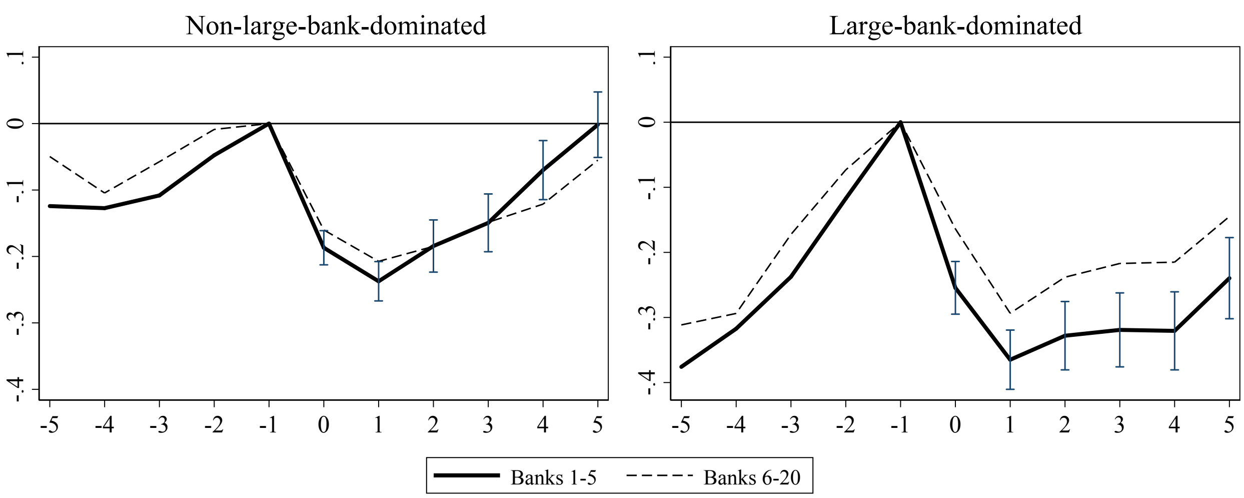


Table A.1: Banking crises defined based on aggregate credit crunches

This table lists the set of banking crises studied in this paper, as defined in Section 2.4. "Banking crises" are defined here as country-year observations that are the first years of aggregate credit crunches, based on aggregate JST data–specifically when the past three-year change in the ratio of bank credit-to-GDP is less than -1 s.d. relative to that country's history. Column 1 indicates the year of the peak level of bank credit-to-GDP, which is used to align event studies in Section 5. Column 2 indicates banking crises that are omitted from our analysis due to lack of or limited balance sheet data on individual banks. Column 3 indicates whether the event is a JST or BVX banking crisis also. Column 4 indicates the year of the initial bank stock decline after the peak level of aggregate bank stock prices (or lack of or limited bank stock data, in which case such an episode is omitted from our bank stock analysis).

Country	Year of credit boom peak before credit crunch	Individual bank balance sheet data available?	JST or BVX banking crisis also?	Year of initial bank stock decline (if bank stock data available)
	(1)	(2)	(3)	(4)
Australia	1891		1	1891
Australia	1952		0	1951
Australia	2008		0	2008
Belgium	1886	No data	1	1883
Belgium	1920		1	1922
Belgium	1929		1	1929
Belgium	2007		1	2008
Canada	1874		1	1875
Canada	1906		1	1907
Canada	1920		1	1920
Canada	1929		0	1929
Canada	1982		1	1981
Canada	1998		0	1998
Denmark	1875		1	1875
Denmark	1884		1	1885
Denmark	1907		1	1907
Denmark	1920		1	1919
Denmark	1931		0	1931
Denmark	1991		1	1990
Denmark	2008		1	2007
Finland	1920		1	1920
Finland	1928		1	1928
Finland	1955		0	1956
Finland	1991		1	1989
France	1907		0	1907
France	1920		0	1921
France	1930		1	1930
France	1992		1	1994
France	2008		1	2007
Germany	1872	Limited data	1	1873
Germany	1889		1	1890
Germany	1911		0	1910
Germany	1930		1	1929
Germany	2000		0	2001
Germany	2008		1	2008
Italy	1889		1	1888
Italy	1928		1	1929
Italy	1973		0	1974
Italy	1993		1	1990
Italy	2008		1	2007
Japan	1882	Limited data	1	No data
Japan	1889	Limited data	1	No data
Japan	1900	Limited data	1	No data
Japan	1906	Limited data	1	Limited data
Japan	1926	Limited data	1	Limited data
Japan	1973		0	1973
Japan	1991		1	1990
Netherlands	1906		1	1907
Netherlands	1920		1	1920
Netherlands	1929		1	1930
Netherlands	2008		1	2008
Norway	1874		0	No data
Norway	1885		0	No data
Norway	1899		1	1902
Norway	1920		1	1919
Norway	1929		1	No data
Norway	1989		1	1987
Norway	2008		1	2008
Portugal	1889		1	Limited data
Portugal	1984		0	1983
Portugal	2008		1	2008

Country	Year of credit boom peak before credit crunch	Individual bank balance sheet data available?	JST or BVX banking crisis also?	Year of initial bank stock decline (if bank stock data available)
	(1)	(2)	(3)	(4)
Spain	1881		1	Limited data
Spain	1889		1	Limited data
Spain	1894		0	Limited data
Spain	1921		1	Limited data
Spain	1930		1	Limited data
Spain	1958		0	1958
Spain	1976		1	1975
Spain	1983		0	1982
Spain	1991		0	1989
Spain	2008		1	2008
Sweden	1885		0	1885
Sweden	1907		1	1907
Sweden	1920		1	1918
Sweden	1930		1	1931
Sweden	1951		0	1952
Sweden	1991		1	1989
Sweden	2008		1	2007
Switzerland	1882	No data	0	No data
Switzerland	1920		1	1919
Switzerland	1930		1	1931
Switzerland	1971		0	1969
Switzerland	1999		0	1998
Switzerland	2007		1	2007
U.K.	1900		0	1901
U.K.	1929		0	1929
U.K.	1950		0	1951
U.K.	1974		1	1973
U.K.	1991		1	1990
U.K.	2008		1	2007
U.S.	1875		1	Limited data
U.S.	1892		1	Limited data
U.S.	1920		0	1920
U.S.	1930		1	1930
U.S.	1989		1	1990
U.S.	2007		1	2007

Table A.2: Top-5 banks and nonfinancials in 1880, 1910, 1970 and 2020 by country

This table reports the top-5 banks (Panel A) and top-5 nonfinancial firms (Panel B) by assets in 1880, 1910, 1970 and 2020. Company names are constant in the database and might therefore deviate from banks' actual historical names in each year.

Panel A: Largest banks

Country	Year	Top 1	Top 2	Top 3	Top 4	Top 5
Australia	1880	Bank of New South Wales	Union Bank of Australia	Bank of Australasia	Commercial Banking Co. of Sydney	National Bank of Australasia
Australia	1910	Bank of New South Wales	Union Bank of Australia	Bank of Australasia	Commercial Banking Co. of Sydney	State Savings Bank of Victoria
Australia	1970	Australia and New Zealand Bank	Bank of New South Wales	Commonwealth Bank of Australia	National Bank of Australasia	The State Savings Bank of Victoria
Australia	2020	Commonwealth Bank of Australia	Australia and New Zealand Bank	Westpac	National Australia Bank	Macquarie Group
Belgium	1880	–	–	–	–	–
Belgium	1910	Societe Generale de Belgique	Caisse Generale Reports et Depots	Soc. Franc. de Banque et de Depots	Caisse Hypothecaire Anversoise	Caisse des Proprietaires
Belgium	1970	Societe Generale de Belgique	Banque de Bruxelles	Kredietbank	Krediet aan de Nijverheid	Banque H. Lambert
Belgium	2020	Fortis Bank (Paribas)	KBC Bank	Dexia Bank Belgium	Bank Brussel Lambert	Sumitomo Mitsui Banking Corp.
Canada	1880	Bank of Montreal	Canadian Bank of Commerce	Merchants Bank	Bank of British North America	Ontario Bank
Canada	1910	Bank of Montreal	Canadian Bank of Commerce	Royal Bank of Canada	Merchants Bank	Imperial Bank of Canada
Canada	1970	Royal Bank of Canada	Canadian Imperial Bank of Comm.	Bank of Montreal	Bank of Nova Scotia	Toronto-Dominion Bank
Canada	2020	Royal Bank of Canada	Toronto-Dominion Bank	Bank of Nova Scotia	Bank of Montreal	Canadian Imperial Bank of Comm.
Denmark	1880	Den Danske Bank	Privatbanken	Kjobenhavns Handelsbank	Fyens Disconto Kasse Bank	Kjøbenhavs Private Laanebank
Denmark	1910	Den Danske Bank	Kjobenhavns Handelsbank	Privatbanken	Københ. Laane- Og Diskontobank	Aarhus Privatbank
Denmark	1970	Kjobenhavns Handelsbank	Den Danske Bank	Privatbanken	Den Danske Provinsbank	Andelsbanken
Denmark	2020	Den Danske Bank	Nordea Bank Danmark	Jyske Bank	Nykredit Bank	Sydbank
Finland	1880	Yhdyspankki Suomessa	Pohjoismaiden Osake Pankki	Suomen Hypoteekkiyhdistys	Waasan Osake Pankki	Kansallis Osake Pankki
Finland	1910	Yhdyspankki Suomessa	Kansallis Osake Pankki	Pohjoismaiden Osake Pankki	Suomen Hypoteekkiyhdistys	Osakeyhtiö Suom. Kaup. Hypo.
Finland	1970	Kansallis Osake Pankki	Pohjoismaiden Yhdyspankki	Postisäästöpankki	Oko Bank plc	Säästöpankkien Keskus O.-P.
Finland	2020	Nordea Bank Finland	OP-Pohjola Group	Danske Bank Finland	Aktia Bank	Ålands Aktiebank
France	1880	Credit Lyonnais	Société Générale	Comptoir d'Éscompte de Paris	Paribas	Crédit Industriel et Commercial
France	1910	Crédit Lyonnais	Société Générale	Comptoir National d'Éscompte	Paribas	Crédit Industriel et Commercial
France	1970	BNP	Crédit Lyonnais	Société Générale	Crédit Foncier de France	Compagnie Bancaire
France	2020	BNP Paribas	Crédit Agricole Group	Société Générale	BPCE Group	Crédit Mutuel-CIC
Germany	1880	Berliner Disconto-Gesellschaft	Deutsche Bank	Norddeutsche Bank, Hamburg	Commerzbank	Dresdner Bank
Germany	1910	Deutsche Bank	Dresdner Bank	Berliner Disconto-Gesellschaft	Darmstädter Bank	A Schaaffhausen'scher Bankverein
Germany	1970	Deutsche Bank	Dresdner Bank	Commerzbank	Bayer. Hypot.- und Wechselbank	Frankfurter Hypothekenbank
Germany	2020	Deutsche Bank	Kreditanstalt für Wiederaufbau	Commerzbank	DZ Bank	UniCredit (HypoVereinsbank)
Italy	1880	Credito Mobiliare Italiano	Monte dei Paschi di Siena	Cassa di Sconto in Genova	Banco di Sconto e di Sete in Torino	Banca di Torino
Italy	1910	Cassa di Risparm. Prov. Lombarde	Banca Commerciale Italiana	Credito Italiano	Banco di Roma	Societa Bancaria Italiana in Milano
Italy	1970	Consorz. di Cred. Opere Pubbliche	Banca Nazionale del Lavoro	Banca Commerciale Italiana	Credito Italiano	Istituto Mobiliare Italiano
Italy	2020	Unicredito Italiano	Gruppo Bancario Intesa Sanpaolo	Gruppo Cassa Depositi e Prestiti	Banco Popolare	Monte dei Paschi di Siena
Japan	1880	–	–	–	–	–
Japan	1910	Yokohama Specie Bank	Mitsui Bank	Nippon Kangyo Bank	Industrial Bank of Japan	Sumitomo Bank
Japan	1970	Sumitomo Bank	Sanwa Bank	Dai-ichi Bank	Tokai Bank	Mitsui Bank
Japan	2020	Mitsubishi UFJ Financial Group	Japan Post Bank	Mizuho Financial Group	Sumitomo Mitsui Financial Group	Norinchukin Bank
Netherlands	1880	–	–	–	–	–
Netherlands	1910	Nederl. Handel Maatschappij	Twentsche Bank	Amsterdamsche Bank	Rotterdamsche Bank	Incasso-Bank
Netherlands	1970	Algemene Bank Nederland (ABN)	Amsterdam-Rotterdam Bank	Nederlandsche Middenstandsbank	Bank Mees & Hope	Nederlandse Credietbank
Netherlands	2020	ING Bank	Rabobank Bank	ABN AMRO Bank	Bank voor Nederl. Gemeenten	Nederlandse Waterschapsbank
Norway	1880	Den Norske Creditbank	Bergens Privatbank	Christiania Bank og Kreditkasse	Bergens Kreditbank	Den Nordenfjeldske Kreditbank
Norway	1910	Centralbanken for Norge	Den Norske Creditbank	Bergens Privatbank	Christiania Bank og Kreditkasse	Bergens Kreditbank
Norway	1970	Den Norske Creditbank	Christiania Bank og Kreditkasse	Bergens Privatbank	Andresens Bank	Fellesbanken
Norway	2020	DNBank	Santander Consumer Bank	Skandiabanken	Bank Norwegian	Gjensidige Bank
Portugal	1880	Banco Lusitano	Banco Aliança	Banco Nacional Ultramarino	Banco Uniao	Banco Comercial de Lisboa
Portugal	1910	Banco Nacional Ultramarino	Banco Lisboa & Açores	Banco Aliança	Banco Commercial do Porto	Banco do Minho
Portugal	1970	Caixa Geral de Depositos	Banco Pinto & Sotto Mayor	Banco Totta & Acores	Banco Português do Atlântico	Banco Borges & Irmao
Portugal	2020	Caixa Geral de Depositos	Banco Commercial Portugues	Banco Espirito Santo	Banco BPI	Santander Totta
Spain	1880	Crédito Mobiliario Español	Banco Castilla	Hipotecario de Espana	Banco de Barcelona	Sociedad de Credito Mercantil
Spain	1910	Hipotecario de Espana	Banco Hispano Americano	Banco de Bilbao	Banco Espanol de Credito	Crédito de la Unión Minera
Spain	1970	Banco Espanol de Credito	Banco Hispano Americano	Banco Central	Banco de Bilbao	Banco de Vizcaya
Spain	2020	Banco de Santander	BBVA	Caixabank	Bankia	Banco de Sabadell

Country	Year	Top 1	Top 2	Top 3	Top 4	Top 5
Sweden	1880	Skanes Enskilda Bank	Skandinaviska Kreditaktiebolaget	Stockholms Enskilda Bank	Inteckningsbanken	Mälareprovinsernas Bank
Sweden	1910	Skandinaviska Kreditaktiebolaget	Inteckningsbanken	Svenska Handelsbank	Stockholms Enskilda Bank	Göteborgs Bank
Sweden	1970	Svenska Handelsbank	Skandinaviska Kreditaktiebolaget	Sveriges Kreditbank	Göteborgs Bank	Stockholms Enskilda Bank
Sweden	2020	Nordea Bank	Skandinaviska Enskilda Banken	Svenska Handelsbank	Swedbank	SBAB Bank
Switzerland	1880	Züricher Kantonalbank	Credit Suisse	Eidgenössische Bank	Leu & Co.	Bank in Winterthur
Switzerland	1910	Swiss Bank Corporation	Credit Suisse	Züricher Kantonalbank	Schweizerische Volksbank	Leu & Co.
Switzerland	1970	UBS	Swiss Bank Corporation	Credit Suisse	Züricher Kantonalbank	Schweizerische Volksbank
Switzerland	2020	UBS	Credit Suisse	Schweizer Verband Raiffeisen	Züricher Kantonalbank	Bank J. Safra Sarasin
UK	1880	National Provincial Bank	London & County Banking Co.	Westminster Bank	Union Bank of London	London Joint Stock Bank
UK	1910	Lloyds Bank	Westminster Bank	Midland Bank	National Provincial Bank	Barclays Bank
UK	1970	Barclays Bank	National Westminster Bank	Midland Bank	Lloyds Bank	Halifax Building Society
UK	2020	Barclays Bank	Royal Bank of Scotland	Lloyds Bank	HSBC Bank	Standard Chartered
USA	1880	Importers & Traders' Nat. Bank	Fourth National Bank, New York	Nat. Bank of Commerce, New York	National Park Bank, New York	American Exchange National Bank
USA	1910	National City Bank, New York	Nat. Bank of Commerce, New York	Continental and Comm. Nat. Bank	First National Bank, New York	First National Bank, Chicago
USA	1970	Bank of America	Citicorp	Chase Manhattan	Manufacturers Hanover	J. P. Morgan & Co.
USA	2020	JPMorgan Chase	Bank of America	Citigroup	Wells Fargo	U.S. Bancorp

Panel B: Largest nonfinancial firms

Country	Year	Top 1	Top 2	Top 3	Top 4	Top 5
Australia	1910	–	–	–	–	–
Australia	1970	BHP	Colonial Sugar	Australian Paper Manufacturers	Comalco	Australian Consolidated Industries
Australia	2020	BHP	Rio Tinto	MMG	Telstra	Woodside Petroleum
Belgium	1910	ACEC	Carrières de Porphyre de Quenast	Société des Glaces Nat. Belges	Liniere La Lys	Fabrique Nationale
Belgium	1970	Petrofina	Solvay	Cockerill	Sidmar	Agfa Gevaert
Belgium	2020	Anheuser-Busch InBev	Solvay	UCB	Proximus Group	Umicore
Canada	1910	Lake Superior Corporation	Granby Mining, Smelting, Power	Canadian Car and Foundry	Dominion Textile Company	Spanish River Pulp & Paper Mills
Canada	1970	BCE	Canadian Pacific Railway	Imperial Oil Ltd	STELCO	Falconbridge
Canada	2020	Enbridge	TC Energy	Suncor Energy	Canadian Natural Resources	Nutrien
Denmark	1910	Store Nordiske Telegrafselskab	Danske Sukkerfabrikker	Forenede Dampskibsselskab	Københavns Telefonselskab	Forenede Bryggerier
Denmark	1970	FL Smidth	Forenede Bryggerier	Superfos	Skandinavisk Tobakskompagni	Danfoss
Denmark	2020	Maersk Group	Ørsted	Carlsberg Group	Novo Nordisk	Vestas Wind Systems
Finland	1910	Finlayson & Co.	Finska Ångfartygs	Kymin	Ph. U Strengberg & Co.	W. Gutzeit
Finland	1970	Enso-Gutzeit	Wartsila	Rauma-Repola	Valmet	Kymin
Finland	2020	Nokia	Stora Enso	UPM-Kymmene	Neste	Kone
France	1910	Messageries Maritimes	Cie. Générale Transatlantique	Mines de Lens	Thomson-Houston	Saint-Gobain
France	1970	Usinor	Wendel-Sidelor (Sacilor)	Total	Rhone Poulenc	Pechiney
France	2020	Total	Renault	Sanofi	Orange	Christian Dior LVMH
Germany	1910	Krupp	Allgem. Elektr.-Gesells. (AEG)	Gelsenkirchener Bergwerks	Hamburg-Amerik. Packetfahrt	Siemens-Schuckertwerke
Germany	1970	Hoechst	Bayer	Siemens	Veba	BASF
Germany	2020	Volkswagen	Daimler	BMW	Deutsche Telekom	Siemens
Italy	1910	ILVA	Navigazione Generale Italiana	Ansaldo	Acciaierie di Terni	S. Ligure-Lomb. Raff. Zuccheri
Italy	1970	Montedison	SIP	Fiat	Eni / ANIC	SNIA Viscosa
Italy	2020	Eni	Fiat-Chrysler	Atlantia	Telecom Italia	Leonardo
Japan	1910	Kawasaki Shipyards	Kuhara Mining	Mitsubishi Shipyards	Kanegafuchi Spinning	Toyo Spinning
Japan	1970	Nippon Steel Corp	Mitsubishi Heavy Industries	Nippon Kokan (Japan Steel)	Hitachi	Nissan Motors
Japan	2020	Toyota Motors	SoftBank Group	Nippon Telegraph and Telephone	Sony	Honda
Netherlands	1910	–	–	–	–	–
Netherlands	1970	Royal Dutch-Shell	Philips'	Unilever	Hoogovens	Akzo
Netherlands	2020	Royal Dutch Shell	Airbus	Unilever	Altice	Heineken
Norway	1910	Norsk Hydro-elektrisk	De norske Salpeterverker	Rjukanfos	Sydvaranger	Union Co.
Norway	1970	Norske Hydro	Akergruppen	Elkem Spigerverket	Borregaard	Kvaerner Industrier
Norway	2020	Equinor	Telenor Group	Norsk Hydro	Yara International	Aker
Portugal	1910	–	–	–	–	–
Portugal	1970	–	–	–	–	–
Portugal	2020	Galp Energia	Jeronimo Martins	Sonae	Mota-Engil	NOS

Country	Year	Top 1	Top 2	Top 3	Top 4	Top 5
Spain	1910	Río Tinto	General Azucarera de España	Duro-Felguera	Comp. Arrendataria de Tabacos	Altos Hornos de Vizcaya
Spain	1970	SEAT	Comp. Esp. Petroleos	Altos Hornos de Vizcaya	Refineria de Petrol. Escombreras	Astilleros Espanoles (AESA)
Spain	2020	Telefónica	Repsol	Abertis Infrastructura	ACS Group	Inditex
Sweden	1910	Svenska Sockererfabriks	LKAB	Stora Kopparbergs Bergslag	AB Separator	Stockholms Allmänna Telefon
Sweden	1970	Ericsson	Volvo	SKF	ASEA	SAAB-Scania
Sweden	2020	LKAB	Volvo	Ericsson	Telia Company	Stora Enso
Switzerland	1910	Nestle	Brown, Boveri	“Motor”	Industrie-Gesellschaft für Schappe	Maggi’s Nahrungsmitteln
Switzerland	1970	Nestle	Ciba	Sandoz	Geigy	Alusuisse
Switzerland	2020	Nestle	Novartis	Roche	Glencore	HOLCIM
UK	1910	Stewarts & Lloyds	Metropolitan Carriage Wagon	Imperial Tobacco Company	J. & P. Coats	British American Tobacco
UK	1970	Royal Dutch-Shell	BP	Imperial Chemical	British-American Tobacco	Rio Tinto-Zinc UK
UK	2020	Royal Dutch-Shell	BP	British-American Tobacco	Vodafone	GlaxoSmithKline
US	1910	United States Steel	American Smelting & Refining	US Rubber	Swift	Armour
US	1970	Exxon Mobil	General Motors	Texaco	Ford Motor	Gulf Oil
US	2020	AT&T	ExxonMobil	Apple	Verizon Communications	Microsoft

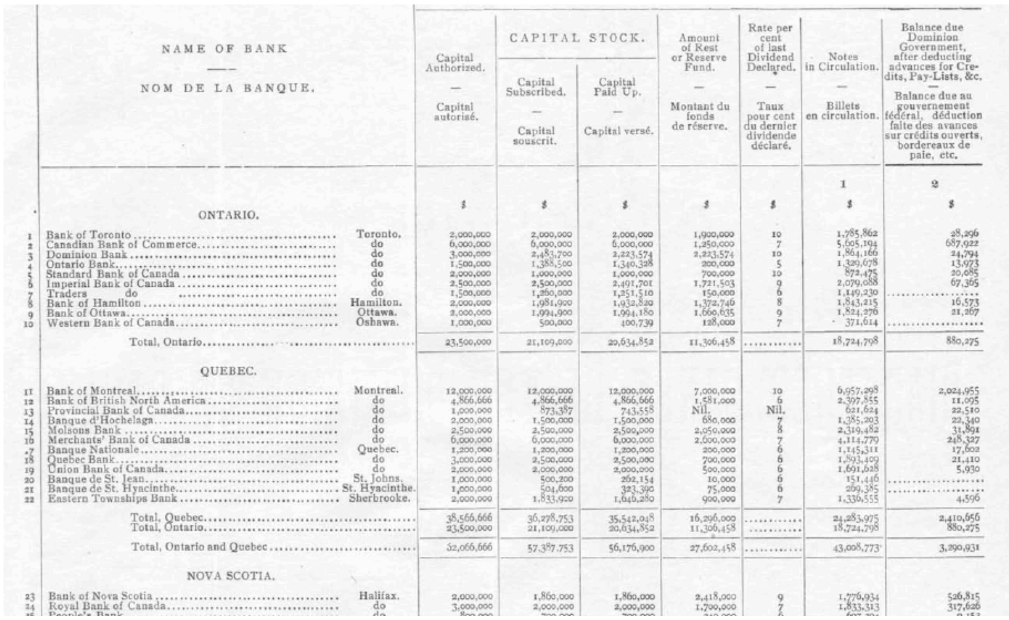
Table A.3: Persistence of banks and nonfinancials

Top-5 firms from the year:	Status in 2020:	Banks %	Nonfinancials %
1880	Top 5	37.1	(no data)
	Top 6-20	1.4	
	Rank 21+	0.0	
	Acquired	54.3	
	Bankrupt	7.1	
		(N=70)	
1910	Top 5	49.4	11.4
	Top 6-20	3.5	10.0
	Rank 21+	0.0	15.7
	Acquired	40.0	57.1
	Bankrupt	7.1	5.7
		(N=85)	*(N=70)*
1970	Top 5	57.7	28.8
	Top 6-20	2.4	26.3
	Rank 21+	0.0	8.8
	Acquired	38.8	33.8
	Bankrupt	1.2	2.5
		(N=85)	*(N=80)*

Data Appendix

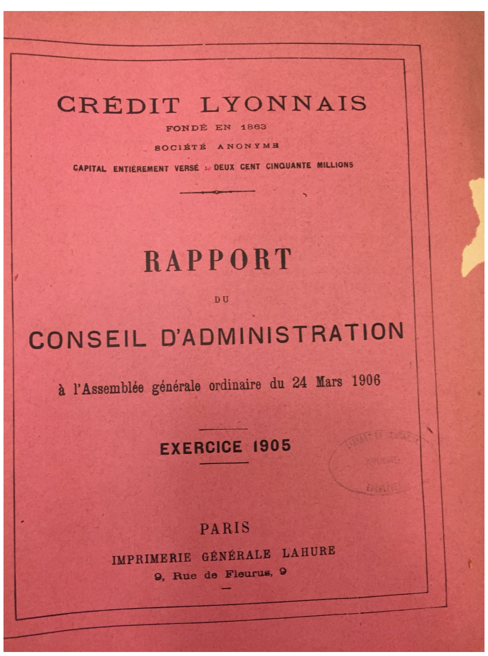
Figure B.1: Historical balance sheet examples

Panel A: Canadian banks in 1900 (cropped from larger table)



	Name of Bank — Nom de la Banque.		Capital Authorized. — Capital autorisé.	Capital Stock. Capital Subscribed. — Capital souscrit.	Capital Paid Up. — Capital versé.	Amount of Rest or Reserve Fund. — Montant du fonds de réserve.	Rate per cent of last Dividend Declared. — Taux pour cent du dernier dividende déclaré.	Notes in Circulation. — Billets en circulation.	Balance due Dominion Government, after deducting advances for Credits, Pay-Lists, &c. — Balance due au gouvernement fédéral, déduction faite des avances sur crédits ouverts, bordereaux de paie, etc.
								1	2
			$	$	$	$	$	$	$
	ONTARIO.								
1	Bank of Toronto	Toronto.	2,000,000	2,000,000	2,000,000	1,900,000	10	1,785,862	28,296
2	Canadian Bank of Commerce	do	6,000,000	6,000,000	6,000,000	1,250,000	7	5,605,194	687,922
3	Dominion Bank	do	3,000,000	2,483,700	2,223,574	2,223,574	10	1,864,166	24,794
4	Ontario Bank	do	1,500,000	1,388,500	1,340,328	200,000	5	1,329,678	13,973
5	Standard Bank of Canada	do	2,000,000	1,000,000	1,000,000	700,000	10	872,475	20,685
6	Imperial Bank of Canada	do	2,500,000	2,500,000	2,491,701	1,721,503	9	2,079,088	67,365
7	Traders do	do	1,500,000	1,260,000	1,251,510	150,000	6	1,149,230	....
8	Bank of Hamilton	Hamilton.	2,000,000	1,981,900	1,932,820	1,372,746	8	1,843,215	16,573
9	Bank of Ottawa	Ottawa.	2,000,000	1,994,900	1,994,180	1,660,635	9	1,824,276	21,267
10	Western Bank of Canada	Oshawa.	1,000,000	500,000	400,739	128,000	7	371,614	....
	Total, Ontario		23,500,000	21,109,000	20,634,852	11,306,458	....	18,724,798	880,275
	QUEBEC.								
11	Bank of Montreal	Montreal.	12,000,000	12,000,000	12,000,000	7,000,000	10	6,957,298	2,024,955
12	Bank of British North America	do	4,866,666	4,866,666	4,866,666	1,581,000	6	2,397,855	11,095
13	Provincial Bank of Canada	do	1,000,000	873,387	743,558	Nil.	Nil.	621,624	22,510
14	Banque d'Hochelaga	do	2,000,000	1,500,000	1,500,000	680,000	7	1,385,203	22,340
15	Molsons Bank	do	2,500,000	2,500,000	2,500,000	2,050,000	8	2,319,482	31,891
16	Merchants' Bank of Canada	do	6,000,000	6,000,000	6,000,000	2,600,000	7	4,114,779	248,327
17	Banque Nationale	Quebec.	1,200,000	1,200,000	1,200,000	200,000	6	1,145,311	17,602
18	Quebec Bank	do	3,000,000	2,500,000	2,500,000	700,000	6	1,893,409	21,410
19	Union Bank of Canada	do	2,000,000	2,000,000	2,000,000	500,000	6	1,691,628	5,930
20	Banque de St. Jean	St. Johns.	1,000,000	500,200	262,154	10,000	6	151,446	....
21	Banque de St. Hyacinthe	St. Hyacinthe.	1,000,000	504,600	323,390	75,000	6	269,385	....
22	Eastern Townships Bank	Sherbrooke.	2,000,000	1,833,900	1,646,280	900,000	7	1,336,555	4,596
	Total, Quebec		38,566,666	36,278,753	35,542,048	16,296,000	....	24,283,975	2,410,656
	Total, Ontario		23,500,000	21,109,000	20,634,852	11,306,458	....	18,724,798	880,275
	Total, Ontario and Quebec		62,066,666	57,387,753	56,176,900	27,602,458	....	43,008,773	3,290,931
	NOVA SCOTIA.								
23	Bank of Nova Scotia	Halifax.	2,000,000	1,860,000	1,860,000	2,418,000	9	1,776,934	526,815
24	Royal Bank of Canada	do	3,000,000	2,000,000	2,000,000	1,700,000	7	1,833,313	317,626

Panel B: Credit Lyonnais, France, in 1905



CRÉDIT LYONNAIS

FONDÉ EN 1863

SOCIÉTÉ ANONYME

CAPITAL ENTIÈREMENT VERSÉ : DEUX CENT CINQUANTE MILLIONS

RAPPORT

DU

CONSEIL D'ADMINISTRATION

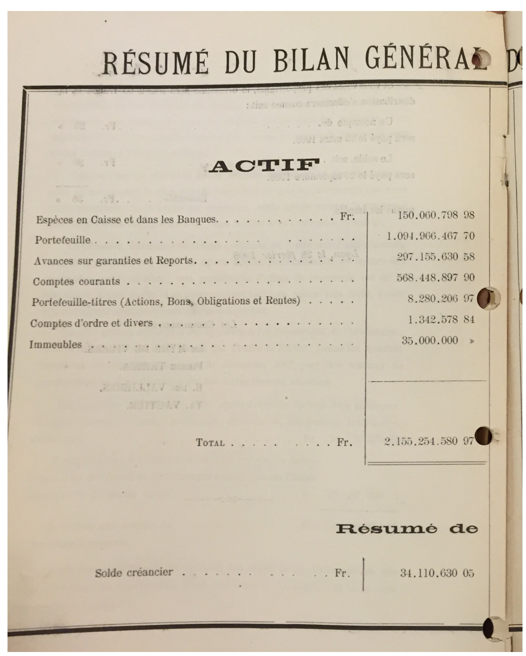
à l'Assemblée générale ordinaire du 24 Mars 1906

EXERCICE 1905

PARIS

IMPRIMERIE GÉNÉRALE LAHURE

9, Rue de Fleurus, 9



RÉSUMÉ DU BILAN GÉNÉRAL

ACTIF

Espèces en Caisse et dans les Banques	Fr.	150.060.798 98
Portefeuille		1.094.966.467 70
Avances sur garanties et Reports		297.155.630 58
Comptes courants		568.448.897 90
Portefeuille-titres (Actions, Bons, Obligations et Rentes)		8.280.206 97
Comptes d'ordre et divers		1.342.578 84
Immeubles		35.000.000 »
Total	Fr.	2.155.254.580 97

Résumé de

Solde créancier	Fr.	34.110.630 05

Figure B.2: Schematic illustration of bank evolution

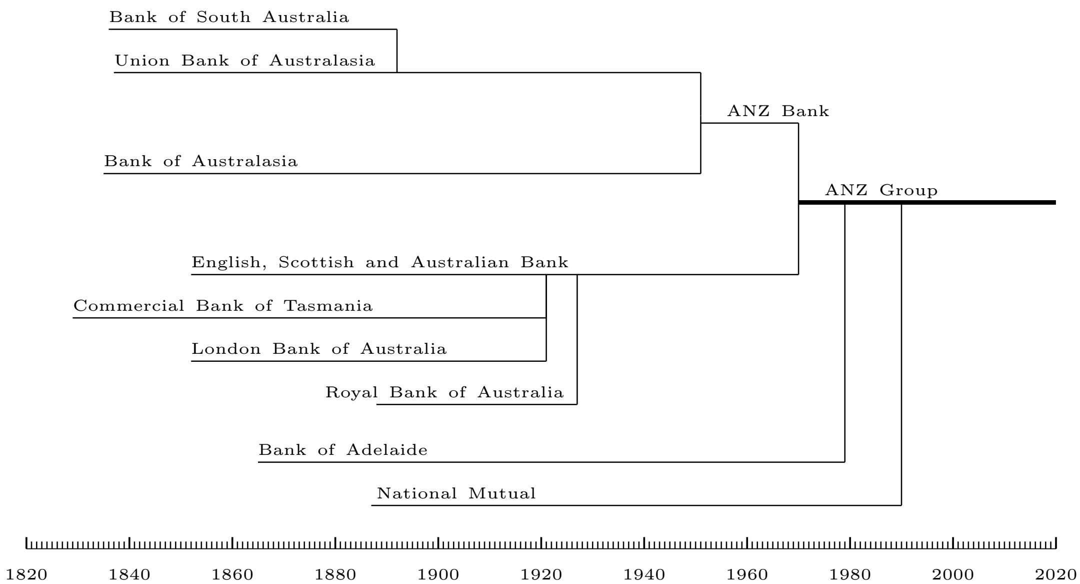


Figure B.3: Credit growth by bank size

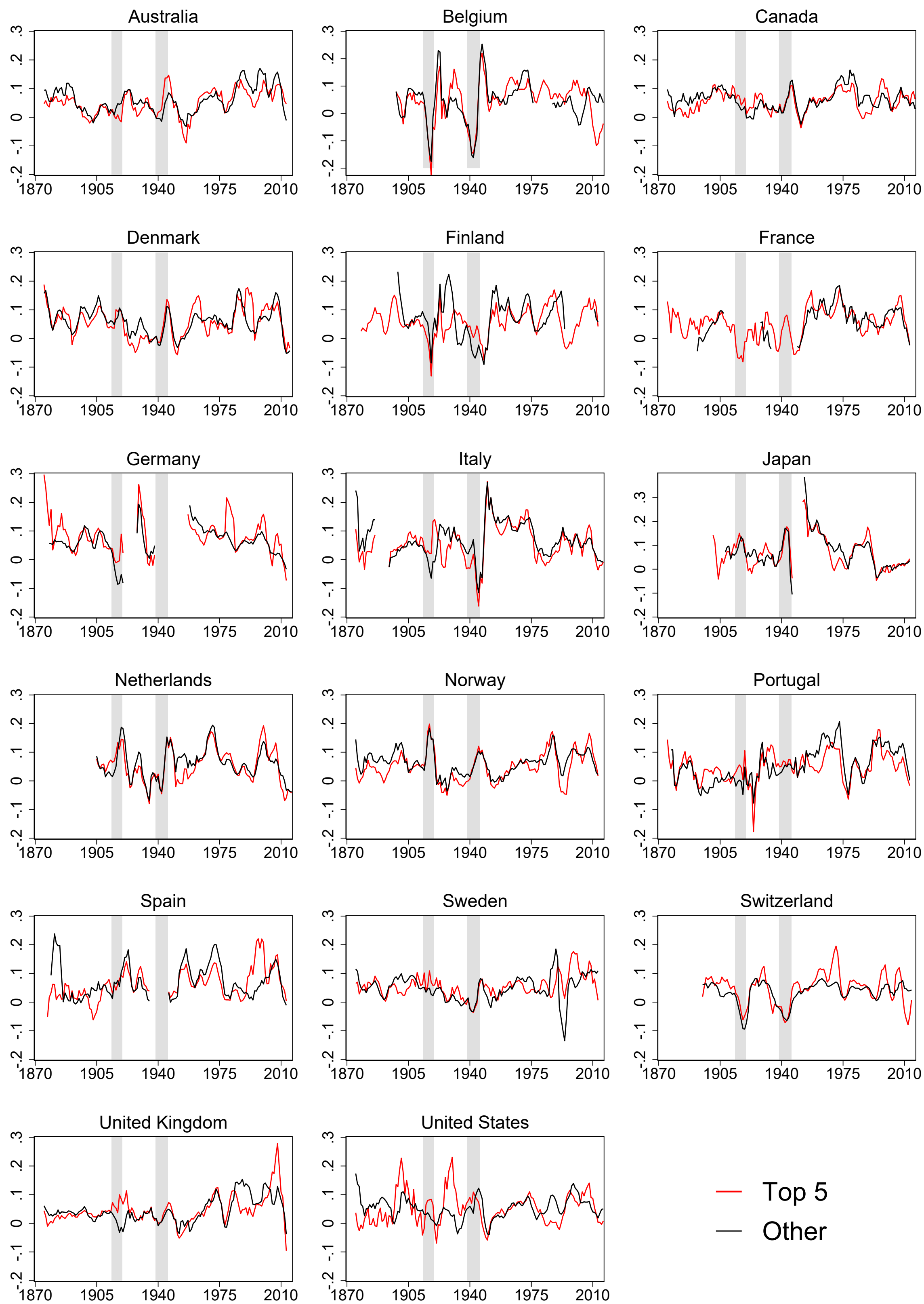


Figure B.4: Ratio of total assets relative to JRST (2021)