Credit Allocation and Macroeconomic Fluctuations*

Karsten Müller† Emil Verner‡

October 31, 2020

Job Market Paper

Click here for the most recent version

Abstract

We study the relationship between credit expansions, macroeconomic fluctuations, and financial crises using a novel database on the sectoral distribution of private credit. Constructed from more than 600 sources, these data allow us to map the sectoral allocation of credit across 116 countries starting in 1940 while matching data on total credit from existing sources. Equipped with this new resource, we document a striking shift in the composition of credit away from primary and manufacturing sectors toward households, construction, real estate, and other non-tradable sectors over the past five decades. Motivated by several salient case studies, including the Eurozone and Japanese banking crises, we then ask whether the allocation of firm credit across different industries plays a role in macroeconomic fluctuations. We find stark differences between different varieties of corporate credit expansions. In particular, we show that lending to the construction, real estate, and non-tradable sectors are associated with a boom-bust pattern in output and elevated financial crisis risk, similar to household credit booms. In contrast, there is no such pattern for tradable-sector credit expansions, which are often followed by stronger output growth. These patterns reject models in which debt plays a uniform role and instead support the idea that pre-determined differences across sectors shape interactions between finance and the real economy.

*We would like to thank Matt Baron, Thorsten Beck, Mathias Drehmann, Stuart Fraser, Charles Grant, Daisuke Ikeda, Òscar Jordà, Şebnem Kalemli-Özcan, Enisse Kharroubi, Paymon Khorrami, Ernest Liu, Atif Mian, James Mitchell, Romain Rancière, Oliver Rehbein, Stephen Roper, Moritz Schularick, Amir Sufi, and Alan M. Taylor for helpful comments. This paper incorporates parts of a draft previously circulated as "Sectoral Credit Around the World, 1940-2014".

†Princeton University, Department of Economics, karstenm@princeton.edu

‡MIT Sloan School of Management, everner@mit.edu

1 Introduction

Rapid expansions in private credit are often followed by growth slowdowns and an increased risk of financial crises (Schularick and Taylor, 2012; Jordà et al., 2013; Mian et al., 2017; Greenwood et al., 2020). However, what credit is used for during credit expansions—and how to tell apart "good" from "bad" booms—remains fundamentally unclear.[1] The main reason for this gap is a lack of data. In contrast to GDP statistics, currently available measures of private credit only contain aggregate data that at best distinguish between firm and household lending. As a result, little is known about the allocation of credit across industries and households, and how this allocation changes during credit booms. This makes it difficult to address questions such as: Which sectors account for the global rise in private debt since the late 1970s? How, exactly, does private credit interact with the business cycle? Why do some credit booms end in severe financial crises, while others do not?

In this paper, we use a new database to show that the sectoral allocation of credit is important for understanding both long-run developments in credit markets and the connection between credit booms, macroeconomic fluctuations, and financial crises. We construct a dataset that tracks the sectoral distribution of outstanding private credit for 116 countries. We combine data from more than 600 primary and secondary sources, many of which were digitized for the first time. By construction, these new time series on credit by economic sector and purpose are consistent with existing aggregate data on private credit. In contrast to existing work that only differentiates between household and firm credit, our data cover up to 82 different industries and four types of household credit. This database allows us to examine the evolution of credit in tradable and non-tradable corporate sectors, and key industries such as manufacturing, construction, and real estate. The data also covers a considerably longer time span than most other sources, going back to 1940 in many cases. We believe these data have many applications in macroeconomics, finance, and international economics.[2]

We begin by documenting three stylized facts about the evolution of private credit markets since World War II. First, the ratio of private credit-to-GDP has risen sharply worldwide in the past five decades, and the increase has been especially rapid in advanced economies. Second, household debt-to-GDP has increased in both advanced and emerging economies, driven by mortgages in the former and consumer credit in the latter. In contrast, firm lending to GDP has been essentially flat

[1] Gorton (2012), for example, notes that "although there is some evidence that the credit booms are associated with house price increases, it is not clear more generally what all the credit is being used for. What is the borrowed money being spent on?"

[2] From the outset, we note that there are many data issues related to creating comparable sectoral credit data series across countries and over long time horizons, which we discuss at length in the text and the data appendix. Our approach is to build on best practices in the construction of national accounts outlined by the United Nations (e.g. United Nations, 2009, 2018) and other data on private credit (e.g. Dembiermont et al., 2013). As such, we view our efforts as a reasonable starting point for constructing sectoral credit data in a transparent and consistent way, which we plan to build on in the future.

in most countries between 1980 and the mid-2000s. Firm lending thus accounts for little of the rise of private indebtedness. These facts are consistent with work by Greenwood and Scharfstein (2013) and Jordà et al. (2016) for a set of advanced economies, which we extend to emerging markets.

Third, while overall corporate debt-to-GDP has remained stable, we show that this masks important composition shifts in firm lending uncovered by the sectoral structure of our credit database. The composition of corporate credit has shifted substantially away from primary and manufacturing sectors toward construction, real estate, and other non-tradables. For example, even in the reconstruction period following World War II, lending to real estate developers and construction companies only accounted for around 10 percent of corporate lending in advanced economies. Today, it accounts for more than 24 percent. Perhaps surprisingly, this compositional shift in corporate credit is quite similar in developed and emerging economies.

Having established these stylized facts, we turn to the question of how expansions in credit across different sectors in the economy are linked to macroeconomic fluctuations and financial crises. To motivate this analysis, we examine several prominent credit booms that resulted in subsequent financial crises and macroeconomic downturns, including Spain and Portugal in the Eurozone crisis, Finland and Norway during the Nordic crises in the early 1990s, and the Japanese and Mexican banking crises of the early 1990s. Although the origins of these credit booms and crises differ, we find some important common patterns. In the run-up to many major financial crises, credit expansion tends to be concentrated among households and non-tradable sector firms—especially construction and real estate and trade, accommodation, and food service. In Spain, for example, lending to firms in the real estate sector grew by 600% (relative to GDP) between 1999 and 2008. Mexico saw a 250% increase in lending to retail and wholesale trade in the five years before the 1994 "Tequila crisis". In contrast, in the run-up to most crises, tradable sector credit—comprising agriculture, mining, and manufacturing—grows little, if at all. In some cases, tradable sector credit even declines. These examples provide initial evidence that the allocation of credit seems to matter, above and beyond overall credit growth, and highlights the usefulness of our disaggregated credit measures for understanding the nature of credit booms.

Next, we investigate the connection between credit expansions, business cycles, and crises more formally. Previous work shows that credit booms, particularly in the household sector, predict lower future output growth and a heightened probability of financial crises. We unpack corporate credit into its subsectors to investigate which types of firm credit expansions are linked to business cycles and crises. We find that credit expansions to the non-tradable sector predict are associated with lower medium-run growth and elevated risk of financial crisis, similar to household credit.

In contrast, tradable sector credit, and manufacturing credit in particular, is not associated with lower growth in the medium run. In some specifications, tradable credit expansions even predict stronger future growth. Tradable sector credit expansions further have essentially zero predictive

ability for financial crises. Further, tradable sector credit grows less quickly in the run-up to financial crises and falls less during crises. These patterns are robust to including a range of macroeconomic controls, using data only up to 2000, and controlling for year fixed effects. The sectoral allocation of credit thus contains useful information to separate good from bad credit booms.

Which theories are most consistent with these empirical facts? These patterns reject models in which credit booms lead to debt overhang in all sectors of the economy. Instead, they point to the importance of sectoral heterogeneity. Specifically, the patterns are consistent with models in which credit expansions finance demand, which expands the non-tradable sector during the boom and is followed by a demand-induced bust when credit conditions tighten (see, e.g., Eggertsson and Krugman, 2012; Schmitt-Grohé and Uribe, 2016; Mian et al., 2020). In addition, we find that non-tradable credit booms are associated with an increase in non-tradable leverage, which points to models where initial financing constraints are most severe in the non-tradable sector due to asymmetric information or contract enforcement problems (e.g., Schneider and Tornell, 2004). Higher leverage in the non-tradable and household sector can cause self-fulfilling crises if debt is denominated in foreign currency (Kalantzis, 2015). Non-tradable and household credit expansion can thus make the economy especially vulnerable to financial crises.

Slow growth after non-tradable and household credit expansions, but faster growth after tradable credit expansions, is also consistent with theories emphasizing that credit booms lead to intersectoral misallocation away from the tradables sector, which hampers growth in the medium run (e.g., Benigno and Fornaro, 2014). Our results also point to the importance of collateral cycles Kiyotaki and Moore (1997), as lending to housing-related sectors is among the strongest signals of future growth slowdowns and crisis. Finally, our results provide new perspectives on the seemingly contrasting results in the literature emphasizing the benefits of credit for growth (Levine, 2005) and studies linking credit booms to future growth slowdowns and crises.

Related literature This paper builds on multiple strands of the literature. First, we build on the literature on macro-financial linkages. Empirically, an influential set of papers shows that banking crises and deep economic downturns tend to follow periods of prolonged growth in credit and asset prices (e.g. Borio and Lowe, 2002; Gourinchas and Obstfeld, 2012; Schularick and Taylor, 2012), with a particular focus on the role of household debt (e.g. Mian and Sufi, 2011, 2014; Jordà et al., 2014; Mian et al., 2017). Greenwood and Hanson (2013), Baron and Xiong (2017), López-Salido et al. (2017), Krishnamurthy and Muir (2017) and Kirti (2018) study risk premia in credit markets and their interaction with the macroeconomy. The view that households are key for understanding debt-driven cycles is also supported by models such as Guerrieri and Lorenzoni (2017), Jones et al. (2011), Martin and Philippon (2017), or Korinek and Simsek (2016). We add to this literature by

studying the role of the sectoral *composition* of credit in business cycle fluctuations.[3]

Second, our focus on credit allocation is also related to the literature on finance and growth. Bertrand et al. (2007), Acharya et al. (2011), and Bai et al. (2018) link banking deregulation in France and the United States to an improved allocation of capital; Wurgler (2000) shows that sectoral investment and value added are more highly correlated in countries with more developed financial sectors. Our results suggest that credit allocation could partially explain why credit has been linked both to major crises but also higher long-run economic growth (also see Büyükkarabacak and Valev, 2010; Beck et al., 2012). Third, our paper also speaks to the literature on corporate debt overhang (Myers, 1977). For example, Duchin et al. (2010), Giroud and Mueller (2016), Şebnem Kalemli-Özcan et al. (2018) show that highly levered firms were more affected by the 2007/2008 financial crisis. We find that growth in firm debt is not always associated with poor future economic performance, depending on the sector.

2 Sectoral Credit Database: Data and Methods

In this section, we discuss the main conceptual and methodological issues involved in constructing sectoral credit data. We address additional conceptual issues and comparisons with other data sources in much greater detail in the Online Appendix.

2.1 Data Sources

Sectoral credit data have been collected by the national authorities of most countries for multiple decades. However, historical data are often not available in digitized form and are not reported on a harmonized basis. As a result, we draw on hundreds of scattered sources to construct these time series. The main source of these data are statistical publications and data appendices published by central banks and statistical offices. In many cases, we use publications from different organizations for the same country, most of which are only available in selected libraries. Large shares of the data were digitized for the first time and copied from PDF or paper documents. Many of the national authorities also shared previously unpublished data with us. In the process, we also discovered many previously untapped sources of total credit to the private sector that allow us to extend existing time series by, at times, many decades. Figure A20 shows an example of what the underlying data look like.

We complement our newly collected data with existing data from the Bank for International Settlements (BIS) (Dembiermont et al., 2013), Jordà et al. (2016), the International Monetary Fund

[3]Related work by Giroud and Mueller (2020) shows that increases in the leverage of publicly listed firms predicts regional contractions in employment.

(IMF)'s International Financial Statistics (IFS) and Global Debt Database (GDD) (Mbaye et al., 2018), and additional data from the print versions of the IFS digitized by Monnet and Puy (2019). These existing sources track broad credit aggregates such as total private credit or household credit for a subset of the countries we consider. We also build on scholarship on individual countries, such as Barnett (1982), De Bonis et al. (2013), or Abildgren (2007).

2.2 Concepts and Methods

We are interested in the sectoral distribution of outstanding credit to the private sector. Ideally, the data should thus follow a harmonized definition of corporations and households, economic sectors and industries, and coverage of debt instruments. In practice, there are systematic differences in classifications across countries and time that require a range of adjustments. To harmonize data from a wide range of sources, we consulted the meta data in historical publications and contacted the national authorities publishing information on sectoral credit. With the help of more than 150 individuals at these institutions, we coded the adjustments needed to resolve inconsistencies into a suite of Stata programs, which produce a harmonized set of tables from the raw data after checking for internal consistency. In the following, we outline the main conceptual issues that necessitate these adjustments and our approach to address them.

Definition of credit instruments All data are end-of-period outstanding claims of financial institutions on the domestic private sector in nominal national currency. In most countries, this definition mainly comprises loans, although we include debt securities wherever they are reported. In practice, domestic credit is almost entirely accounted for by loans, while debt securities are often held by foreign financial institutions. In most countries, these data include foreign currency loans.

Definition of lenders We try to cover the entire financial system wherever possible. In most countries, we predominantly capture credit extended by deposit-taking institutions such as commercial banks, savings banks, credit unions, and other types of housing finance companies. Comparisons with existing sources suggest that, on average, our numbers are in line with broad aggregates such as total domestic credit to the private sector, e.g. in the BIS data on credit to the non-financial private sector or the IMF's IFS (Monnet and Puy, 2019). At times, we find somewhat larger values than the data in Jordà et al. (2016), who largely cover lending by different types of banks.

Definition of households and corporations We follow the System of National Accounts (SNA 2008) in differentiating between households and corporations (United Nations, 2009). In particular, similar to Dembiermont et al. (2013), we include credit to unincorporated businesses and non-profit organizations in the household sector, because these activities can usually not be disentangled from

credit to households for consumption purposes. In practice, this mainly makes a difference for the agricultural sector, which is in many countries dominated by small farmers that may be classified as unincorporated businesses. Overall, we differentiate between the broad sectors "households and non-profit organizations serving households", "non-financial corporations", and "non-bank financial corporations".

Industry classification We classify industries based on the International Standard Industrial Classification of All Economic Activities (ISIC), Revision 4 (United Nations, 2008). Most countries have adopted this standard for reporting sectoral credit data. Industry classifications in credit data are relatively uniform across countries and time. Where classification changes necessitated an adjustment of the raw data, this is documented in detail in the Data Appendix. In almost all countries, we can differentiate between credit to the major "sections" in ISIC, e.g. Agriculture, Mining, or Manufacturing.

Lending to governments The data generally capture credit to the (non-bank) private sector. However, most data sources do not systematically differentiate between lending to private and state-owned corporations; in principle, the data thus also includes lending to state-owned firms. We take great care not to include direct lending to general or local governments. Some countries report lending to non-financial corporations in the "public administration and defence; compulsory social security" sector, corresponding to section O in ISIC Rev. 4. Such lending makes up a negligible part of the domestic credit market.

2.3 Adjustment Methods

Level breaks A key issue when dealing with data from hundreds of individual sources, as we do, is how to deal with level shifts (or "breaks") in the raw data. The perhaps most important challenge is to understand if such breaks arise because of actual economic changes (e.g. large-scale debt write-offs) or because of changes in classification (e.g. in the types of institutions covered by the data provider). To address this issue, we coded classification changes into country-specific adjustment files based on a reading of the meta data, additional methodological publications, and exchanges with the national authorities.

We adjusted breaks due to methodological changes using the following chain-linking procedure. First, we considered whether the sources before and after a break had overlapping data that could be used to chain-link the series, following methods used in previous datasets on private credit (Dembiermont et al., 2013; Monnet and Puy, 2019). Second, where no overlapping data was available, we used reference series, e.g. residential mortgages for a level break in total mortgage lending. Third, where no reference series was available either, we applied a simple method used

in Stock and Watson (2003). They adjust breaks using the median growth rate of the observations immediately before and after a break. The Online Appendix describes these procedures in detail.

Data consistency To guarantee internal consistency of the data, we at times rescale the data to match an aggregate such as "total credit to non-financial corporations" in line with the United Nations' recommendations on backcasting national accounts (United Nations, 2018). This issue usually arises in cases the data was adjusted for breaks. In some countries, raw data on credit by industry do not add up to credit to non-financial corporations because of differences in data collection. In these cases, we rescale the industry-level time series so that their sum matches data on total credit to non-financial corporations. By construction, the final data are internally consistent so that the individual sectors add up to total credit to the private sector.

2.4 Data Coverage

The database covers 116 countries, 52 advanced and 66 emerging economies, from 1940 to 2014.[4] These countries account for around 90% of world GDP today and include economies from all continents. Depending on the country, the number of sectors ranges from 3–82, with an average of 33. Appendix B.4 in the Online Appendix provides more information on the database coverage.

Table 1 compares the coverage in our dataset to that of existing datasets on private credit. Two things stand out. First, the main innovation of our data is that we provide a detailed sectoral breakdown of credit for many countries. This is a fundamental difference to existing datasets, which at best differentiate between household and firm credit. Second, our database introduces new quarterly or monthly data on total credit for many more countries than available in previous work (see Figure A17 in the Online Appendix). Monnet and Puy (2019), for example, compile quarterly data on private credit for 45 countries, while around 90 countries in our dataset have quarterly data since 1980. The combination of detailed sectoral data and data of higher frequency means the total number of observations in our database is at least an order of magnitude larger than that of existing datasets.

2.5 Variable Construction

We construct a country-year panel dataset by combining the new credit data with macroeconomic outcomes, house prices, and value added by sector from multiple data sources. Summary statistics for these variables can be found in Table 2.

[4] We are currently updating the data until 2020.

Table 1: Comparison with Existing Data Sources on Private Credit

Dataset	Start	Freq.	Countries	Sectors	Country-year obs.	Country-sector-time obs.
WB GFDD	1960	Y	200	0	1251	1231
Monnet and Puy (2019)	1940	Q	49	0	3,185	11,678
BIS	1940	Q	44	2	2,046	17,712
IMF IFS	1948	Y/Q/M	186	0	10,504	86,892
IMF GDD	1950	Y	189	2	6,904	10,504
Jordà et al. (2016)	1870	Y	17	3	6,904	6,904
Müller and Verner (2020)	**1910**	**Y/Q/M**	**116**	**3–82 ($\mu = 33$)**	**5,062**	**590,953**

Notes: The data on total credit and sectoral data in Müller-Verner (2018) start in 1910 and 1940, respectively. WB GFDD stands for the World Bank's Global Financial Development Database (Cihák et al., 2013). BIS refers to the credit to the non-financial sector statistics described in Dembiermont et al. (2013). IMF IFS and GDD refer to the International Monetary Fund's International Financial Statistics and Global Debt Database, respectively. The data in Monnet and Puy (2019) is from historical paper editions of the IMF IFS. We count observations until 2014; the data will be updated to 2020 in a forthcoming revision.

Credit variables For the purpose of this paper, we construct sectoral credit aggregates that distinguish between lending to households and different types of non-financial industries. Specifically, we differentiate between credit to agriculture (ISIC Rev. 4 section A); manufacturing and mining (sections B + C); construction and real estate sections (F + L); wholesale and retail trade, accommodation, and food services (sections G + I); as well as transport and communication (sections H + J). We further group together agriculture with manufacturing and mining as "tradable sector" and the other three industries as "non-tradable sector". This grouping is similar to Kalantzis (2015) and other studies in international macroeconomics.[5]

Macroeconomic data We use data on gross domestic product (GDP) in current national currency, population, inflation, and nominal US dollar exchange rates from the World Bank's World Development Indicators, Penn World Tables Version 9.1 (Feenstra et al., 2015), IMF IFS, Inklaar et al. (2018), Jordà et al. (2016), Mitchell (Mitchell), and the UC Davis Nominal GDP Historical Series.[6] Where required, we chain-link time series to adjust for differences across sources. For a few countries, we use data from national sources: Taiwan (National Statistics), the United States (FRED), Saudi Arabia (Saudi Arabian Monetary Authority), the countries of the Eastern Caribbean Monetary Union (ECCB), and Iceland (Statistics Iceland).

[5] In contrast to Kalantzis (2015), we do not include utilities (ISIC sections D and E), which are often heavily regulated. Because utilities are a small to modest share of overall private credit, our results are similar if we include them in non-tradables. Stockman and Tesar (1995) and Betts and Kehoe (2006), for example, use broadly similar definitions of the tradable and non-tradable sectors.

[6] The UC Davis data are available using the following link: http://gpih.ucdavis.edu/GDP.htm.

Table 2: Summary Statistics

Panel A: Summary statistics					
	N	Mean	Std. dev.	10th	90th
Real GDP growth, (t–3,t)	1794	15.58	10.88	3.50	28.80
$\Delta_3 d_{it}^k$	N	Mean	Std. dev.	10th	90th
Non-tradables	1621	0.71	3.57	-2.88	4.76
Tradables	1666	0.08	2.30	-2.51	2.62
Household	1583	2.12	4.16	-1.62	7.62
Agriculture	1669	0.03	0.73	-0.66	0.64
Manuf. and Mining	1675	0.05	1.92	-2.16	2.15
Construction and RE	1655	0.40	1.97	-1.35	2.58
Trade, Accomodation, Food	1662	0.19	1.64	-1.54	1.95
Transport, Comm.	1636	0.12	0.69	-0.52	0.81

Panel B: Correlation matrix for credit expansion variables								
	NT	T	HH	A	BC	FL	GI	HJ
Non-tradables	1							
Tradables	0.47	1						
Households	0.43	0.15	1					
Agriculture (A)	0.21	0.64	0.14	1				
Manuf. and Mining (BC)	0.48	0.88	0.11	0.24	1			
Construction and RE (FL)	0.80	0.30	0.42	0.13	0.32	1		
Trade, Accommodation, Food (GI)	0.79	0.44	0.27	0.21	0.44	0.37	1	
Transport, Comm. (HJ)	0.56	0.29	0.22	0.081	0.32	0.30	0.33	1

Notes: Panel A shows summary statistics for the main estimation sample used in the local projections and panel regressions. Panel B plots Pearson correlation coefficients for three-year changes in the credit-to-GDP ratio $\Delta_3 d_{it}^k$ for all sectors k we use. Sector abbreviations in parentheses refer to ISIC Rev.4 sections.

House prices We obtain data on house prices from the BIS residential property price series, OECD, Dallas Fed International House Price Database (Mack and Martínez-García, 2011), and Jordà et al. (2016). We create indices equal to 100 in 2010 and, where necessary, chain-link these house prices series.

Value added We construct data on sectoral value added from EU KLEMS, the Groningen Growth and Development Centre (GGDC) 10-sector database (Marcel Timmer, 2015), United Nations, OECD STAN, World Input-Output Database (WIOD), and Economic Commission for Latin America and the Caribbean (ECLAC). We evaluate each source on a case-by-case basis and select the one that appears to be of the highest quality. At times, we carefully combine multiple sources by chain-linking individual series.

Financial crises indicators We use data on the onset of systemic banking crises using data from Baron et al. (2019) and Laeven and Valencia (2018). Specifically, we use the data from Baron et al. (2019)—who measure banking sector distress by incorporating data on bank equity crashes—for all countries they are available. For countries where they report no data, we use data from Laeven and Valencia (2018).

3 Stylized Facts About Private Credit Around the World

In this section, we discuss a number of stylized facts about credit markets based on our new database. We start by revisiting facts about the amount of outstanding private credit relative to GDP, and then turn to the main novelty of the data: the sectoral distribution of credit.

Fact #1: Credit/GDP has risen sharply over the past five decades

We begin with a look at the long-run development of total private credit to GDP around the world, a widely used indicator for financial sector development. The novelty of our data for the purpose of this exercise is mainly the extension of long-run credit series to the period before 1960. We have data on total credit for 48 countries since 1940, 57 countries since 1950, and 74 countries since 1960.[7]

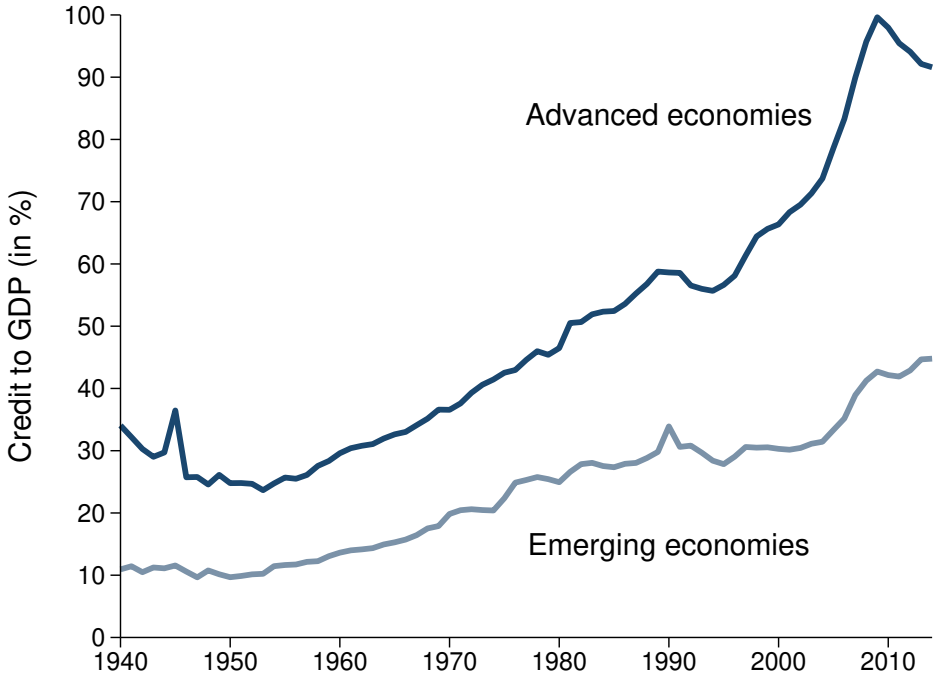
Figure 1 plots the average credit to GDP ratio for advanced and emerging economies.[8] While the "hockey stick" pattern of rising private debt has been well-documented for advanced economies

[7] Figure A16 in the Online Appendix shows how this compares to existing sources.

[8] We classify countries based on the World Bank's definition in 2019. Advanced economies refer to "high income countries", and emerging economies to all others.

(Schularick and Taylor, 2012, e.g.), such "financialization" has taken place to a lesser extent in emerging economies.[9]

Figure 1: Private Credit to GDP (in %) by country group, 1940-2014



Sample: 52 advanced and 65 emerging economies, 1940-2014.
Notes: Average ratio of total private credit to GDP (unweighted).

Fact #2: Household debt has boomed globally, while credit to non-financial firms has stalled

Next, the newly constructed data allows us to provide a first glimpse at what sectoral credit allocation looks like across countries and how it has evolved over time. Figure 2 visualizes the transformation of credit markets over the 70 year time span in the sample by plotting averages of sectoral credit to GDP across countries.

There are pronounced compositional changes over time. Financial institutions in the mid-1970s predominantly lent to non-financial corporations. Starting in the mid-1980s, with the onset of considerable financial deepening, household credit has become increasingly prominent. In fact, the overwhelming bulk of credit growth since around 1980 has been driven by household debt. The ratio of non-financial corporate credit stayed essentially flat between the early 1980s and the mid-2000s. These findings are broadly consistent with what Jordà et al. (2014) find for a sample of 17 advanced economies. A major trend-break here is the Great Financial Crisis 2007-2008. In the run-up to the crisis, household debt increased worldwide but only picked up in the non-financial

[9] Appendix A.1.1 in the Online Appendix shows that these patterns also hold when using balanced samples. A look at GDP-weighted averages suggests that large emerging markets have largely caught up with advanced economies.

corporate sector in 2006 or 2007. As we will show later, this recent growth in corporate lending was primarily driven by lending to the construction and real estate industries. Credit to the non-bank financial sector has also increased since the 1980s but much less than household debt.[10]

What accounts for the rise in household debt all over the globe? Jordà et al. (2014) show that mortgage credit has become disproportionately important in a sample of 17 advanced economies. Here, we broaden the perspective by looking at a total of 116 countries, including 66 emerging economies. Figure 3 plots the ratio of household credit to GDP while differentiating between residential mortgages and other types of household credit ("consumer credit").[11] For advanced economies, we add to the evidence in Jordà et al. (2014) that mortgage lending has not only increased as a fraction of GDP, but also explains most of the rise in household debt since the end of World War II. The data on emerging economies paints an entirely different picture. Here, consumer credit accounts for most of the increase in lending to households, and a considerably larger share. That is, the rise in household debt in emerging economies does not appear to be driven by a "great mortgaging". Figure A5 underscores this point by providing a snapshot for 10 advanced and 8 emerging economies for which we can further disentangle different types of consumer debt.

Fact #3: Firm credit has shifted from tradable sectors to construction, real estate, and other non-tradable sectors

Next, we turn to developments in the corporate credit market. It is a well-known phenomenon that countries undergo structural change as they develop, mainly away from primary sectors towards manufacturing and then service sectors. As such, one may expect to find similar trends in corporate credit. On the other hand, the findings for residential mortgages above suggest an increasing role of the housing sector, at least in advanced economies. Can we detect complementary patterns in the composition of corporate financing?

Figure 4 breaks down firm lending to GDP into six subsectors: agriculture; manufacturing (including mining); construction and real estate; trade, accommodation, and food services; transport and communication; and other sectors. Figure 5 shows each sector's share in total corporate credit. Again, we differentiate between emerging and advanced economies. Consistent with structural change in the credit market, the share of lending to agriculture and industry has declined, particularly since around 1980. This trend has been relatively similar in both advanced and emerging economies. The financing of industry, for example, has not "migrated" from advanced to emerging economies; rather, the decline appears to be relatively uniform, which is somewhat surprising, given the relocation of many manufacturers to developing countries.

[10] Appendix A.1.2 in the Online Appendix provides robustness exercises.

[11] As we discuss in more detail in the Online Appendix, non-mortgage lending to households may not only contain consumer credit but also other types of loans in some countries, e.g. student loans or credit to sole proprietorships.

The second major trend is that construction and real estate lending have come to make up considerable shares of aggregate corporate loan portfolios. In advanced economies, which likely faced the highest demand for financing reconstruction after World War II, in fact had a negligible share of construction credit in the 1950s. Today, this share has risen to more than 24 percent. While the housing boom of the 2000s has clearly played a role, the share had already grown in the 1990s. Strikingly, a similar pattern also holds true in developing countries. In 1960, lending to industry and agriculture accounted for more than 74 percent of corporate financing. Today, the ratio is closer to 25 percent. At the same time, construction and real estate has increased from around 5 percent to 15 percent. The loan portfolio of emerging markets has thus also seen a profound shift.

What about other types of lending? Almost all over the globe, other services have also increased their lending share by a substantial margin. In advanced economies, other services have increased from around 15 percent in 1960 to around 33 percent in recent years. Emerging economies have seen an increase from around 3 percent to 25 percent over the same time period. Taken together, these findings suggest that the financing of manufacturing, the activity perhaps most commonly associated with commercial banking, has come to play only a miniscule role for understanding modern credit markets.[12]

4 Credit Allocation, Business Cycles, and Financial Crises

In this section, we test whether an increase in credit to particular sectors of the economy systematically foreshadows economic downturns and financial crises. To do so, we start by discussing several salient case studies. Then, we turn to a more systematic analysis by relating future GDP growth to varieties of credit expansions using local projections. Finally, we ask whether the sectoral allocation of credit changes in the run-up to systemic banking crises.

4.1 Case studies

To motivate our analysis on the role of credit allocation in shaping macroeconomic fluctuations, we begin by investigating several prominent case studies. We provide a descriptive account of changes in the composition of credit in the run-up to some of the most severe economic downturns associated with banking sector distress in recent decades: the 2000s boom in Spain and Portugal; the Finnish and Norwegian crises of the early 1990s; the Japanese banking crisis starting in 1991; the Mexican Tequila Crisis in 1994; and all major recessions in the United Kingdom since the 1970s. A common feature of these episodes is that they are all associated with a substantial intersectoral re-

[12] Appendix A.1.3 in the Online Appendix shows that these findings look very similar when using a more balanced sample or GDP-weighted averages.

allocation of credit. The rapid expansion in lending in the run-up to these crises primarily finances non-tradable and household sector debt, while primary and manufacturing sector credit often stagnate. Once a crisis occurs, credit to the previously booming non-tradable and household sectors often dramatically contracts, with less of a contraction in the tradable sector.

The Eurozone Crisis: Spain and Portugal

The peripheral countries of the Eurozone experienced a major boom-bust cycle over the period 2000-2012, considerably worsened by a prolonged sovereign debt crisis. The creation of European Monetary Union eliminated currency risk, which led to a large reduction in country spreads and large capital flows from core to peripheral economies, including Spain and Portugal (**?**). These capital inflows financed rapid loan growth from financial institutions in peripheral countries.

Which sectors of the economy did credit expansion finance? Figure 6 shows that this led to a large increase in lending to households, real estate, and construction firms. In relative terms, lending to the real estate sector grew the fastest, while the absolute increase in debt was largest for the household sector. In contrast, credit to the manufacturing sector stagnated. The lending boom was associated with house price booms, along with rising wages and deteriorating competitiveness in the traded sector. This led to productivity stagnation as relatively unproductive firms in the non-tradable sector expanded at the expense of the more productive firms in the tradable sector Reis (2013). Gopinath et al. (2017) highlight within-sector misallocation among manufacturing firms during the boom. However, our data show little evidence for credit growth in the manufacturing sector over this period. The global financial crisis of 2008 led to a reversal of inflows, a sharp contraction in credit, falling asset prices, and severe recessions. Despite the extensive literature discussing the roots of the crisis in peripheral Eurozone countries, to the best of our knowledge, this perspective on the composition of sectoral credit data is new.

The Nordic Crises of the late 1980s and early 1990s: Finland and Norway

Finland and Norway experienced major credit expansions in the 1980s followed by systemic banking crises in the late 1980s (Norway) and early 1990s (Finland).[13] The credit expansion in both Finland and Norway came after substantial deregulation of banking markets and capital flows.

Figure 7 shows the evolution of sectoral credit in Finland and Norway during this period. Household credit saw by far the largest absolute increase, 15 percent from the early 1980s to 1990. Construction and trade, accommodation, and food service also increased rapidly. Manufacturing credit, in contrast, declined relative to GDP during the boom. When the Finish banking crisis arrived in 1990 and accelerated in 1991, credit in all sectors contracted sharply.

[13]Sweden also experienced a severe banking crisis in the early 1990s, but our sectoral credit database does not contain data for Sweden during this period.

In Norway, panel (b) of Figure 7 shows, credit growth was strongest in the construction and real estate sector. Trade, accommodation, and food services, along with household credit, also expanded. In absolute terms, household credit increased the most, by over 20 percentage points relative to GDP, following by construction and real estate (about 8 pp of GDP). In contrast, manufacturing credit barely increased relative to GDP. A combination of external shocks, including the fall in oil prices in 1986, speculative attacks, and rising bankruptcies translated into severe banking sector distress from 1987 through the early 1990s.

The Early 1990s Japanese Banking Crisis

Japan experienced a rapid credit boom in the second half of the 1980s, which culminated in a prolonged period of banking sector distress and slow growth in the 1990s. The credit boom followed a period of gradual financial deregulation in the 1970s and 1980s, including the removal of most capital controls in 1980. The deregulation was accelerated by the 1985 Plaza Accords, which committed Japan to "measures to enlarge consumer and mortgage credit markets" and led to a move from export-based to domestically-oriented growth **?**. This represented a shift away from the "Old Financial Regime" of limiting households' access to consumer and mortgage credit. Deregulation was reinforced by loose monetary policy, which played a key role in the credit expansion **?**. The boom was characterized by surging stock and urban real estate prices, which reinforced speculative investment in land and real estate by real estate finance companies **?**.

Figure 8a shows that the Japanese credit boom was associated with significant intersectoral credit reallocation. In particular, household credit and real estate credit increased by over 50 percent between 1985 and 1990. Credit to the accommodation and food service sectors also increased rapidly. In contrast, manufacturing credit actually declined during this period, suggesting a reallocation of credit toward non-tradables and households and away from the tradable sector, which had been a key driver of Japanese post-war growth.

The 1994-95 Mexican "Tequila Crisis"

The 1994-95 Mexican "Tequila Crisis" illustrates the role of the sectoral allocation of credit in the run-up to a prominent emerging market "sudden stop" episode. Mexico experienced rapid capital inflows, large current account deficits, and real exchange rate appreciation following the capital account liberalization in 1989-90 and exchange rate stabilization. This was followed by a "sudden stop" in capital inflows and large depreciation starting in December 1994, when the government had trouble rolling over its debt. The sudden stop was associated with a severe recession in 1995, driven by a decline in non-tradable output (Kehoe and Ruhl, 2009).

Figure 8b shows the dynamics of sectoral credit resembles the experience of other major crises. From 1988 to 1994, the credit to households, the construction sector, and trade grew rapidly. For example, household credit-to-GDP increased nearly fourfold from 1988 to 1994. Meanwhile, manufacturing credit remained stable relative to GDP during the boom.

Boom-Bust Cycles in the United Kingdom, 1970-2014

The United Kingdom has experienced relatively volatile GDP growth over the past 50 years, characterized by frequent recessions in the mid-1970s, early 1980s, early 1990s, and during the Great Financial Crisis 2007-2008. Figure 9 shows that each of these recession except that of the 1980s—which followed the 1979 energy crisis—were preceded by a relatively sudden and pronounced increase in the ratio of credit to value added in the housing and accommodation/food sectors. In the early 1990s and the Great Financial Crisis, there is also a pronounced increase in household credit (relative to GDP).

In contrast, manufacturing credit has been relatively stable relative to the sector's value added. In the run-up to the 2008 recession, for example, manufacturing credit expanded by less than 10 percentage points relative to value added, compared to an 80 percentage point increase in construction and real estate, and a close to 40 percentage point increase in the accommodation and food sector. These patterns suggest that (i) the sectoral allocation of credit may be informative about future output even outside of major banking crises, and (ii) credit in the non-tradable sector is not only procyclical with regard to GDP but also a sector's value added.

4.2 Credit Allocation and Business Cycles

We now turn to more formally examining the connection between credit expansions and subsequent aggregate output dynamics. Previous work shows that credit expansions predict subsequent GDP growth slowdowns in the medium run. The predictability is stronger for household credit and more modest and immediate for non-financial corporate credit (Mian et al., 2017; IMF, 2017; Drehmann et al., 2018). Our sectoral credit data allows to unpack corporate sector leverage to better understand whether and how the allocation of credit matters for subsequent GDP growth.

We start by grouping sectors into broad tradable and non-tradable sectors. We then examine individual corporate sectors in more detail. Tradable sectors are defined as agriculture (ISIC sector A) and mining and manufacturing (B and C). Non-tradable sectors comprise construction and real estate (F and L), wholesale and retail trade, accommodation, and food services (G and I), and

transport and communication (H and J). This is a broad definition of non-tradables, similar to the definition used by Kalantzis (2015) for sectoral value added.[14]

We estimate the path of real GDP after innovations in sectoral credit-to-GDP using the following Jordà (2005) local projection specification:

$$\begin{aligned}\Delta_h y_{it+h} =& \alpha_i^h + \sum_{j=0}^{J} \beta_{h,j}^{NT} \Delta d_{it-j}^{NT} + \sum_{j=0}^{J} \beta_{h,j}^{T} \Delta d_{it-j}^{T} + \sum_{j=0}^{J} \beta_{h,j}^{HH} d_{it-j}^{HH} \\ &+ \sum_{j=0}^{J} \gamma_{h,j} \Delta y_{it-j} + \epsilon_{it+h}, \quad h = 1, ..., H,\end{aligned} \tag{1}$$

where $\Delta_h y_{it+h}$ is real GDP growth from year t to $t+h$, α_i is a country fixed effect, and Δd_{it}^k is the change in sector k credit-to-GDP from $t-1$ to t. As is standard in the local projection framework, we control for lags of the dependent variable. We chose a conservative lag length of $J = 5$, based on the recommendation in Olea and Plagborg-Møller (2020), who show that impulse responses estimated from lag-augmented local projections are robust to highly persistent data, even for impulse responses at long horizons. We examine a horizon of $H = 10$ years based on the observation that credit expansions and subsequent busts often play out over longer periods. In particular, Mian et al. (2017) estimate that credit expansions typically last for 3-4 years, after which credit growth stalls and output begins contracting. Standard errors are computed using the methods in Driscoll and Kraay (1998) to allow for residual correlation within countries, as well residual correlation across countries in proximate years. We choose a lag length of $ceiling(1.5 \cdot h)$. As an alternative, we also report standard errors two-way clustered on country and year, which tend to be slightly more conservative in our application.

Figure 10 presents the impulse responses of real GDP to innovations in non-tradable sector credit, tradable sector credit, and household credit given by the estimated sequence of coefficients $\{\beta_{h,0}^k\}$. Panel (a) focuses on the two corporate sectors, and panel (b) adds household credit. From the outset, we emphasize these impulse responses are not necessarily causal, but provide a sense of the predicted dynamics of GDP following innovations in sector k credit, holding fixed GDP growth and credit in other sectors.[15]

[14] Our definition of non-tradables differs slightly from Kalantzis (2015) as we do not include utilities (ISIC sectors D and E), as utilities are often heavily regulated. Because utilities are a small to modest share of overall private credit, our results are similar if we include them in non-tradables. A number of studies in international macroeconomics, including Stockman and Tesar (1995) and Betts and Kehoe (2006), employ broadly similar, although less fine, definitions of tradable and non-tradable sectors based on more aggregated value added data.

[15] Note also that our focus is to describe historical data patterns. As such, our analysis is silent about the out-of-sample forecasting ability of credit variables or their importance in explaining business cycle fluctuations, which are open questions (Brunnermeier et al., 2019; Plagborg-Møller et al., 2020; Greenwood et al., 2020).

The left figure in panel (a) of Figure 10 reveals that an innovation in non-tradable sector credit-to-GDP is associated with a slower GDP growth after three to four years. The decline persists for several years, leaving GDP below its initial trend. The right figure in panel (b) shows a different pattern for tradable sector credit. Innovations in tradable sector credit are not associated with lower GDP growth, and the predictive relation is even positive in the medium-term after five years. These patterns provide initial evidence that the relationship between credit expansions and the real economy may differ depending on which sectors are being financed.

Panel (b) adds household credit to the estimation of equation (1). Household credit-to-GDP innovations are a strong predictor of lower GDP after three to four years. This confirms the result in Mian et al. (2017) with a sample that is twice as large. One potential explanation for this medium-run negative predictability is the persistence of credit expansions and the long maturity of household loans Drehmann et al. (2018). The patterns implied by the estimates on d_{it}^{NT} and d_{it}^{T} are similar as in panel (a), but slightly more muted. Because household credit is strongly correlated with non-tradable sector credit, these components capture similar periods of credit expansion. As a result, the estimates for non-tradable sector credit fall by about half with the inclusion of household credit.

Table 3 presents an alternative regression approach to examining the relation between credit expansions and GDP growth in the short and medium run. We estimate the following regressions for $h = 0, ..., 5$:

$$\Delta_3 y_{i,t+h} = \alpha_i^h + \beta_h^{NT} \Delta_3 d_{it}^{NT} + \beta_h^{T} \Delta_3 d_{it}^{T} + \beta_h^{HH} \Delta_3 d_{it}^{HH} + \epsilon_{it+h}, \tag{2}$$

where the left-hand-side is the change in log real GDP from year $t-3+h$ to $t+h$, α_i^h is a country fixed effect, and $\Delta_3 d_{it}^k$ is the three-year change in sector k credit-to-GDP. That is, we fix the right-hand-side to be the three-year change in credit-to-GDP shift the dependent variable successively one period forward in each column of the table.

Panel (a) in Table 3 shows that non-tradables credit expansion is positively correlated with GDP growth contemporaneously. In the medium run, however, the sign reverses. At the strongest horizon of $h = 3$, the estimate implies that a one standard deviation in $\Delta_3 d^{NT}$ is associated with -0.90 percent lower growth from t to $t + 3$. The pattern for household credit is similar, though household credit has a weaker contemporaneously correlation with growth (column 1) and stronger predictability further into the future (columns 5-6). The estimate in column (5) at the $h = 4$ horizon implies that one standard deviation increase in $\Delta_3 d_{it}^{HH}$ is associated with -1.51 percent lower growth from $t + 1$ to $t + 4$. In contrast, an expansion in tradable sector credit is associated with positive growth in both the short and medium run, although the individual estimates are not statistical significant.

Table 3: Credit Expansion and GDP Growth

Panel A: Non-tradable, tradable, and household sector credit						
	Dependent variable: GDP growth over...					
$\Delta_3 d_{it}^S$	(1) (t-3,t)	(2) (t-2,t+1)	(3) (t-1,t+2)	(4) (t,t+3)	(5) (t+1,t+4)	(6) (t+2,t+5)
Tradables	0.20	0.12	0.12	0.23	0.27	0.27
	(0.16)	(0.19)	(0.19)	(0.17)	(0.19)	(0.20)
Non-tradables	0.39**	0.14	-0.11	-0.25**	-0.20**	-0.095
	(0.084)	(0.10)	(0.11)	(0.082)	(0.063)	(0.083)
Households	0.055	-0.045	-0.20*	-0.36**	-0.56**	-0.59**
	(0.097)	(0.089)	(0.078)	(0.099)	(0.14)	(0.15)
Observations	1483	1425	1365	1306	1246	1186
# Countries	62	62	62	62	62	62
R^2	.055	.0062	.015	.053	.092	.091
Panel B: Individual corporate sectors						
	Dependent variable: GDP growth over...					
$\Delta_3 d_{it}^S$	(1) (t-3,t)	(2) (t-2,t+1)	(3) (t-1,t+2)	(4) (t,t+3)	(5) (t+1,t+4)	(6) (t+2,t+5)
Agriculture	-0.66	-0.54	-0.37	-0.17	0.073	0.27
	(0.51)	(0.50)	(0.44)	(0.33)	(0.31)	(0.31)
Manuf. and Mining	0.44*	0.33	0.30	0.35	0.31	0.26
	(0.20)	(0.23)	(0.24)	(0.25)	(0.25)	(0.25)
Construction and RE	0.33**	0.050	-0.20	-0.42	-0.30	-0.082
	(0.11)	(0.14)	(0.20)	(0.30)	(0.31)	(0.26)
Trade, Accommodation, Food	0.70*	0.40	0.099	0.12	0.21	0.27
	(0.31)	(0.30)	(0.27)	(0.34)	(0.37)	(0.33)
Transport, Comm.	-0.62	-0.79+	-0.86**	-0.96**	-1.07**	-1.04**
	(0.54)	(0.43)	(0.28)	(0.25)	(0.26)	(0.34)
Households	0.085	-0.018	-0.18**	-0.34**	-0.56**	-0.61**
	(0.098)	(0.086)	(0.064)	(0.081)	(0.12)	(0.12)
Observations	1483	1425	1365	1306	1246	1186
# Countries	62	62	62	62	62	62
R^2	.068	.017	.023	.063	.1	.1

Notes: This table presents the results from estimating the following linear regression model:

$$\Delta_3 y_{it+3+h} = \alpha_i + \sum_k^K \beta^k \Delta_3 d_{it}^k + u_{it}, \quad h = 0, ..., 5$$

where $\alpha_i^{(h)}$ is a country fixed effect and $\Delta_3 d_{it}^k$ the change in the credit/GDP ratio for sector k from $t-3$ to t. Driscoll and Kraay (1998) standard errors in parentheses with lag length $ceiling(1.5(3+h))$. +, * and ** denote significance at the 10%, 5% and 1% level.

4.2.1 Individual corporate sectors

Figure 11 breaks down the components of non-tradable and tradable credit and shows the impulse responses for individual corporate sectors separately. We estimate the following local projection specification:

$$\Delta_h y_{it+h} = \alpha_i^h + \sum_{j=0}^{J} \sum_{k \in K} \beta_{h,j}^k \Delta d_{it-j}^k + \sum_{j=0}^{J} \gamma_{h,j} \Delta y_{it-j} + \epsilon_{it+h}, \quad h = 1, ..., H, \tag{3}$$

where K consists of the following sectors: Agriculture; Manufacturing and Mining; Construction and Real Estate; Trade, Accommodation, and Food Services; Transport and Communication; and Households. As with the previous analysis, we present results from local projections both with and without household credit.

The estimates for the more disaggregated sectors are less precise, as the individual credit variables contain more noise than the tradable and non-tradable aggregates, but the patterns are interesting. Panel (a) in Figure 11 reveals that, within tradables, the estimate on agriculture is imprecise, and agriculture credit appears to be unrelated or slightly positively related to future growth. Innovations in manufacturing credit are associated with similar or even gradually higher growth in the medium run.

Within non-tradable sectors, construction and real estate credit has the strongest negative medium-term predictability for GDP growth. Wholesale and retail trade (G) and accommodation and food services (I)—a narrower definition of non-tradables closer to the definitnion in Mian and Sufi (2014)—is also associated with lower subsequent growth, but the estimates are not statistically significant. The impulse response for transport and communication (H and J) also implies lower output but is more uncertain.

In Figure 11 panel (b), we include household credit to the local projection specification (3). Household credit is again a strong predictor a subsequent growth slowdown. Household credit picks up part of the variation related to the construction and real estate and trade, accommodation, and food services, so the impulse responses for these variables are more muted than in panel (a), but remain qualitatively similar. The null or even positive predictive relation between manufacturing credit innovations and medium term output is virtually unaffected by the inclusion of household debt.

These results provide a richer understanding of connection between credit expansions and growth by highlighting important sectoral heterogeneity. Overall, non-tradable sector credit broadly defined, especially construction and real estate, is associated with growth slowdowns, along with household credit. On the other hand, tradable sector credit expansions are, if anything, associated with higher future growth. These patterns mesh well with the case studies outlined above and shows

that these patterns are more general.

4.2.2 Robustness

Sector Size or Sector Leverage? Accounts of credit booms and crises often highlight a reallocation of real resources from the tradable to the the non-tradable sector (e.g., Mendoza and Terrones (2008)). Kalantzis (2015) finds that an increase in non-tradable relative to tradable value added predicts financial crises. Does slower growth after non-tradable credit expansions reflect an increase in the size of the non-tradable sector, or does it also partly reflect an increase in sectoral *leverage* and financial risk?

We use two approaches to address this question. First, Figure A13 panel (b) presents results from estimating (1) with additional controls for non-tradable and tradable sector value added shares. Second, Figure A13 panel (b) presents estimates impulse responses from (1), but where we replace sectoral credit-to-GDP with credit scaled by *sectoral value added*. Credit-to-value-added should come closer to capturing an increase in sectoral leverage.[16] Both specifications suggest that the increase in credit, not just an increase in activity, in the non-tradable sector matters for predicting future growth slowdown.

Additional controls Figure A10 panel (a) includes a variety of additional controls for the local projection specification (1).[17] First we add the following additional macroeconomic controls: CPI inflation, short-term interest rates, and the change in the log US dollar exchange rate. The controls are included in the same form as the baseline variables, namely for lags $j = 0, ..., 5$. These variables help account for changes in monetary policy, which Brunnermeier et al. (2019) argue can drive both credit and output dynamics. The impulse responses with these controls are similar to the baseline.

Second, in a separate test reported in Figure A10 panel (a), we control for contemporaneous ($t-1$ to t) and lagged house price growth. Credit expansions, especially in the household, construction, and real estate sectors, are closely connected to house price dynamics. We do not take a stand to what extent house price dynamics drive credit, or vice versa. Instead, we simply want to test whether credit contains additional information, over and above the information in house prices. The impulse responses with house price controls are similar to the baseline, which suggests that credit, not just asset prices, is informative about future growth.

Third, panel (a) in Figure A10 reports estimates of (1) that include year fixed effects in order to account for common shocks and time trends. Given that credit dynamics have an important global

[16] A drawback of this specification is that the number of observations falls by over half because of missing sectoral value added data for many countries and time periods.

[17] Figure A11 presents the same robustness checks for local projections using individual sector credit as in equation (3).

component, the impulse responses are slightly attenuated with year fixed effects, but the patterns remain similar to the baseline.

Subsamples Panel (b) in Figure A10 estimates impulse response from equation (1) for various subsamples. Restricting the sample to data up to the year 2000 leads to quantitatively similar dynamics as the baseline, showing that the baseline results are not solely driven by the Great Recession. This accords with the evidence from the case studies in section 4.1, which illustrate that non-tradable and household sector credit expansions preceded several prominent crises in pre-2000 period. Panel (b) also reports estimates separately for advanced and emerging markets. The relation between credit expansions in the non-tradable and household sectors and subsequent lower growth is stronger in advanced than emerging economies.

Individual sectors separately Our baseline approach estimates the impulse response to innovations in sector k credit-to-GDP, holding fixed credit in sectors $k' \neq k$. This captures the incremental information in sector k credit. However, one may be concerned about multicollinearity, given that sectoral credit growth clearly contains a common country-specific component. Figure A12 thus presents impulse responses from local projection when individual sectors are included separately. The qualitative dynamics of real GDP following innovations in credit are similar to the multivariate local projections in Figure 10 and Equation (3). One difference is that the positive medium-run GDP response to innovations in tradable and manufacturing credit is smaller and not statistically significant.

4.3 Sectoral Credit Expansion and Financial Crises

Why are some types of credit expansions associated with economic downturns, while others are not? One potential channel could be that risks to financial stability vary with what credit is being used for. Because financial crises are associated with large costs in permanently lost output (e.g. Cerra and Saxena, 2008; Reinhart and Rogoff, 2009a), this may create a link between sectoral credit expansions and future macroeconomic performance. The importance of sectoral financial stability risks, and regulatory tools to address them, is also subject of an ongoing debate among policy makers (e.g. Basel Commitee on Banking Supervision, 2019).

Existing work by Büyükkarabacak and Valev (2010) and Jordà et al. (2014) suggests that household and housing-related debt are particularly associated with the likelihood of a systemic banking crisis; Greenwood et al. (2020) find that household and firm credit predict crises similarly when interacted with asset prices.

We attempt to shed additional light on this issue by asking whether there are systematic differences in which types of credit growth tend to be followed by financial crises. We start with

a descriptive analysis that shows how credit allocation changes around the precise start of such crises. To do so, we look at one-year changes in the ratio of credit to GDP. To make these variables more comparable, we subtract the country mean and standardize them to have a mean of zero and standard deviation of one.

Figure 12 plots their average values for five years before and after a systemic banking crisis (as in Gourinchas and Obstfeld, 2012).[18] Panel (a) shows that, as documented by previous work, household credit tends to expand above the country average in the run-up to crises. However, there is a stark difference between the growth of private credit to the non-tradable and tradable sectors. Non-tradable sector credit expands at approximately twice the right, surpassing the growth of household debt in the three years immediately before before crises. Panels (b) and (c) decompose these broad sectors into the by now familiar five industry groups. This shows that the growth rates of manufacturing, mining, and agriculture credit are, on average, muted in the run-up to financial fragility episodes, while there is an almost equivalently strong credit expansion in the construction, real estate, trade, accommodation, and food sectors. Lending to transport and communication also appears to pick up in the immediate run-up to crises, but shows an overall more muted pattern.

Next, we turn to a more formal analysis by running predictive panel regressions of the following type:

$$Crisis_{it+1 \text{ to } it+h} = \alpha_i^{(h)} + \sum_{k \in K} \beta_k^{(h)} \Delta_3 d_{it}^k + \epsilon_{it+h}, \tag{4}$$

where $\alpha_i^{(h)}$ is a country fixed effect and $\Delta_3 d_{it}$ the change in the credit/GDP ratio for sector k from $t-3$ to t. $Crisis_{it+1 \text{ to } it+h}$ is a dummy variable that equals one if country i experiences the start of a systemic banking crisis between year $t+1$ and $t+h$, as in Greenwood et al. (2020). We restrict the sample to the period 1944 to 2010 to keep the number of observations across horizons constant. We thus estimate the predictive content of different credit expansions for cumulative crisis probabilities. As a baseline, we use the crisis dates from Baron et al. (2019) and supplement them with data from Laeven and Valencia (2018) for countries where they report no data. Standard errors are computed using the methods in Driscoll and Kraay (1998) for up to $ceiling(1.5 \times h)$ lags, which allow residual serial correlation within countries and across countries in close-by years. We explore other specifications below.

To compare a range of different linear and nonlinear models, we evaluate the relationship between sectoral credit growth and crises through the lens of the widely used Area Under the Curve (AUC) statistic, the integral from plotting a classifier's true positive against its false positive rate (usually referred to as receiver operating characteristic, or ROC). The interpretation of the AUC

[18] The results look almost equivalent if we use panel fixed effects regressions to further de-mean the data with respect to the average number of crises or additionally add year fixed effects.

statistic is a given model's ability to classify the data into crisis and non-crisis periods, where an AUC of 0.5 is usually thought of as containing classification ability no better than a coin toss. We also standardize the credit growth variables so that they have a mean of zero and standard deviation of one to aid interpretation. Note, however, that we are concerned with describing historical data patterns around crisis events, not a forecasting exercise.

Table 4 reports the results of running multivariate regressions. Panel A examines the predictive content of tradable, non-tradable, and household credit. Non-tradable and household credit expansions predict elevated probability of a financial crisis at one to 4 year horizons. In terms of magnitudes, a one standard deviation higher three-year change in non-tradable sector credit to GDP is associated with a 5.6 percent higher crisis probability over the next four years. This is sizeable relative to the unconditional probability of a crisis within 4 years in the estimation sample of around 14.1 percent. For households, the magnitude is around 4.8 percent. In contrast, tradable sector credit expansion has no predictive power for financial crises; the estimates on tradable sector credit are mostly negative, quantitatively small, and not statistically significant at any horizon.

Panel B shows the results for the individual corporate sectors, which further supports the notion that banking crises tend to be preceded by credit expansions in specific sectors of the economy. In particular, we find a strong role for lending to various subsectors of the non-tradable sector: both lending to firms in the construction and real estate business and particular trade, accommodation, and food is associated with future crises. At horizons of 2-4 years in particular, these types of firm credit expansions have predictive power that rivals that of household credit. Importantly, credit to the primary sectors and manufacturing have virtually no predictability for banking crises.

Table 4: Sectoral Credit Expansions and Financial Crises

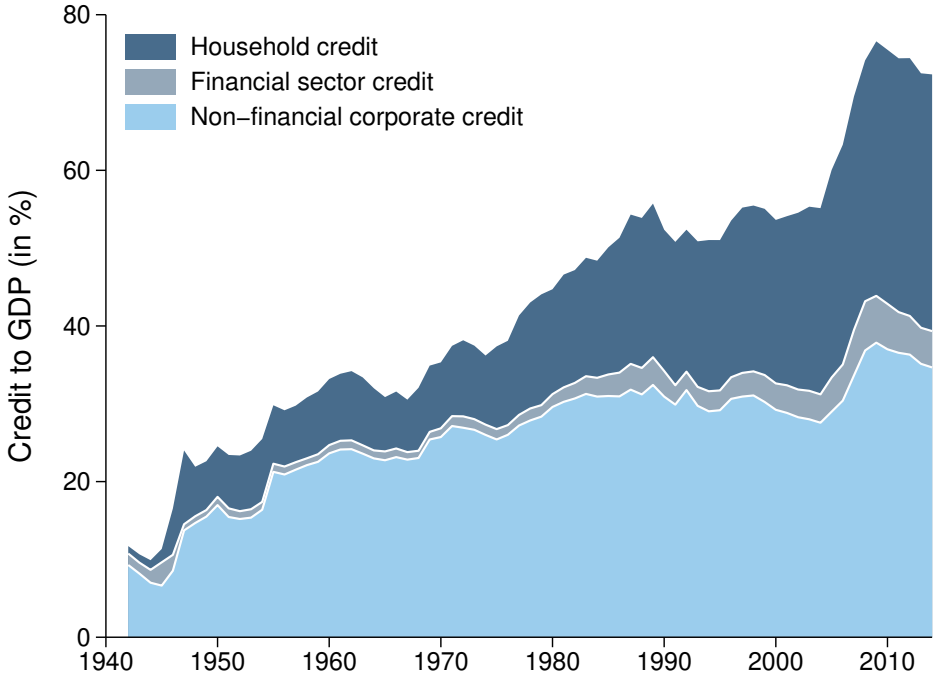
Panel A: Non-tradable, tradable, and household sector credit				
	Dependent variable: Crisis within...			
	1 year	2 years	3 years	4 years
Tradables	-0.004	-0.007	-0.008	-0.006
	(0.008)	(0.010)	(0.010)	(0.008)
Non-tradables	0.047**	0.057**	0.063**	0.056**
	(0.012)	(0.010)	(0.013)	(0.017)
Households	0.016	0.033**	0.042**	0.048**
	(0.010)	(0.011)	(0.013)	(0.014)
Observations	1,833	1,838	1,842	1,845
# Countries	84	84	84	84
# Crises	57	56	56	56
AUC	0.72	0.71	0.69	0.68
SE of AUC	0.03	0.02	0.02	0.02
Panel B: Individual corporate sectors				
	Dependent variable: Crisis within...			
	1 year	2 years	3 years	4 years
Agriculture	0.005	0.006	0.000	-0.006
	(0.006)	(0.011)	(0.014)	(0.013)
Manuf. and Mining	-0.010	-0.015	-0.013	-0.006
	(0.011)	(0.013)	(0.012)	(0.010)
Construction and RE	0.044**	0.052**	0.049**	0.040**
	(0.013)	(0.011)	(0.009)	(0.010)
Trade, Accommodation, Food	0.021*	0.030**	0.039**	0.041**
	(0.008)	(0.009)	(0.012)	(0.014)
Transport, Communication	-0.004	-0.007	-0.006	-0.012
	(0.007)	(0.007)	(0.009)	(0.013)
Households	0.014	0.031*	0.041**	0.048**
	(0.011)	(0.012)	(0.013)	(0.013)
Observations	1,833	1,838	1,842	1,845
# Countries	84	84	84	84
# Crises	57	56	56	56
AUC	0.74	0.72	0.71	0.70
SE of AUC	0.03	0.02	0.02	0.02

This table presents the results of the following multivariate linear regression model:

$$Crisis_{it+1\ to\ it+h} = \alpha_i^{(h)} + \sum_{k \in K} \beta_k^{(h)} \Delta_3 d_{it}^k + \epsilon_{it+1\ toit+h}$$

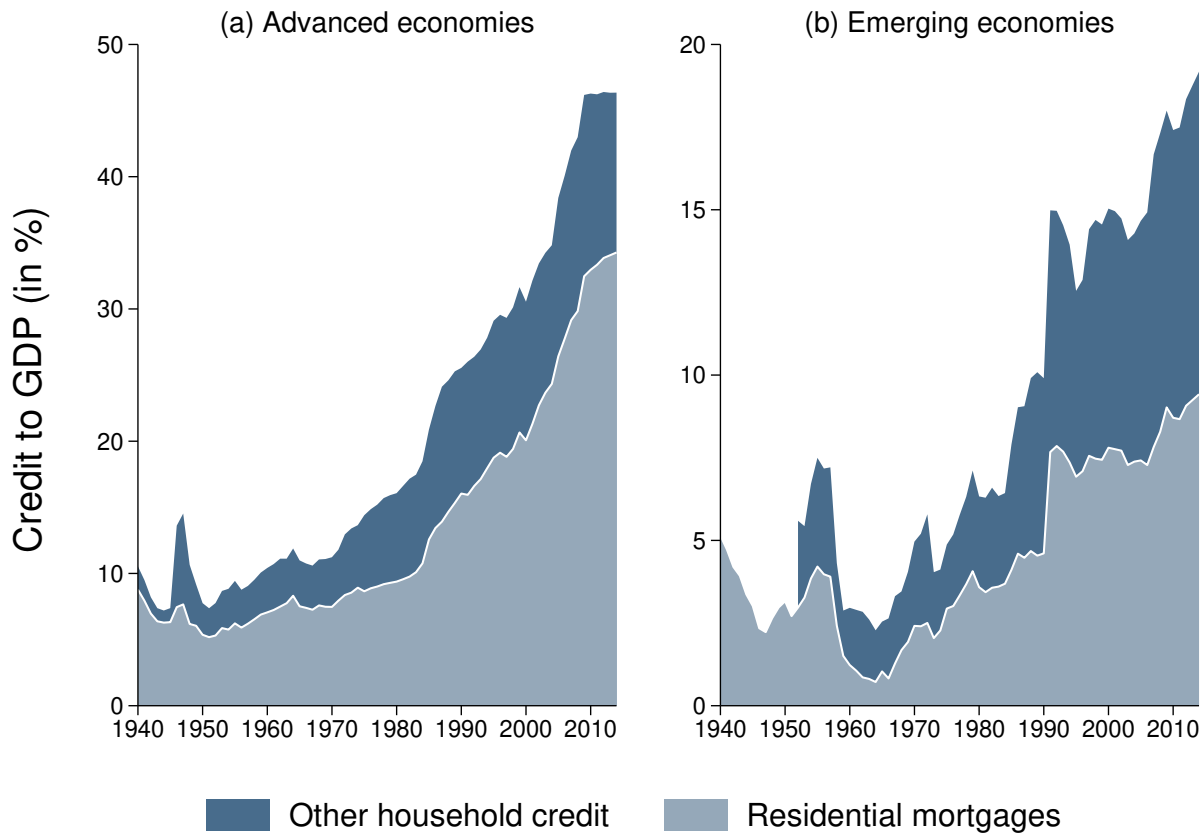
where $Crisis_{it+1toit+h}$ is a dummy variable that equals one for the start of a systemic banking crisis within h years, $\alpha_i^{(h)}$ is a country fixed effect and $\sum_{k \in K} \beta_k^{(h)} \Delta_3 d_{it}^k$ describes a vector of changes in the credit/GDP ratio from $t-3$ to t. In Panel A, we differentiate between the tradable, non-tradable, and household sectors. In Panel B, we use individual corporate sectors. Driscoll and Kraay (1998) standard errors in parentheses allow for lags of 0, 2, 3, and 5 years in columns 1-4, respectively. +, * and ** denote significance at the 10%, 5% and 1% level.

Figure 2: Private Credit to GDP, by Sector



Sample: 51 advanced and 46 emerging economies, 1940-2014.
Notes: Average ratio of sectoral credit to GDP (unweighted).

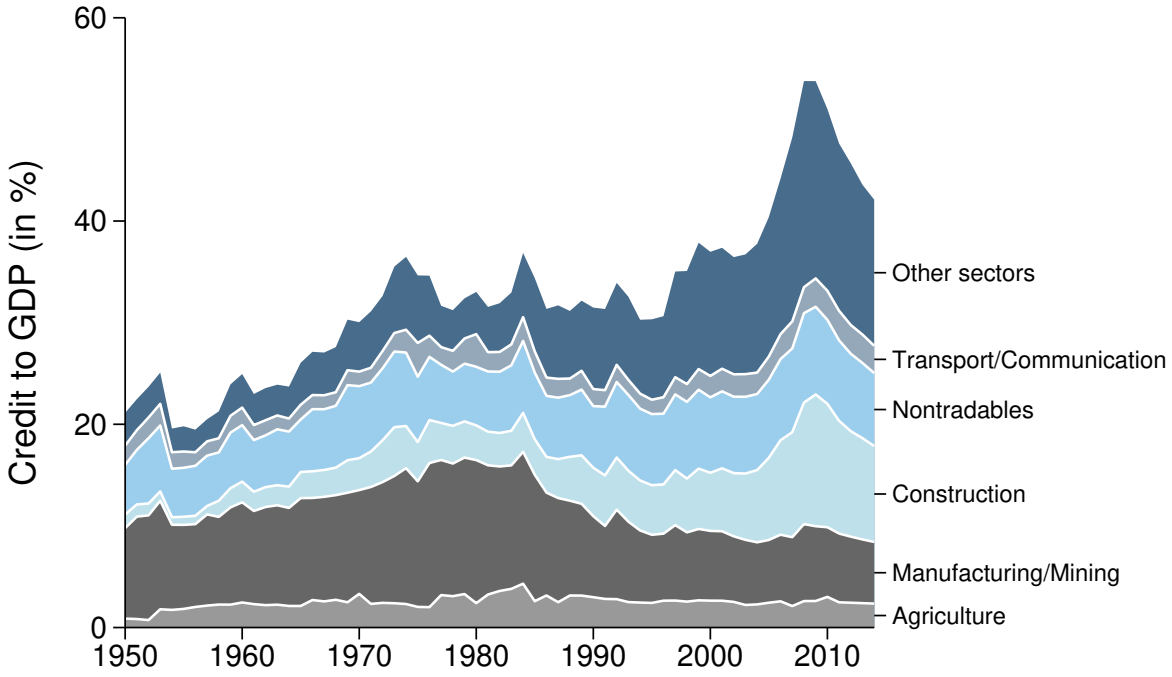
Figure 3: Household Credit to GDP, by Type and Country Group



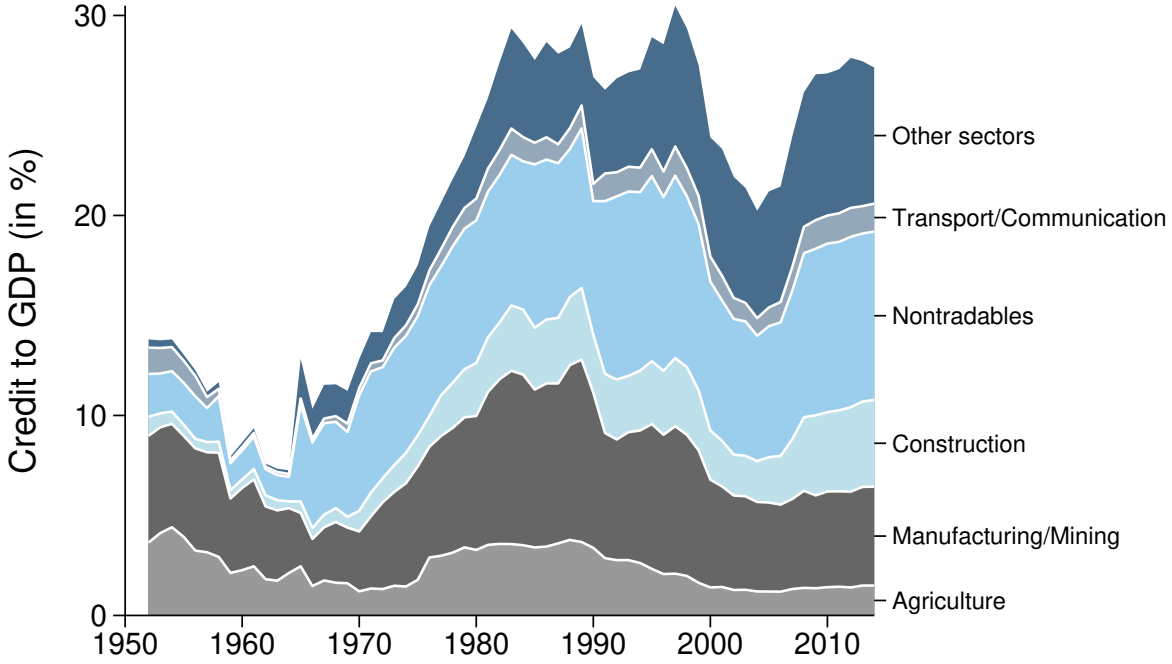
Sample: 49 advanced and 49 emerging economies, 1940-2014.
Notes: Average ratio of household credit to GDP (unweighted) split by type.

Figure 4: Corporate Credit Composition, by Country Group

(a) Advanced Economies



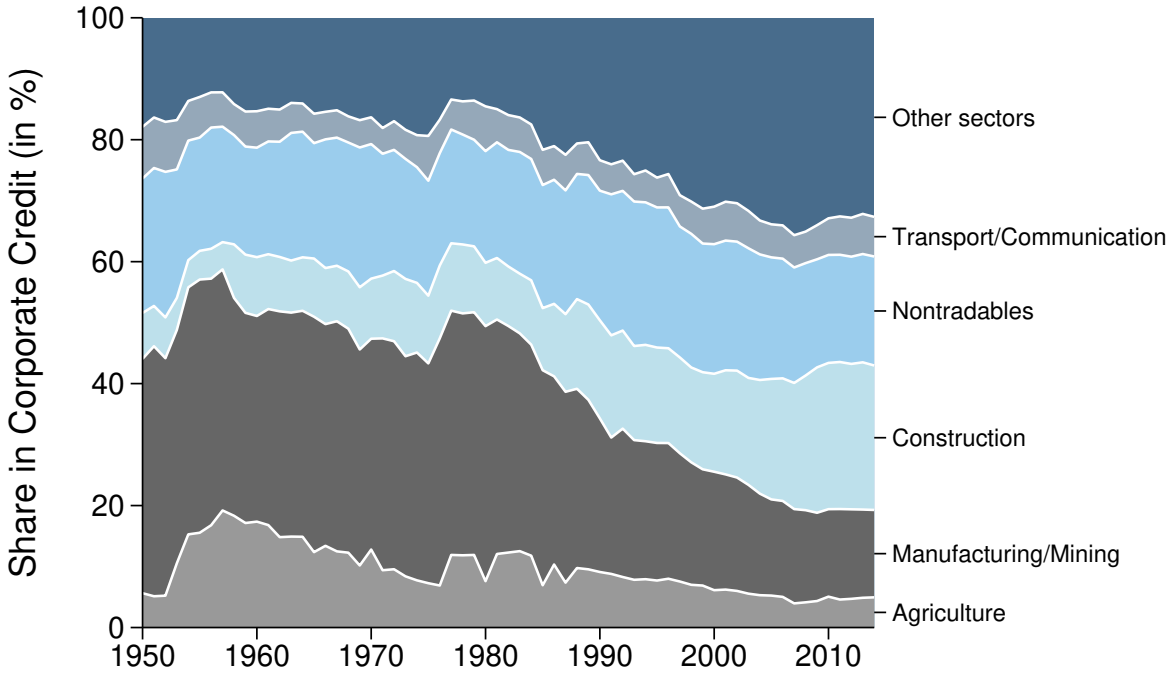
(b) Emerging Economies



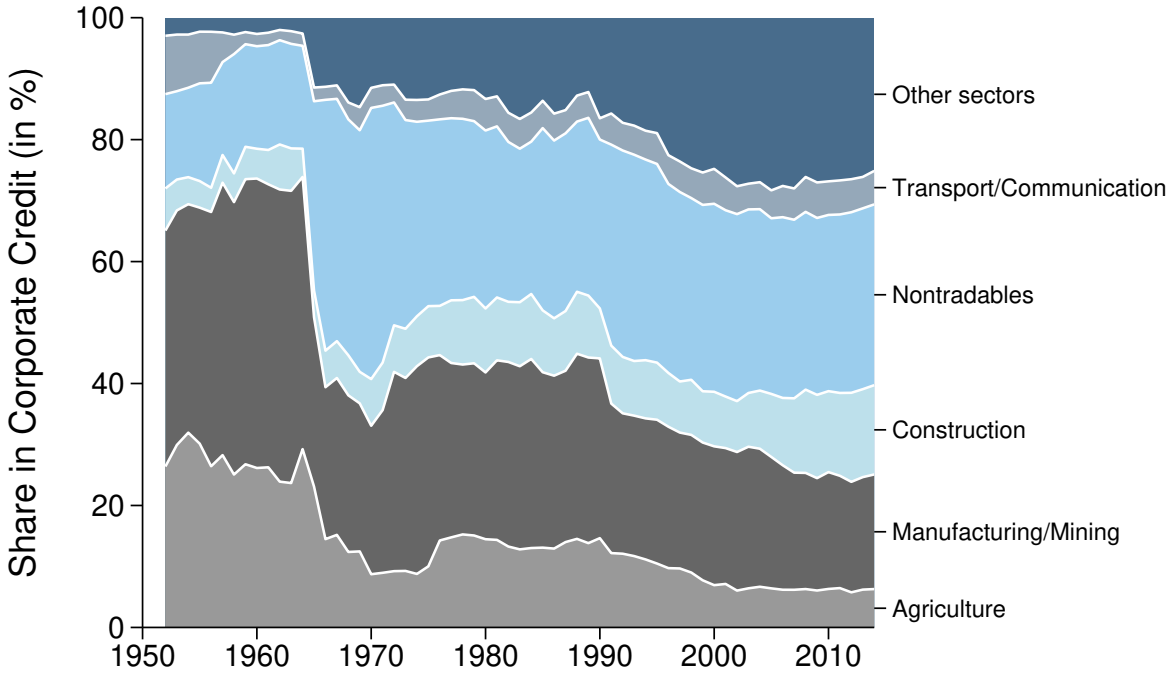
Sample: 35 advanced and 35 emerging economies, 1940-2014.
Notes: Panel A plots the average ratio of non-financial corporate credit to GDP (unweighted) for advanced economies, Panel B the average ratio for emerging economies.

Figure 5: Sector Shares in Corporate Credit

(a) Advanced economies



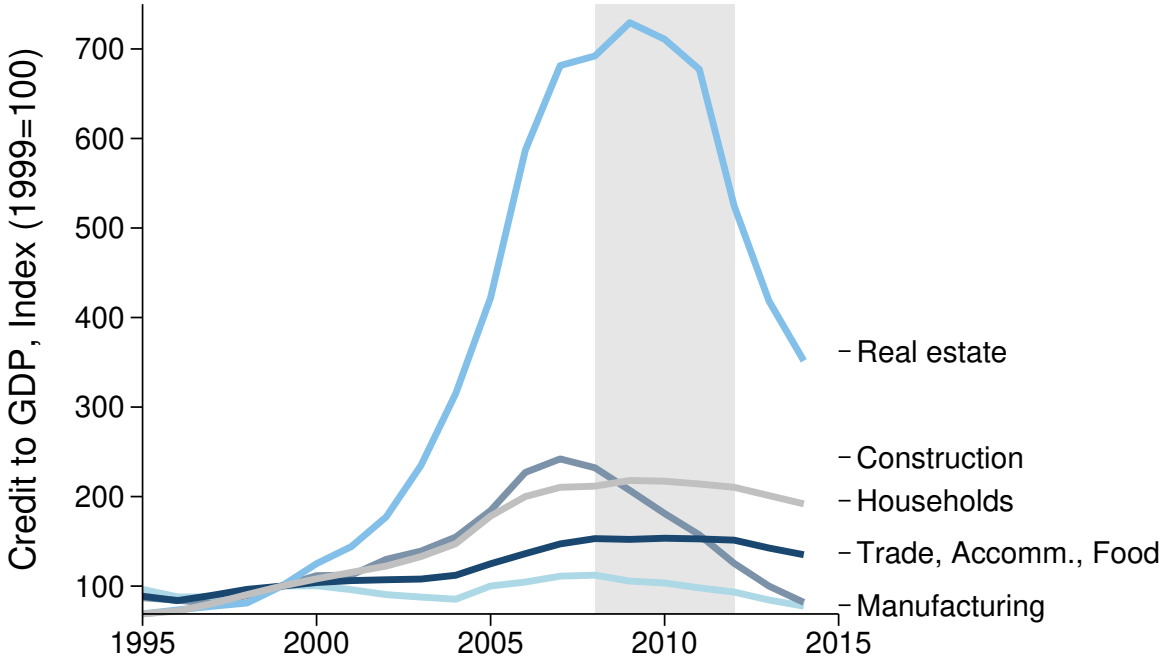
(b) Emerging economies



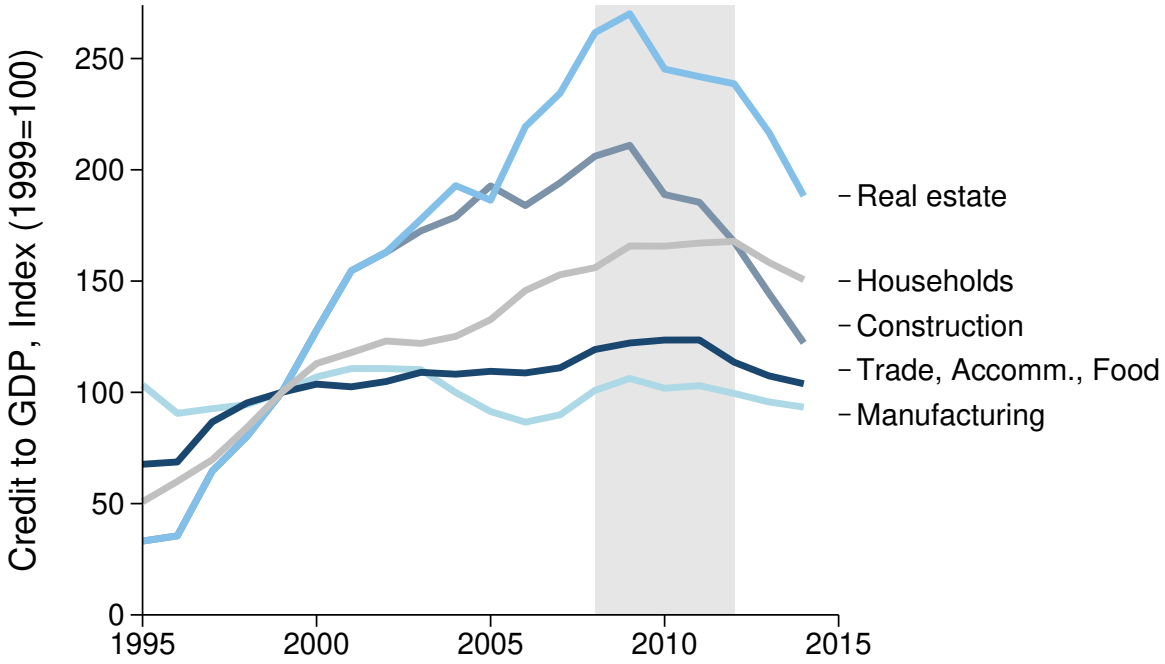
Sample: 35 advanced and 46 emerging economies.
Notes: Average ratio of individual sectors in total corporate credit.

Figure 6: The Spanish and Portuguese Financial Crises

(a) Spain



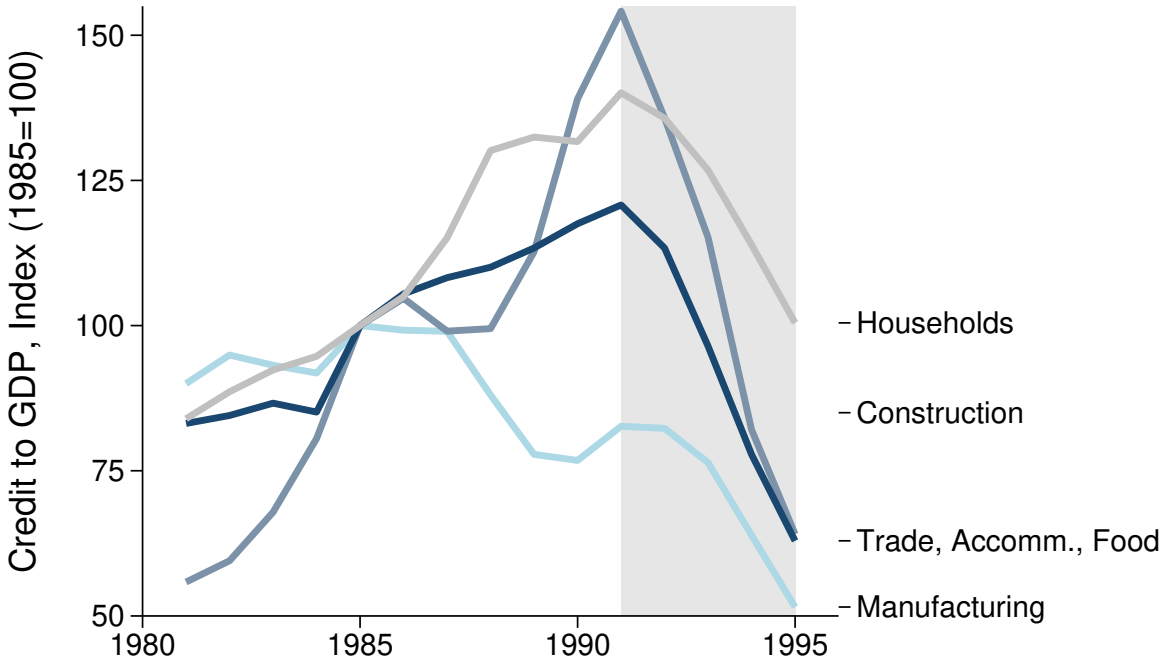
(b) Portugal



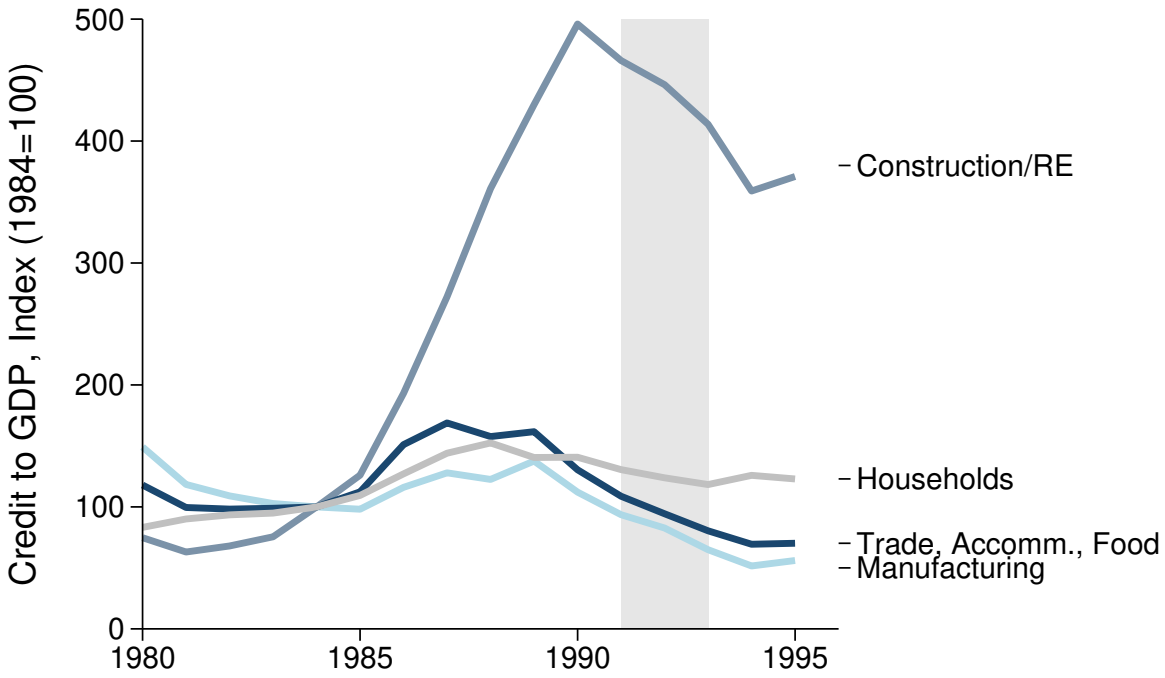
Notes: This figure plots the ratio of sectoral credit to value added for the construction (ISIC Rev. 4 section F), real estate (L), trade/accommodation/food (G + I), and manufacturing (C) industries around the time of the Eurozone crisis. We also plot data on household credit to GDP. The areas shaded in gray mark years the countries were in a systemic banking crisis as defined by Laeven and Valencia (2018).

Figure 7: The Finnish and Norwegian Financial Crises

(a) Finland



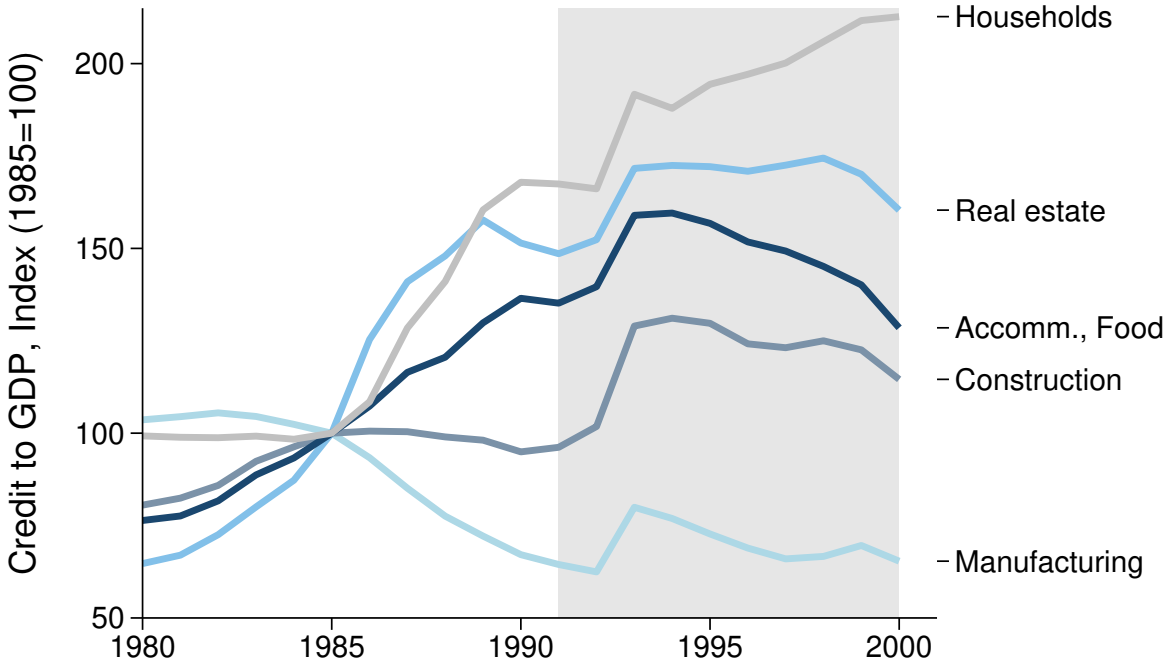
(b) Norway



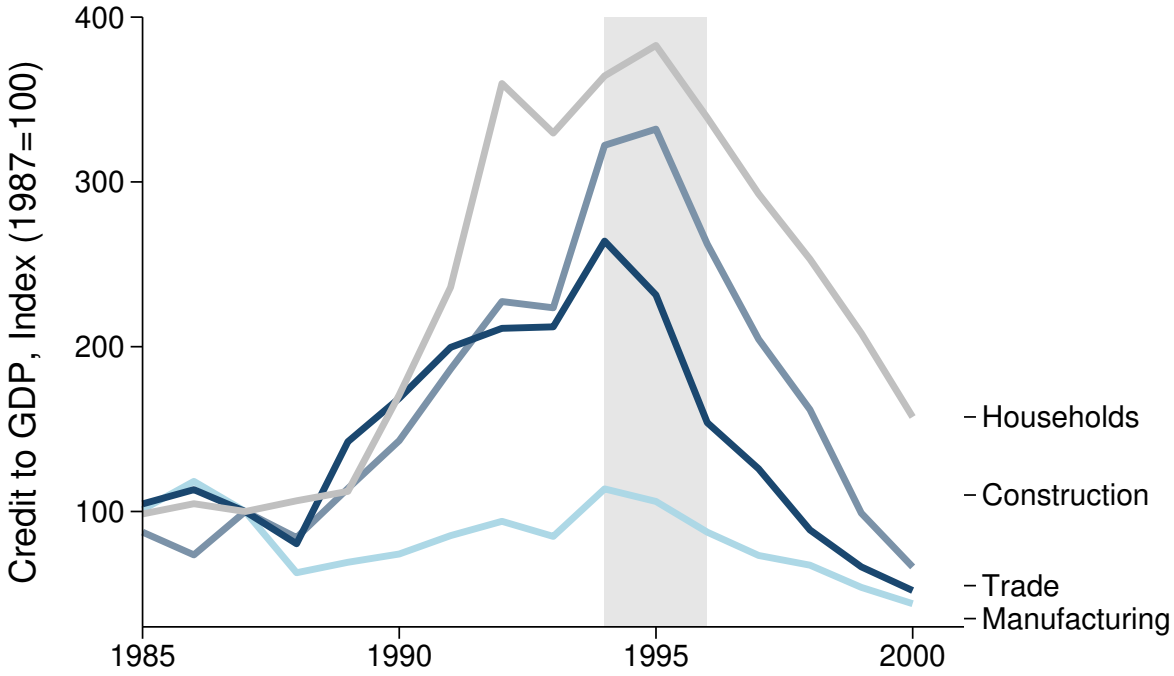
Notes: This figure plots the ratio of sectoral credit to value added for the construction (ISIC Rev. 4 section F), construction/real estate (F + L), trade/accommodation/food (G + I), and manufacturing (C) industries around the time of the Scandinavian banking crises. We also plot data on household credit to GDP. The areas shaded in gray mark years the countries were in a systemic banking crisis as defined by Laeven and Valencia (2018).

Figure 8: The 1991 Japanese and 1994 Mexican Financial Crises

(a) Japanese Crisis

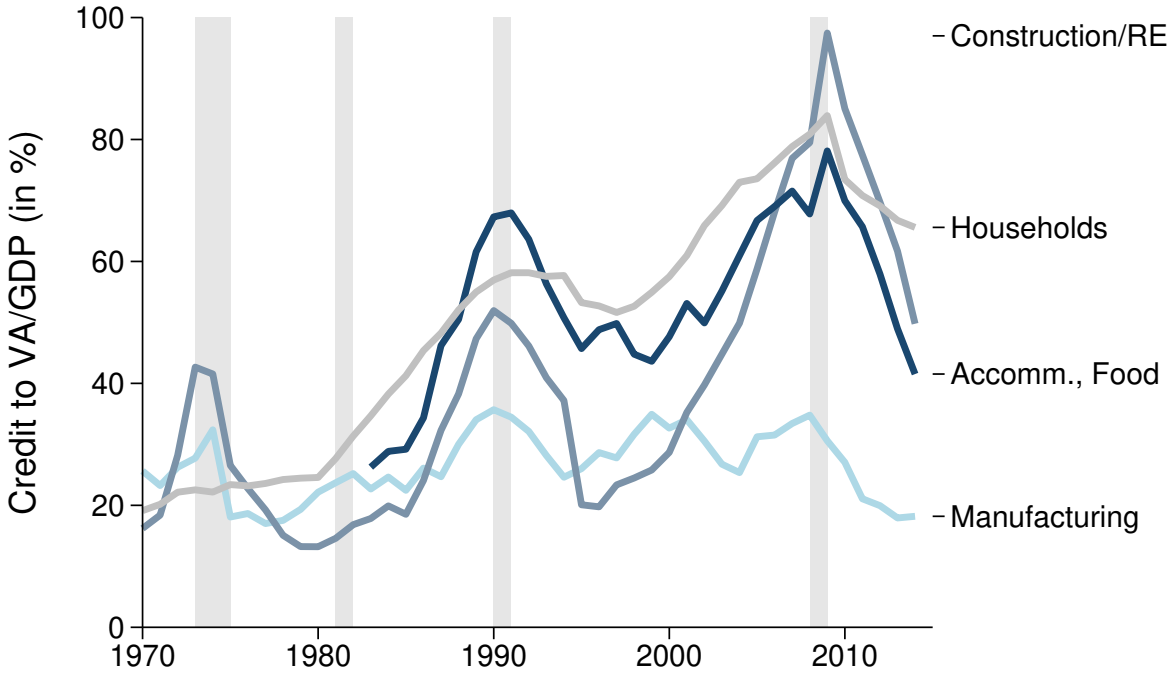


(b) Mexican Tequila Crisis



Notes: These figures plot the ratio of sectoral credit to value added for the construction (ISIC Rev. 4 section F), real estate (L), trade (G), accommodation/food (I), and manufacturing (C) industries around the time of the early 1990s Japanese and Mexico banking crises. We also plot data on household credit to GDP. The areas shaded in gray mark the onset of the Japanese 1991 crisis in panel (a) and the years Mexico was in a banking crisis according to Laeven and Valencia (2018) in panel (b).

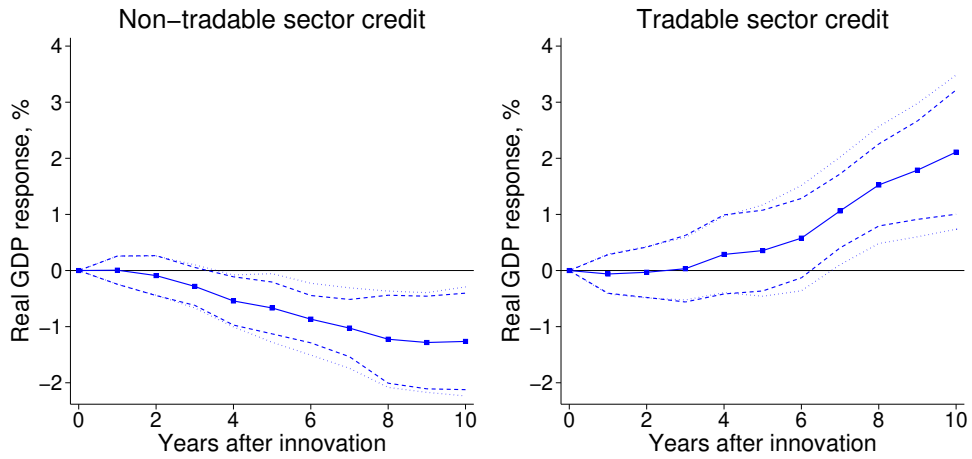
Figure 9: Industry Leverage and Household Debt Cycles in the United Kingdom



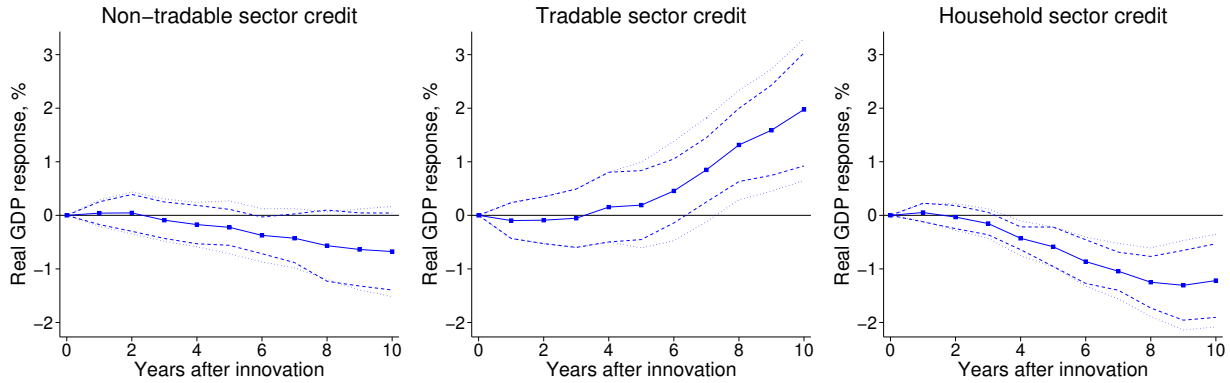
Notes: This figure plots the ratio of sectoral credit to value added for the construction/real estate (ISIC Rev. 4 sections F + L), accommodation/food (section I), and manufacturing (section C) industries between 1970 and 2014. We also plot data on household credit to GDP. The areas shaded in gray are recession years.

Figure 10: Output Dynamics after Credit Expansions in Tradable, Non-Tradable, and Household Sectors

(a) Non-tradable and Tradable Sector Credit



(b) Non-tradable, Tradable, and Household Sector Credit



Notes: This figure presents local projection impulse responses of real GDP following innovations in tradable sector credit, non-tradable sector credit, and household credit (all measured relative to GDP).

Panel (a) presents local projection impulse response estimates from:

$$\Delta_h y_{it+h} = \alpha_i + \sum_{j=0}^{J} \beta_j^{NT} \Delta d_{it-j}^{NT} + \sum_{j=0}^{J} \beta_j^{T} \Delta d_{it-j}^{T} + \sum_{j=0}^{J} \gamma_j \Delta y_{it-j} + \epsilon_{it+h}, \quad h = 1, ..., H.$$

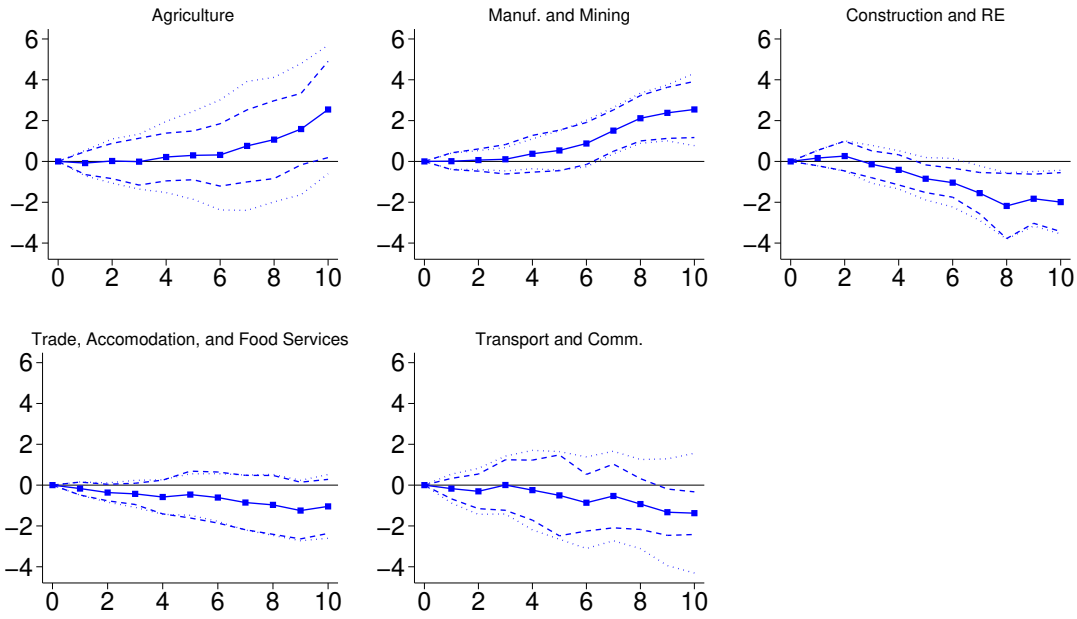
Panel (b) present the same specification but also includes household credit:

$$\Delta_h y_{it+h} = \alpha_i + \sum_{j=0}^{J} \beta_j^{NT} \Delta d_{it-j}^{NT} + \sum_{j=0}^{J} \beta_j^{T} \Delta d_{it-j}^{T} + \sum_{j=0}^{J} \beta_j^{HH} d_{it-j}^{HH} + \sum_{j=0}^{J} \gamma_j \Delta y_{it-j} + \epsilon_{it+h}, \quad h = 1, ..., H.$$

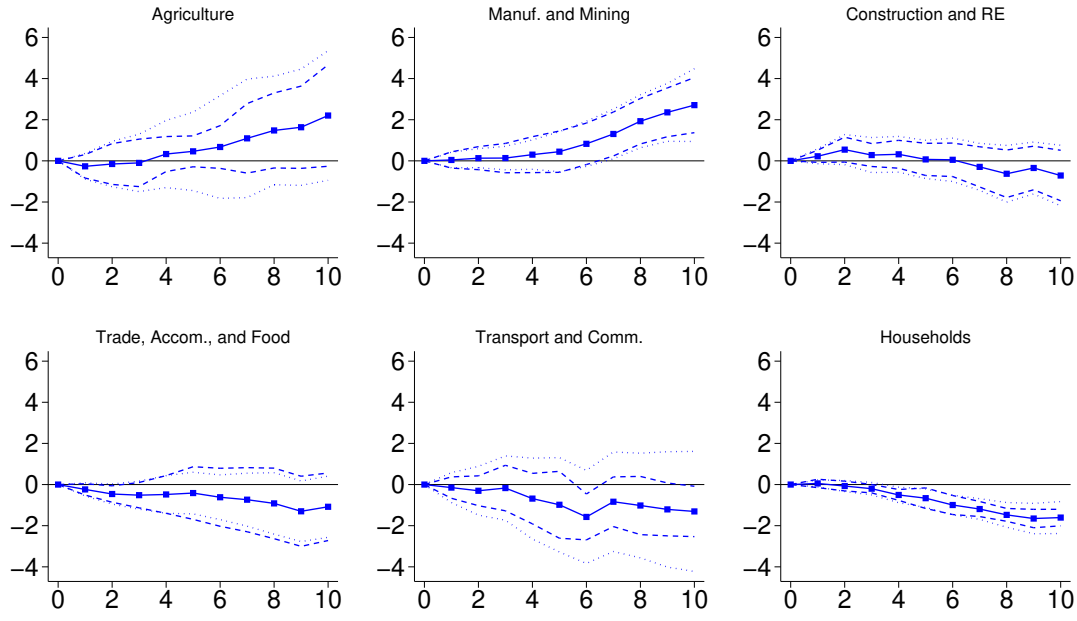
Dashed lines represent 95% confidence intervals computed using Driscoll-Kraay standard errors, and dotted lines represent 95% confidence intervals from standard errors two-way clustered on country and year.

Figure 11: Output Dynamics after Credit Expansions: Unpacking Corporate Sector Credit Expansions

(a) Non-financial Corporate Sectors



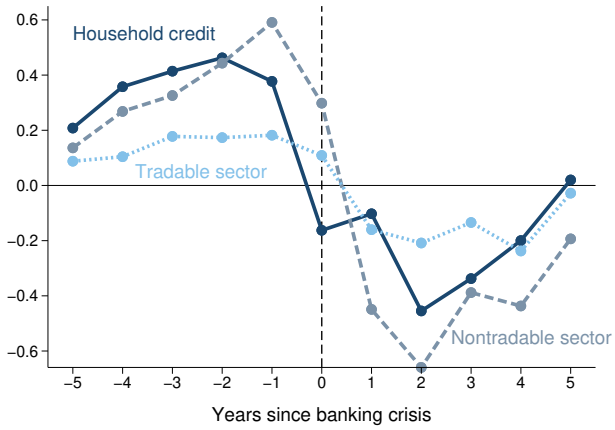
(b) Non-financial Corporate Sectors and Household Sector Credit



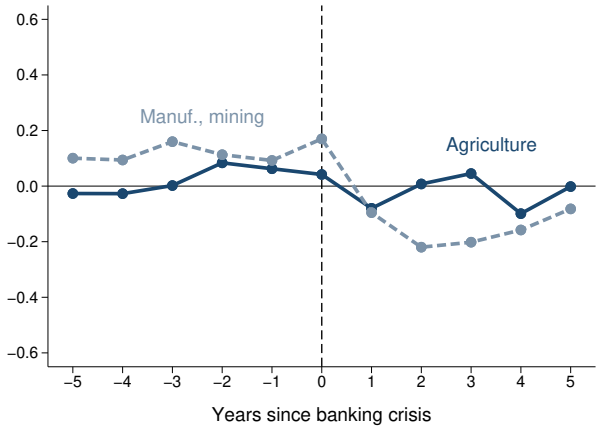
Notes: This figure presents local projection impulse response of real GDP to innovations in the sectoral credit to GDP ratio from estimating Equation (3). Responses are estimated for credit in Agriculture, Mining and Manufacturing (Tradables), Construction and Real Estate, Wholesale and Retail Trade, and Transport and Communications (Non-tradables). Dashed lines represent 95% confidence intervals computed using Driscoll-Kraay standard errors, and dotted lines represent 95% confidence intervals from standard errors two-way clustered on country and year.

Figure 12: Credit Dynamics Around Systemic Banking Crises

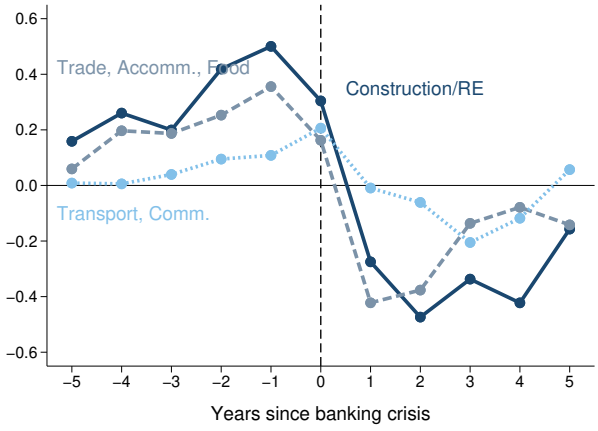
(a) Tradable vs. Non-Tradable Sector



(b) Tradable Sector Industries



(c) Non-Tradable Sector Industries



Notes: This figure plots average changes in the sectoral credit-to-GDP ratio around systemic banking crises in 84 countries between 1951 and 2009. The horizontal axis represents the number of years before and after a crisis. The credit growth variables are standardized to have a mean of zero and standard deviation of one, and are de-meaned by country.

Table 5: Sectoral Credit Expansions and Financial Crises – Multivariate Regressions

						Tradables		Non-tradables		Households	
		N	# Countries	# Crises	AUC	β	$[t]$	β	$[t]$	β	$[t]$
(1)	Baseline (LPM, country FE)	1,842	84	56	0.69	-0.01	-0.81	0.06	4.75**	0.04	3.22**
(2)	LPM, country + year FE	1,842	84	56	0.69	0.00	0.33	0.05	2.60*	0.03	3.61**
(3)	Logit	1,842	84	213	0.69	0.00	0.22	0.05	3.27**	0.03	2.77**
(4)	Logit, country FE	1,052	37	207	0.69	-0.02	-0.70	0.13	3.67**	0.10	4.30**
(5)	Logit, RE-Mundlak	1,842	84	213	0.86	-0.01	-0.56	0.04	3.42**	0.04	3.14**
(6)	Lags of 1-year changes	1,837	84	213	0.69	-0.01	-0.79	0.09	4.85**	0.05	3.14**
(7)	Boom (>= Mean + 2 $\times$ SD)	1,842	84	56	0.59	0.03	0.44	0.27	3.65**	0.12	2.31*
(8)	Boom (>= 80th percentile)	1,842	84	56	0.69	0.00	0.12	0.09	5.15**	0.15	4.07**
(9)	RR dates	1,081	45	138	0.63	-0.04	-1.25	0.11	3.20**	0.02	0.81
(10)	LV dates only	1,709	83	36	0.65	-0.01	-0.97	0.04	3.82**	0.03	1.78+
(11)	BVX dates only	1,032	37	42	0.74	0.00	-0.12	0.08	4.64**	0.05	3.74**
(12)	Pre-2000 only	1,089	56	29	0.63	-0.02	-2.36*	0.07	4.69**	0.05	2.95**
(13)	Advanced economies	1,031	38	36	0.72	-0.01	-0.64	0.06	4.08**	0.04	2.90**
(14)	Emerging economies	811	46	20	0.65	-0.01	-0.54	0.07	3.43**	0.04	2.38*
(15)	Value added controls	703	44	30	0.70	-0.01	-0.32	0.08	3.23**	0.03	1.61
(16)	Credit/value added	703	44	30	0.69	0.04	2.06*	0.07	2.62*	0.03	2.47*

This table presents the results of variants of the following multivariate linear regression model:

$$Crisis_{it+3} = \alpha_i + \beta_1 \Delta_3 d_{it}^T + \beta_2 \Delta_3 d_{it}^{NT} + \beta_3 \Delta_3 d_{it}^{HH} + \epsilon_{it+3}$$

where $Crisis_{it+3}$ is a dummy variable that equals one for the start of a systemic banking crisis in country i over the next three years, α_i is a country fixed effect and $\Delta_3 d_{it}^T$, $\Delta_3 d_{it}^{NT}$, and $\Delta_3 d_{it}^{HH}$ are changes in the credit/GDP ratio for the tradable, non-tradable, and household sectors from $t-3$ to t. We compute Driscoll and Kraay (1998) standard errors with 2 lags, except for logit models. +, * and ** denote significance at the 10%, 5% and 1% level.

Model (1) is our baseline specification, a linear probability model (LPM) with country fixed effects (FE), where banking crises are defined as in Baron et al. (2019) and Laeven and Valencia (2018) for the remaining countries. Model (2) adds year FE. Model (3) is a logit model with standard errors clustered by country. Model (4) reports results from a conditional/FE logit model, which drops countries that never experienced a crisis. Model (5) is a random effects logit model that includes averages of the dependent and independent variables as covariates, as suggested by Mundlak (1978). Model (6) replaces the independent variables in the baseline model with three lags of one-year changes in credit/GDP; we report linear combinations of the coefficients. Model (7) replaces the independent variables with dummy variables equal to one if the 3-year change in credit/GDP is equal to its mean plus two standard deviations or higher. Model (8) creates a similar credit boom indicator following Greenwood et al. (2020) equal to one if the 3-year change in credit/GDP is equal to its 80th percentile or higher. Model (9) uses the systemic banking crisis dates from Reinhart and Rogoff (2009b). Model (10) only uses crisis dates from Laeven and Valencia (2018), and model (11) only the dates from Baron et al. (2019). Model (12) restricts the sample to the years before 2000. Models (13) and (14) restrict the sample to countries classified as high-income and low-income/middle-income by the World Bank in 2019, respectively. Model (15) controls for three-year changes in sectoral value added/GDP. Model (16) replaces d_{it}^T and d_{it}^{NT} with versions scaled over value added instead of GDP.

In Table 5, we subject these baseline findings to a range of robustness tests. We start by again considering multivariate regressions with all credit terms, as in Table 4. We focus on estimates from running Equation (4) with a 3-year horizon.

The first set of exercises explores different model specifications. Row (2) adds year fixed effects to our baseline model to soak up waves of financial crises or global cycles in the same year. Rows (3)-(5) estimate Equation (4) using nonlinear estimators; we report marginal effects. In particular, we consider a standard logit model, a "fixed effects" (conditional) logit model, and a random effects logit model including country-specific averages of all variables proposed by Mundlak (1978). The random effects approach allows for an unbiased estimation of nonlinear panel models by replacing year fixed effects with averages of the dependent and independent variables, which (i) gets around the well-known incidental parameter bias issue, and (ii) allows us to keep countries that never experienced a crisis in the sample, which are dropped in a nonlinear "fixed effects" model; see Caballero (2016) for an application to banking crises. These alternative estimation methods yield very similar results compared to our baseline estimates.

Row (6) replaces three year changes of credit/GDP ($\Delta_3 d_{it}^k$) with three lags of one-year changes (Δd_{it}^k) and reports linear combinations of the coefficients, similar to Schularick and Taylor (2012). Rows (7) and (8) define "credit booms" as periods where the three-year change in credit-to-GDP is two standard deviations above its mean (or higher), or alternatively in the top quintile of the distribution (as in Greenwood et al., 2020). Again, these exercises yield similar conclusions.

Next, we consider alternative chronologies of financial crises. Row (9) uses the dates compiled by Reinhart and Rogoff (2009b); rows (10) and (11) only use the data from either Baron et al. (2019) or Laeven and Valencia (2018). These tests result in widely differing samples, Laeven and Valencia (2018) cover many more countries than the other two chronologies. Nevertheless, the broad patterns remain consistent: credit to households, the non-tradable sector, and construction/real estate continues to dominate these regressions, with no role for manufacturing credit.

We also consider sub-samples of the data. Row (12) restricts the sample to the period before 2000, while rows (13) and (14) differentiate between advanced and emerging economies. These splits reveal one important fact: credit expansions in the non-tradable sector are a fairly universal precursor of crises.

As a last exercise, we again investigate whether sectoral credit growth merely captures increases in sector size or higher leverage. We follow the approach used in the local projections above and either control for the shares of value added in GDP (in row 15) or replace growth in credit-to-GDP with growth in credit-to-value added. The results from these exercises suggest again that credit expansions in non-tradables and the household sector are more closely associated with future crises.

Table A1 in the Online Appendix provides additional robustness when breaking up the non-tradable and tradable sectors in their subcomponents. This shows that credit to construction and real estate as well as trade, acommodation, and food services are robust predictors of crises similar to household debt. In Table A2, Table A3, and Table A4, we consider univariate regressions where we enter credit growth to sector k one-by-one, rather than holding fixed credit in sector $k' \neq k$. These exercises confirm our baseline findings that lending to the non-tradable household sectors drives the relationship between credit expansions and financial crises. While tradable sector credit is at times also correlated with future crises in univariate regressions, the predictive ability of these models (as measured by the AUC) is much lower than that of models with only non-tradable services or households. Differences in the AUCs also suggest that lending to households or the construction and real estate sectors are less reliable predictors both in the pre-2000 period and particularly in emerging economies.

The patterns we document here have several important implications. First, they suggest that the sectoral allocation of credit expansions matters for the build-up of financial sector risks. Non-tradable sector and household credit expansions pose greater financial stability risks than tradable sector credit expansions. Second, while household debt and construction/real estate play an important role, banking crises are not solely driven by housing. In both advanced and emerging economies, we find a robust role for credit to other non-tradable sectors, in particular trade, accomodation, and food services. As we discuss in the next section, non-tradable sector credit may be a reflection of expanding household credit demand, but may also pose additional financial stability risks because of financing and enforcement constraints in the nontraded sector. Third, this new evidence from sectoral credit helps in interpreting the mixed results of prior studies on the role of corporate debt in predicting business cycle downturns and crises. Corporate credit expansions financing non-tradables and tradables appear to have starkly different implications for financial stability. This perspective only becomes clear from looking at disaggregated credit data, which are not available in other datasets lending to the private sector.

5 Discussion

Why are lending booms to the non-tradable and household sector—but not to the tradable sector—followed by growth slowdowns and increased financial crisis risk? In this section, we discuss theories that can shed light on these findings.

First, what drives increases in credit? The case studies in section 4.1 highlight that credit booms are often followed by events that lead banks to expand the supply of available credit, such as financial liberalization, increased banking competition, or capital inflows. Indeed, Mian et al. (2017) and Krishnamurthy and Muir (2017) find that credit expansions are associated with lower

credit spreads, which then spike during crises. Existing work has emphasized a role for collateral quality (Gorton and Ordoñez, 2014, 2019), lending standards (Greenwood and Scharfstein, 2013; Kirti, 2018), and overoptimistic beliefs on the part of borrowers and lenders (e.g. Geanakoplos, 2010; Burnside et al., 2016; Bordalo et al., 2018). In the discussion that follows, we do not take a stand on what drives different types of credit expansions. Instead, we take these expansions as given and discuss how they may interact with growth and financial stability.

Demand boom and bust Credit booms that finance an increase in demand have contrasting effects on the tradable sector versus the non-tradable and household sectors. Expanded access to credit leads households to expand borrowing to finance consumption. This leads to higher demand for domestic non-tradables, increasing the size of the non-tradable sector and the price of non-tradables Mian and Sufi (2018); Mian et al. (2020). In turn, credit to the non-tradable sector may expand as the sector increases in size. If the non-tradable sector is financing constrained, the increase in demand and price of non-tradables can relax borrowing constraints, leading to higher non-tradable sector leverage. In part, therefore, a non-tradable credit expansion may simply reflect a credit-financed demand boom. If such an expansion is accompanied by an increase in the real exchange rate, credit demand of the tradable sector may even fall due to a loss of competitiveness. Credit expansion that primarily finances demand pushes up wages and prices and leads to a reallocation away from tradables. This leaves the economy more vulnerable to a reversal in credit conditions. In particular, downward nominal rigidity along with frictions in monetary policy imply that elevated debt and a reduction in credit availability depresses spending and leads to a demand-driven bust (Eggertsson and Krugman, 2012; Korinek and Simsek, 2016; Schmitt-Grohé and Uribe, 2016). This mechanism is close to a widely accepted view about the sources of the Eurozone crisis (Brunnermeier and Reis, 2019).

Asymmetric financing constraints The non-tradable sector may disproportionately benefit from credit booms not just because it is more exposed to demand booms but also because it is initially more financing-constrained. Many studies in the international finance literature argue that financial frictions, such as contract enforcement problems or asymmetric information, are more severe in the non-tradable sector, in part because the typical firm in the non-tradable sector is small (e.g. Tornell and Westermann, 2002; Schneider and Tornell, 2004; Kalantzis, 2015); For example, in the model of **?**, it is more difficult for bank creditors to monitor loans issued to the non-tradable compared to the tradable sector. This implies that an increase in bank credit supply (e.g., driven by capital inflows) leads to a larger reduction in spreads on loans to the non-tradable sector and thus a larger increase in lending to the non-tradable sector.

If the non-tradable and household sectors are subject to more severe financing constraints, leverage in the non-tradable and household sectors may pose a higher risk of a crisis. In **?**, a reversal of capital flows leads to a sharp increase in the cost of borrowing in the non-tradable sector and a resulting fall in output. In emerging markets, where debt is often denominated in foreign currencies, a self-fulfilling currency crisis tightens balance sheets for non-tradables, which leads to a sharp fall in non-tradable output (Schneider and Tornell, 2004). Kalantzis (2015), for example, shows that such a crisis is more likely to occur after an increase in the size of the non-tradable sector. Reallocation frictions to the tradable sector imply that the fall in output is not offset by more tradable activity in the short run (Kehoe and Ruhl, 2009).

Collateral and cash flow constraints An abundance of credit may also disproportionately benefit sectors with more easily collateralizable assets, such as housing. Credit booms are often coupled with rising house prices, which increases collateral values and supports greater lending to households, construction and real estate firms, and other sectors where land and structures are more likely to be used as collateral (Chaney et al., 2012).

A sharp fall in collateral values then leads to reduced access to credit and a fall in spending or investment, as in the classic credit cycles model of Kiyotaki and Moore (1997). However, the evidence on financial crises in Section 4.3 shows that, while housing and real estate play an important role, they are not the whole story. Credit to other non-tradable industries such as trade, accommodation, and food services, industries usually also increases before crises. While real estate assets may also be important for firms in these industries, data on liquidation values of assets in Kermani and Ma (2020) suggest that, in the United States, firms in the whole/retail/restaurant sectors do not have particularly high liquidation values.

In some models, firms' borrowing capacity depends on the cash flows their operations generate (e.g. Stiglitz and Weiss, 1981; Holmstrom and Tirole, 1997). In open economy models, financial constraints also depend on current income (e.g. Mendoza, 2002). In line with this intuition, Lian and Ma (2020) show that most debt of US non-financial corporations is cash flow-based rather than asset-based. However, their data suggest that the wholesale/retail/restaurant sector ("Shops" in their Figure II) does not disproportionately rely on cash flow-based lending, at least in the United States.

A related argument is that differences in industry liquidity could generate asymmetric boom-bust patterns. In Diamond et al. (2020), the anticipation of high liquidation values in the future allows firms to increase their leverage but can crowd out their pledgeability (or willingness to commit cash flows). During downturns, when the liquidity of industry insiders declines, this can lead to sell-off of assets to less productive outsiders, which reduces average productivity (also see Shleifer and Vishny, 1992). While they model a single industry, sectoral differences in the

cyclicality of industry liquidity (e.g. higher cyclicality in construction and real estate) could give rise to differential boom-bust cycles.

Misallocation Credit booms can also sow the seeds of slower growth through a misallocation of resources. Credit expansion financing households and non-tradable sector firms can contribute to intersectoral misallocation, as productivity growth is often faster in the tradable industries such as manufacturing. Benigno and Fornaro (2014) build a two-sector model, where a fall in the interest rate fuels a demand boom that shifts resources from the (productive) tradable to the (stagnant) non-tradable sector. Because of learning by doing in the tradable sector, this leads to a slowdown in productivity growth (although not a financial crisis). In the model of Matsuyama (2008) (Section 5.2), a shock to the net worth of borrowers leads to credit reallocation towards less productive firms with higher private benefits, which leads to an economic slowdown. Rodrik and Subramanian (2009) argue that the limited growth benefits from financial globalization are explained by capital inflows appreciating the real exchange rate and thereby hurting the tradable sector.

Existing evidence broadly supports this view. Reis (2013) suggests that capital inflows led to misallocation in Portugal in the 2000s. Borio et al. (2016) shows that credit growth is accompanied by lower labor productivity growth in a sample of 21 advanced economies. Paul (2017) shows that banking crises in 17 advanced economies tend to follow declining total factor or labor productivity. Gorton and Ordoñez (2019) find that credit booms tend to start with higher productivity growth, which falls quickly during booms that end badly. Our results are consistent with this literature in that credit expansions in the non-tradable sector systematically predict downturns and crises, which could reflect misallocation.

Our work is also related to research on the role of financial frictions in explaining differences in capital misallocation across countries in the macro-development literature (e.g. Restuccia and Rogerson, 2008; Buera et al., 2011). Dynamic models with financial frictions (e.g. Midrigan and Xu, 2014; Moll, 2014), however, would usually predict that a decrease in financing frictions leads to capital inflows and improved capital allocation across firms, which increases productivity growth. Gopinath et al. (2017) use data on manufacturing firms in Spain to document an increased dispersion in the return to capital across firms before the Eurozone crisis, consistent with rising misallocation of resources.

Finance and growth Our evidence on the contrasting macroeconomic outcomes following different sectoral credit expansions also speaks to the literature on finance and growth. This literature finds a positive association between economic growth and measures such as private credit to GDP (e.g. Levine et al., 2000; Levine, 2005), while the more recent literature on credit cycles finds that credit growth predicts an elevated risk of financial crises and *lower* medium-run growth. Some of

this difference is likely explained by differences in the horizon, i.e. long-run growth vs. short-run credit booms (Loayza and Ranciere, 2006). But our sectoral evidence also suggests that which sector is borrowing may be key: tradable sector credit expansions are not associated with weaker growth and, in some cases, with stronger future growth.

6 Conclusion

There is increasing awareness that credit markets play a key role in macroeconomic fluctuations. However, a lack of comparable cross-country data on the structure of credit markets has left many questions unanswered. We make three main contributions that can be summarized as follows.

First, we show that credit allocation across different industries plays a role in business cycle fluctuations. Our results suggest that previous work has underestimated the potential role of corporate debt in macroeconomic outcomes because only credit growth in specific industries—construction and real estate, as well as other non-tradable sectors—predict a boom-bust pattern in output and higher likelihood of financial crises. Interpreted through the lens of models in the spirit of (Mendoza, 2002), this suggests that the effects of debt may not be created equal. Instead, credit expansions may affect the macroeconomy in a predictable manner depending on what they finance. The hope is that these patterns can serve as a starting point for models that systematically differentiate between the effects of different types of credit.

Second, we map a new set of stylized facts about the development of credit markets since World War II. The perhaps most striking feature is that, by many metrics, traditional firm lending has largely stalled between 1980 and today. This, however, hides a secular shift of corporate loans away from the tradable sector toward construction, real estate, and other non-tradable services. We also show that the "hockey stick" pattern of rising household credit in advanced economies has been largely mirrored by emerging economies, but with a key difference: most of the growth in household debt in emerging markets has been driven by consumer credit rather than lending for house purchases.

Third, we present a new database on private credit by economic sector for 116 countries. These data allow a first systematic look at the composition of credit around the world and what accounts for the secular rise in private debt around the world. Because of its disaggregated nature, we hope these data will be useful for many other applications bridging finance and macroeconomics.

References

Abildgren, K. (2007). Financial Liberalisation and Credit Dynamics in Denmark in the Post-World War II Period. Technical report.

Acharya, V. V., J. Imbs, and J. Sturgess (2011). Finance and Efficiency: Do Bank Branching Regulations Matter? *Review of Finance 15*(1), 135–172.

Bai, J. J., D. Carvalho, and G. M. Phillips (2018). The Impact of Bank Credit on Labor Reallocation and Aggregate Industry Productivity. *The Journal of Finance 73*(6), 2787–2836.

Barnett, C. (1982). Commercial Banking in Belize 1960-1980. *Social and Economic Studies 31*(4), 136–170.

Baron, M., E. Verner, and W. Xiong (2019). Banking Crises Without Panics. Technical report.

Baron, M. and W. Xiong (2017, 01). Credit Expansion and Neglected Crash Risk. *The Quarterly Journal of Economics 132*(2), 713–764.

Basel Commitee on Banking Supervision (2019). Towards a Sectoral Application of the Countercyclical Capital Buffer. Working Paper 36.

Beck, T., B. Büyükkarabacak, F. K. Rioja, and N. T. Valev (2012, March). Who Gets the Credit? and Does It Matter? Household Vs. Firm Lending across Countries. *The B.E. Journal of Macroeconomics 12*(1), 1–46.

Benigno, G. and L. Fornaro (2014, January). The Financial Resource Curse. *Scandinavian Journal of Economics 116*(1), 58–86.

Bertrand, M., A. Schoar, and D. Thesmar (2007). Banking Deregulation and Industry Structure: Evidence from the French Banking Reforms of 1985. *The Journal of Finance 62*(2), 597–628.

Betts, C. M. and T. J. Kehoe (2006, October). U.S. real exchange rate fluctuations and relative price fluctuations. *Journal of Monetary Economics 53*(7), 1297–1326.

Bordalo, P., N. Gennaioli, and A. Shleifer (2018). Diagnostic Expectations and Credit Cycles. *The Journal of Finance 73*(1), 199–227.

Borio, C., E. Kharroubi, C. Upper, and F. Zampolli (2016, January). Labour Reallocation and Productivity Dynamics: Financial Causes, Real Consequences. BIS Working Papers 534.

Borio, C. and P. Lowe (2002). Asset Prices, Financial and Monetary Stability: Exploring the Nexus. BIS Working Papers 114.

Brunnermeier, M. and R. Reis (2019, September). A Crash Course on the Euro Crisis. Working Paper 26229, National Bureau of Economic Research.

Brunnermeier, M. K., D. Palia, K. A. Sastry, and C. A. Sims (2019, August). Feedbacks: Financial Markets and Economic Activity. Working Papers 257, Princeton University, Department of Economics, Center for Economic Policy Studies.

Buera, F. J., J. P. Kaboski, and Y. Shin (2011, August). Finance and Development: A Tale of Two Sectors. *American Economic Review 101*(5), 1964–2002.

Burnside, C., M. Eichenbaum, and S. Rebelo (2016). Understanding Booms and Busts in Housing Markets. *Journal of Political Economy 124*(4), 1088–1147.

Büyükkarabacak, B. and N. T. Valev (2010, June). The Role of Household and Business Credit in Banking Crises. *Journal of Banking & Finance 34*(6), 1247–1256.

Caballero, J. A. (2016). Do Surges in International Capital Inflows Influence the Likelihood of Banking Crises? *The Economic Journal 126*(591), 281–316.

Cerra, V. and S. C. Saxena (2008, March). Growth Dynamics: The Myth of Economic Recovery. *American Economic Review 98*(1), 439–57.

Chaney, T., D. Sraer, and D. Thesmar (2012). The Collateral Channel: How Real Estate Shocks Affect Corporate Investment. *American Economic Review 102*(6), 2381–2409.

Cihák, M., A. Demirgüç-Kunt, E. Feyen, and R. Levine (2013). Financial Development in 205 Economies, 1960 to 2010. *Journal of Financial Perspectives 1*(2), 17–36.

Şebnem Kalemli-Özcan, L. Laeven, and D. Moreno (2018, April). Debt Overhang, Rollover Risk, and Corporate Investment: Evidence from the European Crisis. NBER Working Papers 24555, National Bureau of Economic Research, Inc.

De Bonis, R., F. Farabullini, M. Rocchelli, A. Salvio, and A. Silvestrini (2013). A Quantitative Look at the Italian Banking System: Evidence from a New Dataset Since 1861. Technical report.

Dembiermont, C., M. Drehmann, and S. Muksakunratana (2013, March). How Much Does the Private Sector Really Borrow - A New Database for Total Credit to the Private Non-financial Sector. *BIS Quarterly Review*.

Diamond, D. W., Y. Hu, and R. G. Rajan (2020). Pledgeability, Industry Liquidity, and Financing Cycles. *The Journal of Finance 75*(1), 419–461.

Drehmann, M., M. Juselius, and A. Korinek (2018, April). Going with the Flows: New Borrowing, Debt Service and the Transmission of Credit Booms. NBER Working Papers 24549.

Driscoll, J. and A. Kraay (1998). Consistent Covariance Matrix Estimation With Spatially Dependent Panel Data. *The Review of Economics and Statistics 80*(4), 549–560.

Duchin, R., O. Ozbas, and B. A. Sensoy (2010). Costly External Finance, Corporate Investment, and the Subprime Mortgage Credit Crisis. *Journal of Financial Economics 97*(3), 418 – 435. The 2007-8 financial crisis: Lessons from corporate finance.

Eggertsson, G. B. and P. Krugman (2012). Debt, Deleveraging, and the Liquidity Trap: A Fisher-Minsky-Koo Approach. *The Quarterly Journal of Economics 127*(3), 1469–1513.

Feenstra, R. C., R. Inklaar, and M. P. Timmer (2015, October). The Next Generation of the Penn World Table. *American Economic Review 105*(10), 3150–3182.

Geanakoplos, J. (2010). The Leverage Cycle. In *NBER Macroeconomics Annual 2009, Volume 24*, NBER Chapters, pp. 1–65. National Bureau of Economic Research, Inc.

Giroud, X. and H. Mueller (2020). Firm Leverage and Employment Dynamics. Technical report.

Giroud, X. and H. M. Mueller (2016, 10). Firm Leverage, Consumer Demand, and Employment Losses During the Great Recession. *The Quarterly Journal of Economics 132*(1), 271–316.

Gopinath, G., c. Kalemli-Özcan, L. Karabarbounis, and C. Villegas-Sanchez (2017). Capital Allocation and Productivity in South Europe. *The Quarterly Journal of Economics 132*(4), 1915–1967.

Gorton, G. and G. Ordoñez (2014, February). Collateral Crises. *American Economic Review 104*(2), 343–78.

Gorton, G. and G. Ordoñez (2019, 01). Good Booms, Bad Booms. *Journal of the European Economic Association 18*(2), 618–665.

Gorton, G. B. (2012, September). Some Reflections on the Recent Financial Crisis. Working Paper 18397, National Bureau of Economic Research.

Gourinchas, P.-O. and M. Obstfeld (2012, January). Stories of the Twentieth Century for the Twenty-first. *American Economic Journal: Macroeconomics 4*(1), 226–65.

Greenwood, R. and S. G. Hanson (2013). Issuer Quality and Corporate Bond Returns. *The Review of Financial Studies 26*(6), 1483–1525.

Greenwood, R., S. G. Hanson, A. Shleifer, and J. A. Sørensen (2020). Predictable Financial Crises. Technical report.

Greenwood, R. and D. Scharfstein (2013, May). The Growth of Finance. *Journal of Economic Perspectives 27*(2), 3–28.

Guerrieri, V. and G. Lorenzoni (2017). Credit Crises, Precautionary Savings, and the Liquidity Trap. *The Quarterly Journal of Economics 132*(3), 1427–1467.

Holmstrom, B. and J. Tirole (1997, August). Financial Intermediation, Loanable Funds, and the Real Sector. *The Quarterly Journal of Economics 112*(3), 663–91.

IMF (2017). Global Financial Stability Report October 2017: Is Growth at Risk? Technical report.

Inklaar, R., H. de Jong, J. Bolt, and J. van Zanden (2018). Rebasing 'Maddison': New Income Comparisons and the Shape of Long-run Economic Development. GGDC Research Memorandum GD-174.

Jones, C., V. Midrigan, and T. Philippon (2011, April). Household leverage and the recession. Working Paper 16965, National Bureau of Economic Research.

Jordà, Ò. (2005, March). Estimation and Inference of Impulse Responses by Local Projections. *American Economic Review 95*(1), 161–182.

Jordà, Ò., M. Schularick, and A. M. Taylor (2013). Sovereigns Versus Banks: Credit, Crises, and Consequences. Working Paper Series 2013-37.

Jordà, Ò., M. Schularick, and A. M. Taylor (2014, September). The Great Mortgaging: Housing Finance, Crises, and Business Cycles. NBER Working Papers 20501.

Jordà, Ò., M. Schularick, and A. M. Taylor (2016, September). Macrofinancial History and the New Business Cycle Facts. In *NBER Macroeconomics Annual 2016, Volume 31*, NBER Chapters. National Bureau of Economic Research, Inc.

Kalantzis, Y. (2015, 03). Financial Fragility in Small Open Economies: Firm Balance Sheets and the Sectoral Structure. *The Review of Economic Studies 82*(3), 1194–1222.

Kehoe, T. J. and K. J. Ruhl (2009, July). Sudden Stops, Sectoral Reallocations, and the Real Exchange Rate. *Journal of Development Economics 89*(2), 235–249.

Kermani, A. and Y. Ma (2020). Asset Specificity of Non-Financial Firms. Technical report.

Kirti, D. (2018, January). Lending Standards and Output Growth. IMF Working Papers 2018/023, International Monetary Fund.

Kiyotaki, N. and J. Moore (1997, April). Credit Cycles. *Journal of Political Economy 105*(2), 211–48.

Korinek, A. and A. Simsek (2016, March). Liquidity Trap and Excessive Leverage. *American Economic Review 106*(3), 699–738.

Krishnamurthy, A. and T. Muir (2017, September). How Credit Cycles across a Financial Crisis. Working Paper 23850, National Bureau of Economic Research.

Laeven, L. and F. Valencia (2018, September). Systemic Banking Crises Revisited. IMF Working Papers 18/206.

Levine, R. (2005, 00). Finance and Growth: Theory and Evidence. In P. Aghion and S. Durlauf (Eds.), *Handbook of Economic Growth*, Volume 1 of *Handbook of Economic Growth*, Chapter 12, pp. 865–934. Elsevier.

Levine, R., N. Loayza, and T. Beck (2000, August). Financial Intermediation and Growth: Causality and Causes. *Journal of Monetary Economics 46*(1), 31–77.

Lian, C. and Y. Ma (2020). Anatomy of Corporate Borrowing Constraints. Technical report.

Loayza, N. V. and R. Ranciere (2006, June). Financial Development, Financial Fragility, and Growth. *Journal of Money, Credit and Banking 38*(4), 1051–1076.

López-Salido, D., J. C. Stein, and E. Zakrajšek (2017). Credit Market Sentiment and the Business Cycle*. *The Quarterly Journal of Economics 132*(3), 1373–1426.

Mack, A. and E. Martínez-García (2011). A Cross-Country Quarterly Database of Real House Prices: A Methodological Note. Globalization Institute Working Papers 99, Federal Reserve Bank of Dallas.

Marcel Timmer, Gaaitzen J. de Vries, K. d. V. (2015). *Patterns of Structural Change in Developing Countries*. Routledge.

Martin, P. and T. Philippon (2017, July). Inspecting the Mechanism: Leverage and the Great Recession in the Eurozone. *American Economic Review 107*(7), 1904–37.

Matsuyama, K. (2008, June). *Aggregate Implications of Credit Market Imperfections*, pp. 1–60. University of Chicago Press.

Mbaye, S., M. Moreno Badia, and K. Chae (2018). Global Debt Database: Methodology and Sources. IMF Working Papers 18/111.

Mendoza, E. G. (2002, January). *Credit, Prices, and Crashes: Business Cycles with a Sudden Stop*, pp. 335–392. University of Chicago Press.

Mendoza, E. G. and M. E. Terrones (2008, May). An Anatomy Of Credit Booms: Evidence From Macro Aggregates And Micro Data. Working Paper 14049, National Bureau of Economic Research.

Mian, A. and A. Sufi (2011, August). House Prices, Home Equity-based Borrowing, and the US Household Leverage Crisis. *American Economic Review 101*(5), 2132–56.

Mian, A. and A. Sufi (2014). What Explains the 2007–2009 Drop in Employment? *Econometrica 82*(6), 2197–2223.

Mian, A., A. Sufi, and E. Verner (2020). How Does Credit Supply Expansion Affect the Real Economy? The Productive Capacity and Household Demand Channels. *The Journal of Finance 75*(2), 949–994.

Mian, A. R. and A. Sufi (2018, February). Finance and Business Cycles: The Credit-driven Household Demand Channel. NBER Working Papers 24322.

Mian, A. R., A. Sufi, and E. Verner (2017). Household Debt and Business Cycles Worldwide. *Quarterly Journal of Economics*.

Midrigan, V. and D. Y. Xu (2014, February). Finance and Misallocation: Evidence from Plant-Level Data. *American Economic Review 104*(2), 422–58.

Mitchell, B. *International Historical Statistics*.

Moll, B. (2014, October). Productivity Losses from Financial Frictions: Can Self-Financing Undo Capital Misallocation? *American Economic Review 104*(10), 3186–3221.

Monnet, E. and D. Puy (2019, September). One Ring to Rule Them All? New Evidence on World Cycles. IMF Working Papers 19/202, International Monetary Fund.

Mundlak, Y. (1978). On the Pooling of Time Series and Cross Section Data. *Econometrica 46*(1), 69–85.

Myers, S. C. (1977). Determinants of Corporate Borrowing. *Journal of Financial Economics 5*(2), 147–175.

Olea, J. L. M. and M. Plagborg-Møller (2020). Local Projection Inference is Simpler and More Robust Than You Think.

Paul, P. (2017). Historical Patterns of Inequality and Productivity around Financial Crises. Working Paper Series 2017-23, Federal Reserve Bank of San Francisco.

Plagborg-Møller, M., L. Reichlin, G. Ricco, and T. Hasenzagl (2020). When is Growth at Risk? *Brookings Papers on Economic Activity, forthcoming*.

Reinhart, C. M. and K. S. Rogoff (2009a, May). The Aftermath of Financial Crises. *American Economic Review 99*(2), 466–72.

Reinhart, C. M. and K. S. Rogoff (2009b). *This Time Is Different: Eight Centuries of Financial Folly*, Volume 1 of *Economics Books*. Princeton University Press.

Reis, R. (2013). The Portuguese Slump and Crash and the Euro Crisis. *Brookings Papers on Economic Activity*, 143–193.

Restuccia, D. and R. Rogerson (2008). Policy Distortions and Aggregate Productivity With Heterogeneous Establishments. *Review of Economic Dynamics 11*(4), 707 – 720.

Rodrik, D. and A. Subramanian (2009, April). Why Did Financial Globalization Disappoint? *IMF Staff Papers 56*(1), 112–138.

Schmitt-Grohé, S. and M. Uribe (2016). Downward Nominal Wage Rigidity, Currency Pegs, and Involuntary Unemployment. *Journal of Political Economy 124*(5), 1466–1514.

Schneider, M. and A. Tornell (2004). Balance Sheet Effects, Bailout Guarantees and Financial Crises. *The Review of Economic Studies 71*(3), 883–913.

Schularick, M. and A. M. Taylor (2012, April). Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008. *American Economic Review 102*(2), 1029–61.

Shleifer, A. and R. W. Vishny (1992, September). Liquidation Values and Debt Capacity: A Market Equilibrium Approach. *Journal of Finance 47*(4), 1343–66.

Stiglitz, J. E. and A. Weiss (1981). Credit Rationing in Markets with Imperfect Information. *The American Economic Review 71*(3), 393–410.

Stock, J. H. and M. W. Watson (2003, September). Forecasting Output and Inflation: The Role of Asset Prices. *Journal of Economic Literature 41*(3), 788–829.

Stockman, A. C. and L. L. Tesar (1995, March). Tastes and Technology in a Two-Country Model of the Business Cycle: Explaining International Comovements. *American Economic Review 85*(1), 168–185.

Tornell, A. and F. Westermann (2002, September). Boom-Bust Cycles in Middle Income Countries: Facts and Explanation. Working Paper 9219, National Bureau of Economic Research.

United Nations (2008). International Standard Industrial Classification of All Economic Activities, Revision 4. Technical report.

United Nations (2009). System of National Accounts 2008. Technical report.

United Nations (2018). Handbook on Backcasting. Technical report.

Wurgler, J. (2000). Financial Markets and the Allocation of Capital. *Journal of Financial Economics 58*(1-2), 187–214.

Credit Allocation and Macroeconomic Fluctuations
Online Appendix

Karsten Müller Emil Verner

This appendix supplements our paper *Credit Allocation and Macroeconomic Fluctuations*. The first part describes the methodology and coverage of the new database on sectoral credit. We outline the structure of the database; provide details on the coverage and compare it with that of previous data efforts on private credit; describe technical issues on sectoral classifications and data adjustments; and show that the aggregates of our newly constructed credit data closely track those of existing databases. The second part provides additional results for the stylized facts and empirical results in the main paper.

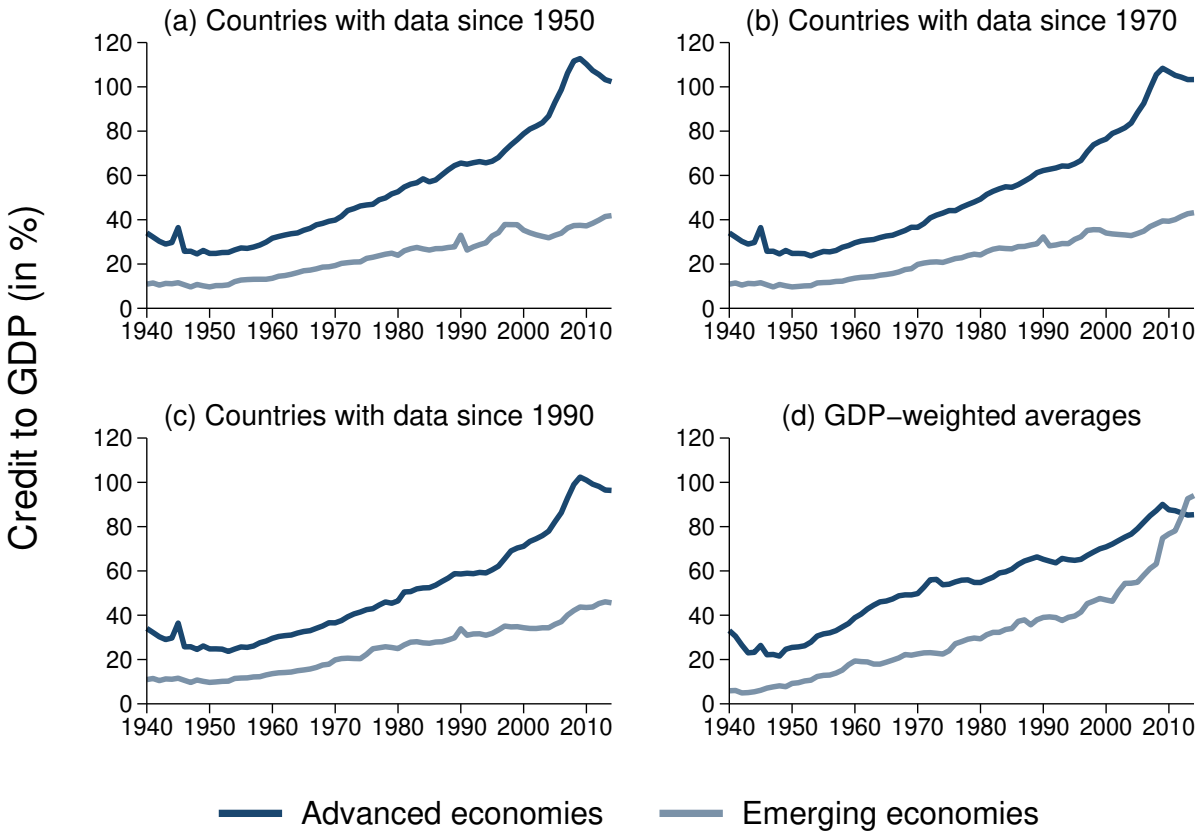
Table of Contents

A Additional Results

A.1 Robustness for stylized facts

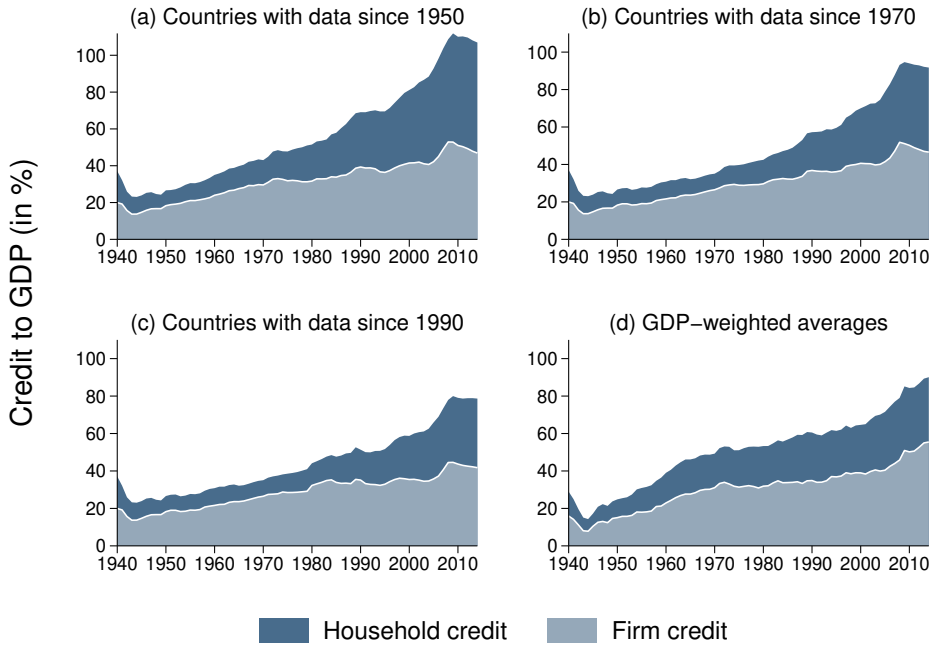
A.1.1 Aggregate Trends

Figure A1: Total Credit to GDP (in %), 1940-2014



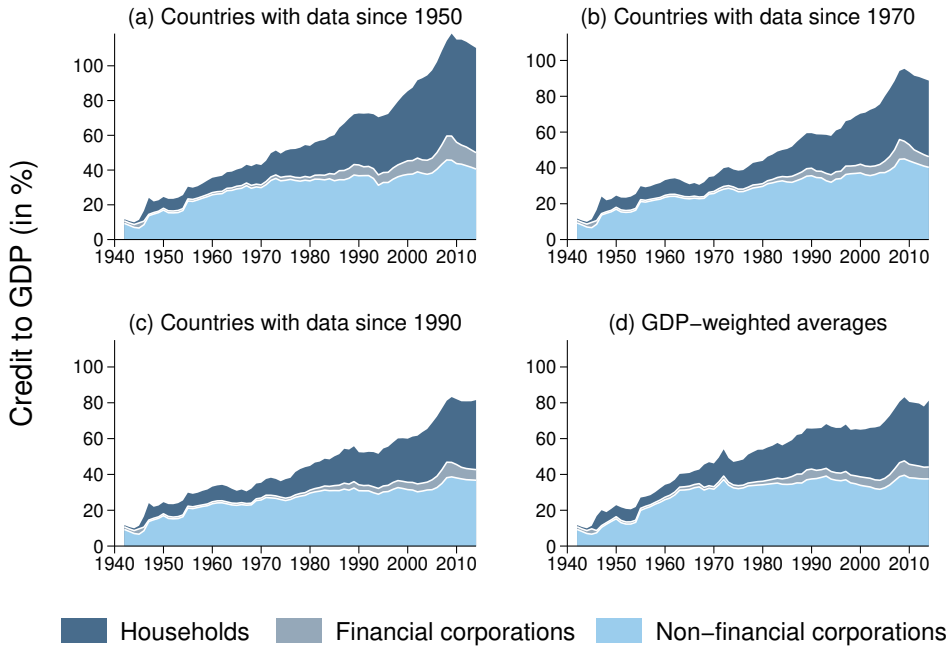
Sample: 26, 39, 46, and 52 advanced, and 24, 41, 53, and 65 emerging economies in panels (a), (b), (c), and (d), respectively.
Notes: Average ratio of total private credit to GDP (unweighted), except in panel (d).

Figure A2: Total Credit Decomposition - Firms vs. Households



Sample: 16, 30, 38, and 52 advanced, and 1, 12, 27 and 61 emerging economies in panels (a)-(d), respectively.
Notes: Average ratio of total private credit to GDP (unweighted), except in panel (d).

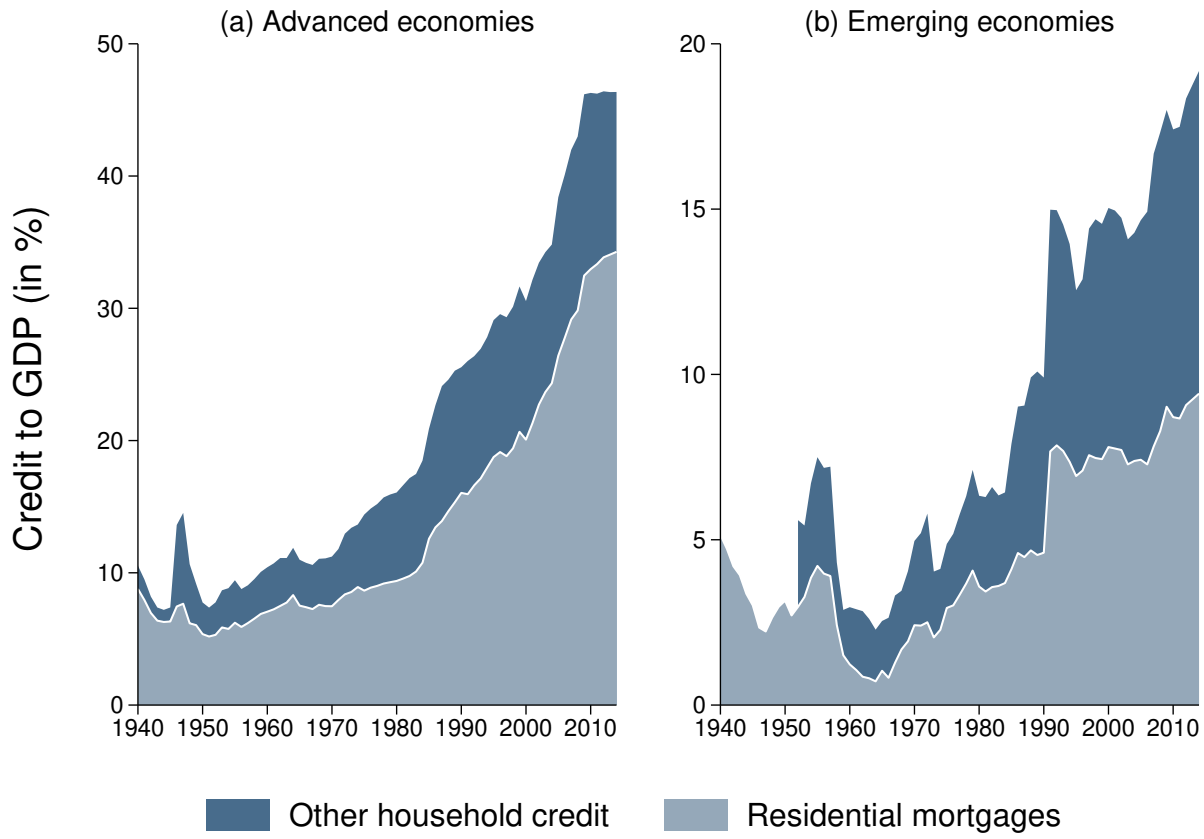
Figure A3: Total Credit Decomposition - Households, Non-Financial Firms, and Financial Sector



Sample: 8, 17, 29, and 51 advanced and 0, 5, 14, 46 emerging economies in panels (a), (b), (c), and (d), respectively.
Notes: Average ratio of total private credit to GDP (unweighted), except in panel (d).

A.1.2 The Share of Household Credit

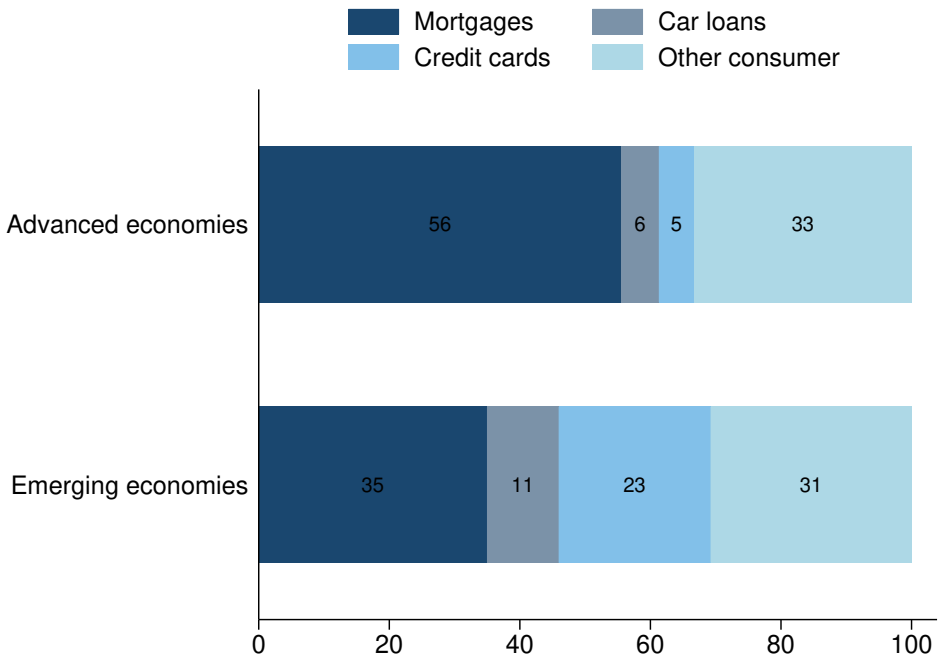
Figure A4: Household Credit to GDP (in %) for Countries With Data Before 1980



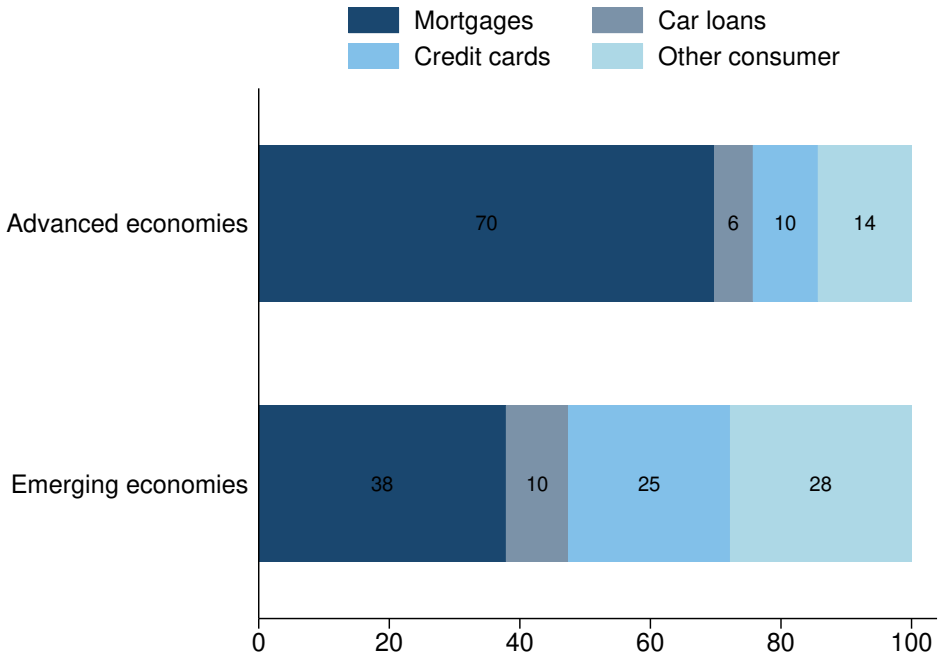
Sample: 24 advanced and 8 emerging economies, 1940-2014.
Notes: Average ratio of household credit to GDP (unweighted).

Figure A5: Composition of Household Credit (in %), 2009-2014 (average)

(a) Equal-weighted averages



(b) GDP-weighted averages

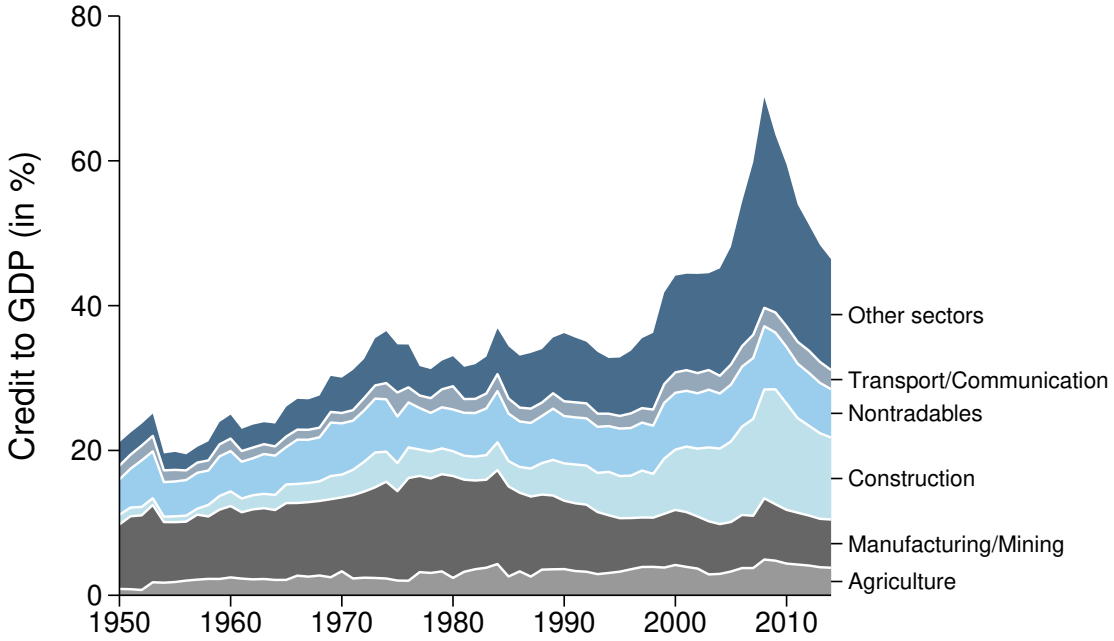


Sample: 10 advanced and 8 emerging economies with non-missing data for each loan purpose.
Notes: Average share of household credit by loan purpose during the period 2009-2014.

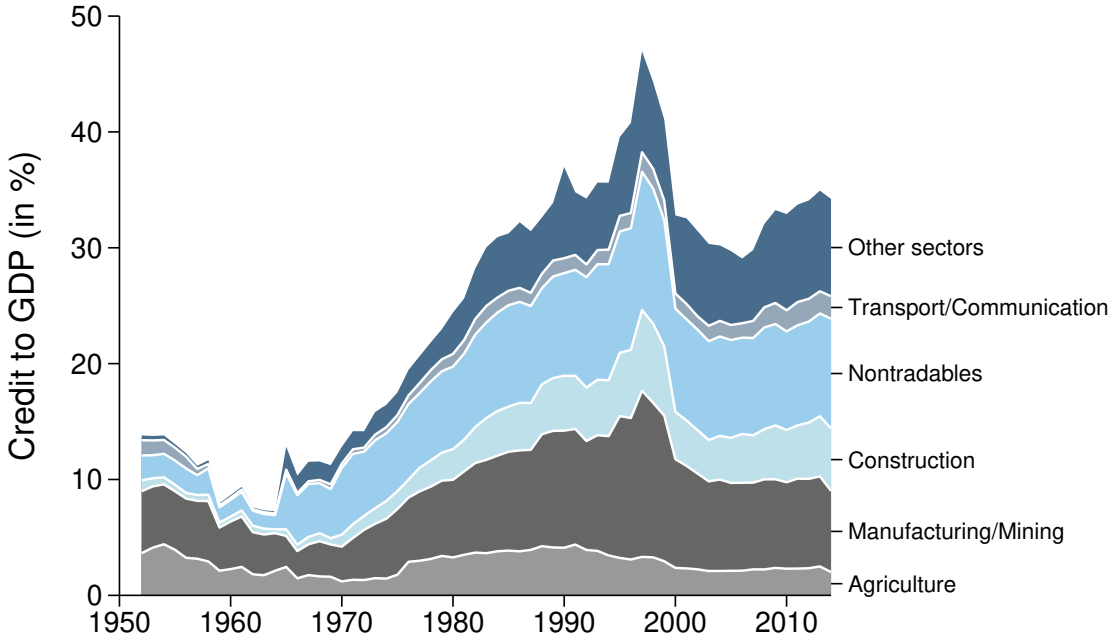
A.1.3 Structural Change in Corporate Credit

Figure A6: Robustness – Corporate Credit to GDP Composition (Balanced Panel)

(a) Advanced economies



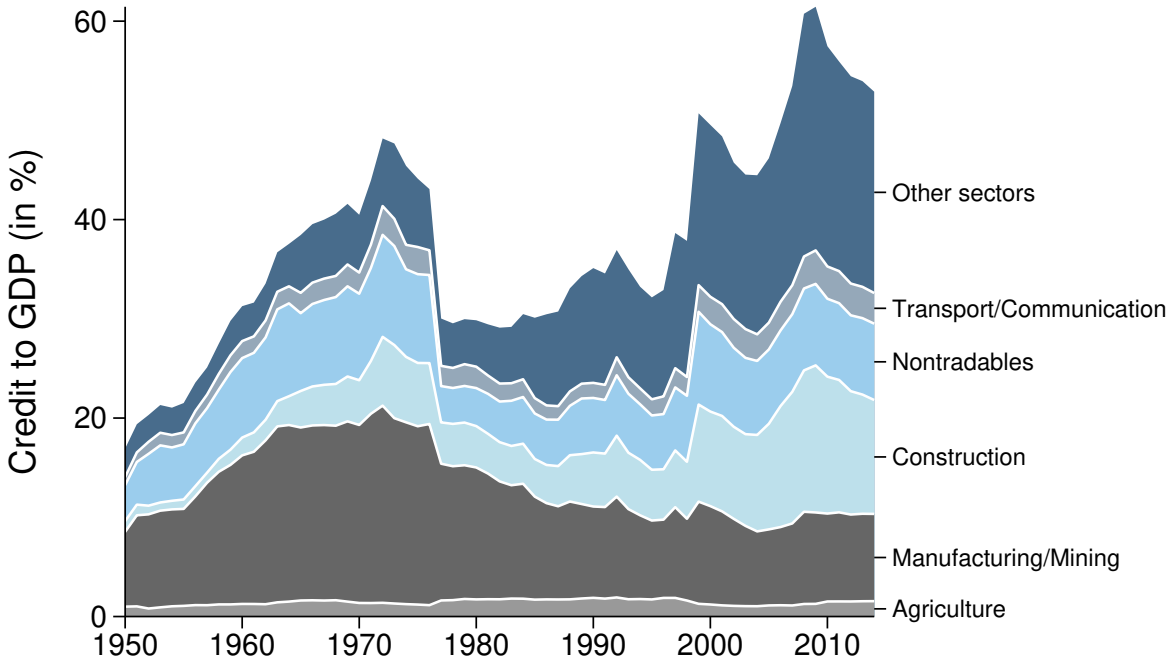
(b) Emerging economies



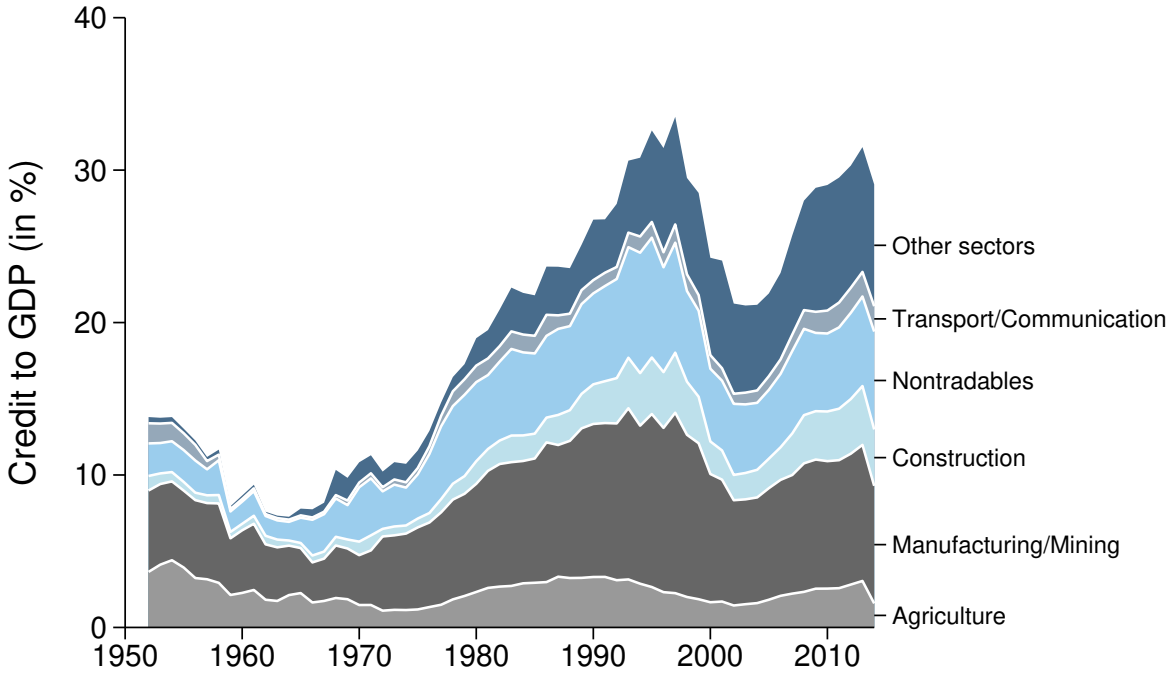
Sample: 13 advanced and 11 emerging economies.
Notes: Average ratio of corporate credit to GDP (unweighted) for countries with data since at least 1980.

Figure A7: Robustness – Corporate Credit to GDP Composition (GDP weighted)

(a) Advanced economies



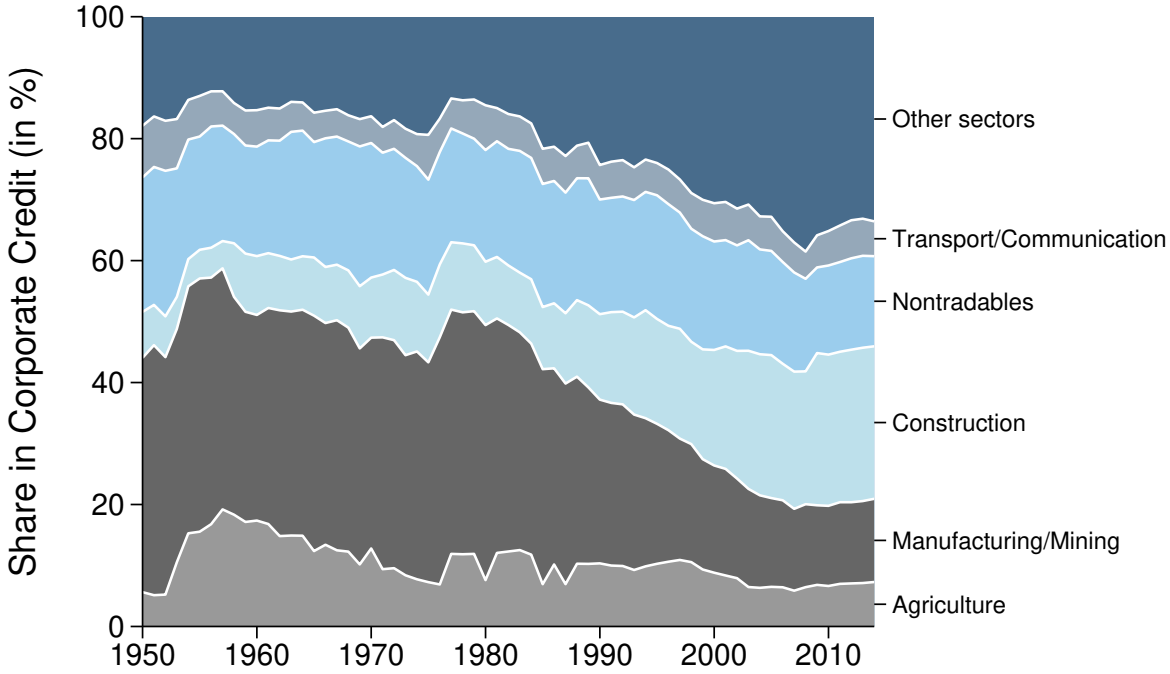
(b) Full sample (GDP weighted)



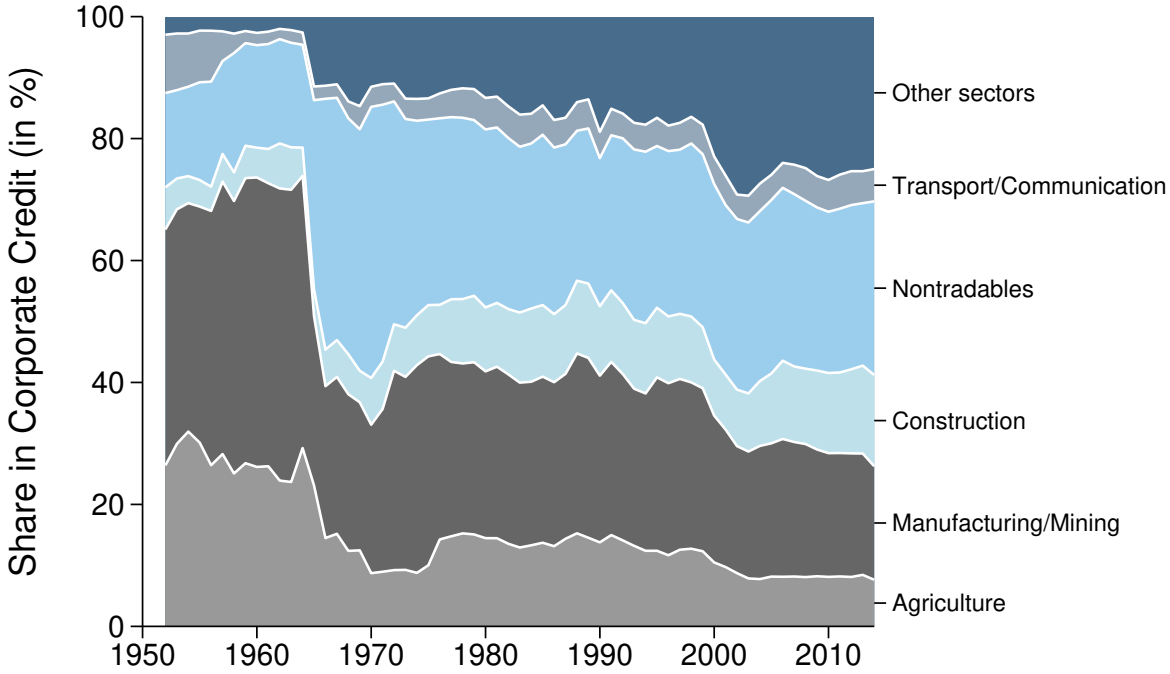
Sample: 35 advanced and 46 emerging economies.
Notes: Panel A plots the average ratio of corporate credit to GDP (GDP-weighted) for advanced economies, Panel B the average ratio for emerging economies.

Figure A8: Robustness – Sector Shares in Corporate Credit (Balanced Panel)

(a) Advanced economies



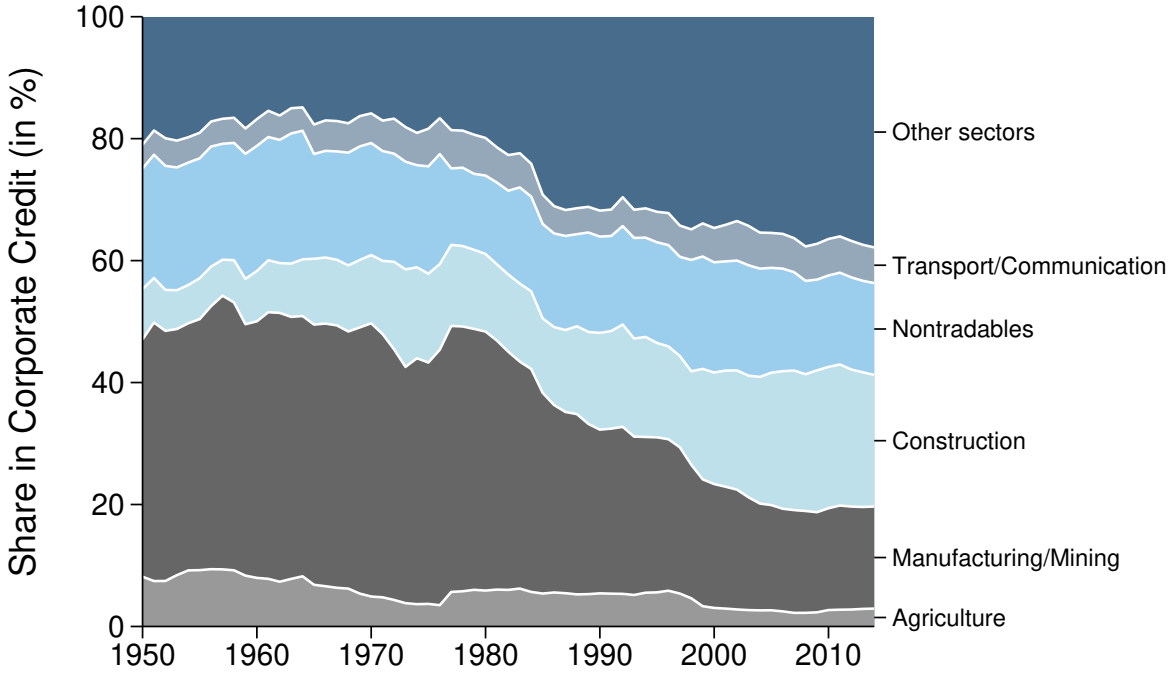
(b) Emerging economies



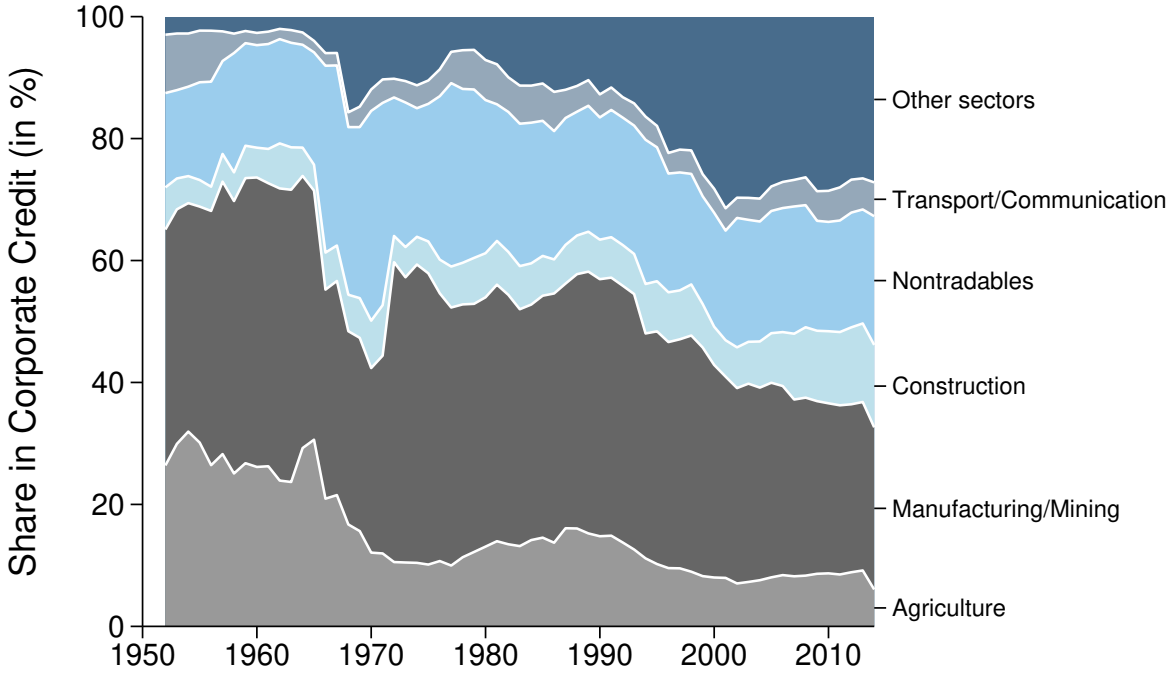
Sample: 13 advanced and 11 emerging economies.
Notes: Average ratio of individual sectors in corporate credit (unweighted) for countries with data since at least 1980.

Figure A9: Robustness – Sector Shares in Corporate Credit (GDP-weighted)

(a) Advanced economies



(b) Emerging economies

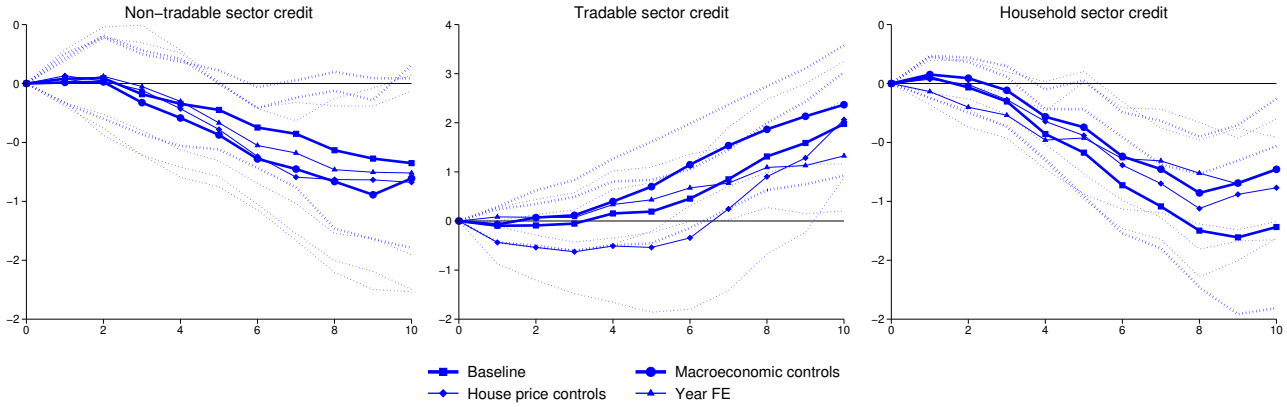


Sample: 35 advanced and 46 emerging economies.
Notes: Average ratio of individual sectors in corporate credit (GDP-weighted).

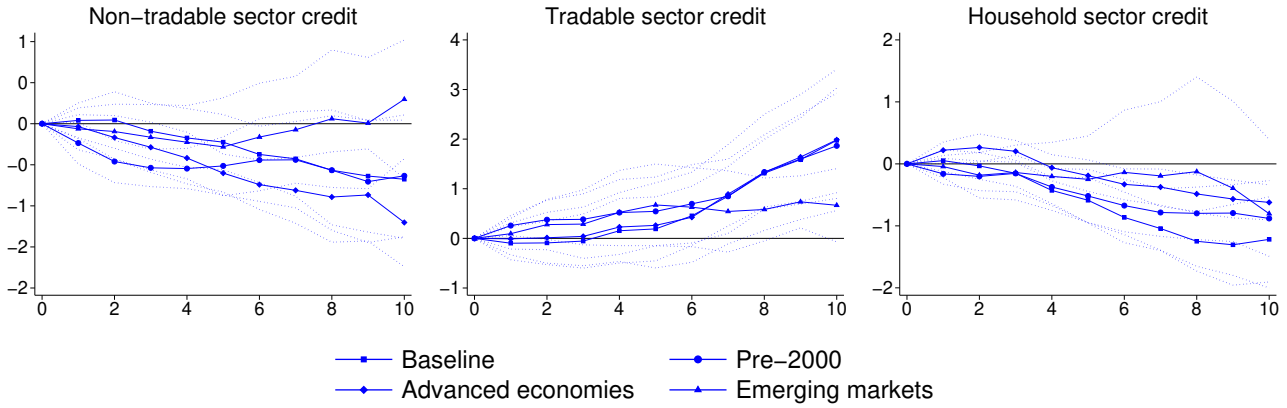
A.2 Local projections

Figure A10: Robustness – Output Dynamics after Credit Expansions in Tradable, Non-Tradable, and Household Sectors

(a) Additional controls



(b) Subsamples



Notes: These figures presents local projection impulse responses of real GDP following innovations in tradable sector credit, non-tradable sector credit, and household credit (all measured relative to GDP). Panel (a) compares estimations with additional control variables to the baseline specification. Panel (b) considers subsamples.

Panel (a) presents local projection impulse response estimates from:

$$\Delta_h y_{it+h} = \alpha_i + \sum_{j=0}^{J} \beta_j^{NT} \Delta d_{it-j}^{NT} + \sum_{j=0}^{J} \beta_j^{T} \Delta d_{it-j}^{T} + \sum_{j=0}^{J} \gamma_j \Delta y_{it-j} + \epsilon_{it+h}, \quad h = 1, ..., H.$$

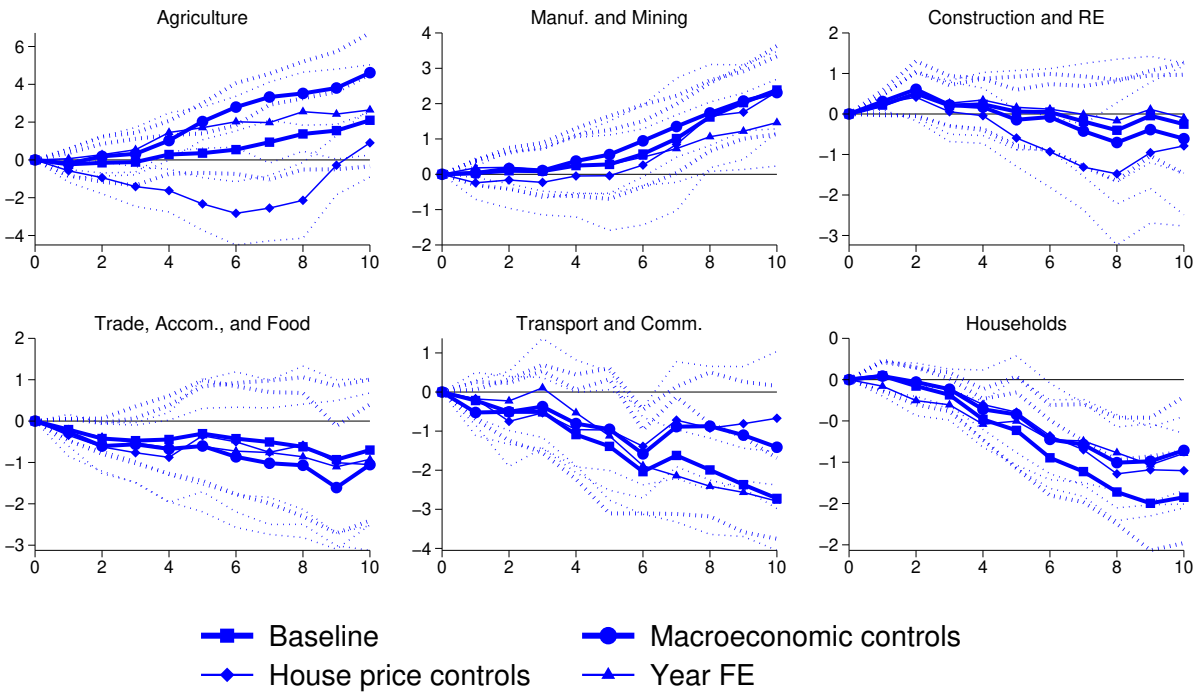
Panel (b) present the same specification but also includes household credit:

$$\Delta_h y_{it+h} = \alpha_i + \sum_{j=0}^{J} \beta_j^{NT} \Delta d_{it-j}^{NT} + \sum_{j=0}^{J} \beta_j^{T} \Delta d_{it-j}^{T} + \sum_{j=0}^{J} \beta_j^{HH} d_{it-j}^{HH} + \sum_{j=0}^{J} \gamma_j \Delta y_{it-j} + \epsilon_{it+h}, \quad h = 1, ..., H.$$

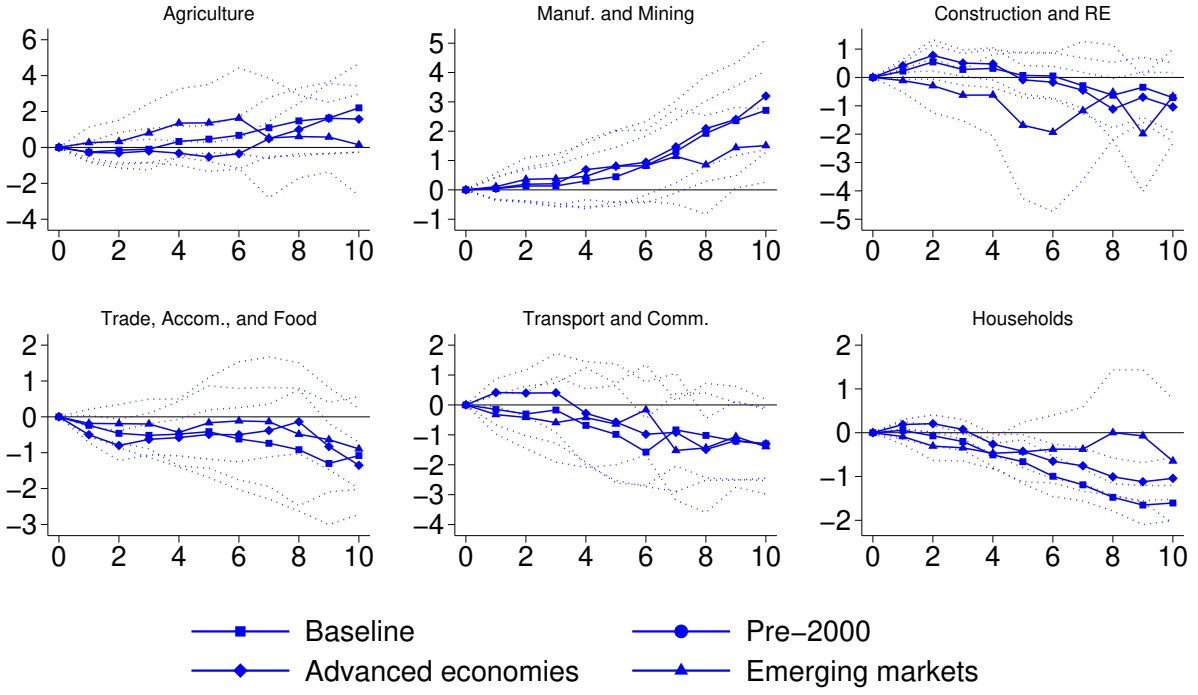
Dashed lines represent 95% confidence intervals computed using Driscoll-Kraay standard errors, and dotted lines represent 95% confidence intervals from standard errors two-way clustered on country and year.

Figure A11: Robustness – Output Dynamics after Credit Expansions: Unpacking Corporate Sector Credit Expansions

(a) Additional controls

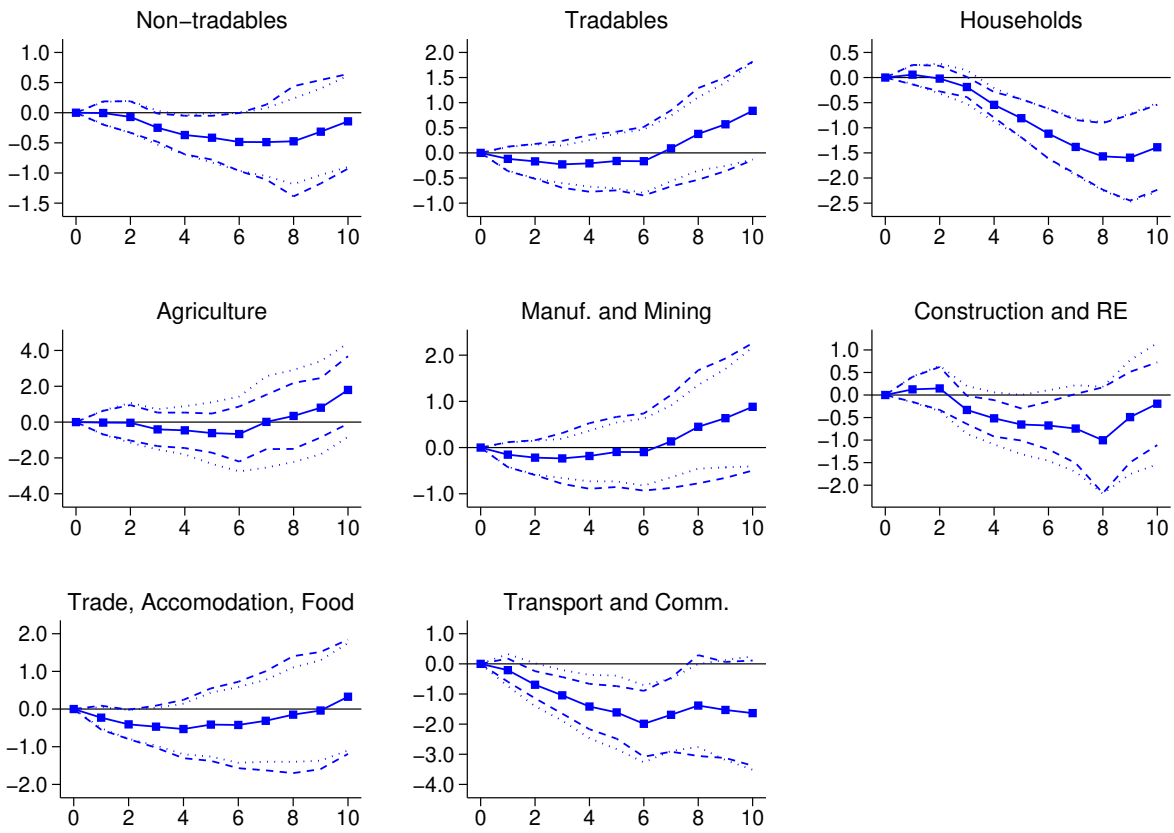


(b) Subsamples



Notes: Dotted lines represent 95% confidence intervals computed using Driscoll-Kraay standard errors. See text.

Figure A12: Robustness – Output Dynamics after Credit Expansions: Sectors One-by-One



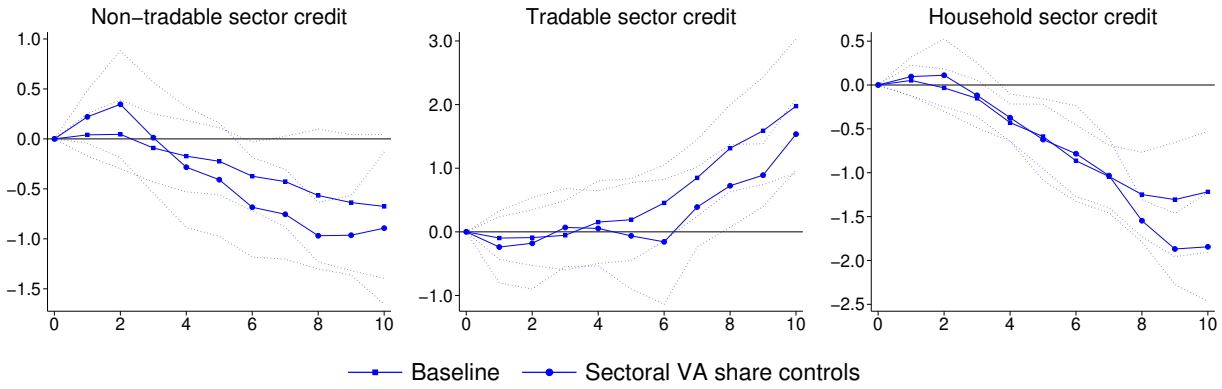
Notes: Each panel presents the impulse response of real GDP to an innovation in credit-to-GDP based on estimates from a separate local projection specification:

$$\Delta_h y_{it+h} = \alpha_i + \sum_{j=0}^{J} \beta_j^k \Delta d_{it-j}^k + \sum_{j=0}^{J} \gamma_j \Delta y_{it-j} + \epsilon_{it+h}, \quad h = 1, ..., H.$$

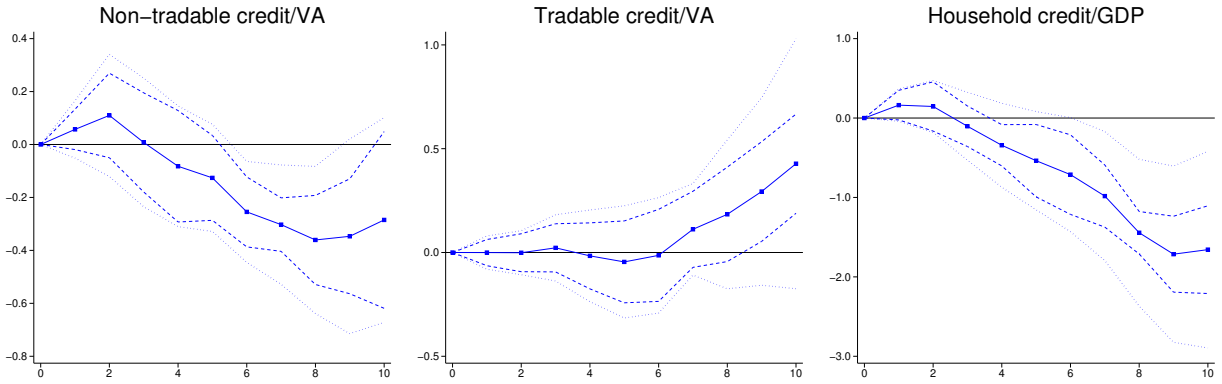
In contrast to our baseline results in Figure 10 and Figure 11, each specification only includes credit-to-GDP for sector k. Dashed lines represent 95% confidence intervals computed using Driscoll-Kraay standard errors, and dotted lines represent 95% confidence intervals from standard errors two-way clustered on country and year.

Figure A13: Output Dynamics after Credit Expansions: Sector Size vs Sector Leverage

(a) Controlling for sector value added shares



(b) Corporate Sectoral Credit Scaled by Value Added



Notes: This figure presents two tests to disentangle the role of sectoral leverage from changes in sector size.
Panel (a) presents the impulse response of real GDP to an innovation in sectoral credit from the following local projection specification:

$$\Delta_h y_{it+h} = \alpha_i + \sum_{j=0}^{J} \beta_j^{NT} \Delta \tilde{d}_{it-j}^{NT} + \sum_{j=0}^{J} \beta_j^{T} \Delta \tilde{d}_{it-j}^{T} + \sum_{j=0}^{J} \beta_j^{HH} d_{it-j}^{HH} + \sum_{j=0}^{J} \gamma_j \Delta y_{it-j} + \epsilon_{it+h}, \quad h = 1, ..., H.$$

In contrast to our baseline results in Figure 10, credit in corporate sector k is scaled by value added in that sector, i.e., $\tilde{d}_{it}^{k} = 100 \cdot \frac{D_{it}^{k}}{VA_{it}^{k}}$.

Panel (b) presets estimates of (1) using credit variables scaled by GDP with additional controls for changes in the non-tradable and tradable value added shares.
Dashed lines represent 95% confidence intervals computed using Driscoll-Kraay standard errors, and dotted lines represent 95% confidence intervals from standard errors two-way clustered on country and year.

A.3 Financial crisis prediction

Table A1: Robustness – Individual Sectors and Financial Crises (Multivariate)

				Agric.		Manuf. and Mining		Construction and RE		Trade, Acc., and Food		Transport and Comm.		Households	
		N	AUC	β	$[t]$	β	$[t]$	β	$[t]$	β	$[t]$	β	$[t]$	β	$[t]$
(1)	Baseline (LPM, country FE)	1,842	0.71	0.00	0.03	-0.01	-1.14	0.05	5.47**	0.04	3.16**	-0.01	-0.72	0.04	3.16**
(2)	LPM, country + year FE	1,842	0.70	0.00	0.41	0.00	-0.27	0.03	2.07*	0.03	2.47*	-0.01	-0.67	0.03	3.23**
(3)	Logit	1,842	0.70	0.00	0.57	0.00	-0.11	0.03	2.42*	0.03	2.43*	0.00	-0.11	0.03	2.74**
(4)	Logit, country FE	1,052	0.72	0.01	0.38	-0.05	-1.91+	0.08	2.79**	0.15	4.77**	-0.03	-1.09	0.10	4.11**
(5)	Logit, RE-Mundlak	1,842	0.86	0.00	0.38	-0.01	-1.12	0.03	2.36*	0.04	4.12**	-0.01	-1.53	0.04	3.16**
(6)	Lags of 1-year changes	1,837	0.71	0.00	0.12	-0.02	-1.10	0.07	6.41**	0.06	2.83**	-0.01	-0.75	0.05	3.13**
(7)	Boom (>= Mean + 2 × SD)	1,842	0.58	0.04	0.50	0.07	0.70	0.11	2.75**	0.06	1.32	0.05	0.84	0.16	3.40**
(8)	Boom (>= 80th percentile)	1,842	0.72	0.03	1.14	-0.01	-0.30	0.07	3.43**	0.07	2.07*	-0.03	-1.88+	0.14	3.73**
(9)	RR dates	1,081	0.63	0.00	-0.13	-0.05	-1.61	0.09	7.69**	0.06	1.62	0.00	0.14	0.01	0.82
(10)	LV dates only	1,709	0.66	0.00	-0.01	-0.01	-0.86	0.04	3.37**	0.02	2.38*	-0.01	-0.87	0.03	1.79+
(11)	BVX dates only	1,032	0.75	0.02	0.66	-0.02	-1.16	0.06	4.59**	0.06	3.08**	0.00	-0.05	0.05	3.05**
(12)	Pre-2000 only	1,089	0.66	-0.01	-0.37	-0.02	-1.42	0.05	6.03**	0.05	2.66**	-0.01	-0.45	0.04	2.93**
(13)	Advanced economies	1,031	0.74	0.01	1.25	-0.03	-2.35*	0.05	5.55**	0.03	1.42	0.00	0.39	0.04	2.44*
(14)	Emerging economies	811	0.71	-0.07	-1.79+	0.02	0.97	0.03	1.03	0.05	4.70**	-0.04	-1.36	0.05	6.35**
(15)	Value added controls	703	0.73	0.02	1.53	-0.05	-1.83+	0.05	3.25**	0.08	1.95+	0.01	1.10	0.03	1.57
(16)	Credit/value added	638	0.75	0.30	3.00**	0.02	1.06	0.01	0.69	0.04	2.11*	0.00	0.34	0.04	4.06**

This table presents the results of the following multivariate linear regression model:

$$Crisis_{it+3} = \alpha_i^{(h)} + \sum_{k \in K} \beta_k^{(h)} \Delta_3 d_{it}^k + \epsilon_{it+1\ to it+h}$$

where $Crisis_{it+3}$ is a dummy variable that equals one for the start of a systemic banking crisis within the next three years, $\alpha_i^{(h)}$ is a country fixed effect and $\sum_{k \in K} \beta_k^{(h)} \Delta_3 d_{it}^k$ describes a vector of changes in the credit/GDP ratio from $t-3$ to t. In Panel A, we differentiate between the tradable, non-tradable, and household sectors. In Panel B, we use individual corporate sectors. Driscoll and Kraay (1998) standard errors in parentheses allow for lags of 0, 2, 3, and 5 years in columns 1-4, respectively. +, * and ** denote significance at the 10%, 5% and 1% level.

Model (1) is our baseline specification, a linear probability model (LPM) with country fixed effects (FE), where banking crises are defined as in Baron et al. (2019) and Laeven and Valencia (2018) for the remaining countries. Model (2) adds year FE. Model (3) is a logit model with standard errors clustered by country. Model (4) reports results from a conditional/FE logit model, which drops countries that never experienced a crisis. Model (5) is a random effects logit model that includes averages of the dependent and independent variables as covariates, as suggested by Mundlak (1978). Model (6) replaces the independent variables in the baseline model with three lags of one-year changes in credit/GDP; we report linear combinations of the coefficients. Model (7) replaces the independent variables with dummy variables equal to one if the 3-year change in credit/GDP is equal to its mean plus two standard deviations or higher. Model (8) creates a similar credit boom indicator following Greenwood et al. (2020) equal to one if the 3-year change in credit/GDP is equal to its 80th percentile or higher. Model (9) uses the systemic banking crisis dates from Reinhart and Rogoff (2009b). Model (10) only uses crisis dates from Laeven and Valencia (2018), and model (11) only the dates from Baron et al. (2019). Model (12) restricts the sample to the years before 2000. Models (13) and (14) restrict the sample to countries classified as high-income and low-income/middle-income by the World Bank in 2019, respectively. Model (15) controls for three-year changes in sectoral value added/GDP. Model (16) replaces d_{it}^k with versions scaled over value added instead of GDP.

Table A2: Robustness – Sectoral Credit Expansions and Financial Crises (Univariate)

		Tradables				Non-tradables				Households			
		β	$[t]$	AUC	N	β	$[t]$	AUC	N	β	$[t]$	AUC	N
(1)	Baseline (LPM, country FE)	0.02	3.19**	0.57	2,701	0.07	7.94**	0.65	2,045	0.07	4.35**	0.63	3,080
(2)	LPM, country + year FE	0.03	4.34**	0.57	2,700	0.05	3.94**	0.65	2,044	0.05	4.29**	0.63	3,080
(3)	Logit	0.02	2.44*	0.57	2,701	0.06	5.11**	0.65	2,045	0.05	4.97**	0.63	3,080
(4)	Logit, country FE	0.07	4.02**	0.58	1,723	0.15	6.75**	0.65	1,213	0.15	9.77**	0.63	2,267
(5)	Logit, RE-Mundlak	0.02	3.14**	0.81	2,701	0.05	4.82**	0.84	2,045	0.06	4.38**	0.80	3,080
(6)	Lags of 1-year changes	0.04	3.23**	0.57	2,692	0.09	7.87**	0.66	2,041	0.09	4.23**	0.63	3,080
(7)	Boom (>= Mean + 2 $\times$ SD)	0.09	2.16*	0.51	2,701	0.25	4.69**	0.55	2,045	0.24	4.54**	0.54	3,080
(8)	Boom (>= 80th percentile)	0.05	2.34*	0.55	2,701	0.12	6.08**	0.62	2,045	0.17	3.56**	0.61	3,080
(9)	RR dates	0.00	0.17	0.49	1,706	0.08	3.49**	0.60	1,167	0.04	1.96+	0.52	2,098
(10)	LV dates only	0.02	1.75+	0.55	2,430	0.05	3.31**	0.62	1,911	0.06	2.90**	0.61	2,654
(11)	BVX dates only	0.04	3.54**	0.60	1,440	0.09	6.52**	0.68	1,100	0.08	5.57**	0.66	1,898
(12)	Pre-2000 only	0.02	1.98+	0.55	1,768	0.06	6.00**	0.63	1,223	0.05	3.15**	0.58	2,042
(13)	Advanced economies	0.01	1.75+	0.54	1,380	0.06	5.78**	0.65	1,080	0.07	3.12**	0.66	1,912
(14)	Emerging economies	0.04	2.49*	0.61	1,321	0.07	3.33**	0.65	965	0.07	4.44**	0.59	1,168
(15)	Value added controls	0.04	4.07**	0.59	1,822	0.09	4.86**	0.67	761	0.07	4.35**	0.63	3,080
(16)	Credit/value added	0.03	2.27*	0.66	1,632	0.08	3.70**	0.67	748	.	.	.	.

This table presents the results of variants of the following univariate linear regression model:

$$Crisis_{it+3} = \alpha_i^{(h)} + \beta_k^{(h)} \Delta_3 d_{it}^k + \epsilon_{it+3}$$

where $Crisis_{it+3}$ is a dummy variable that equals one for the start of a systemic banking crisis within the next three years, α_i is a country fixed effect, and $\Delta_3 d_{it}^k$ is the change in the credit/GDP ratio for sector k (the tradable, non-tradable, or household sector) from $t-3$ to t. Here, we set $h = 2$. We compute Driscoll and Kraay (1998) standard errors with 3 lags, except for logit models. +, * and ** denote significance at the 10%, 5% and 1% level.

Model (1) is our baseline specification, a linear probability model (LPM) with country fixed effects (FE), where banking crises are defined as in Baron et al. (2019) and Laeven and Valencia (2018) for the remaining countries. Model (2) adds year FE. Model (3) is a logit model with standard errors clustered by country. Model (4) reports results from a conditional/FE logit model, which drops countries that never experienced a crisis. Model (5) is a random effects logit model that includes averages of the dependent and independent variable as covariates, as suggested by Mundlak (1978). Model (6) replaces the independent variable in the baseline model with three lags of one-year changes in credit/GDP; we report linear combinations of the coefficients. Model (7) replaces the independent variable with a dummy variable equal to one if the 3-year change in credit/GDP is equal to its mean plus two standard deviations or higher. Model (8) creates a similar credit boom indicator following Greenwood et al. (2020) equal to one if the 3-year change in credit/GDP is equal to its 80th percentile or higher. Model (9) uses the systemic banking crisis dates from Reinhart and Rogoff (2009b). Model (10) only uses crisis dates from Laeven and Valencia (2018), and model (11) only the dates from Baron et al. (2019). Model (12) restricts the sample to the years before 2000. Models (13) and (14) restrict the sample to countries classified as high-income and low-income/middle-income by the World Bank in 2019, respectively. Model (15) controls for three-year changes in sectoral value added/GDP. Model (16) replaces d_{it}^T and d_{it}^{NT} with versions scaled over value added instead of GDP (not possible for household credit).

Table A3: Robustness – Tradable and Construction/RE Sectors and Financial Crises (Univariate)

		Agriculture				Manuf. and Mining				Construction and RE			
		β	$[t]$	AUC	N	β	$[t]$	AUC	N	β	$[t]$	AUC	N
(1)	Baseline (LPM, country FE)	0.01	2.01*	0.54	2,931	0.02	1.45	0.55	2,771	0.06	7.61**	0.61	2,555
(2)	LPM, country + year FE	0.01	3.12**	0.54	2,931	0.02	2.57*	0.55	2,770	0.05	4.09**	0.61	2,551
(3)	Logit	0.01	1.55	0.54	2,931	0.01	1.46	0.55	2,771	0.05	4.67**	0.61	2,555
(4)	Logit, country FE	0.03	1.42	0.55	1,941	0.04	2.91**	0.56	1,809	0.11	6.65**	0.61	1,670
(5)	Logit, RE-Mundlak	0.01	1.60	0.79	2,931	0.01	1.69+	0.80	2,771	0.04	4.03**	0.82	2,555
(6)	Lags of 1-year changes	0.02	2.02*	0.53	2,921	0.03	1.47	0.55	2,766	0.08	7.76**	0.61	2,552
(7)	Boom (>= Mean + 2 $\times$ SD)	0.10	1.21	0.51	2,931	0.04	0.65	0.51	2,771	0.12	3.37**	0.53	2,555
(8)	Boom (>= 80th percentile)	0.03	2.80**	0.53	2,931	0.02	1.16	0.53	2,771	0.10	4.75**	0.59	2,555
(9)	RR dates	-0.01	-0.85	0.52	1,928	0.00	-0.15	0.52	1,751	0.07	4.94**	0.55	1,541
(10)	LV dates only	0.01	1.20	0.53	2,602	0.01	1.15	0.54	2,500	0.04	2.97**	0.57	2,356
(11)	BVX dates only	0.04	2.35*	0.58	1,561	0.02	1.74+	0.56	1,490	0.08	7.32**	0.65	1,346
(12)	Pre-2000 only	0.01	1.62	0.51	1,955	0.01	0.65	0.54	1,809	0.05	5.11**	0.58	1,621
(13)	Advanced economies	0.02	2.22*	0.56	1,486	0.00	0.06	0.51	1,424	0.06	6.06**	0.64	1,285
(14)	Emerging economies	0.01	0.81	0.53	1,445	0.03	1.95+	0.59	1,347	0.05	1.78+	0.56	1,270
(15)	Value added controls	0.01	0.49	0.55	2,022	0.03	2.47*	0.59	1,869	0.07	5.65**	0.65	1,006
(16)	Credit/value added	0.03	1.98+	0.64	1,782	0.01	0.64	0.65	1,677	0.03	2.69**	0.62	1,259

This table presents the results of the following univariate linear regression model:

$$Crisis_{it+3} = \alpha_i^{(h)} + \beta_k^{(h)} \Delta_3 d_{it}^k + \epsilon_{it+3}$$

where $Crisis_{it+3}$ is a dummy variable that equals one for the start of a systemic banking crisis within the next three years, $\alpha_i^{(h)}$ is a country fixed effect and $\sum_{k=0}^{K} \beta_k^{(h)} \Delta_3 d_{it}^k$ is a vector of three-year changes in the credit/GDP ratio of the agriculture, manufacturing, or construction/real estate sector from $t-3$ to t. Driscoll and Kraay (1998) standard errors in parentheses allow for 3 lags. +, * and ** denote significance at the 10%, 5% and 1% level.

Model (1) is our baseline specification, a linear probability model (LPM) with country fixed effects (FE), where banking crises are defined as in Baron et al. (2019) and Laeven and Valencia (2018) for the remaining countries. Model (2) adds year FE. Model (3) is a logit model with standard errors clustered by country. Model (4) reports results from a conditional/FE logit model, which drops countries that never experienced a crisis. Model (5) is a random effects logit model that includes averages of the dependent and independent variables as covariates, as suggested by Mundlak (1978). Model (6) replaces the independent variables in the baseline model with three lags of one-year changes in credit/GDP; we report linear combinations of the coefficients. Model (7) replaces the independent variables with dummy variables equal to one if the 3-year change in credit/GDP is equal to its mean plus two standard deviations or higher. Model (8) creates a similar credit boom indicator following Greenwood et al. (2020) equal to one if the 3-year change in credit/GDP is equal to its 80th percentile or higher. Model (9) uses the systemic banking crisis dates from Reinhart and Rogoff (2009b). Model (10) only uses crisis dates from Laeven and Valencia (2018), and model (11) only the dates from Baron et al. (2019). Model (12) restricts the sample to the years before 2000. Models (13) and (14) restrict the sample to countries classified as high-income and low-income/middle-income by the World Bank in 2019, respectively. Model (15) controls for three-year changes in sectoral value added/GDP. Model (16) replaces d_{it}^T and d_{it}^{NT} with versions scaled over value added instead of GDP (not possible for household credit).

Table A4: Robustness – Non-tradable and Household Sectors and Financial Crises (Univariate)

		Trade, Accom., and Food				Transport and Comm.				Households			
		β	$[t]$	AUC	N	β	$[t]$	AUC	N	β	$[t]$	AUC	N
(1)	Baseline (LPM, country FE)	0.05	5.22**	0.64	2,680	0.01	1.49	0.55	2,214	0.07	4.35**	0.63	3,080
(2)	LPM, country + year FE	0.05	4.44**	0.64	2,679	0.01	1.29	0.55	2,208	0.05	4.29**	0.63	3,080
(3)	Logit	0.05	4.38**	0.64	2,680	0.02	2.00*	0.55	2,214	0.05	4.97**	0.63	3,080
(4)	Logit, country FE	0.16	6.27**	0.65	1,732	0.04	1.59	0.54	1,334	0.15	8.40**	0.63	2,267
(5)	Logit, RE-Mundlak	0.05	5.26**	0.82	2,680	0.01	1.60	0.82	2,214	0.06	4.38**	0.80	3,080
(6)	Lags of 1-year changes	0.09	5.12**	0.64	2,677	0.03	1.54	0.55	2,212	0.09	4.23**	0.63	3,080
(7)	Boom (>= Mean + 2 $\times$ SD)	0.12	1.66+	0.52	2,680	0.09	1.34	0.51	2,214	0.24	4.54**	0.54	3,080
(8)	Boom (>= 80th percentile)	0.10	4.62**	0.58	2,680	0.01	0.91	0.53	2,214	0.17	3.56**	0.61	3,080
(9)	RR dates	0.04	2.33*	0.56	1,689	0.04	2.73**	0.53	1,282	0.04	1.96+	0.52	2,098
(10)	LV dates only	0.05	4.49**	0.63	2,410	0.01	0.96	0.52	2,016	0.06	2.90**	0.61	2,654
(11)	BVX dates only	0.07	3.01**	0.65	1,466	0.02	2.21*	0.58	1,206	0.08	5.57**	0.66	1,898
(12)	Pre-2000 only	0.05	3.34**	0.62	1,730	0.00	0.44	0.53	1,363	0.05	3.15**	0.58	2,042
(13)	Advanced economies	0.03	2.89**	0.60	1,367	0.02	1.78+	0.57	1,199	0.07	3.12**	0.66	1,912
(14)	Emerging economies	0.07	8.49**	0.67	1,313	0.00	-0.21	0.50	1,015	0.07	4.44**	0.59	1,168
(15)	Value added controls	0.07	3.50**	0.64	1,774	0.03	4.22**	0.57	1,486	0.07	4.35**	0.63	3,080
(16)	Credit/value added	0.04	2.91**	0.69	1,214	0.02	2.18*	0.67	1,220	.	.	.	.

This table presents the results of the following univariate linear regression model:

$$Crisis_{it+3} = \alpha_i^{(h)} + \beta_k^{(h)} \Delta_3 d_{it}^k + \epsilon_{it+3}$$

where $Crisis_{it+3}$ is a dummy variable that equals one for the start of a systemic banking crisis within the next three years, $\alpha_i^{(h)}$ is a country fixed effect and $\sum_{k=0}^{K} \beta_k^{(h)} \Delta_3 d_{it}^k$ is a vector of three-year changes in the credit/GDP ratio of the trade, accommodation, and food, transport and communication, or household sector from $t-3$ to t. Driscoll and Kraay (1998) standard errors in parentheses allow for 3 lags. +, * and ** denote significance at the 10%, 5% and 1% level.

Model (1) is our baseline specification, a linear probability model (LPM) with country fixed effects (FE), where banking crises are defined as in Baron et al. (2019) and Laeven and Valencia (2018) for the remaining countries. Model (2) adds year FE. Model (3) is a logit model with standard errors clustered by country. Model (4) reports results from a conditional/FE logit model, which drops countries that never experienced a crisis. Model (5) is a random effects logit model that includes averages of the dependent and independent variables as covariates, as suggested by Mundlak (1978). Model (6) replaces the independent variables in the baseline model with three lags of one-year changes in credit/GDP; we report linear combinations of the coefficients. Model (7) replaces the independent variables with dummy variables equal to one if the 3-year change in credit/GDP is equal to its mean plus two standard deviations or higher. Model (8) creates a similar credit boom indicator following Greenwood et al. (2020) equal to one if the 3-year change in credit/GDP is equal to its 80th percentile or higher. Model (9) uses the systemic banking crisis dates from Reinhart and Rogoff (2009b). Model (10) only uses crisis dates from Laeven and Valencia (2018), and model (11) only the dates from Baron et al. (2019). Model (12) restricts the sample to the years before 2000. Models (13) and (14) restrict the sample to countries classified as high-income and low-income/middle-income by the World Bank in 2019, respectively. Model (15) controls for three-year changes in sectoral value added/GDP. Model (16) replaces d_{it}^T and d_{it}^{NT} with versions scaled over value added instead of GDP (not possible for household credit).

B Database Overview

We construct a new database on the sectoral distribution of private credit for 116 countries from 1940 to 2014. To do so, we draw on more than 600 country-specific sources, many of which were digitized for the first time. We systematically document the underlying sources and adjustment steps in a collection of standardized spreadsheets and provide a suite of Stata programs transform the raw data into a harmonized set of time series.

The spreadsheets contain detailed information on the sources used for each country and sector. It also documents breaks in the time series we identified based on a reading of the metadata, statistical manuals, and other publications, as well as conversations with individuals at the national authorities.

The software routines, written in Stata, read in the raw data from often many different sources for a single country and harmonize the data based on a set of programs. All adjustments are recorded in country-specific `.do` files and the series documentation in the spreadsheet collection.

The remainder of this data appendix will outline these two parts of the database, give more details on the conceptual issues involved in constructing sectoral credit data, and show how the data compare to existing sources.

B.1 Acknowledgements

This database is the result of a more than five-year process of data collection, retrieval, and harmonization. We would not have been able to undertake this effort without the generous support and guidance of the national authorities compiling the underlying data sources. While there were too many people involved to thank all of them individually, we would like to point out those who most patiently answered our requests and took the time to search and compile often non-public data from obscure sources. We would like to thank, without implicating, and in no particular order: Mads Kristoffersen (Danmarks Nationalbank), Walter Antonowicz and Clemens Jobst (Austrian National Bank), Marek Zeman (Czech National Bank), Karen Larsen (Statistics Denmark), David Tennant (University of the West Indies at Mona), Jaime Odio Chinchilla (Banco Central de Costa Rica), Constance Kabibi Kimuli (Bank of Uganda), Hannah Walton and Amy Lawford (Bank of England), Azza Al Harthy (Central Bank of Oman), Keith Venter and Esté Nagel (Reserve Bank of South Africa), Hrönn Helgadóttir (Bank of Iceland), Gunnar Axel Axelsson (Statistics Iceland), Ferhat Akpinar (Turkish Banking Regulation and Supervision Agency), Dorotha Michel (Central Bank of Seychelles), Katharina Østensen (Statistics Norway), Johanna Honkanen (Bank of Finland), Ivana Brziakova (National Bank of Slovakia), Ilona Haderer (Swiss National Bank), Sayako Konno (Bank of Japan), Jurgita Maslauskaite (Bank of Lithuania), Benita Tvardovska (Financial and Capital Market Commission Latvia), Gerli Rauk (Eesti Pank), Carol Msonda (Reserve Bank

of Malawi), Daniele Westig (European Mortgage Federation), Rosabel Guerrero (Bangko Sentral ng Pilipinas), Taghreed Zedan (Central Bank of Jordan), Noémi Uri (Central Bank of Hungary), Arad May (Bank of Israel), Scott Walker (Australian Prudential Regulation Authority), Michael Leslie and Ian McIlraith (Reserve Bank of New Zealand), Lynne Mackie (Statistics New Zealand), Bryan Grant (Central Bank of Belize), Pornpen Powattanasatien (Bank of Thailand), Róisín Flaherty (Central Bank of Ireland), Maximilian Dell (Deutsche Bundesbank), Reet Nestor (Statistics Estonia), Jide Lewis (Bank of Jamaica), Jesús Saurina (Banco de España), Meder Abdyrahmanov (National Bank of Kyrgyz Republic), Pilar Mateo Mejía (Banco Central de la República Dominicana), Agenor Olivardia (Instituto Nacional de Estadística y Censo de Panama), Athanasios Eliades (Central Bank of Cyprus), George Theodoulou (Statistics Cyprus), Anahit Safyan (National Statistical Service of Armenia), and Eric Monnet (Banque de France). We would further like to thank Aissata Thiam, Sungho Park, Flemming Slok, Yash Roy, Michelle Girouard, Sarah Guo, Gudrun Müller, and Nils Hübel for excellent research assistance. All remaining errors are ours.

B.2 Part 1: Spreadsheet collection

The first part of the database is a set of spreadsheets based on a common template for all countries. There are three spreadsheet files for each country:

- **Documentation file** Lists the sources used for total credit and the broad sectors households, non-financial corporations, and financial corporations, including links to data available online (where applicable). Provides the monthly time range each source is used for a particular sector, which lenders are covered, in which currency the data are reported, the original format of the raw data, as well as a set of notes.

- **Input file** Contains the raw data from each of the sources listed in the documentation file. For some countries, this may be more than 10 sources per sector, especially for total private credit. Also contains notes on specifics of particular sectors in a particular country.

- **Adjustment file** Contains a list of breaks in the time series that are due to changes in classification or coverage, not due to true jumps in the data, based on a reading of the metadata of the data source and communication with national authorities.

Taken together, these spreadsheets allow users to track where each individual data point in the database comes from and which adjustments are made to the raw data. They also serve as a repository of different data sources on credit in a particular country, which may be useful for some applications.

B.3 Part 2: Software routines

The second part of the database is a set of software routines, written in Stata code. These routines read in, merge, process, cross-validate, and harmonize the raw data contained in the spreadsheets. To easily allow for adjustments of individual countries, there is one `.do` file for every country based on a common template. These files call a range of programs, and add individual adjustments where necessary, following these conceptual steps:

1. **Read in the spreadsheets**
   `data_open.ado`
2. **Merge the data sources into one time series per sector**
   `data_consolidate.ado`
3. **Calculate data for missing sectors based on accounting identities**
   `data_fillin.ado`
4. **Check for the internal consistency of the raw data based on accounting identities**
   `data_consistency.ado`
5. **Optional: Apply data adjustments**
   (a) **Read in the file containing level breaks, if any**
   `adjust_setup.ado`
   (b) **Chain-link older data subject to level break using overlapping data**
   `adjust_overlap.ado`
   (c) **Chain-link older data subject to level break using a reference time series**
   `adjust_reference.ado`
   (d) **Chain-link older data subject to level break using median growth rate method**
   `adjust_overlap.ado`
   (e) **Rescale data to match aggregates**
   `adjust_rescale.ado`
   (f) **Check that all data containing level breaks were adjusted**
   `adjust_check.ado`
6. **Where available, interpolate intra-year data for total and household using monthly and quarterly data from the IMF IFS, Monnet and Puy (2019), and BIS**
   `data_interpolate.ado`

7. **Check for internal consistency of adjusted data based on accounting identities**
   `data_consistency.ado`

8. **Compare the raw and adjusted data with existing data sources**
   `data_comparison.ado`

9. **Save raw and adjusted data**

These software routines allow for a transparent construction of sectoral credit data and easily allow for changes in methodology.

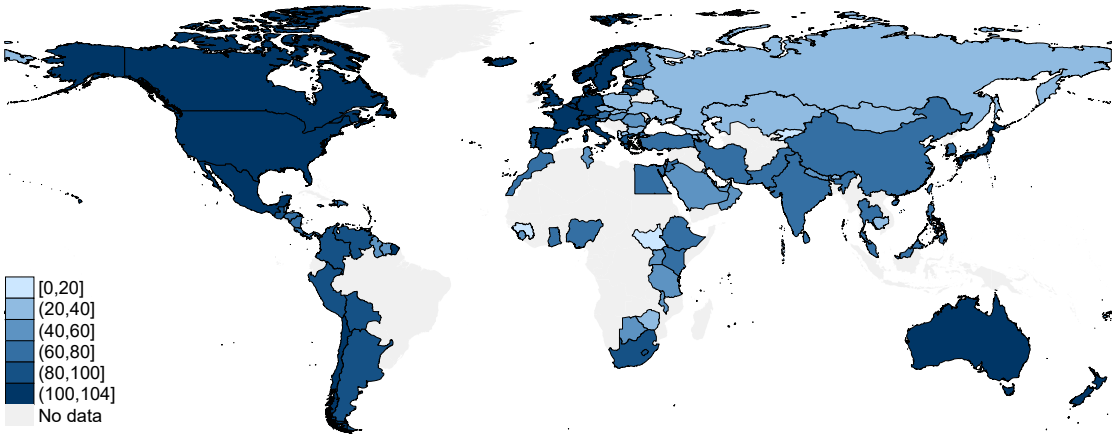
B.4 Database coverage

The Great Financial Crisis of 2007-08 has brought about a renewed interest in credit markets, prompting a few important efforts in assembling more detailed data for research purposes. The Bank of International Settlements has been at the forefront with its compilation of a "long series on credit to the private sector" (Dembiermont et al., 2013). Another important and much-cited line of work by Óscar Jordà, Moritz Schularick, and Alan Taylor, starting with Schularick and Taylor (2012), have resulted in the *Jordà-Schularick-Taylor Macrohistory Database* (Jordà et al., 2016). These efforts added to existing data compiled in the World bank's Global Financial Development Database (Cihák et al., 2013), which in turn largely builds on the International Monetary Fund's International Financial Statistics. Recently, the IMF has combined these data with a few additional sources in the Global Debt Database (Mbaye et al., 2018). Monnet and Puy (2019) digitized and harmonized quarterly data from the IMF's International Financial Statistics, including data on total credit to the private sector.

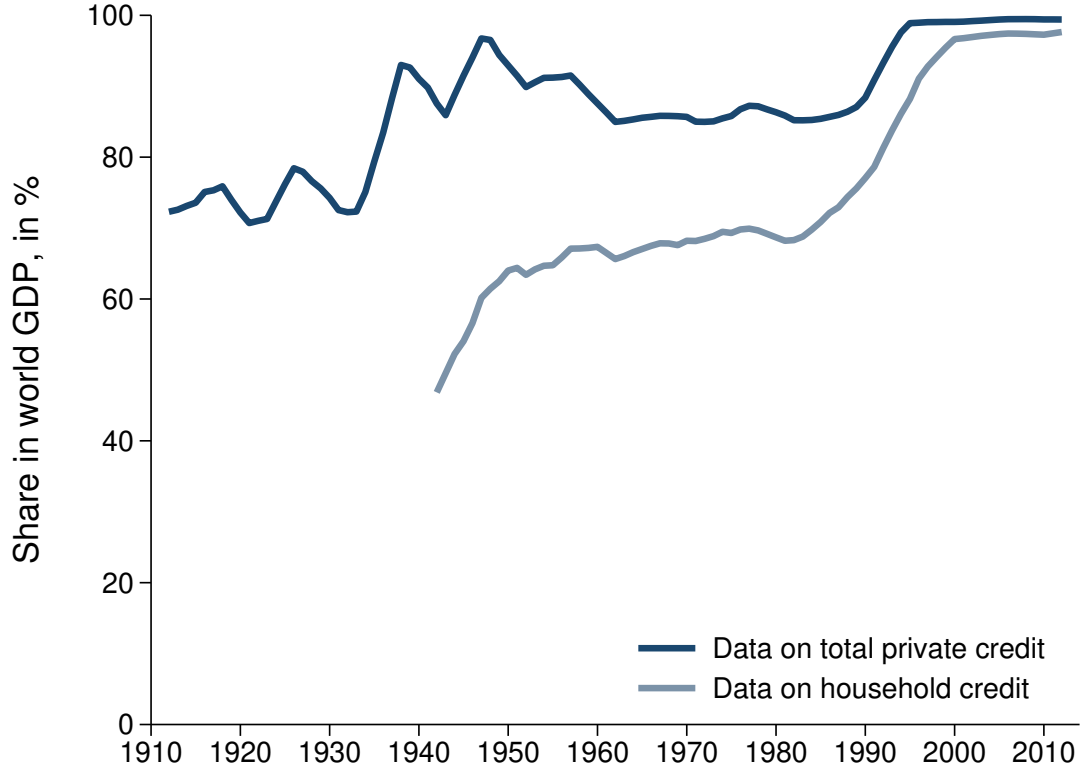
We add to this body of work by adding data on the sectoral allocation of credit and extending historical time series on household/firm and total private credit. The collection and dissemination of sectoral credit data by national authorities has largely moved in line with contemporary paradigms in central banking. As a result, the shift away from money and credit policies in many countries in the 1980s has brought about a somewhat paradox pattern in data availability: detailed credit data are often easier to retrieve for developing than advanced countries. For a few noteworthy cases, the United States, Sweden, China, and Russia, there exist no detailed publicly available sectoral credit data that is readily available; we are still in the process of constructing estimates for these countries. In other cases, such as Austria, Belgium or Finland, there are extensive historical data but scattered across many different sources (and even government agencies). On the other extreme, Kenya, Costa Rica, and Pakistan have data from a single source starting in 1947, 1953, and 1953, respectively.

Figure A14: Global Database Coverage

(a) Geographical Coverage, by Years in Sample



(b) Share of Database Countries in World GDP



Notes: Panel (a) plots countries with data on total private credit by the number of years in the database, starting in 1910. Panel (b) plots the share of countries with total and household credit data in our database in world GDP from 1940 to 2014.

Table A5 compares our dataset with existing efforts (replicating Table 1 from the main paper). The database includes an unbalanced panel of credit data for 116 countries, starting in 1940, covering 3–82 sectors. The total number of unique country-sector-time observations is 590,953, with data frequency ranging from monthly to yearly. Overall, there are 5,062 country-year observations.

Table A5: Comparison with Existing Data Sources on Private Credit

Dataset	Start	Freq.	Countries	Sectors	Country-year obs.	Country-sector-time obs.
WB GFDD	1960	Y	200	0	1251	1231
Monnet and Puy (2019)	1940	Q	49	0	3,185	11,678
BIS	1940	Q	44	2	2,046	17,712
IMF IFS	1948	Y/Q/M	186	0	10,504	86,892
IMF GDD	1950	Y	189	2	6,904	10,504
Jordà et al. (2016)	1870	Y	17	3	6,904	6,904
Müller and Verner (2020)	**1910**	**Y/Q/M**	**116**	**3–82 ($\mu = 33$)**	**5,062**	**590,953**

Notes: The data on total credit and sectoral data in Müller-Verner (2018) start in 1910 and 1940, respectively. WB GFDD stands for the World Bank's Global Financial Development Database (Cihák et al., 2013). BIS refers to the credit to the non-financial sector statistics described in Dembiermont et al. (2013). IMF IFS and GDD refer to the International Monetary Fund's International Financial Statistics and Global Debt Database, respectively. The data in Monnet and Puy (2019) is from historical paper editions of the IMF IFS. We count observations until 2014; the data will be updated to 2020 in a forthcoming revision.

Figure A14a shows a world map with the initial year data becomes available. All continents are well-represented, including many small open economies in Africa, Southeast Asia and throughout the Caribbean. There is no strong geographical pattern regarding the length of the available time series: countries from all continents feature data starting before 1960. A noticeable pattern is the relatively recent entry of countries of the former Soviet Union in Central and Eastern Europe. Table A6 lists the availability for all countries included in the database and the time periods for which data on broad sectors are available.

How does the coverage in the dataset compare to the size of the world economy? This is an important question because, unlike previous research, our data cover many small open economies that do not contribute much to world GDP. Figure A14b plots the share of the countries for which we have data on total and household credit in the database in world GDP. The data cover more than 80% of world GDP since at least 1935 and around 95% today for total credit. Household credit is available for at least 60% of world GDP since around 1950 and hovers around 90% today.

Table A6: Credit Data Coverage For Broad Sectors by Country

No.	Country	Total credit	Household/ firm credit	Residential mortgages	Major corporate sectors					
					Finance	NFC	Agriculture	Manuf., Mining	Construction	Other
1	Albania	2000-2014	2000-2014	2007-2014	2001-2014	2001-2014	2000-2014	2000-2014	2000-2014	2000-2014
2	Anguilla	1991-2014	1991-2014	1991-2014	1992-2014	1992-2014	1991-2014	1991-2014	1991-2014	1991-2014
3	Antigua & Barbuda	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014
4	Argentina	1952-2014	1952-2014	1952-2014	1952-2014	1952-2014	1952-2014	1952-2014	1952-2014	1952-2014
5	Armenia	1998-2014	1998-2014	2005-2014	2003-2014	2003-2014	—	1998-2014	1998-2014	1998-2014
6	Australia	1948-2014	1948-2014	1948-2014	1948-2014	1948-2014	1948-2014	1948-2014	1948-2014	1948-2014
7	Austria	1946-2014	1949-2014	1948-2014	1949-2014	1946-2014	1946-2014	1946-2014	1963-2014	1946-2014
8	Azerbaijan	2000-2014	2000-2014	2006-2014	2001-2014	2001-2014	2000-2014	2000-2014	2000-2014	2000-2014
9	Bahrain	1998-2014	1998-2014	2006-2014	1998-2014	1998-2014	1998-2014	1998-2014	1998-2014	1998-2014
10	Barbados	1966-2014	1966-2014	1975-2014	1969-2014	1969-2014	1966-2014	1966-2014	1966-2014	1966-2014
11	Belgium	1976-2014	1976-2014	1976-2014	1976-2014	1976-2014	1976-2014	1976-2014	1976-2014	1976-2014
12	Belize	1970-2014	1970-2014	1970-2014	1976-2014	1976-2014	1970-2014	1970-2014	1976-2014	1970-2014
13	Bhutan	1983-2014	2005-2014	—	—	—	1983-2014	1983-2014	1983-2014	1983-2014
14	Bolivia	1964-2014	1964-2014	2003-2014	1999-2014	2003-2014	1964-2014	1964-2014	1964-2014	1964-2014
15	Botswana	1990-2014	1990-2014	1995-2014	1990-2014	1990-2014	1990-2014	1990-2014	1990-2014	1990-2014
16	Bulgaria	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014
17	Cambodia	2000-2014	2004-2014	2008-2014	2000-2014	2004-2014	2000-2014	2000-2014	2000-2014	2000-2014
18	Canada	1942-2014	1942-2014	1954-2014	1942-2014	1942-2014	1942-2014	1942-2014	1942-2014	1942-2014
19	Chile	1993-2014	1993-2014	1993-2014	1998-2014	1998-2014	1993-2014	1993-2014	1993-2014	1993-2014
20	China	1952-2009	1994-2009	—	—	—	1952-2009	—	—	1952-2009
21	Colombia	1952-2014	1988-2014	1985-2014	1983-2014	1988-2014	1952-2014	1952-2014	1952-2014	1952-2014
22	Costa Rica	1956-2014	1985-2014	1985-2014	1999-2014	1999-2014	1956-2014	1956-2014	1985-2014	1956-2014
23	Curaçao & St. Maarten	1978-2014	1978-2014	—	—	1978-2014	—	1978-2014	1978-2014	1978-2014
24	Cyprus	1963-2007	1963-2007	2005-2007	2005-2007	2005-2007	1963-2007	1963-2007	1963-2007	1963-2007
25	Czech Republic	1992-2014	1992-2014	1997-2014	1992-2014	1992-2014	1992-2014	1992-2014	1992-2014	1992-2014
26	Denmark	1951-2014	1951-2014	1993-2014	1981-2014	1981-2014	1951-2014	1978-2014	1978-2014	1951-2014
27	Dominica	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014
28	Dominican Republic	1996-2014	1996-2014	1996-2014	2006-2014	2006-2014	1996-2014	1996-2014	1996-2014	1996-2014

Table A6: Sectoral Credit Data Coverage by Country (continued)

No.	Country	Total credit	Household/ firm credit	Residential mortgages	Major corporate sectors					
					Finance	NFC	Agriculture	Manuf., Mining	Construction	Other
29	Egypt	1991-2014	1991-2014	—	—	—	1991-2014	1991-2014	—	1991-2014
30	Estonia	1995-2014	1995-2014	1997-2014	1995-2014	1995-2014	1995-2014	1995-2014	1995-2014	1995-2014
31	Ethiopia	2000-2014	—	—	—	—	2000-2014	—	2000-2014	2000-2014
32	Fiji	1973-2014	1973-2014	1973-2014	1980-2014	1980-2014	1973-2014	1973-2014	1973-2014	1973-2014
33	Finland	1948-2014	1948-2014	1977-2014	1948-2014	1948-2014	1948-2014	1948-2014	1948-2014	1948-2014
34	France	2006-2014	2006-2014	2006-2014	2006-2013	2006-2014	2006-2014	2006-2014	2006-2014	2006-2014
35	Georgia	2003-2014	2003-2014	2006-2014	2003-2014	2003-2014	2003-2014	2003-2014	2003-2014	2003-2014
36	Germany	1949-2014	1949-2014	1949-2014	1968-2014	1968-2014	1949-2014	1949-1968	1951-2014	1949-2014
37	Ghana	1997-2014	2005-2014	—	—	—	1997-2014	1997-2014	1997-2014	1997-2014
38	Greece	1950-2014	1950-2014	1950-2014	1990-2014	1990-2014	1950-2014	1950-2014	2002-2014	1950-2014
39	Grenada	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014
40	Guatemala	1990-2014	1990-2014	2006-2014	2013-2014	2013-2014	1990-2014	1990-2014	1990-2014	1990-2014
41	Guyana	1993-2014	1993-2014	1993-2014	1993-2014	1993-2014	1993-2014	1993-2014	—	1993-2014
42	Haiti	1999-2014	1999-2014	1999-2014	1999-2014	1999-2014	1999-2014	1999-2014	1999-2014	1999-2014
43	Honduras	1958-2014	1958-2014	1958-2014	—	—	1958-2014	1958-2014	1958-2014	1958-2014
44	Hong Kong	1965-2014	1965-2014	1978-2014	1965-2014	1965-2014	1965-2003	1965-2014	1965-2014	1965-2014
45	Hungary	1995-2014	1995-2014	2000-2014	1995-2014	1995-2014	1995-2014	1995-2014	1995-2014	1995-2014
46	Iceland	1950-2014	1958-2014	1958-2014	1970-2014	1970-2014	1950-2014	1955-2014	1970-2014	1950-2014
47	India	1972-2014	1972-2014	1973-2014	1973-2014	1973-2014	1972-2014	1972-2014	1972-2014	1972-2014
48	Iran	1967-2012	—	—	—	—	1967-2012	1967-2012	1967-2012	1967-2012
49	Israel	1974-2014	1974-2014	2002-2014	1991-2014	1991-2014	1974-2014	1974-2014	1974-2014	1974-2014
50	Italy	1948-2014	1948-2014	1997-2014	1948-2014	1948-2014	1948-2014	1965-2014	1948-2014	1948-2014
51	Jamaica	1967-2014	1970-2014	—	1967-2014	1970-2014	1967-2014	1967-2014	1967-2014	1967-2014
52	Japan	1948-2014	1948-2014	1965-2014	1948-2014	1948-2014	1948-2014	1948-2014	1948-2014	1948-2014
53	Jordan	1964-2014	1964-2014	—	1964-2014	1964-2014	1964-2014	1964-2014	1964-2014	1964-2014
54	Kazakhstan	1997-2014	1997-2014	—	1997-2014	1997-2014	1997-2014	1997-2014	1997-2014	1997-2014
55	Kenya	1947-2014	1965-2014	—	1965-2014	1965-2014	1947-2014	1947-2014	1965-2014	1947-2014
56	Kuwait	1972-2014	1972-2014	2000-2014	1972-2014	1972-2014	1972-2014	1972-2014	1972-2014	1972-2014

Table A6: Sectoral Credit Data Coverage by Country (continued)

No.	Country	Total credit	Household/ firm credit	Residential mortgages	Major corporate sectors					
					Finance	NFC	Agriculture	Manuf., Mining	Construction	Other
57	Kyrgyz Republic	1996-2014	1996-2014	2003-2014	—	—	1996-2014	1996-2014	1996-2014	1996-2014
58	Latvia	2000-2014	2000-2014	2003-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014
59	Lesotho	2002-2014	2002-2014	—	—	—	2008-2014	2002-2014	2002-2014	2002-2014
60	Lithuania	1995-2014	1995-2014	2004-2014	1995-2014	1995-2014	1995-2014	1995-2014	1995-2014	1995-2014
61	Macedonia	2004-2014	2004-2014	2004-2014	2004-2014	2004-2014	2004-2014	2004-2014	2004-2014	2004-2014
62	Malawi	1990-2014	1990-2014	2013-2014	2013-2014	2013-2014	1990-2014	1990-2014	1990-2014	1990-2014
63	Malaysia	1968-2014	1971-2014	1971-2014	1996-2014	1996-2014	1968-2014	1968-2014	1968-2014	1968-2014
64	Maldives	1985-2014	1985-2014	—	—	—	1985-2014	1985-2014	1985-2014	1985-2014
65	Malta	1969-2014	1969-2014	1969-2014	1969-2014	1969-2014	1969-1992	1969-2014	1969-2014	1969-2014
66	Mauritius	1967-2014	1967-2014	1979-2014	1967-2014	1967-2014	1967-2014	1967-2014	1992-2014	1967-2014
67	Mexico	1942-2014	1984-2014	1942-2014	1979-2014	1984-2014	1942-2014	1969-2014	1969-2014	1942-2014
68	Mongolia	2000-2014	2000-2014	2008-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014
69	Montserrat	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014
70	Morocco	1977-2014	1993-2014	1993-2014	2001-2014	2001-2014	1977-2014	1977-2014	1977-2014	1977-2014
71	Nepal	1975-2014	2002-2014	—	1979-2007	—	1975-2014	1975-2014	2002-2014	1975-2014
72	Netherlands	2010-2014	2010-2014	2010-2014	2010-2014	2010-2014	2010-2014	2010-2014	2010-2014	2010-2014
73	New Zealand	1940-2014	1940-2014	1956-2014	1940-2014	1994-2014	1940-2014	1940-2014	1956-2014	1940-2014
74	Nicaragua	1960-2014	1995-2014	1960-2014	—	—	1960-2014	—	—	1960-2014
75	Nigeria	1960-2014	1966-1992	—	1960-2014	—	1960-2014	1960-2014	1960-2014	1960-2014
76	Norway	1946-2014	1946-2014	1946-2014	1947-2014	1946-2014	1946-2014	1946-2014	1946-2014	1946-2014
77	Oman	1990-2014	1990-2014	—	1990-2014	1990-2014	1990-2014	1990-2014	1990-2014	1990-2014
78	Pakistan	1953-2014	1982-2014	2003-2014	1953-2014	1982-2014	1953-2014	1953-2014	1953-2014	1953-2014
79	Panama	1963-2014	1963-2014	1963-2014	1970-2014	1975-2014	1963-2014	1963-2014	1963-2014	1963-2014
80	Peru	1947-2014	1947-2014	2001-2014	1990-2014	1990-2014	1947-2014	1947-2014	1947-2014	1947-2014
81	Philippines	1980-2014	1981-2014	1997-2014	1999-2014	1999-2014	1980-2014	1980-2014	1980-2014	1980-2014
82	Poland	2002-2014	2002-2014	2002-2014	2002-2014	2002-2014	2002-2014	2002-2014	2002-2014	2002-2014
83	Portugal	1966-2014	1966-2014	1966-2014	1966-2014	1966-2014	1966-2014	1966-2014	1973-2014	1966-2014
84	Qatar	1977-2014	1977-2014	1977-2014	1980-2002	1980-2002	1977-2002	1977-2014	1977-2014	1977-2014

Table A6: Sectoral Credit Data Coverage by Country (continued)

No.	Country	Total credit	Household/ firm credit	Residential mortgages	Major corporate sectors					
					Finance	NFC	Agriculture	Manuf., Mining	Construction	Other
85	Romania	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014
86	Russia	2002-2014	2002-2014	2005-2014	2002-2014	2002-2014	2002-2014	2002-2014	2002-2014	2002-2014
87	Saudi Arabia	1970-2014	1998-2014	1998-2014	1970-2014	1998-2014	1970-2014	1970-2014	1970-2014	1970-2014
88	Seychelles	1997-2014	1997-2014	—	1997-2014	1997-2014	1997-2014	1997-2014	1997-2014	1997-2014
89	Sierra Leone	1996-2014	2001-2014	—	2004-2014	—	1996-2014	1996-2014	1996-2014	1996-2014
90	Singapore	1962-2014	1980-2014	1991-2014	1963-2014	1980-2014	1962-2014	1962-2014	1962-2014	1962-2014
91	Slovak Republic	1992-2014	1992-2014	2003-2014	1992-2014	1992-2014	1992-2014	1992-2014	1992-2014	1992-2014
92	Slovenia	1994-2014	1994-2014	2004-2014	1994-2014	1994-2014	1994-2014	1994-2014	1994-2014	1994-2014
93	South Africa	1994-2013	1994-2013	—	1994-2013	1994-2013	1994-2013	1994-2013	1994-2013	1994-2013
94	South Korea	1952-2014	1952-2014	1967-2014	1954-2014	1967-2014	1952-2014	1952-2014	1952-2014	1952-2014
95	Spain	1992-2014	1992-2014	1992-2014	1992-2014	1992-2014	1992-2014	1992-2014	1992-2014	1992-2014
96	Sri Lanka	1996-2014	1996-2014	2009-2014	—	—	1996-2014	2009-2014	1996-2014	1996-2014
97	St. Kitts & Nevis	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014
98	St. Lucia	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014
99	St. Vincent & Grenadines	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014
100	Suriname	1969-2014	1969-2014	1985-2014	—	—	1969-2014	1969-2014	1969-2014	1969-2014
101	Switzerland	1985-2014	1985-2014	1985-2014	1985-2014	1985-2014	1997-2014	1985-2014	1985-2014	1985-2014
102	Taiwan	1956-2014	1956-2014	1997-2014	1997-2014	1997-2014	1956-2014	1956-2014	1997-2014	1956-2014
103	Tanzania	1967-2014	2003-2014	—	1967-2014	2003-2014	1967-2014	1967-2014	1967-2014	1967-2014
104	Thailand	1965-2014	1965-2014	1981-2014	1965-2014	1965-2014	1965-2014	1965-2014	1965-2014	1965-2014
105	Trinidad & Tobago	1946-2014	1954-2014	1987-2014	1963-2014	1963-2014	1946-2014	1946-2014	1963-2014	1946-2014
106	Tunisia	1962-2014	1962-2014	2002-2014	2007-2014	2007-2014	1962-2014	1962-2014	1962-2014	1962-2014
107	Turkey	2002-2014	2002-2014	2002-2014	2002-2014	2002-2014	2002-2014	2002-2014	2002-2014	2002-2014
108	Uganda	1991-2014	2004-2014	2010-2014	2004-2007	2004-2007	1991-2014	1991-2014	1991-2014	1991-2014
109	Ukraine	2000-2014	2000-2014	2006-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014
110	United Arab Emirates	1998-2014	1998-2014	—	1998-2014	1998-2014	1998-2014	1998-2014	1998-2014	1998-2014
111	United Kingdom	1946-2014	1946-2014	1963-2014	1946-2014	1946-2014	1946-2014	1946-2014	1946-2014	1946-2014
112	United States	1936-2014	1936-2014	1936-2014	—	—	1936-2014	—	—	1936-2014

Table A6: Sectoral Credit Data Coverage by Country (continued)

No.	Country	Total credit	Household/ firm credit	Residential mortgages	Major corporate sectors					
					Finance	NFC	Agriculture	Manuf., Mining	Construction	Other
113	Venezuela	2004-2014	2004-2014	2004-2014	2004-2014	—	2004-2014	2004-2014	2004-2014	2004-2014
114	Zimbabwe	1991-2014	1991-2014	—	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014

Figure A15a shows that the total number of observations in our dataset is an order of magnitude above that of the data from the BIS, IMF International Financial Statistics (IFS) and Global Debt Database (GDD), World Bank Global Financial Development Database (GFDD), Jordà et al. (2016), and Monnet and Puy (2019). Figure A16 compares the number of countries in the sample by their availability of total, household/firm, and mortgage credit. Our database more than doubles the number of countries with data on household credit since 1970 to existing sources.

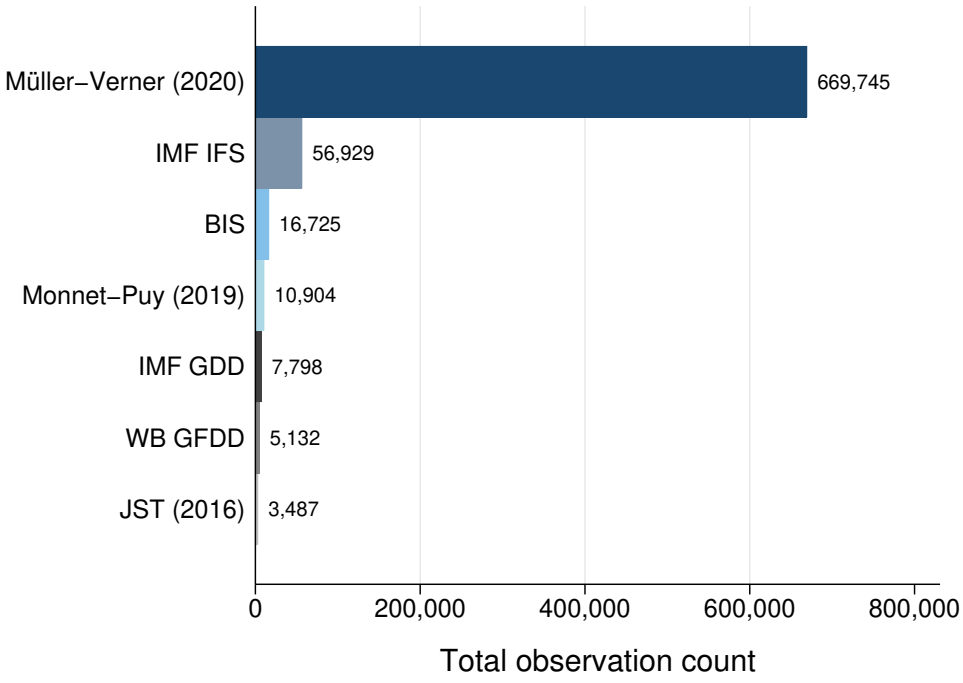
Another contribution is that our dataset increases the number of countries with monthly or quarterly data on credit markets, in particular relative to the widely-used BIS data, as well as Monnet and Puy (2019). Figure A17 shows this pattern. For around 20 countries, there is data for the period before 1960, but only in half of the cases with higher than yearly frequency. From the early 2000s on, almost all countries report data at least at quarterly frequency. A major increase in coverage occurs around 1990, which is driven both by the entry of countries of the former Soviet Union as well as many other emerging markets.

Our dataset allows a much deeper look into corporate and household credit markets by differentiating between different industries and purposes. Because of differing classification standards and levels of detail in the reporting, the number of the coverage varies much more here compared to the different types of household lending. Figure A18 highlights this by showing the total number of sub-sectors across countries over time. We plot the average number of sectors per country-year, as well as confidence intervals for the 10th, 25th, 75th and 90th percentiles. The number of sectors ranges from 3–82, with an average of 33.

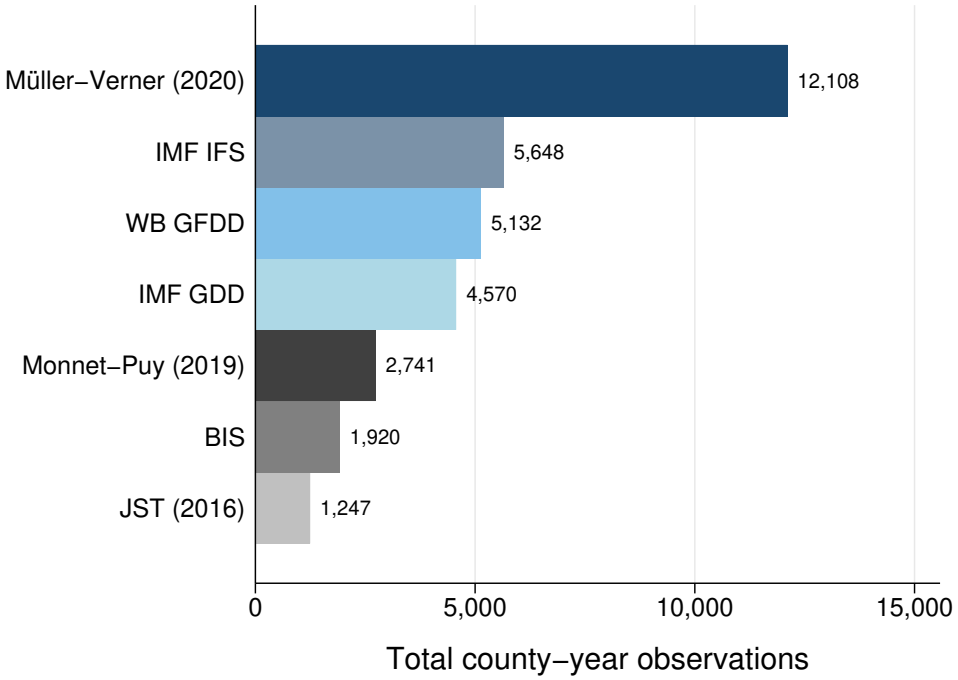
Another addition of the newly collected data is the availability of household credit by type. The most obvious distinction here is between residential mortgages and all other types of credit. Figure A19a shows that this breakdown is available for a substantial fraction of countries. For a smaller number of 83 countries, there are also explicit data on consumer credit, which also include car loans and credit cards. These detailed categories are available for an even smaller, but still sizeable group of around 44 and 25 countries for credit card and car loans, respectively. As we outline in more detail below, the classification of consumer credit across countries does not follow harmonized guidelines. In some countries, the category is strictly limited to loans financing the purchase of durable goods, while in others it covers all household loans that are not mortgages. To aid comparisons, we thus use the residual of total household credit and residential mortgages as proxy for consumer credit. In the dataset, however, we also report a time series on consumer credit as reported by the national authorities, which is at times somewhat lower than the residual. This discrepancy usually arises because countries report additional household credit categories such as student loans or loans to sole proprietors. Because such additional breakdowns are rare, we did not systematically collect them.

Figure A15: Comparing the Observation Count of Datasets on Private Credit

(a) Total Observations



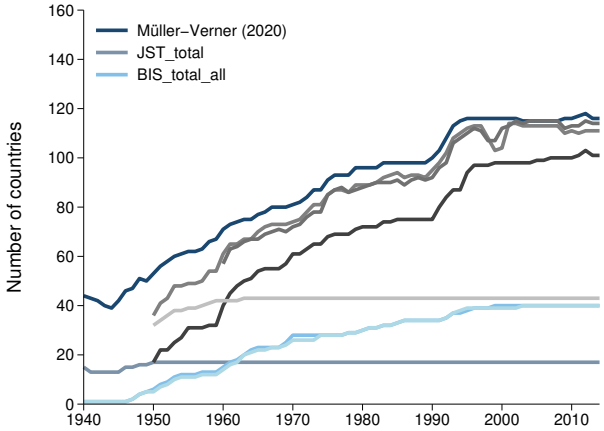
(b) Country-Year Observations



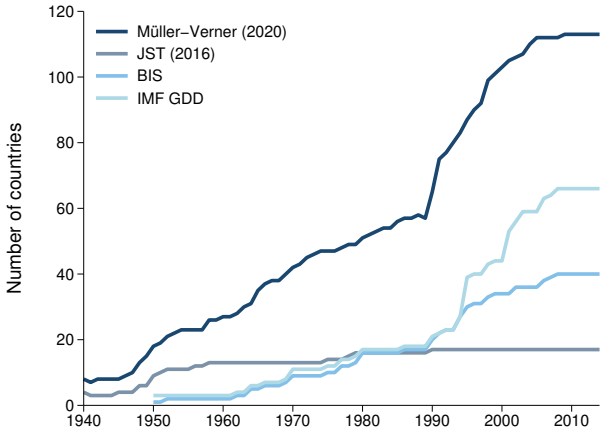
Notes: These figures compare the number of observations in different datasets on private credit. Panel (a) counts the total number of country-(sector)-time observations. Panel (b) counts country-year observations.

Figure A16: Comparing the Country Coverage of Different Sources on Private Credit Data

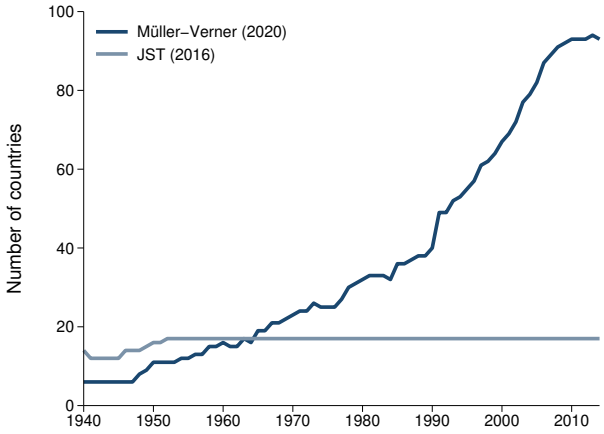
(a) Countries with Total Credit Data



(b) Countries with Household/Firm Credit Data

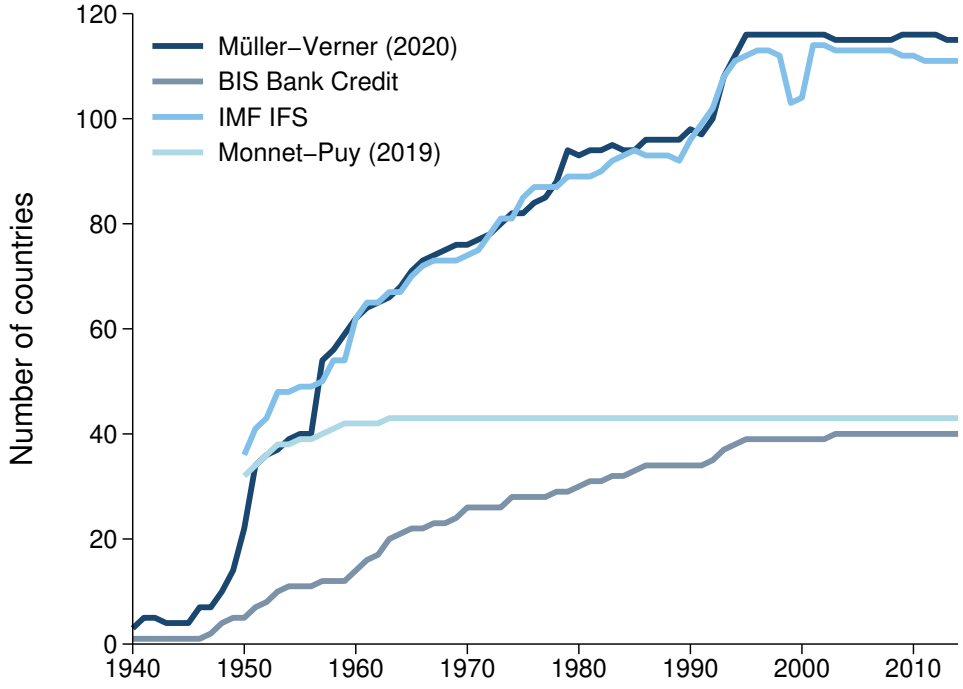


(c) Countries with Mortgage Credit Data



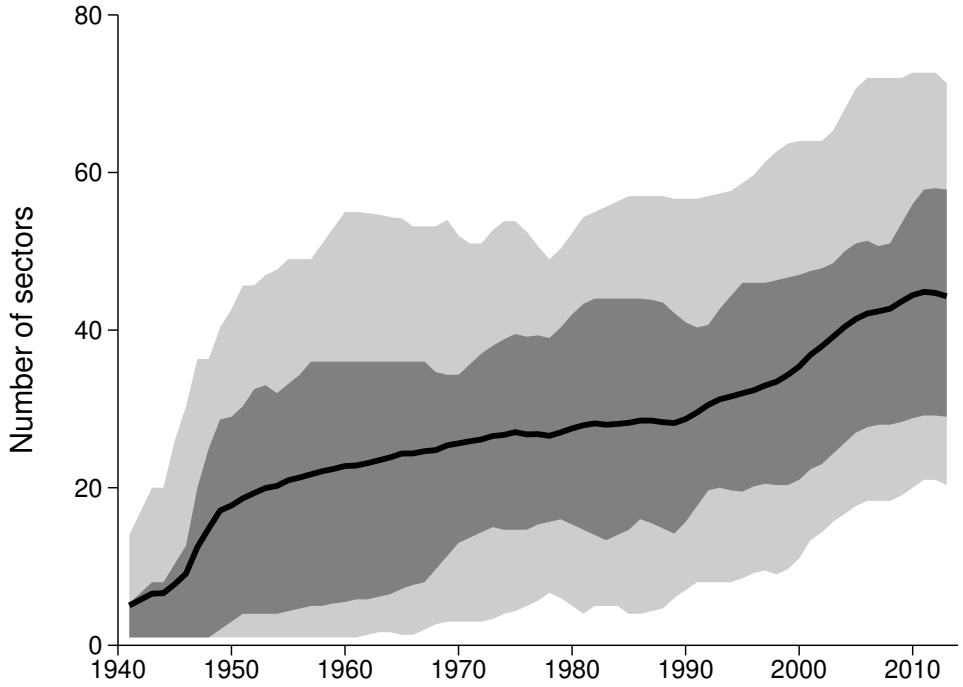
Notes: These graphs compare the coverage of different datasets on total credit (panel a), household/firm credit (panel b), and mortgage credit (panel c) over time. We compare our data to that compiled by the IMF IFS and GDD (Mbaye et al., 2018), BIS (Dembiermont et al., 2013), Jordà et al. (2016), Monnet and Puy (2019), and World Bank GFDD. See text for more details.

Figure A17: Country Coverage With Quarterly or Monthly Data



Notes: This graph plots the number of countries with intra-year data over time. Data from the BIS or Monnet and Puy (2019) are quarterly, data in our dataset and the IMF IFS monthly or quarterly.

Figure A18: Numbers of Sectors per Country-Year Observation



Notes: This graph plots the average number of sectors per country-year observation. The shaded areas represent the 10th, 25th, 75th, and 90th percentiles.

Figure A19 provides an overview for the availability of additional data breakdowns. Panel (a) shows the number of countries where we can differentiate between household credit depending on whether it is used for residential mortgages or otherwise. Panel (b) shows where we can differentiate between total mortgage lending (as in Jordà et al. (2016)) and residential mortgages. In Panel (c), we show that around 20 countries have data on credit by manufacturing sub-sectors since the 1970s, and more than 50 since 2000.

C Details on Data Construction

C.1 Credit data sources and classification

The principal data sources for this project were publications by national central banks and statistical offices. To identify the availability of detailed credit data, we followed four simple steps.

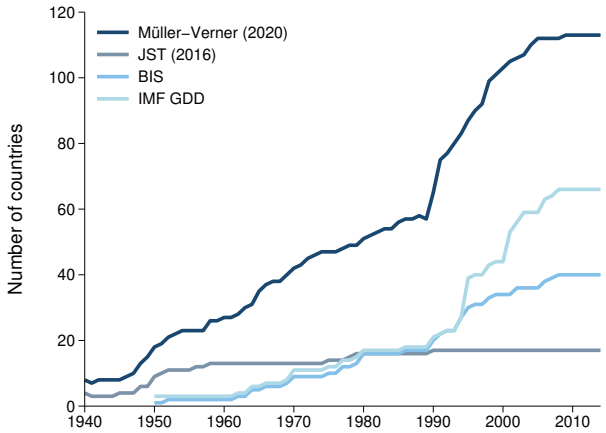
Step 1: Identifying time series online We started by consulting the websites of national central banks and other regulators, as well as statistical offices. Since the online data availability is often broader, we used the native language versions in most cases. Typically, the online databases of the national authorities contain time series for at least the most recent years, usually in the range of 10 to 25 years.

Step 2: Identifying data in PDF format or supervisory files Next, we turned to the source publications of the data, often only available in their original languages, especially for historical data. In many cases, these were the annual reports and statistical bulletins published by national central banks or statistical yearbooks and abstracts published by statistical agencies. At times, further data were available from old research publications such as working papers or compilations of historical data (e.g. the Bank of England's "Statistical Abstract" or Swiss National Bank's "Historical Time Series"). In many cases, the data were not collected for public dissemination but supervisory purposes and thus only available as Excel sheets or PDF files for one period (e.g. in Israel or South Africa). Another variant we often encountered was the collection and publication of sectoral data as part of financial stability reports (e.g. in Slovenia). We combined the raw data by copying the data—sometimes from hundreds of individual files—into time series format.

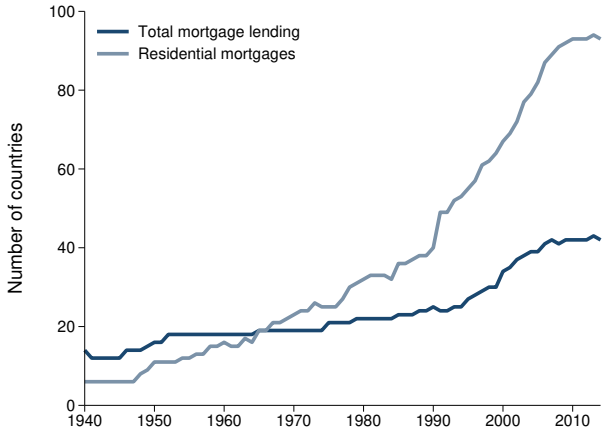
Step 3: Contacting the national authorities As a third step, we contacted the statistics and banking supervision departments of all national authorities who collected or published sectoral credit data at any point in time via email. The vast majority of agencies responded and provided helpful pointers to historical sources. In many cases, they also shared unpublished data with us. At

Figure A19: Country Coverage for Special Aggregates

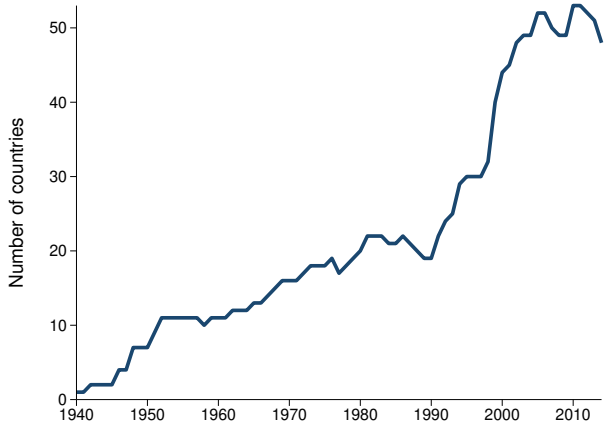
(a) Number of Sample Countries with Mortgages/Non-Mortgage Household Credit



(b) Number of Sample Countries with Total/Residential Mortgage Data



(c) Number of Sample Countries With Data on Manufacturing Sub-Sectors



Notes: These graphs plot the number of countries with data on residential mortgages and other types of household credit (panel a), data on residential and total mortgages (panel b), and data on manufacturing sub-sectors on the ISIC section-level (panel c, e.g. manufacture of food).

times, our enquiry also prompted an overhaul of existing data and we were sent corrected versions which were more comparable over time. Interestingly, there were also a few cases where we were informed that no data was available before a certain date. When we consulted historical documents, however, it turned out there was indeed more data the providers were not aware of.

Step 4: Digitizing additional historical data Lastly, for countries without an online depository for historical publications, or where we suspected additional data, we searched the libraries of multiple universities and central banks for easily retrievable volumes. The Bank of Japan gratefully sent us large amounts of paper volumes containing historical data starting in 1948 via mail, which were photocopied from their archives. Large parts of the database are newly digitized time series we collected from such historical publications. Figure A20 plots an example of what these historical data usually look like.

It is worth noting why certain countries were consciously not included in the database. Especially in developing countries which actively pursue credit policies, i.e. targeted credit controls, the classification of sectors and economic activities is at times difficult to compare with other economies or often yields only one or two comparable sub-sectors. We do not include such cases. We further required countries to have at least 10 years of available data when we started collecting data in 2015.

For total credit, we retrieved additional data from existing sources. These include the BIS long series on lending to the private sector, the IMF International Financial Statistics, UN Statistical Yearbooks and the League of Nations' Commercial Banks and Statistical Yearbook publications. The latter two allow us to create long-run time series for the broadest range of countries we are aware of. For some countries, we also create new historical total credit series from national sources.

C.2 Definition and coverage of lending institutions and credit

We tried to achieve the broadest possible coverage of domestic private credit markets. There are, however, trade-offs we had to make in regards to (1) the type of lending institutions, and (2) what constitutes "credit".

C.2.1 Definition of lending institutions

The coverage of lending institutions varies from country to country, depending on the laws governing data compilation as well as the structure of the financial system. In many countries, increases in the market share of non-bank financial institutions have led to a broader coverage over time, often encompassing all lenders including leasing institutions, specialized financing companies, in-

Figure A20: Source Example – Canada, Data on Sectoral Credit, 1950-1952

17.—Loans of Chartered Banks, according to Class, Outstanding at Sept. 30, 1950-52

NOTE.—The classification of chartered bank loans was revised in 1950; the figures in this table are, therefore, not comparable with those for 1947-49 in the 1951 Year Book, pp. 1043-1044.

Class of Loan	1950	1951	1952
	$'000	$'000	$'000
Government and Other Public Services—			
Provincial governments	23,600	24,859	6,349
Municipal governments and school districts	91,505	114,531	102,399
Religious, educational, health and welfare institutions	33,143	45,912	43,284
Totals, Government and Other Public Services	148,248	185,302	152,032
Financial—			
Investment dealers and brokers to the extent payable on call or within thirty days	101,177	107,091	135,173
Trust, loan, mortgage, investment and insurance companies and other financial institutions	85,983	91,720	107,519
Totals, Financial	187,160	198,811	242,692
Personal—			
Individuals, for other than business purposes, on the security of marketable stocks and bonds	243,370	255,605	274,324
Individuals, for other than business purposes, *n.e.s*	218,201	211,303	227,992
Totals, Personal	461,571	466,908	502,316
Agricultural, Industrial and Commercial—			
Farmers	255,783	298,936	334,202
Industry—			
Chemical and rubber products	29,175	54,257	30,322
Electrical apparatus and supplies	14,310	41,388	22,886
Food, beverages and tobacco	122,514	171,968	168,366
Forest products	76,057	115,685	136,500
Furniture	16,188	19,776	14,363
Iron and steel products	53,389	97,509	95,641
Mining and mine products	26,015	33,381	47,991
Petroleum and products	22,914	31,055	32,813
Textiles, leather and clothing	138,862	213,377	157,963
Transportation equipment	30,102	46,437	52,810
Other products	55,180	63,118	53,156
Public utilities, transportation and communication companies	53,912	87,937	67,526
Construction contractors	122,736	151,774	158,643
Grain dealers and exporters	93,124	98,558	186,518
Instalment finance companies	96,476	100,830	149,397
Merchandisers	436,144	542,869	483,967
Other business	135,492	133,837	139,047
Totals, Agricultural, Industrial and Commercial	1,778,373	2,302,692	2,332,111
Grand Totals	**2,575,352**	**3,153,713**	**3,229,151**

Note: This figure shows a scan from the Canada Year Book containing data on credit by sector/type.

vestment trusts, and so on. In other cases, disaggregated data exists only for commercial bank lending.

While the data collected by the Bank of International Settlements clearly shows that non-bank financial institutions can make up a significant share of total credit (Dembiermont et al., 2013; Drehmann, 2013), it would be incorrect to simply "scale up" disaggregated data covering only commercial banks, for example, to match some broader aggregate total credit volume. Different types of financial institutions, after all, fulfill different economic functions. As a compromise, we thus use the most comprehensive lender coverage for which we were able to identify disaggregated *non-financial corporate credit* data. It should be noted that even this compromise comes at a cost, since for many countries there are separate tables for different institutions (e.g. "commercial banks" and "other financial institutions"), which often had to be copied by hand and manually summed up. In general, form follows function in terms of coverage: most countries adjust the scope of covered institutions to include the bulk of the local financial system.

In some countries, the reporting standards for (disaggregated) non-financial corporate credit data diverge from that of broader sectoral aggregates. For example, detailed industry-level data are often only available for commercial banks, while broader sectors may include other lending institutions such as other MFIs. We dealt with these cases using one of two strategies. If the broader aggregates (households, non-bank financial, etc.) were also available for the same lender coverage as the disaggregated corporate credit data, we usually stuck with the conservative approach of limiting the lender coverage but retaining a representative picture of these intermediaries' balance sheet. In the example above, this would mean limiting the data to commercial banks. If, however, there was no data on the broad sectors available for the same lender coverage, or we had reason to believe that non-bank lenders or other MFIs made up a considerable market share of the credit market, we re-scaled the raw industry-level data. In particular, we multiplied the share of each industry in the total reported corporate credit market with the share of the credit market in the broader total credit aggregates that may also include other lenders. Implicitly, this assumes that the composition of the total corporate credit market portfolio is similar to that of the reporting institutions.

We use five different classifications for the coverage of lending institutions: "Commercial Banks (Banks)", "Credit Institutions (CIs)", "Monetary Financial Institutions (MFIs)", "All lenders", and "All lenders (incl. government)". We broadly follow the European Central Bank's definitions of MFIs and CIs. CIs include commercial banks and all other deposit-taking institutions, such as savings banks or credit cooperatives. MFIs additionally include money market funds (MMFs) and similar entities. "All lenders" further expands the definition to include all non-bank institutions, such as non-deposit taking specialised housing or shipping lenders, as well as investment trusts. Direct loans by the central bank are generally not included in these statistics, and we exclude them

wherever they are separately reported. The institutional coverage of the raw data is noted for each individual data source in the series documentation file. Note that the reported lender coverage in the documentation refers to the raw data: where there are differences between different raw data sources that had to be adjusted to make them comparable, this is described in detail on a case-by-case basis.

Because of data limitations, we do not systematically differentiate by bank ownership, i.e. whether lenders are privately or state-owned. Since government ownership of banks is considerable in some countries (La Porta et al., 2002), this also guarantees the broadest possible coverage. In many emerging economies in particular, development banks have substantial market shares in the financing of sectors that are deemed national priorities.

In many countries, the share of covered institutions increases over time. When adjusting the data, we sometimes make the assumption that the more recent data is more accurate and scale up the older data using overlapping values. Costa Rica is a good example, where the statistics only include the "banking system" from 1956 to 1985 and the "total financial system" starting in 1985. To correct for a small level-shift in the data—which is most pronounced for mortgage lending—we scale up the pre-1985 data using the overlapping values to avoid exaggerated movements arising from the reclassification. Implicitly, we thus assume that the growth rates of the "banking system" are representative of the "total financial system" before 1985. The underlying assumptions are rarely strong: in most cases, differences in coverage come from commercial banks versus all monetary financial institutions, where the latter often include credit unions or savings banks with large market shares in residential mortgages but little other activities. In cases where the deviations in coverage are large or we have other background information (communicated via personal contact from or obtained from documents published by the national authorities), we stay on the conservative side and stick with a smaller coverage that is comparable over time. For more details on data adjustments and robustness tests, also see section C.4.2.

C.2.2 Definition of credit instruments

Debt contracts come in different forms, with a major distinction between "debt securities" (mostly bonds) and "loans" (mostly bank credit). Depending on the country and time period, different types of credit may be more or less important, even though bank credit is still the overwhelming form of debt financing in almost all countries in the database. Unfortunately, most countries do not separately report the type of underlying contract. Instead, definitions are often vague—such as "Total Loans and Advances", "Domestic Lending" or "Claims"—and details are not always easy to verify. We thus include the broadest definition available where a distinction is made, e.g. the sum of "Loans" and "Debt securities" in the case of Greece. We retrieve data on end-of-period outstanding amounts of credit in all currencies, including lending in foreign currency, which can make up a

significant fraction. Here again, form usually follows function in reporting classifications. In the few countries who do not report foreign currency lending, we manually verified that it plays little to no role.

We have not been able to systematically identify sectoral data for other types of claims or equity stakes, which might be especially relevant for credit to the non-bank financial sector. Inter-financial claims in advanced financial systems often take the form of repos, swaps, or other instruments. Due to the lack of more detailed information, we usually use a version of "credit to non-bank financial institutions". These time series—usually taken from broader surveys of the central bank—have a flow-of-funds type of character and usually include all claims. As explained in section C.4.5 below, we have invested significant resources to achieve the best possible comparability of the data with other loan aggregates, e.g. to households or industrial sub-sectors.

An important distinction further has to be made between "gross" and "net" credit. All of the values we collected are "gross" in two respects. First, they constitute outstanding amounts (i.e. stocks) of credit without subtracting bank liabilities such as deposits, as is the case for some data published by the IMF. Second, they are gross of non-performing loans and thus *include* overdue claims. The latter is dictated by data availability, as most countries do not separately report sectoral breakdowns of non-performing loans (NPLs).[19] Since the desirability of excluding NPLs further depends on the application, we give preference to the data comparability across countries. Note that this has been standard procedure in previous efforts in collecting private credit data.

C.3 Sectoral and industry classification

The dataset includes credit for up to 82 individual sectors, where we differentiate between *broad sectors* (non-financial corporations, households, non-bank financial corporations) and *non-financial corporate sectors* (e.g. manufacturing, transport and communication). Given the detailed nature of the data and heterogeneous availability, the panel is strongly unbalanced. The average country reports values for 33 different sectors, the median country for 29. The data include lending to the sectors defined in more detail below irrespective of the ownership of the borrower: this means that lending to public (state-owned) corporations is sometimes included in the data (see also section C.3.4).

Note that, in general, we only collected data on the broad sectors where more detailed industry data was available. In some countries, the broader aggregates are available for longer time periods, and the current coverage could be extended to include these data. Table **??** shows a full outline of the sectoral structure of the data.

[19] Where countries report NPLs that are not included in the outstanding amounts, we manually add up the series. This is only the case for a handful of sources and noted in the series documentation.

C.3.1 Classification of broad sectors

For the classification of credit into broad sectors, we follow the System of National Accounts (SNA 2008) (United Nations, 2009) and use the groups "households and non-profit organizations serving households", "non-financial corporations", and "non-bank financial corporations". In the publications we used as sources, the latter group is sometimes also referred to as "other financial corporations" or, somewhat confusingly, simply "financial corporations". Note that we always *exclude* interbank credit. Where the classification in the raw broad sectoral data was unclear, we verified it in personal contact with the respective authorities.

Since a breakdown of households into sole proprietors and private persons is usually not available, the sector includes *all* lending to households.[20] We further add the category "corporate credit", defined as the sum of credit to all non-financial and non-bank financial corporations. The data on credit by broad sectors are in many countries reported in a separate survey from credit to different industries. In some countries, data on credit to non-financial corporations, non-bank financial corporations, and households are reported in the same survey. Where the classification was unclear, or there were multiple diverging sources, we inquired about the exact concepts with the publishing organization.

It is important to note that a careful compilation of household and corporate credit data at times leads to differences with existing data sources, such as Jordà et al. (2016). The reason is that other datasets often construct time series on corporate or household credit as a residual from total credit data without acknowledging important classification differences. In particular, sole proprietorships are often not systematically classified as household or corporate credit. In other cases, "total credit to the non-financial private sector" also includes (1) lending to corporations engaged in public administration or (2) lending to non-bank financial corporations. We have taken great care in describing the data coverage for each individual source in detail in the series documentation and making necessary adjustments to enable cross-country comparisons.

C.3.2 Classification of credit to financial institutions (excluding banks)

Financial sector lending (excluding the interbank market) deserves a few extra comments, because of the special attention that was required in compiling these data. Depending on the country classification, tables on credit by non-financial corporate sectors (see Appendix C.3.3) sometimes include credit to the (non-bank) financial sector; sometimes they do not. As a result, tables on the credit market structure by individual industries were often matched to the non-bank data from broader surveys, which required clarification from the national authorities whether and to which extent these

[20] There are some exceptions to this rule because the industry classification in some countries explicitly includes sole proprietorships as corporations. These cases are documented accordingly.

tables are comparable.[21] In some cases, the tables on credit by industry explicitly only included non-financial corporations but still reported a time series on ISIC section K, usually as *Finance and insurance activities* or similar. The values for these data series were usually very small, and when consulted, the data providers in all of these cases recommended us to use non-bank financial series from broader surveys as more accurate reflections. We thus excluded the finance series from the industry breakdown tables in these cases.

The time series exclude lending to banks or other MFI because interbank markets fundamentally differ compared to other types of credit. In a few cases it was not possible to disentangle non-bank financial and interbank credit, especially in historical sources. We usually excluded the values with unclear classification, unless the national authorities were able to assure us that interbank lending only made up an insignificant fraction of the data, or the growth rates of interbank and other financial lending were likely very similar. All of these cases are noted in the time series documentation of the respective country tables.

C.3.3 Classification of non-financial corporate industries

One of the main contributions of the dataset is that it enables a cross-country comparison of the corporate credit market, which requires a classification of industrial sectors according to unified categories. Since many countries have implemented the United Nations' International Standard Industrial Classification of All Economic Activities (ISIC), we use its most recent version, Revision 4 (Rev. 4), to classify sectors.[22] However, some countries—including some major ones, notably Germany—have not yet adopted this classification and continue to use older revisions of the ISIC categories. Other countries use national classifications broadly in line with ISIC classification, which also applies to many historical sources. Sometimes, these differences can create challenges for the cross-country comparability of the industry credit data, which we address in detail in section C.4.5.

We let the data dictate the sectoral detail used for the classification. Since more detailed data are only available in a few cases, and are often excessively noisy, we retrieve data up to the 2-digit ("division") level in ISIC Rev. 4 for the sections A ("Agriculture, Forestry, and Fishing") and C ("Manufacturing"). For other sectors, we only record data on the 1-digit level ("section"). Data for the sectors "Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use" (T) and "Activities of extraterritorial organizations and bodies" (U) are only available sporadically and are bundled together with the category "Activity not stated" (Z). Table **??** shows the resulting sectoral structure for broad and industrial sectors used to classify the data. In many countries, the most detailed available data is on the 1-digit (section)

[21] In the overwhelming majority of cases, these data are directly comparable.

[22] See United Nations (2008) for more details on the ISIC classification and conversion tables.

level. Where only broader data were available, we assigned them to multiple sections. For example, many countries report a time series for "credit to industry", which includes the ISIC Rev. 4 sections B ("Mining and Quarrying") and C ("Manufacturing"), because mining and quarrying activities are often negligible. The data were then assigned to the total of the two sections ("B + C"). Note that, compared to the ISIC classification, we exclude lending to monetary financial institutions (including the central bank).

C.3.4 Classification of credit to public administration

The data generally refer to total credit to the (non-bank) private sector, in line with the seminal efforts by the World Bank and others. However, it is important to note that the ISIC Rev. 4 classification includes a section *O* on "Public administration and defence; compulsory social security". This section is often included in industry breakdowns adding up to an aggregate non-financial corporate series. Some countries, especially those not strictly following the ISIC scheme, report time series with labels such as "government services", which often do not come with additional clarifications. As we highlight in the example for Denmark in section C.4.3, unclear classification can further arise because not all government activities are in public administration. Since the dataset is primarily concerned with credit to the private sector, we did not systematically gather other data for lending to general or local governments.

The overwhelming majority of data sources does not differentiate by the ownership of borrowing firms. As a result, the credit data in many cases includes lending both to private *and public* corporations; this is true both for financial and non-bank financial borrowers. Including public corporations may be particularly important to capture lending to state-dominated sectors such as utilities and paints a more comprehensive picture of credit exposures.

C.4 Adjustments and harmonization

This section outlines a guideline for the adjustments undertaken to make the raw data comparable across time and countries. Note that these adjustments only apply to the time series in the "adjusted" tables, with the important exception of changes in currency (see section C.4.1). Further adjustments were made for individual countries or even specific time series in consultation with the national authorities where necessary. All of these detailed changes are described in the series documentation and input file.

We report raw and adjusted versions of all time series. Interested researchers can thus easily investigate how the adjustments change the original data for individual countries. The data for 64 out of the 116 countries in the database had at least one minor adjustment.

While adjustments leave the growth rates of sectoral credit aggregates almost universally unchanged, they do affect the *level* of outstanding credit, particularly as one goes back further in time. In section D, we show that despite the trade-offs required in compiling a novel dataset from such detailed sources, the resulting values are remarkably consistent with those of existing sources.

C.4.1 Adjusting for currency changes

The raw data for some countries had to be adjusted in order to be comparable across time where currency changes occurred. For example, the values for Azerbaijan were reported in *second manat* for 2000 to 2005 and in *third manat* afterwards. To arrive at a consistent time series, we thus converted the old values to *third manat* using the applied conversion rate of 5,000 to 1. These cases are usually straightforward and noted in the series documentation.

The issue of currency conversion is perhaps most salient for the countries of the Eurozone. Here, we converted the data using the irrevocable Euro exchange rates. Researchers interested in using the sectoral data for exchange rate applications would thus have to convert back their original pre-Euro currencies using the respective irrevocable exchange rates.

C.4.2 Adjusting for level-shifts

A major issue when compiling long-run time series from multiple sources are level-shifts in the data arising from re-classifications due to changes in sectoral classification, the scope of covered institutions, and inclusion of foreign currency loans. In many cases, there are overlapping values for the period in which a shift occurs. We adjusted older values at the break date (usually upward) using the `adjust_overlap.ado` program with the simple chain-linking formula

$$New\ value_{it} = \frac{New\ series_{i,t+1}}{Old\ series_{i,t+1}} \times Old\ series_{i,t}. \tag{5}$$

The remaining values of the old series were then re-calculated backwards using their period-on-period growth rates. This is the same approach used in Dembiermont et al. (2013) and Monnet and Puy (2019). The procedure implicitly assumes that more recent data are more accurate and that the growth rates of the old series are representative of the data covered by the new series.

For some level shifts, no overlapping data is available. In these cases, we used one of two approaches. First, if available, we replaced the *New Series* and *Old Series* terms in the adjustment term $\frac{New\ series_{i,t+1}}{Old\ series_{i,t+1}}$ in equation 5 with a reference series that is conceptually related to the type of sectoral credit aggregate that we want to adjust, e.g. by using total mortgage credit as a reference series for adjusting a break in residential mortgages. This procedure is implemented in the `adjust_reference.ado` program. Second, if no such reference series was available, we followed the procedure in Stock and Watson (2003), who calculate "typical" growth rates of the series

in question during that time period under the assumption that the actual, unobserved growth rate is unlikely to be substantially different. In particular, they first calculate growth rates of the two periods before and after the level-shift, and then take the median value of these four percentage changes to arrive at the "typical" growth rate. Since the data in our case often has monthly frequency, we use the median of the annualized growth rates three periods before and after a level-shift. This is implemented in the `adjust_median.ado` program. We then follow the procedure outlined above for the overlapping values and adjust the older values backwards using their period-on-period growth rates.

Note that level-shifts are not always straightforward to detect, especially in historical data. However, we could usually infer the nature of such shifts by reading the meta data and table footnotes in historical documents. The identification of shifts was thus entirely done by reading data descriptions and is not based on econometric tests to keep the number of adjustments as small as possible.

Another challenge is that individual jump-corrected sectoral time series no longer add up to match aggregates. For example, after adjusting a break in total private credit and household credit, the sum of household and corporate credit will no longer add up to total private credit. To address this, we re-scale all break-adjusted series to match the next available aggregate, a process that the United Nations' suggested guidelines for backcasting national accounts data call "rebalancing" (United Nations, 2018). This procedure is implemented in the `adjust_rescale.ado` program. Consider, for example, a country where manufacturing and its subsectors exhibit a level-shift that is adjusted using overlapping data. After this adjustment, the sum of the sub-sectors no longer adds up to total manufacturing credit. To remedy this, we first calculate the sum of the individual break-adjusted manufacturing sub-sectors, and then multiply the share of each sub-sector with total break-adjusted manufacturing credit. In practice, these adjustments only make a minor difference to the individual data points, but they guarantee internal consistency in the data by construction.

Special issues when adjusting level-shifts in industry-level data Some series exhibit level-shifts arising from changes in classification. Such jumps were treated using the procedure outlined above in section C.4.2. This technique imposes the assumption that the *growth rates* of a time series followed the path displayed by the observed, possibly imperfectly matched data. But since the most recent values in the vast majority of countries follow ISIC Rev. 4 classification, it does not impair the comparison of *outstanding amounts* of credit and thus the credit market structure. The reason is that credit *growth rates* even between imperfectly matched series over time are likely to be highly correlated and driven by the same industry and macroeconomic shocks.

As an example, consider the case of Germany. For data on credit by industrial sectors, we rely on two sources: time series reported in the Bundesbank's statistical database starting in 1968, which

broadly follows ISIC Rev. 3.1; and data copied by hand from historical editions of the *Monthly Report* publication starting in 1948 available in PDF from the Bundesbank's website, which does not follow ISIC classification. To classify the data according to ISIC Rev. 4, we assigned the time series "Electrical engineering, precision instruments and optical goods" and "Lending to manufacture of electrical and optical equipment" to sum of the divisions 26 ("Manufacture of computer, electronic and optical products") and 27 ("Manufacture of electrical equipment") in section C ("Manufacturing"). Imperfect matching of sectors classifications are unlikely to play an important role in our setting. First, assigning the time series to the ISIC Rev. 4 divisions is relatively straightforward using the ISIC Correspondence tables and documentation documents published by the Bundesbank. Second, the shocks generating the *growth rates* of the first time series ("Electrical engineering, precision instruments and optical goods") are likely to be highly correlated with those to the second time series ("Lending to manufacture of electrical and optical equipment"). Since these growth rates were used to adjust for a random level-shift in the data (see section C.4.2), the shocks to the respective sectors would have to diverge significantly in order to arrive at strongly biased values at the end of the series in 1948. This seems unlikely. In other words, as long as one can assume the most current data to be correct, the compiled time series are probably representative of credit market developments over time for all practical purposes.

C.4.3 Adjusting discrepancies between national data sources

Surveys on the detailed breakdown of credit by industries at times do not directly correspond to broader classifications such as "non-financial institutions". The reason is that some economic activities, in particular agriculture, are often undertaken by sole proprietors, which are included in household credit. There may further be differences in the compilation of the statistics, e.g. due to difference in supervisory disclosure requirements or financial instruments, which result in slight discrepancies.[23] None of these discrepancies were large or irreconcilable and the classification was undertaken in accordance with information from the national authorities. As shown in the respective country tables, the sum of the industrial sectors in the raw data is always equivalent or close to the aggregate data on "non-financial corporations", or the sum of "non-financial corporations" and "non-bank financial corporations" (depending on the survey).

To illustrate the issue, Figure A21 shows a comparison of credit data reported separately by broad institutional sectors and detailed industries for Denmark, kindly provided by the Danish *Nationalbanken*. The raw data here are a typical example of how a few noteworthy deviations between surveys on detailed sub-sectors (left) and broad sectors (right) can arise (note that, overall, this is rather rare). In particular, total corporate credit is not equal to sum of the industry sub-sectors,

[23]The Bank of England has two excellent publications outlining how such differences can arise (Bank of England, 2012, 2017).

because the latter do not differentiate between non-financial corporations and sole proprietorships in classifying industrial activity. The table also shows how the sub-sector "Employees, etc." (DKK 410,936) refers only to a fraction of total household credit, the residual of which is made up by lending to sole proprietorships.

In cases such as the Danish example, we usually adjusted the underlying industry-level values by calculating their share in the manual sum of all industries and multiplied it with the broader sectoral values for non-financial corporate credit. This achieves that the classification of corporations versus households remains comparable, while at the same time retaining a reasonable reflection of the industry exposures of the financial system, irrespective of an industry's typical legal form of organization. In many cases, we received additional guidance from the national authorities in how to best achieve comparability with other countries and followed their advice. As mentioned above, we document all such adjustments in great detail in the Excel file and further provide the unadjusted raw data for robustness checks.

C.4.4 Adjusting for changes in sector classification over time

In many countries, older publications or historical files use different sectoral classifications than the most recent data. It is thus necessary to adjust for these changes over time to arrive at consistent time series. Such differences broadly fall into two categories: changes in classification between different versions of ISIC (often from Rev. 3.1 to Rev. 4) or changes where at least one source did not follow ISIC classification.

Changes across ISIC versions Where the data were classified according to an older version of ISIC, it was usually straightforward to assign values to the ISIC Rev. 4 buckets. We used the conversion tables available from the United Nations' statistics division to adjust tables using older revisions.[24] Three issues demand further explanation.

First, many countries adapt ISIC classifications in line with national requirements, and the resulting (sub-)categories may differ slightly from the United Nations recommendation. Where it was the case, e.g. for the General Industrial Classification of Economic Activities within the European Communities (NACE), the differences were of minor importance on the 2-digit level and documents of the national authorities were consulted to resolve any remaining issues.

[24] See https://unstats.un.org/unsd/classifications/Econ/ISIC.cshtml for more details on the ISIC classification and conversion tables.

Figure A21: Discrepancies between Broad and Detailed Sector Classification – The Case of Denmark

DNPUDDKB - Lending to Activities for Danish residents	2015M07	million DKK	2015M07	DNPUD - Lending to sectors - ONLY Danish residents
All industries in total	1,357,346		1,357,346	X000: All sectors domestic and foreign
Agriculture, forestry and fishing	74,125	371,157	331,939	- X100: Non-financial corporations
Mining and quarrying	497		241,363	- - X2aa: Monetary Financial Institutions (MFI)
Manufacturing	58,624	462,630	167,669	- - X2bb: Other financial institutions excl. insurance corp. and pension funds
Electricity, gas, steam and air conditioning supply	13,443		53,688	- - X2cc: Insurance corporations and pension funds
Water supply; sewerage, waste management and remediation activities	2,465	37,620	36,468	- X300: General government
Construction	20,304	75,002	112,216	- - X410: Households - sole proprietors and unincorporated partnerships
Wholesale and retail trade; repair of motor vehicles and motorcycles	64,744	410,936	410,330	- - X430: Households - employees, etc.
Transportation and storage	21,148		3,673	- X500: Non-profit institutions serving households
Accommodation and food service activities	7,288			
Information and communication	6,889			
Financial and insurance activities	462,630			
Real estate activities	107,867			
Professional, scientific and technical activities	28,713			
Administrative and support service activities	20,430			
Public administration, defence; compulsory social security	37,618			
Education	2,957			
Human health and social work activities	6,851			
Arts, entertainment and recreation	2,718			
Other service activities	6,219			
Activities of households as employers; undifferentiated goods- and servi	877			
Activities of extraterritorial organisations and bodies	2			
Employees, etc.	410,936			

Note: The screenshot shows how different modes of data compilation can lead to discrepancies between broad sectoral and more detailed non-financial corporate credit classifications. Note, in particular, the different total values of total non-financial corporate credit and the sum of the sub-sectors (DKK 331,939 and DKK 371,157, respectively), despite the same total credit values for both surveys (DKK 1,357,346). The table also shows how the sub-sector "Employees, etc." (DKK 410,936) refers only to a (albeit large) fraction of total household credit, which also includes lending to sole proprietorships.

Second, many changes between the most frequently occurring re-classification in the data between ISIC Rev. 3.1 and Rev. 4 are on the 3-digit or even 4-digit level.[25] Where countries only report less detailed data, it was thus not possible to adjust sectoral data from the ground up, and we had to use some discretion. For full transparency, the individual country tables in the series documentation and input files report the exact time series used for each ISIC category from every source. The divisions of the manufacturing sector are by far the most frequently reported and their classification has changed only slightly across ISIC revisions. As a result, these series are largely comparable across time even without adjustments and do not exhibit jumps in data values. Where no clear assignment was possible, we used the sum of the available time series and matched it to the sum of multiple divisions.

Third, ISIC Rev. 4 introduced two entirely new sections—"Water supply; sewerage, waste management and remediation activities" (E) and "Information and communication" (J)—and split up "Real estate, renting and business activities" into "Real estate" (L), "Professional, scientific and technical activities" (M), and "Administrative and support service activities" (N). Since many of the re-classifications are on the detailed division or group levels, some discretion had to be used to assign values to the most appropriate categories. We took a conservative approach and assigned only time series where the divisions were relatively clean. Where it was not possible, we calculated the sum of multiple divisions and assigned it to the broader sections, again documenting the original time series used in the country table.

Changes across non-ISIC classifications Where the raw data was not compiled in accordance with the ISIC classification, adjustments across time were done in accordance with notes in the original statistical publications and with help of the country authorities. The description and documentation of the original data in footnotes or additional documents usually provided a clear picture of the sectors captured. For example, the time series "Kuljetus, varastointi ja tietoliikenne" ("Transport, storage and communications") for Finland starting in 1958 was assigned to the ISIC Rev. 4 sections "Transportation and storage" (H) and "Information and communication" (J).

C.4.5 Miscellaneous issues for cross-country harmonization.

The possibly most challenging aspect of the data adjustment process was to make the sectoral values comparable across countries. Luckily, the industrial classification used for credit market surveys is remarkably similar across countries, even where it does not strictly follow the ISIC scheme.

As for all other adjustments to the raw data, we refrained from using unclear classifications. An example for such ambiguity are time series with descriptions like "Services", where they do not clearly specify details, documentations are not available or unclear, and national authorities did

[25] Note that changes on the 4-digit level are minor and make up negligible parts of the credit market.

not respond to email enquiries. In such cases, we assigned the values as "Activity not stated" (Z). Where other service sectors were specified—i.e. electricity, gas, and water supply (D and E), trade (G), transport (H), information and communication (J), accommodation and food services (I), and non-bank finance (K)—it was sometimes possible to classify such time series as the sum of the sections L to S (business, government, social, and personal services).[26]

Despite the widespread adoption of the ISIC classification, some countries use different categories for reports on credit to industrial sectors. One of the issues, the treatment of credit to general or local governments, has already been mentioned in section C.3.4. Other issues include series descriptions whose meaning is fairly straightforward but not directly specified in the ISIC scheme. To pick the German example once more, ISIC section E ("Water supply; sewerage, waste management and remediation activities") was largely bundled together with agricultural activities (A) in the series "Agriculture, forestry, and water regulation and supply" before 1968. However, there is an additional category "Public utilities" in the raw data. Since mining and quarrying is captured in yet another series ("Mining"), and transport and communication classified under "Others", "Public utilities" mostly refers to the provision of electricity and gas. It is thus assigned to ISIC section D. Such detailed information on the sectoral classifications were obtained from footnotes or additional documentation documents. We hope these examples illustrate the significant care and resources we invested in making the time series comparable across countries and time.

C.4.6 Data revisions

Data revisions may contain information about data quality and further matter for users interested in forecasting/nowcasting exercises using the sectoral credit data. Overall, data revisions are a relatively minor issue for sectoral credit data, and mainly arise from institutions dropping out of the sample or other changes in classification. Most data we retrieved are not revised at all, and data based on supervisory returns are almost never revised.

The statistical data in some source publications, e.g. the historical data for Austria and Greece, are revised with a one period lag, possibly in line with the audit of individual institutions. To circumvent the issue, we always retrieved and copied the data in reverse chronological order, starting with the newest available. Where revisions play a role, the database should in principle reflect the most current values.

[26] Note that public administration (section O) only makes up a tiny fraction of total credit in most countries.

D Comparability With Other Sources

We cross-checked the data with six major sources of credit data: the BIS long series on credit to the private sector (Dembiermont et al., 2013), the World Bank Global Financial Development Database (Cihák et al., 2013), the IMF's Global Debt Database (GDD), the IMF's International Financial Statistics (IFS) data on total private credit, historical IMF IFS volumes by Monnet and Puy (2019), and the Macrohistory Database assembled by Jordà et al. (2016). Where we detected significant discrepancies, we inquired about them with the national authorities. In this section, we show that the aggregates in our data closely track these other sources.

D.1 Discussion of existing data sources

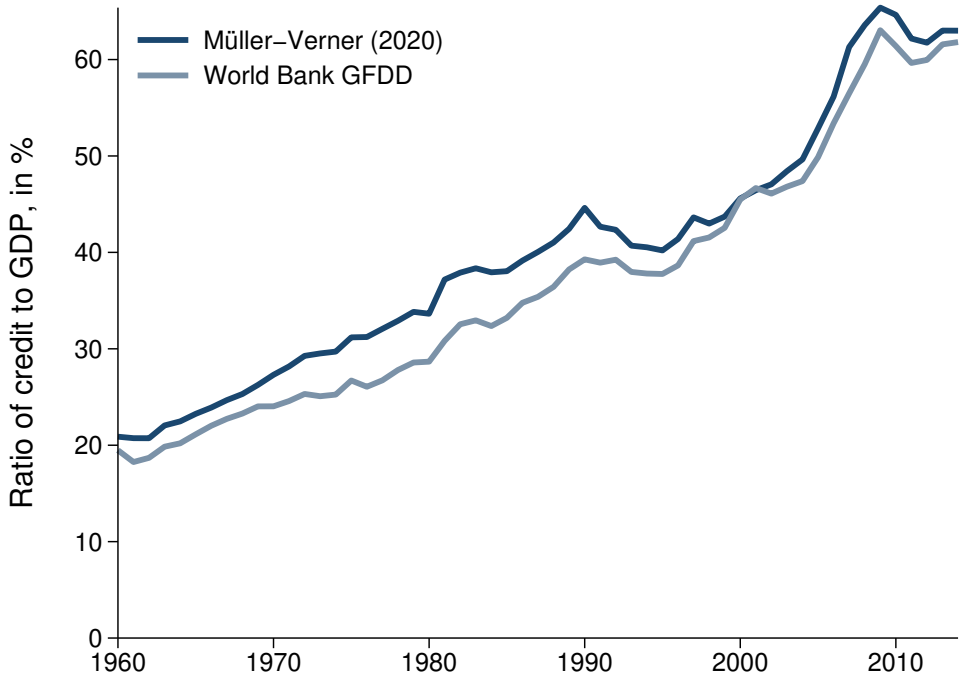
In Table 1 above, we already plotted the coverage of existing sources on credit market data as well as our database. Before comparing the six alternative resources with the newly compiled data, it is important to highlight important classification differences. Apart from differences in the available countries, sectors, and time periods, they also differ in their coverage of lending institutions. Jordà et al. (2016) largely capture bank credit. The World Bank's Global Financial Development Database (Cihák et al., 2013) and the BIS data on credit to the private sector (Dembiermont et al., 2013) include multiple time series for banks and total credit by all financial institutions. The recent IMF Global Debt Database also reports multiple series, but always include loans and debt securities. The IMF's International Financial Statistics and Monnet and Puy (2019) capture total private credit, which often only includes commercial banks. It is important to keep these different classification regimes in mind when comparing the data.

D.2 Comparing total credit values

Due to the different sample composition highlighted above, we compare the total credit values in our database in six stages with (1) the World Bank Global Financial Development; (2) the IMF Global Debt Database; (3) the IMF International Financial Statistics; (4) the historical IMF data digitized and harmonized by Monnet and Puy (2019); (5) the BIS credit to the non-financial private sector data; and (6) the historical data by Jordà et al. (2016).

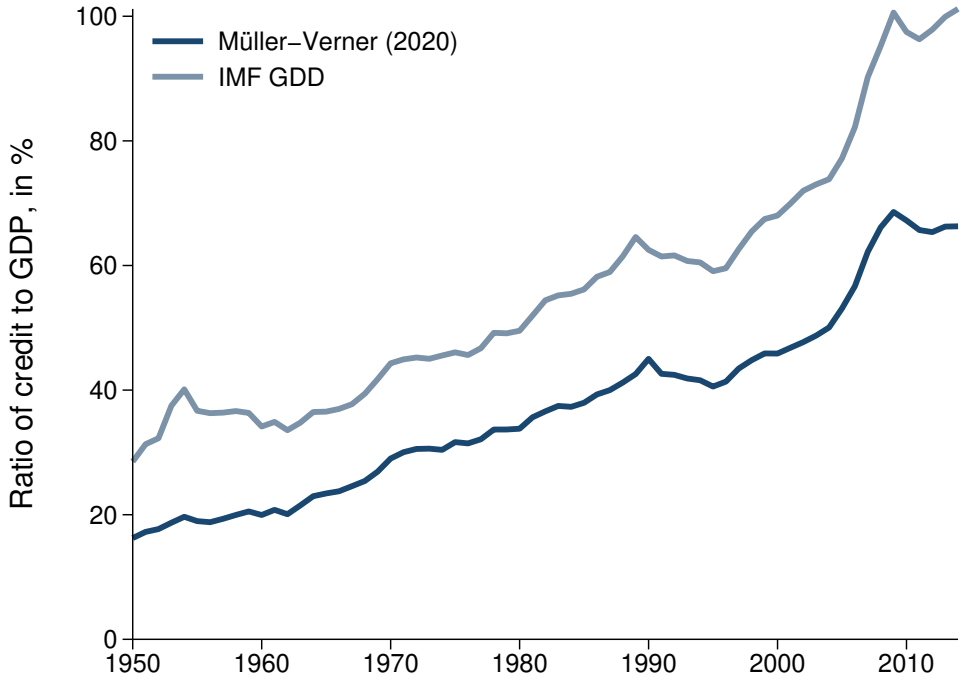
Figure A22 starts by plotting our data side-by-side with the total values from the World Bank's Global Financial Development database starting from 1960, when the World Bank data become available. The sample here are 114 countries for which there is data for both sources. The graph shows that our series closely tracks the World Bank data throughout, both in terms of its trend and overall level (measured as a percentage of GDP).

Figure A22: Comparison with World Bank Data



Sample: 114 countries in our dataset and the World Bank's Global Financial Development Database, 1960-2014.
Notes: Average ratio of total private credit to GDP (unweighted).

Figure A23: Comparison with IMF Global Debt Database



Sample: 104 countries in our dataset and the International Monetary Fund's Global Debt Database, 1950-2014.
Notes: Average ratio of total private credit to GDP (unweighted).

The recently introduced IMF Global Debt Database features the perhaps broadest cross-country credit dataset that singles out lending to firms and households. For the vast majority of countries, however, it appears to merely consolidate existing data from the BIS and other sources, rather than adding newly collected data from primary and secondary sources (as we do). As a result, they do not provide long-run data series. Figure A23 shows that the broader coverage of lending institutions yields higher ratios of credit to GDP in their dataset in a sample of 104 overlapping countries, but the overall *trend* in total credit appears highly similar to that in our data.

An early attempt at constructing data on private credit are the IMF's International Financial Statistics. Figure A24 compares this data source with our data and shows that the overlapping values are highly similar. Monnet and Puy (2019) recently digitized and harmonized some of the older credit data for from the print volumes of the International Financial Statistics. Figure A25 shows that the data track each other almost one to one in the overlapping sample of 43 countries.

Next, we compare our dataset with the data compiled by the BIS (Dembiermont et al., 2013). Figure A26 plots the average values for a sample of 40 countries for which the BIS total bank credit series is available (note that the BIS data on bank credit also includes lending by other MFIs). Again, we can see that this time series closely tracks the aggregate credit in our data. It is also instructive to further compare the data with the BIS time series on "total credit", which is supposed to capture total credit in the economy coming from all sources. We can see that this series closely follows the *trend* of the other values, but at a considerably higher level.

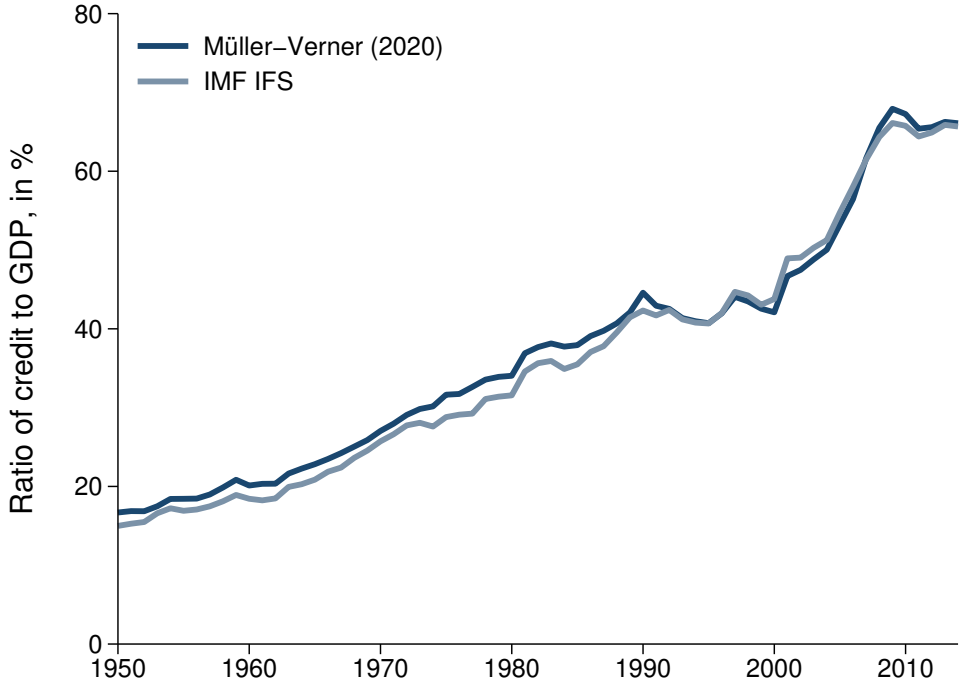
As a last exercise, we compare our data with the values compiled in the "Jordà-Schularick-Taylor Macrohistory Database" (Jordà et al., 2016). Again, we restrict the sample to the overlapping country-years in both data sources and plot the result in Figure A27. For the 17 overlapping countries, the picture is reassuringly very similar to the other data sources. However, our data suggest slightly higher credit to GDP ratios, which is likely because we capture lending by all monetary financial institutions in most countries, while Jordà et al. (2016) largely only consider bank credit.

Overall, our new credit data closely track other existing sources. For the sources that use a similar coverage of lending institutions, the deviations are marginal; for those with a different lender coverage, the gap with our data is constant over time, suggesting similar trends. A natural interpretation of the sectoral data we have compiled is thus that it represents the underlying sectoral structure of the already known and widely used credit aggregates, plus further extended historical data on total private credit.

D.3 Comparing individual country series

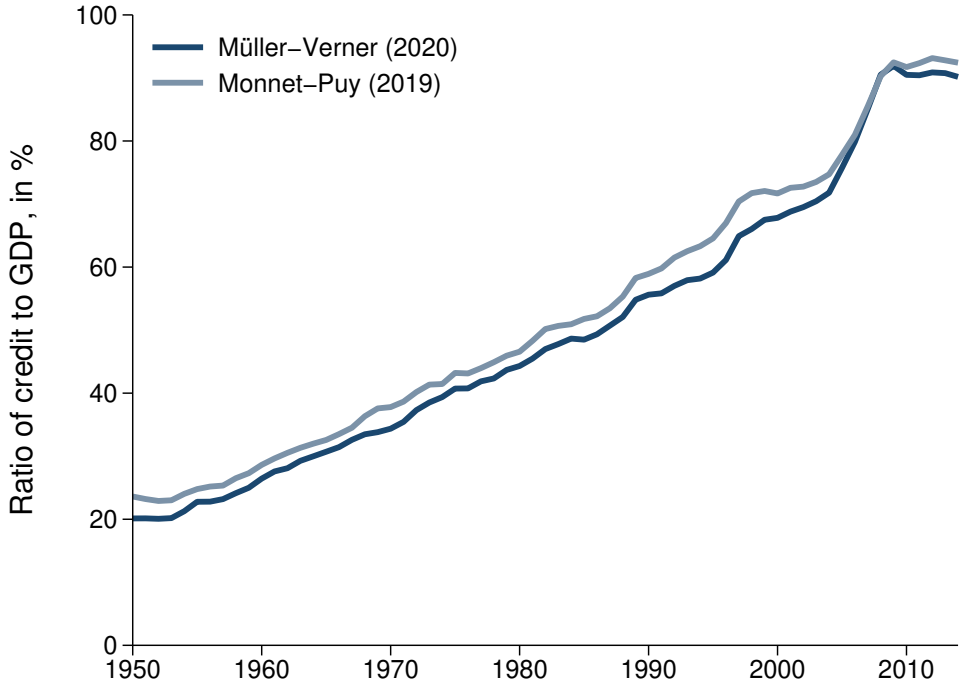
To get a closer look at the individual countries, we plot total credit for a panel of 40 countries where our database overlaps with the IMF GDD, IMF IFS, World Bank, and BIS datasets in Figure A28.

Figure A24: Comparison with IMF International Financial Statistics



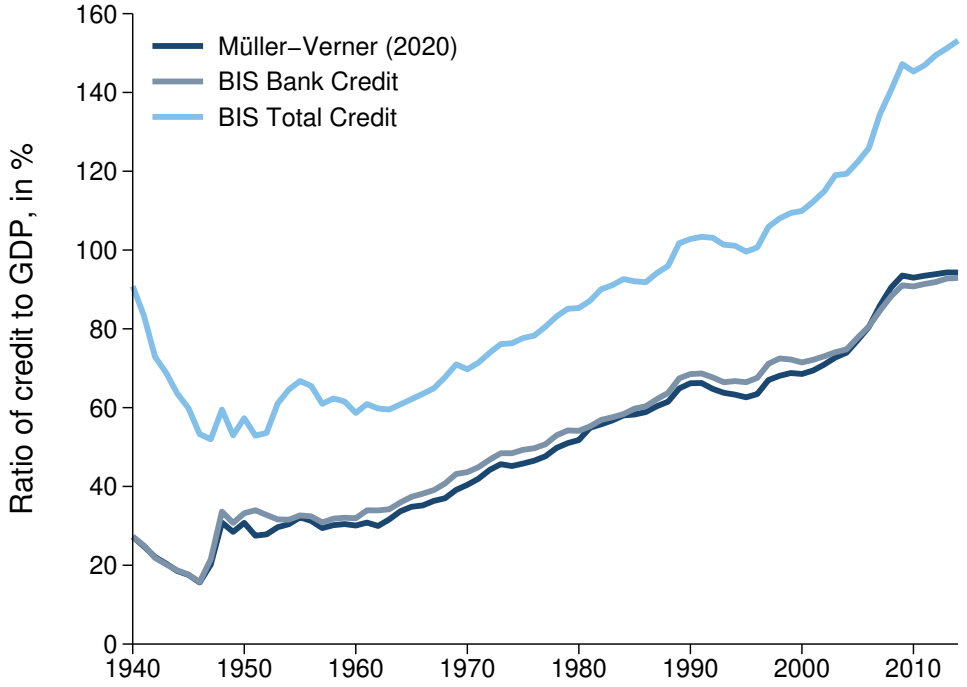
Sample: 114 countries in our dataset and the IMF's International Financial Statistics, 1948-2014.
Notes: Average total private credit to GDP (unweighted). IFS variables *FOSAOP* and *22D* (Claims on Private Sector).

Figure A25: Comparison with IMF data from Monnet and Puy (2019)



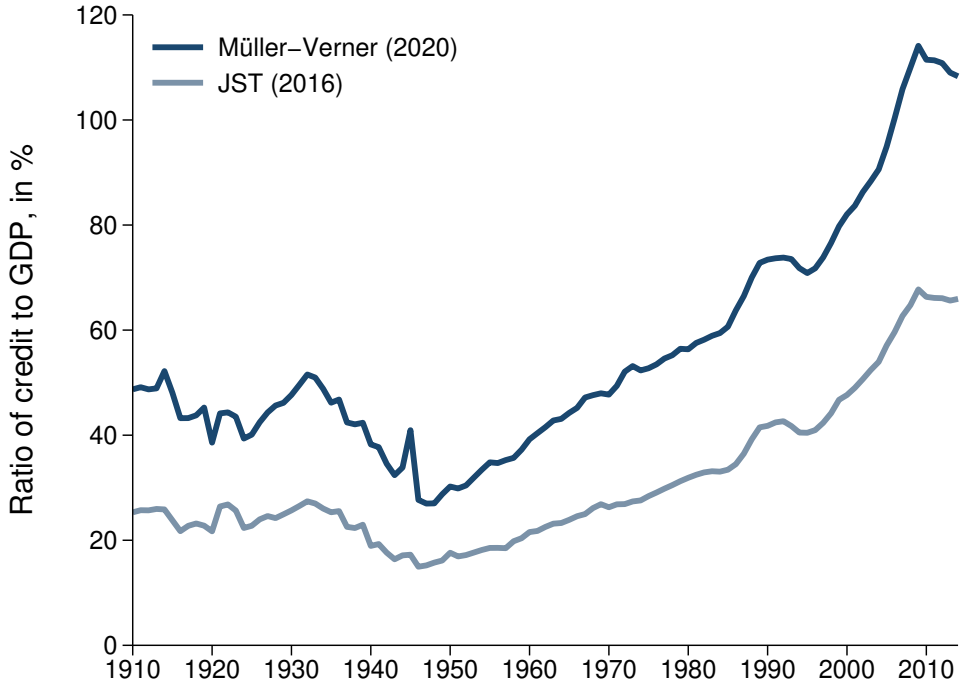
Sample: 43 countries in our dataset and the IMF data digitized and harmonized by Monnet and Puy (2019), 1950-2014.
Notes: Average ratio of total private credit to GDP (unweighted).

Figure A26: Comparison with BIS Total and Bank Credit Data



Sample: 40 countries in our dataset and the BIS private credit data, 1940-2014.
Notes: Average ratio of total private credit to GDP (unweighted).

Figure A27: Comparison with Jordà et al. (2016) Data



Sample: 17 countries in our dataset and the Jordà et al. (2016) data on private credit, 1940-2014.
Notes: Average ratio of total private credit to GDP (unweighted).

Reassuringly, the pattern here is similar to that of the averages above: none of the countries exhibit an unreasonable discrepancy.

D.4 Comparing broad sectoral credit values

The previous section suggests that our new credit dataset essentially provides a sectoral breakdown of the total private credit known from other sources, while also adding additional data on total outstanding credit. In this section, we provide additional evidence that our data is also highly similar to data on household credit put together by the IMF Global Debt Database and the BIS, as well as mortgage credit data from Jordà et al. (2016).

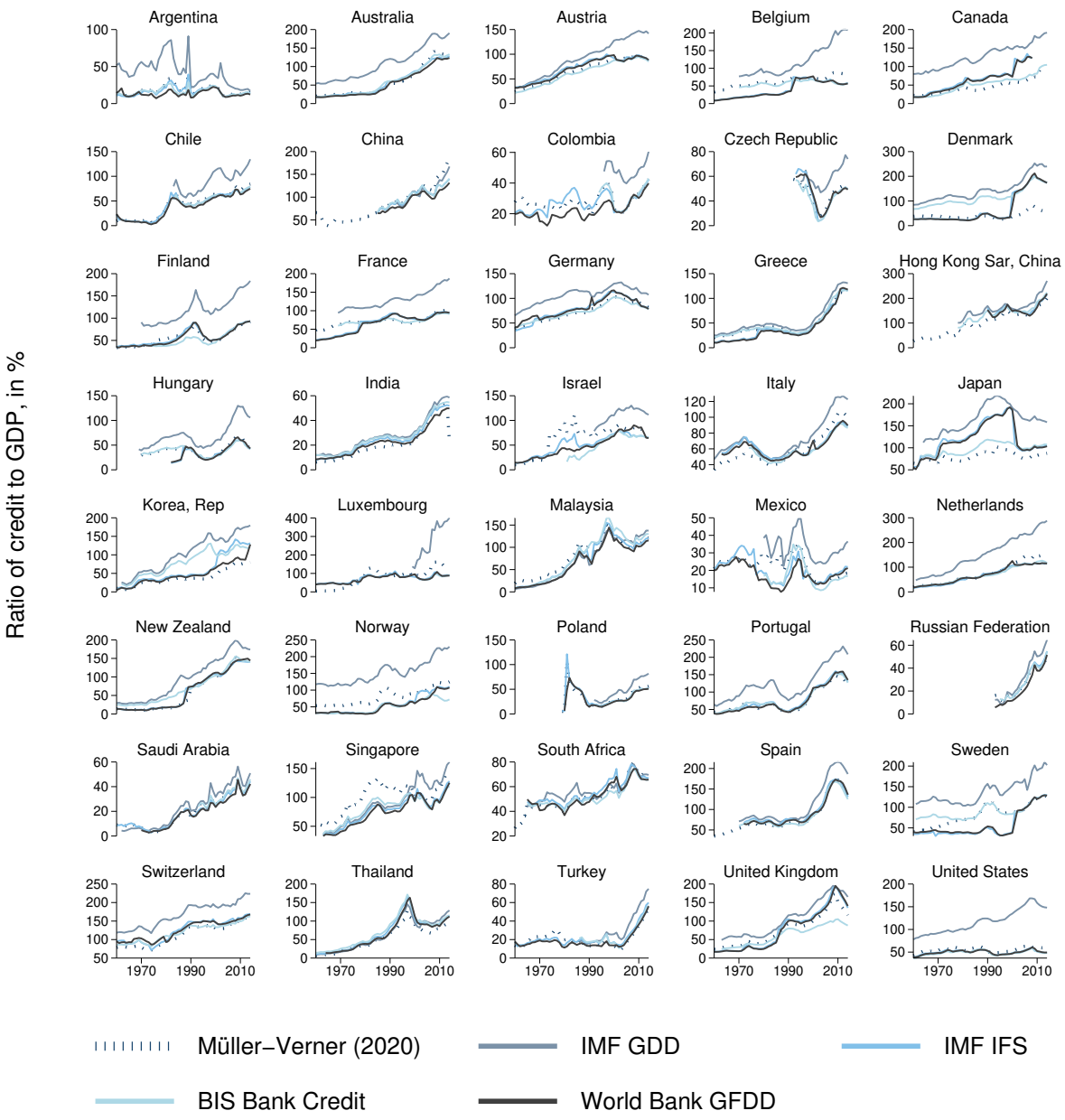
Figure A29a shows the evolution of BIS household credit and the newly compiled data over time in a sample of 40 countries. Note that these series have substantially different creditor coverage: as we could see above in Figure A26, the total volumes of our data almost perfectly track the BIS data on *bank* credit, while *total* credit is substantially higher. Despite these differences, the two series follow highly similar trends over time and exhibit the same patterns. This is particularly reassuring because the GDP data in the time series are compiled from completely separate sources, which could lead to measurement error.

Next, we compare the new data with the IMF Global Debt Database on outstanding household credit scaled over GDP, which yields an overlapping sample of 66 countries. Given the slightly broader coverage in the IMF GDD data, it is unsurprising that the values there are slightly higher. Apart from this minor difference, the trend of the series track each other closely.

As a last exercise for household credit, we compare our data with Jordà et al. (2016). The overlapping sample consists of 17 countries. Our data tracks their data well but exhibits a slightly higher growth trend, likely because we include more types of lenders compared to their work (which mainly comprises of bank credit).

Another unique feature of our data is that we can differentiate between total mortgages and residential mortgages. In a final check, we thus also compare our total mortgage data with that in Jordà et al. (2016). Again, the time series closely track each other for the 17 overlapping countries, but our data exhibit a somewhat higher growth trend.

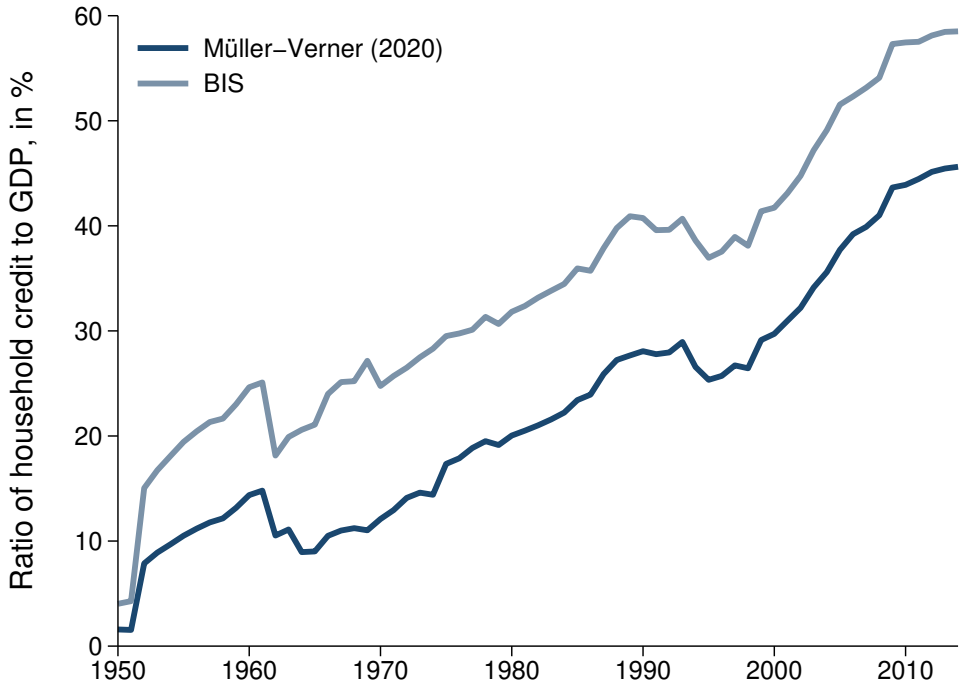
Figure A28: Comparison with IMF, World Bank, and BIS Data, by Country



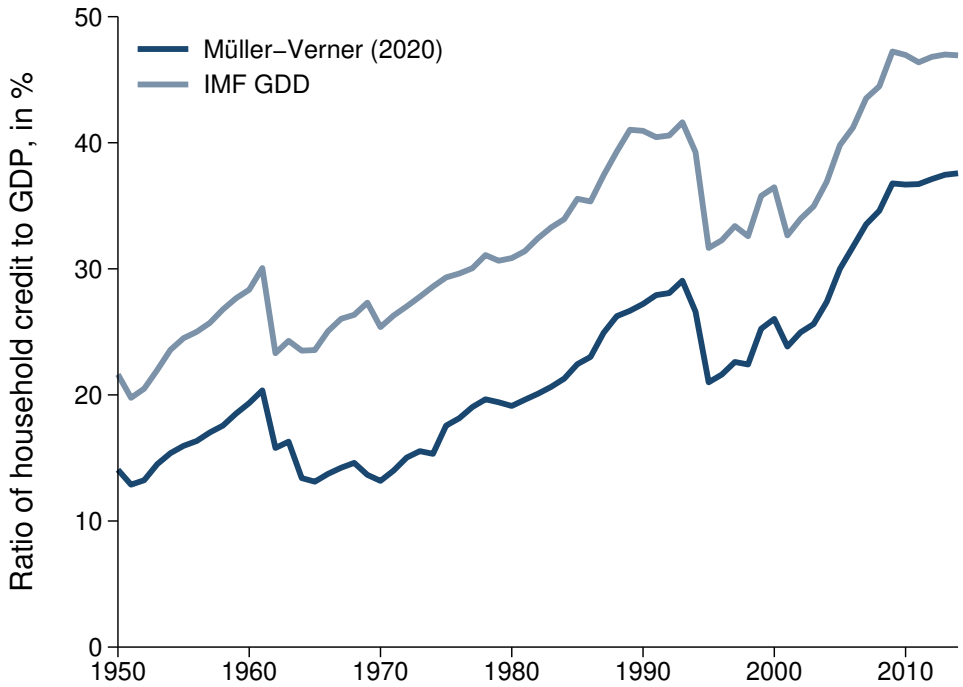
Sample: 40 countries where our database overlaps with the IMF IFS and GDD, World Bank, and BIS data.
Notes: Average ratio of total private credit to GDP (unweighted).

Figure A29: Comparison with BIS and IMF GDD Household Credit Data

(a) BIS Data

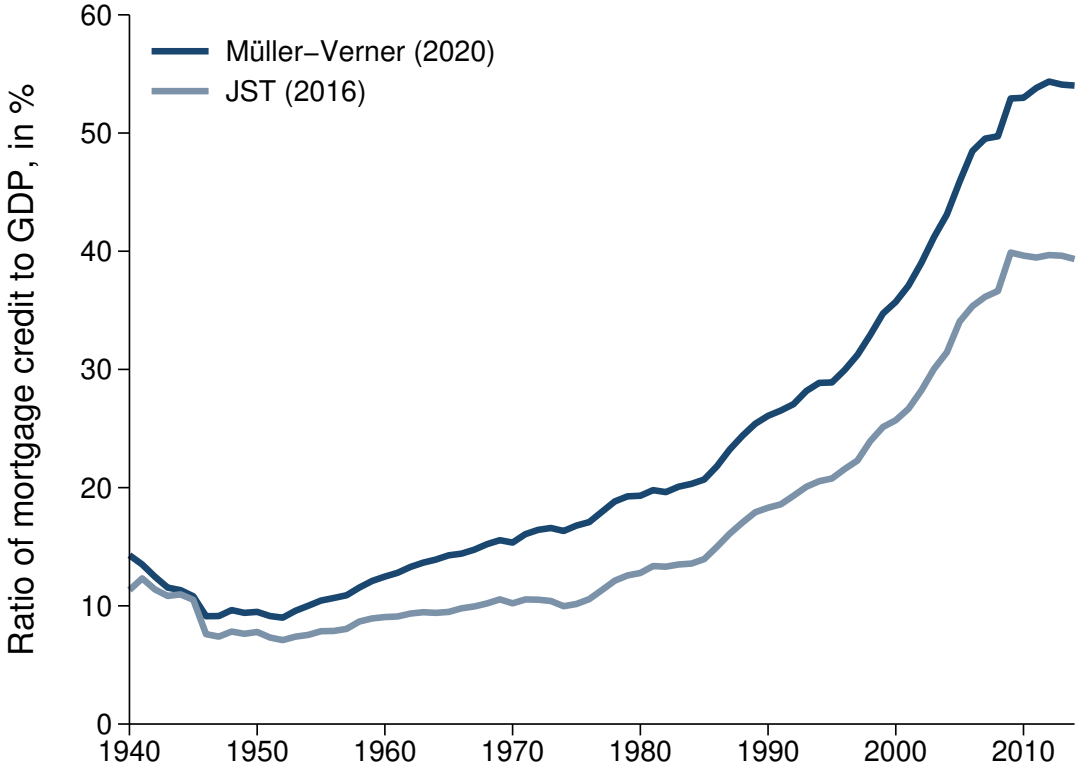


(b) IMF Global Debt Database



Sample: In panel (a), 40 countries in our dataset and the BIS data on credit to the non-financial private sector, 1940-2014. In panel (b), 66 countries in our dataset and the International Monetary Fund's Global Debt Database, 1950-2014. Notes: Average ratio of total private credit to GDP (unweighted).

Figure A30: Comparison with Jordà et al. (2016) Mortgage Data



Sample: 17 countries in our dataset and the Jordà et al. (2016) data on private credit, 1940-2014.
Notes: Average ratio of total private credit to GDP (unweighted).

References

Bank of England (2012). Lending to Businesses – A New Data Source. Technical report.

Bank of England (2017). Publication of Additional Data Relating to Monetary Financial Institutions' Lending to Businesses. Technical report.

Baron, M., E. Verner, and W. Xiong (2019). Banking Crises Without Panics. Technical report.

Cihák, M., A. Demirgüç-Kunt, E. Feyen, and R. Levine (2013). Financial Development in 205 Economies, 1960 to 2010. *Journal of Financial Perspectives 1*(2), 17–36.

Dembiermont, C., M. Drehmann, and S. Muksakunratana (2013, March). How Much Does the Private Sector Really Borrow - A New Database for Total Credit to the Private Non-financial Sector. *BIS Quarterly Review*.

Drehmann, M. (2013, June). Total Credit As an Early Warning Indicator for Systemic Banking Crises. *BIS Quarterly Review*.

Driscoll, J. and A. Kraay (1998). Consistent Covariance Matrix Estimation With Spatially Dependent Panel Data. *The Review of Economics and Statistics 80*(4), 549–560.

Greenwood, R., S. G. Hanson, A. Shleifer, and J. A. Sørensen (2020). Predictable Financial Crises. Technical report.

Jordà, Ò., M. Schularick, and A. M. Taylor (2016, September). Macrofinancial History and the New Business Cycle Facts. In *NBER Macroeconomics Annual 2016, Volume 31*, NBER Chapters. National Bureau of Economic Research, Inc.

La Porta, R., F. Lopez-De-Silanes, and A. Shleifer (2002, 02). Government Ownership of Banks. *Journal of Finance 57*(1), 265–301.

Laeven, L. and F. Valencia (2018, September). Systemic Banking Crises Revisited. IMF Working Papers 18/206.

Mbaye, S., M. Moreno Badia, and K. Chae (2018). Global Debt Database: Methodology and Sources. IMF Working Papers 18/111.

Monnet, E. and D. Puy (2019, September). One Ring to Rule Them All? New Evidence on World Cycles. IMF Working Papers 19/202, International Monetary Fund.

Mundlak, Y. (1978). On the Pooling of Time Series and Cross Section Data. *Econometrica 46*(1), 69–85.

Reinhart, C. M. and K. S. Rogoff (2009). *This Time Is Different: Eight Centuries of Financial Folly*, Volume 1 of *Economics Books*. Princeton University Press.

Schularick, M. and A. M. Taylor (2012, April). Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008. *American Economic Review 102*(2), 1029–61.

Stock, J. H. and M. W. Watson (2003, September). Forecasting Output and Inflation: The Role of Asset Prices. *Journal of Economic Literature 41*(3), 788–829.

United Nations (2008). International Standard Industrial Classification of All Economic Activities, Revision 4. Technical report.

United Nations (2009). System of National Accounts 2008. Technical report.

United Nations (2018). Handbook on Backcasting. Technical report.