Credit Allocation and Macroeconomic Fluctuations*

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Abstract

We study the relationship between credit expansions, macroeconomic fluctuations, and financial crises using a novel database on the sectoral distribution of private credit for 116 countries starting in 1940. Theory predicts that the sectoral allocation of credit matters for distinguishing between "good" and "bad" credit booms. We test the prediction that lending to households and the non-tradable sector, relative to the tradable sector, contributes to macroeconomic boom-bust cycles by (i) fueling unsustainable demand booms, (ii) increasing financial fragility, and (iii) misallocating resources across sectors. We show that credit to non-tradable sectors, including construction and real estate, is associated with a boom-bust pattern in output, similar to household credit booms. Such lending booms also predict elevated financial crisis risk and productivity slowdowns. In contrast, tradable-sector credit expansions are followed by stable output and productivity growth without a higher risk of a financial crisis. Our findings highlight that what credit is used for is important for understanding macro-financial linkages.

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1 Introduction

Rapid expansions in private credit are often, but not always, followed by growth slowdowns and an increased risk of financial crises (Schularick and Taylor, 2012; Jordà, Schularick, and Taylor, 2013; Mian, Sufi, and Verner, 2017; Greenwood, Hanson, Shleifer, and Sørensen, 2020). However, how private credit interacts with the business cycle remains fundamentally unclear. Why do some credit booms end badly, while others do not? How can we tell apart "good" from "bad" booms (Gorton and Ordoñez, 2019)? Does it matter who borrows during these booms? In this paper, we argue that the sectoral allocation of credit is important for understanding the connection between credit booms, macroeconomic fluctuations, and financial crises.

Theories of credit cycles that allow for sectoral heterogeneity propose three channels linking growth in credit to certain sectors with boom-bust cycles in the real economy. First, credit to households and non-tradable firms can fuel unsustainable demand booms that end in busts (e.g. Schmitt-Grohé and Uribe, 2016). Second, compared to the tradable sector, these sectors may disproportionately contribute to a build-up of financial fragility (e.g., Schneider and Tornell, 2004). Third, because average productivity growth is higher in the tradable sector, expansions in credit to non-tradable firms and households may lead to a misallocation of resources across sectors (e.g., Reis, 2013; Benigno and Fornaro, 2014). However, sectoral heterogeneity on the borrower side does not play a role in prominent credit cycle theories that focus on, for example, intermediary balance sheets (e.g., Brunnermeier and Sannikov, 2014; He and Krishnamurthy, 2013) or differences in beliefs (e.g., Geanakoplos, 2010; Bordalo, Gennaioli, and Shleifer, 2018). Whether the *allocation* of credit matters for boom-bust cycles empirically thus remains an open question.

To examine the link between sectoral credit allocation and macroeconomic outcomes, we construct a novel database on private credit for 116 countries, starting in 1940, by drawing on more than 600 sources. Existing datasets on credit distinguish, at best, between firm and household lending. In contrast, our database covers up to 60 different industries and four types of household credit. This allows us to differentiate between credit to the tradable and non-tradable sectors, and key industries such as manufacturing, construction, and non-tradable services. By construction, these new time series on credit by economic sector are consistent with existing aggregate data on private credit. The data also cover a considerably longer time span than other sources. We believe these data have many applications in macroeconomics, finance, and international economics.[1]

[1]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, Drehmann, and Muksakunratana, 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.

Equipped with this database, we investigate how expansions in credit across different sectors of the economy are linked to macroeconomic fluctuations. To motivate this analysis, we examine several prominent credit booms that resulted in major economic 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 crises of the 1990s. Although the origins of these boom-bust episodes differ, we find important commonalities. In the run-up to these downturns, credit expansion tends to be concentrated among households and non-tradable sector firms—especially construction and real estate, as well as trade, accommodation, and food services. In Spain, for example, lending to firms in the real estate sector grew by 600% between 1999 and 2008. In contrast, in the run-up to most crises, tradable sector credit grows little and, in some cases, even declines.

A more formal investigation of the connection between credit expansions and business cycles confirms these patterns. Previous work shows that credit booms predict lower future output growth. The predictability is particularly strong for household debt, while the results for corporate debt are mixed (Jordà, Schularick, and Taylor, 2016; Mian et al., 2017; Jordà, Kornejew, Schularick, and Taylor, 2020; Greenwood et al., 2020; Giroud and Mueller, 2020). Our data allow us to unpack corporate credit into its subsectors to ask which types of firm credit expansions are linked to business cycles.

Consistent with important sectoral heterogeneity in corporate debt expansions, we find that credit to the non-tradable sector predicts lower medium-run growth, similar to household debt. In contrast, tradable sector credit—and manufacturing credit in particular—is associated with stable or, in some specifications, higher growth in the medium run. As a result, separating major credit booms by whether credit flows disproportionately toward non-tradables and households predicts whether these booms foreshadow growth slowdowns. These patterns are robust to including a range of macroeconomic controls, excluding the 2007/2008 financial crisis, and controlling for year fixed effects or growth trends. They are also similar in advanced and emerging economies. Importantly, the results also hold after controlling for the evolution of sectoral value added, showing that credit matters over and above changes in sectoral activity.

Why does credit to households and non-tradable sectors, but not to the tradable sector, foreshadow lower future economic growth? Guided by theory, we explore three channels. First, credit growth to non-tradables and households may reflect that credit finances a demand boom, which may sow the seeds of a future bust (e.g., Schmitt-Grohé and Uribe, 2016; Korinek and Simsek, 2016; Mian, Sufi, and Verner, 2020). For example, compared to the tradable sector, non-tradable sector output has a much lower export share and is twice as proximate to final consumption demand. Consistent with this prediction, we find that household and non-tradable credit expansions are associated with a relative expansion in consumption relative to GDP, increasing shares of the non-tradable sector in output and employment, an appreciation of the real exchange rate, and an increase in house prices.

Second, lending to non-tradables and households can increase financial fragility if these sectors face tighter (ex-ante) financing constraints or are more sensitive to changes in credit supply (Tornell and Westermann, 2002). These types of credit booms thus increase vulnerability to a reversal in credit conditions, especially in the presence of foreign currency debt (e.g., Krugman, 1999; Kalantzis, 2015). To illustrate that the non-tradable sector is likely to be more sensitive to changes in credit supply, we document that non-tradable sector firms are, on average, smaller and more reliant on loans collateralized by real estate compared to tradable sector firms.

Consistent with differential financial fragility, we find that credit expansions to the non-tradable sector, even more so than to households, are associated with a considerably higher likelihood of future systemic banking crises. Lending to these sectors also falls dramatically after the onset of crises, indicating that these sectors are more adversely affected by credit contractions. In contrast, lending to the tradable sector has essentially no relationship with banking crises and also falls less after the onset of crises. Using the 2008 Spanish and Portuguese banking crises as a case study, we find that differences in the severity of loan losses across sectors may partially account for these patterns. At their peak, the ratio of non-performing loans was twice as high in the non-tradable compared to the tradable sector and—because pre-crisis credit growth was concentrated among non-tradable industries—the latter accounted for only a small fraction of total loan losses.

Third, credit booms may lead to a misallocation of resources away from more productive sectors, as emphasized in, among others, Reis (2013), Benigno and Fornaro (2014), and Borio, Kharroubi, Upper, and Zampolli (2016). Because the level and growth rate of productivity is generally higher in tradable industries (e.g., Duarte and Restuccia, 2010; Mano and Castillo, 2015), a reallocation away from tradables can cause lower aggregate productivity growth in the medium run. We show that, consistent with this idea, credit growth to the non-tradable and household sectors predicts lower future labor and total factor productivity. Lending to the tradable sector, on the other hand, is associated with higher productivity growth.

Taken together, the patterns we document suggest that credit expansions are not created equal. They highlight that "good" and "bad" booms can be differentiated based on what the borrowed money is used for along dimensions emphasized by economic theory. Beyond comparing household and firm debt, differentiating between different types of corporate credit expansions—which previous work could not do because of a lack of data—is important. This analysis suggests that the distinction between housing and non-housing credit, or household and firm credit, may not be sufficient for understanding why credit booms go bust; non-tradable services matter as well. Further, our results provide a new perspective on the tension between the literature emphasizing the benefits of credit for growth (Levine, 2005) and studies linking credit booms to economic downturns. One interpretation of our findings is that differentiating between types of credit along dimensions highlighted by theory may go some way in explaining why credit is sometimes linked to growth and at other times to crises. An important policy implication is that regulations aimed at curbing lending as a whole may risk restricting the types of credit associated with positive future economic outcomes.

To be clear, the distinction between tradable and non-tradable sectors we emphasize likely captures various characteristics that may matter for the nature of credit cycles, as we discuss in section 2.4. These include a sector's sensitivity to household demand and changes in financing conditions, as well as differences in productivity. While we do not take a strong stand on the underlying source of sectoral heterogeneity, distinguishing between tradable and non-tradable sectors appears to capture important empirical regularities and provides a useful marker for tying empirics to theory.

The remainder of the paper is structured as follows. Section 2 discusses our conceptual framework for why credit expansion in certain sectors may be linked to boom-bust cycles. Section 3 describes our novel sectoral credit database and presents new stylized facts about the evolution of credit markets around the world since 1945. Sections 4 and 5 present case study and empirical evidence on sectoral credit booms and business cycles. Section 6 explores the mechanisms, and Section 7 provides concluding remarks.

2 Conceptual Framework

In this section, we outline theoretical predictions about the connection between credit growth in different sectors of the economy and macroeconomic outcomes. We focus our discussion on credit cycle models highlighting asymmetries between household, non-tradable, and tradable sector credit expansions.[2]

Standard open economy macroeconomic models predict that expansions in credit should be associated with stronger future growth. In response to higher expected future income or productivity, basic permanent income hypothesis models predict that households and firms borrow to increase consumption and investment today (e.g., Aguiar and Gopinath, 2007; Arezki, Ramey, and Sheng, 2016). In a similar vein, many studies argue that credit depth is a marker of financial development, so that rising credit should contribute to stronger long-run growth (see, e.g., Levine, 2005).[3]

However, recent empirical studies find that rapid credit expansions are associated with future growth slowdowns and financial crises (e.g., Schularick and Taylor, 2012; Jordà et al., 2013; Mian

[2]Non-tradable sector firms produce goods and services that can only be consumed domestically, so production in the non-tradable sector must equal demand for non-tradables. Tradable sectors, on the other hand, produce goods that can be sold domestically and internationally, so tradable sector output is not constrained by domestic demand.

[3]For example, dynamic models with financial frictions (e.g. Midrigan and Xu, 2014; Moll, 2014) predict that a decrease in financing frictions leads to capital inflows and improved capital allocation across firms, which increases productivity growth.

et al., 2017; Greenwood et al., 2020). This literature shows that credit booms are often associated with increased credit supply, reflected in lower credit spreads (Mian et al., 2017; Krishnamurthy and Muir, 2017), relaxed lending standards (Greenwood and Hanson, 2013; López-Salido, Stein, and Zakrajšek, 2017; Kirti, 2018), and overoptimistic beliefs on the part of the lenders and borrowers (e.g. Geanakoplos, 2010; Burnside, Eichenbaum, and Rebelo, 2016; Bordalo et al., 2018).[4]

Existing studies on credit cycles at best distinguish between household and corporate sectors, but not between who is borrowing within the corporate sector. However, models of credit cycles with sectoral heterogeneity predict that which sectors are borrowing matters for the dynamics of output following credit expansions. A key ingredient of these models is that the severity of financing constraints varies across sectors. Specifically, a common assumption is that firms in the tradable sector are less constrained than households or firms in the non-tradable sector. Many of these studies argue that financial frictions, such as contract enforcement problems or asymmetric information, are particularly severe in the non-tradable sector, in part because the typical firm in that sector is small (e.g. Tornell and Westermann, 2002; Schneider and Tornell, 2004; Kalantzis, 2015; Ozhan, 2020).[5]

Next, we outline three channels through which the sectoral allocation of credit may affect macroeconomic fluctuations: (i) credit-induced demand boom and bust; (ii) asymmetric financial fragility; and (iii) resource misallocation driven by sectoral differences in productivity growth.

2.1 Credit-Induced 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. Such credit booms can lead to a demand-driven boom and bust. Table 1 shows that the share of exports to value added is substantially lower in the non-tradable sector. Non-tradable output is also more proximate to final household demand based on input-output tables. These descriptive statistics suggest that the non-tradable sector is more sensitive to credit expansions that finance a boom in domestic demand.

To fix ideas, consider a credit expansion that boosts demand in the economy by increasing lending to households. In the model of Schmitt-Grohé and Uribe (2016), this is modeled as a reduction

[4] 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.

[5] Schneider and Tornell (2004) motivate this asymmetry as follows: "The assumption that T-sector firms have access to perfect capital markets, whereas the N-sector faces credit market imperfections is motivated by two institutional features of middle-income countries. First, bank credit is the major source of external finance for N-sector firms. In contrast, many T-sector firms have access to international capital markets because they can pledge export receivables as collateral to foreign lenders. Banks in turn are strongly exposed to the N-sector and do not hedge real exchange rate risk. Second, systemic bailout guarantees apply to bank debt."

in international interest rates faced by a small open economy.[6] This increase in credit supply boosts households' demand for both tradable and non-tradable consumption goods. While tradables can be imported from abroad, non-tradables must be produced at home. To meet the higher demand of households, the non-tradable sector expands and increases the price of the goods and services it produces, leading to a real exchange rate appreciation (Mian and Sufi, 2018; Mian et al., 2020). The rise in labor demand from the non-tradable sector, in turn, raises wages and worsens the competitiveness of the tradable sector. If credit is proportional to the scale of production, a credit supply shock increases non-tradable debt-to-GDP and may even lead to a fall in tradable debt-to-GDP. Thus, a credit-induced demand boom boosts household and non-tradable sector credit, but not tradable sector credit.

Suppose that the credit expansion reverses due to an increase in international interest rates (Schmitt-Grohé and Uribe, 2016) or, more broadly, mean reversion in credit market conditions (e.g., Eggertsson and Krugman, 2012; Greenwood and Hanson, 2013; López-Salido et al., 2017). This leads to a fall in household demand for both non-tradable and tradable consumption goods. Schmitt-Grohé and Uribe (2016) show that, in the presence of downward nominal wage rigidity and monetary policy frictions, the fall in demand induced by household debt and the reversal of the interest rate leads to a drop in output and employment, as wages cannot adjust downward.[7] An expansion in credit to non-tradable sector firms and households can thus reflect a credit-financed demand-driven boom and bust.

2.2 Asymmetric Financial Fragility

The non-tradable sector may play a disproportionate part in credit booms not just because it is more exposed to demand booms, but also because it is more sensitive to financing conditions than the tradable sector. In Schneider and Tornell (2004), for example, the tradable sector has access to perfect financial markets while the non-tradable sector cannot commit to repay. This difference in financing constraints, in turn, means that changes in credit supply can lead to disproportionate growth of debt in the non-tradable sector, which makes the economy vulnerable to reversals in financing conditions. As a result, it is credit to firms in the non-tradable sector that can be the source of financial crises.

Table 1 provides some descriptive statistics supporting the view that the non-tradable sector is more sensitive to financing conditions. Specifically, we present data on the share of small businesses and the share of loans secured by real estate. Consistent with evidence in Tornell and West-

[6] In Schmitt-Grohé and Uribe (2016), firms are assumed to be unconstrained, so only households respond to the fall in the interest rate by borrowing more.

[7] In addition to nominal rigidities, reallocation frictions to the tradable sector imply that the fall in output is not offset by more tradable activity in the short run, as resources can only gradually be reallocated away from the non-tradable sector suffering a demand short-fall to the tradable sector (e.g., Kehoe and Ruhl, 2009).

ermann (2002) and others, the share of firms with less than 10 employees is considerably higher in the non-tradable sector. This difference is not limited to comparing construction and real estate with manufacturing. Small firms are also more common in largely local service sectors, such as food and accommodation. We also draw on data on the types of collateral used in lending to different sectors published in a few countries; for the United States, we use Compustat and the 2003 Survey of Small Business Finance (SSBF). These statistics show that debt collateralized by real estate is considerably more common in the non-tradable compared to the tradable sector.[8] This is not only true for the construction and real estate industries but also for other non-tradable services. The reliance on real estate collateral suggests that loans to the non-tradable sector may be riskier (Berger, Frame, and Ioannidou, 2016; Luck and Santos, 2019) and more exposed to swings in asset prices and aggregate financing conditions (Kiyotaki and Moore, 1997; Chaney, Sraer, and Thesmar, 2012; Lian and Ma, 2020).

Another way to rationalize why the non-tradable sector may be more sensitive to credit supply than the tradable sector could be differences in recovery values to creditors. The model of Ozhan (2020), for example, assumes that it is more difficult for bank creditors to monitor loans issued to households and the non-tradable compared to the tradable sector. This implies that an increase in bank credit supply leads to a larger reduction in spreads of firms in the non-tradable sector. However, a reversal of financing conditions leads to a sharp increase in the cost of borrowing and defaults in the non-tradable sector and a resulting fall in output.

More broadly, a banking crisis may lead to a particularly pronounced contraction in lending to more constrained and bank-dependent households and non-tradable firms. In emerging markets, where debt is often denominated in foreign currencies, credit expansions may result in a currency mismatch on the balance sheets of non-tradable firms and households, which are less likely to have income in foreign currency. The presence of foreign currency debt amplifies the impact of negative shocks (Mendoza, 2010). This can create the possibility for a self-fulfilling currency crisis, which tightens balance sheets for non-tradables and leads to a sharp fall in output (Schneider and Tornell, 2004; Mendoza, 2002). In Kalantzis (2015), for example, a crisis is more likely to occur after an increase in the debt (and leverage) of the non-tradable sector.[9]

2.3 Misallocation and Asymmetric Productivity Dynamics

Credit booms that primarily finance household and non-tradable sector debt could also sow the seeds of slower growth through a misallocation of resources across sectors. One reason could be

[8] Greenwald, Krainer, and Paul (2020) document that small firms in the U.S. are more likely to borrow using secured credit and to use real estate as a form of collateral.

[9] Note that our results are not driven solely by currency mismatch, as they also hold in advanced economies where currency mismatch is limited.

that productivity growth is generally higher in tradable industries such as manufacturing. Using a sample of 56 countries over 1989–2012, Mano and Castillo (2015) estimate that labor productivity in the tradable sector is 20% higher than in the non-tradable sector and that annual productivity growth has been 2.5% higher in the tradable sector (see Table 1). Similarly, Duarte and Restuccia (2010) document that labor productivity growth in a sample of 29 countries from 1956-2004 was highest in agriculture and manufacturing and lowest in services.[10] Lower productivity growth in non-tradables may reflect, among other things, that non-tradables are less subject to competitive pressures (Besley, Fontana, and Limodio, 2021), while tradable sectors are better able to absorb foreign knowledge advances.

Motivated by these facts, Benigno and Fornaro (2014) build a two-sector model where a credit expansion fuels a demand boom that shifts resources from the (productive) tradable to the (stagnant) non-tradable sector. Because technology in the tradable sector improves through learning by doing, this leads to a slowdown in productivity growth, a "financial resource curse." In a similar vein, Reis (2013) builds a model where capital inflows intermediated through an underdeveloped financial system lead to a misallocation of credit to less productive firms in the non-tradable sector. This lowers aggregate productivity and takes resources away from the tradable sector. These frameworks imply that increased credit and investment in the tradable sector should be associated with stronger subsequent productivity and output growth. A related argument in Rodrik and Subramanian (2009) is that capital inflows can hurt aggregate productivity growth by driving up the real exchange rate, which makes the tradable sector—which comprises the most productive industries in many countries—less competitive.

Bleck and Liu (2018) build a two sector model with heterogeneity in financing constraints due to differential asset specificity across sectors. Following an increase in credit availability, sectors with lower asset specificity see a reinforcing spiral of credit growth, rising collateral values, and investment. This leads to misallocation away from sectors with high asset specificity. Using the measure of asset redeployability from Kim and Kung (2016), they find that non-tradable sectors such as trade and construction have the highest asset redeployability (lowest asset specificity), while tradable sectors such as agriculture, manufacturing, and mining have the lowest asset redeployability (highest asset specificity).

Gorton and Ordoñez (2019) propose an alternative mechanism linking "unproductive" credit booms to crises. Empirically, they show that credit booms coinciding with a slowdown in productivity growth—which could be driven by disproportionate growth in lending to non-tradable sectors—are more likely to end in crises. To explain this fact, they build a model where lenders endogenous choose whether to produce information about the quality of a project's collateral, de-

[10]For example, Duarte and Restuccia (2010) find average productivity growth was highest in agriculture (4.0%), second in manufacturing (3.1%), and lowest in services (1.3%). In 28 out of 29 countries in their sample, productivity growth was lowest in services.

pending on how productive the project is. After a positive productivity shock, a temporary drop in information production fuels a credit boom in which an increasing number of assets can be pledged as collateral. As a result, an increasing number of unproductive projects are financed, until there is a realization that information production is too low. At that point, collateral is examined again, leading to a credit crunch and a drop in output.

2.4 Underlying Sources of Sectoral Heterogeneity

Our analysis is organized around distinguishing between sectors we refer to as tradable or non-tradable. As we show, the non-tradable sector has characteristics associated with greater sensitivity to domestic household demand and credit supply, and also tends to have lower productivity. These differences may be driven by tradability itself. For example, non-tradables producers may be smaller and more financing constrained precisely because they are limited to serving domestic markets, which limits their ability to grow. Non-tradable firms may also be more financing-constrained because they cannot pledge export receivables to international lenders. Similarly, producers of non-tradable goods and services may be less productive because they are less exposed to international competition.

However, tradability may also be a marker that happens to correlate with these characteristics. We do not take a strong stand on the underlying source of heterogeneity that generates these differences, but rather highlight that this heterogeneity matters for understanding credit cycles. As we show, grouping sectors based on characteristics such as industries' proximity to final household demand, share of small firms, or reliance on real estate collateral yields similar results, as these characteristics are highly correlated with our tradable/non-tradable classification for major sectors. As a result, while much of our theoretical discussion is centered around open-economy models distinguishing between tradables and non-tradables, our findings can also be interpreted through the lens of other models with sectoral heterogeneity where lending to certain sectors is more likely to result in slowdowns and crises.

3 Sectoral Credit Database: Data and Methods

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

3.1 Data Coverage

Existing datasets on private credit at best differentiate between household and firm credit. These aggregated data, however, are not suitable for testing whether we can tell apart "good" from "bad" credit booms depending on what the borrowed money is used for.

To remedy this, we construct a new database on the sectoral allocation of private credit for 1940 to 2014.[11] We assembled data on credit by sector for 116 countries, which account for around 90% of world GDP today, and include 52 advanced and 64 emerging economies. The number of sectors ranges from 2–60, with an average of 16. We also considerably extended the coverage and frequency of data on total private credit, for which we cover up to 189 countries. Appendix B.4 in the Online Appendix provides more information on the database coverage.

Table 2 compares our database to existing datasets on private credit. Panel A highlights the difference of our approach. The most disaggregated available data in Jordà, Schularick, and Taylor (2016) differentiates between household, firm, and mortgage credit for 17 advanced economies. Our database contains a more detailed sectoral breakdown for many more countries, spanning more than three times the country-year observations in Jordà et al. (2016) and more than four times the data on household and firm credit published by the Bank for International Settlements (BIS). Because of the sectoral structure and the often higher frequency of our data, it contains a total of 476,555 observations, orders of magnitude more than previous work.

Panel B shows how our database extends series on total credit to the private sector. Here, we add long-run data starting in 1910 for a significant number of countries. As a result, our data here is also more comprehensive than existing work.

3.2 Data Sources

Sectoral credit data have been collected by national authorities in 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. A large share of the data was digitized for the first time from PDF or paper documents. Many 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, in some cases by many decades. Figure A23 shows an example of what the underlying data look like.

[11] We are currently updating the data to 2020.

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 (IMF)'s International Financial Statistics (IFS) and Global Debt Database (GDD) (Mbaye, Moreno Badia, and Chae, 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, Farabullini, Rocchelli, Salvio, and Silvestrini (2013), or Abildgren (2007).

3.3 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 metadata in historical publications and contacted the national authorities publishing information on sectoral credit.

The resulting dataset measures end-of-period outstanding claims of financial institutions on the domestic private sector. 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. We also include foreign currency loans.

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 bank 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.

To classify different sectors of the economy, 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.[12] Overall, we differentiate between the broad sec-

[12] 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.

tors "households and non-profit organizations serving households," "non-financial corporations," and "non-bank financial corporations."

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 parlance, e.g., Agriculture, Mining, or Manufacturing.

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.[13]

3.4 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. Perhaps the 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 metadata, 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), who 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

[13]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.

Nations' recommendations on backcasting national accounts (United Nations, 2018). This issue usually arises in cases where 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.

3.5 Variable Construction

For the analysis in this paper, 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 key variables can be found in Table 3.

Credit variables For the purpose of this paper, we construct sectoral credit aggregates that distinguish between lending to households and a set of broad 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.[14]

Macroeconomic data We use data on gross domestic product (GDP) in current national currency, investment, consumption, population, inflation, and nominal US dollar exchange rates from the World Bank's World Development Indicators, Penn World Tables Version 9.1 (Feenstra, Inklaar, and Timmer, 2015), IMF IFS, GGDC (Inklaar, de Jong, Bolt, and van Zanden, 2018), Jordà et al. (2016), Mitchell (1998), and the UC Davis Nominal GDP Historical Series.[15] 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). For labor and total factor productivity, we use data from the Total Economy Database (TED), following Gorton and Ordoñez (2019). Data on effective real exchange rates comes from the World Bank, BIS, and Bruegel (Darvas, 2012).

[14]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), among other studies in international macroeconomics, also use broadly similar definitions of the tradable and non-tradable sectors.

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

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, Verner, and Xiong (2020) and Laeven and Valencia (2018). Specifically, we use the data from Baron et al. (2020)—who measure banking sector distress with data on bank equity crashes and narrative information on the occurrence of panics and widespread bank failures—for all countries they are available. For countries where they report no data, we use data from Laeven and Valencia (2018). For robustness, we also use banking crisis start dates from Reinhart and Rogoff (2009b).

3.6 Stylized Facts About Private Credit Around the World

In this section, we discuss three 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 here is mainly the extension of long-run credit series to the period before 1960.[16] Figure 1 plots the average credit to GDP ratio for advanced and emerging economies.[17] This figure confirms the "hockey stick" pattern

[16]We have data on total credit for 48 countries since 1940, 65 countries since 1950, and 100 countries since 1960.Figure A19 in the Online Appendix shows how this compares to existing sources.

[17]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.

of rising private debt in advanced economies documented by Schularick and Taylor (2012), but also reveals that the rise in credit is less pronounced in emerging economies.[18]

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

The newly constructed data allows us to provide a first glimpse at sectoral credit allocation over time using a large number of countries. Figure 2 plots averages of sectoral credit to GDP over time. This shows that almost the entire growth in credit to GDP since the early 1980s is accounted for by a rise in household debt and, to a lesser extent, lending to non-bank financial institutions. Relative to GDP, lending to non-financial corporations has changed little. This confirms previous evidence in Jordà et al. (2016), who showed a similar pattern for a much smaller sample of 17 advanced economies.[19]

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 finding of rising household debt may 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 3 plots the share of six subsectors in total corporate credit: agriculture; mining and manufacturing; construction and real estate; trade, accommodation, and food services; transport and communication; and other sectors. Figure A6 in the Online Appendix shows the same pattern by breaking down corporate credit over GDP. 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.

The second major trend is that construction and real estate lending have come to make up considerable shares of corporate loan portfolios. In advanced economies, the share of construction credit in the 1950s was negligible. Today, this share has risen to more than 24 percent. This shift is large and cannot be fully accounted for by an increase in construction value added. While the

[18] 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.

[19] Appendix A.1.1 and Appendix A.1.2 in the Online Appendix provide robustness exercises and additional results.

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 a significantly smaller role for understanding modern credit markets.[20]

4 Case Studies

To motivate our analysis, 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 reallocation 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.

4.1 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 (Baldwin and Giavazzi, 2015). These capital inflows financed rapid loan growth from financial institutions in peripheral countries.

[20]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.

Which sectors of the economy did credit expansion finance? Figure 4 shows 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, Kalemli-Özcan, Karabarbounis, and Villegas-Sanchez (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 sectoral composition of credit is new.

4.2 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).[21] The credit expansion in both Finland and Norway came after substantial deregulation of banking markets and capital flows.

Figure 5 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 Finnish banking crisis arrived in 1990 and accelerated in 1991, non-tradables and households saw the sharpest credit contractions.

In Norway, panel (b) of Figure 5 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 percentage points 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.

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

4.3 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 away from export-based to domestically-oriented growth (Quinn and Turner, 2020). 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 (Cargill, 2000). 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 (Ueda, 2000).

Figure 6a 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.

4.4 The 1994-95 Mexican "Tequila Crisis"

The 1994-95 Mexican 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 6b 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 wholesale and retail 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.

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

The United Kingdom has experienced recessions in the mid-1970s, early 1980s, early 1990s, and during the Great Financial Crisis 2007-2008. Figure 7 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 grew 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 the sector's value added.

5 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. This predictability has been found to be stronger for household credit, while evidence for non-financial corporate credit is mixed (Mian et al., 2017; IMF, 2017; Drehmann, Juselius, and Korinek, 2018; Jordà et al., 2020; Greenwood et al., 2020; Giroud and Mueller, 2020). Our sectoral credit data allows us to unpack firm credit to better understand whether and how the allocation of credit matters for subsequent GDP growth.

5.1 Tradable vs. Non-Tradable Sector Credit

We start by grouping sectors into broad tradable and non-tradable sectors, as suggested by the theories we outlined above. We then examine individual corporate sectors in more detail. We estimate the path of real GDP after innovations in sectoral credit-to-GDP using the following Jordà (2005) local projection specification:

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

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 choose 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 8 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) presents results from an estimation that includes the tradable and non-tradable corporate sectors, and panel (b) presents results that add household credit to the specification, as in (1). From the outset, we emphasize that 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.[22]

The left panel Figure 8(a) reveals that an increase in non-tradable sector credit-to-GDP is associated with slower GDP growth after three to four years. The decline persists for several years, leaving GDP below its initial trend. In terms of magnitudes, a one percentage point innovation in non-tradable credit-to-GDP predicts 0.7% lower cumulated GDP growth over the next five years. The right figure in panel (b) shows a different pattern for tradable sector credit. Growth in tradable sector credit is not associated with lower GDP growth, and the predictive relation is even positive

[22] 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, Palia, Sastry, and Sims, 2019; Plagborg-Møller, Reichlin, Ricco, and Hasenzagl, 2020; Greenwood et al., 2020).

in the medium-term after five years. A one percentage point innovation in tradable credit-to-GDP predicts 0.5% stronger cumulated growth over the next five years and 2.0% cumulated over ten years.

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.[23] The patterns implied by the estimates on d_{it}^{NT} and d_{it}^{T} are similar to panel (a), but slightly more muted. As non-tradable and household credit are relatively strongly correlated (see Table 3), the estimates for non-tradable sector credit fall by about 20% with the inclusion of household credit. This is consistent with non-tradable and household credit capturing similar periods of credit expansions, which theory suggests may be explained by similar exposure to credit-induced demand booms or because these sectors are more financing constrained and thus more exposed to credit supply shocks (e.g., Schneider and Tornell, 2004).

Table 4 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 and shift the dependent variable successively one period forward in each column of the table.

Panel A in Table 4 presents the estimates of (2) for tradable and non-tradable credit, and Panel B adds household credit, as in (2). Non-tradable credit expansions are positively correlated with GDP growth contemporaneously. In the medium run, however, the sign reverses. At the strongest horizon of $h = 3$, the estimate in Panel B implies that a one standard deviation increase in $\Delta_3 d^{NT}$ is associated with -.74 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 Panel B column (5) for the $h = 4$ horizon implies that a one standard deviation increase in $\Delta_3 d_{it}^{HH}$ is associated with -1.57 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 statistically significant.

[23] One potential explanation for the horizon of this negative predictability is the persistence of credit expansions and the long maturity of household loans (Drehmann et al., 2018).

5.2 Individual Corporate Sectors

The previous section showed that expansions in firm credit to the tradable and non-tradable sectors have differing predictive content for future GDP growth. However, it is important to understand which industries drive these patterns for two reasons. First, we want to differentiate between housing and other non-tradable industries. This is important because the factors linking non-tradable credit expansions to boom-bust cycles in models such as Schneider and Tornell (2004)—exposure to demand booms, asymmetric financing constraints, and sectoral differences in productivity—are not specific to real estate. As such, the predictions of these models might differ from a model centered around collateral values (e.g., Justiniano, Primiceri, and Tambalotti, 2015; Favilukis, Ludvigson, and Van Nieuwerburgh, 2017). Second, classifying sectors as tradable or non-tradable is not an exact science. This means it is important to show that our results are linked to industries which clearly fall into one or the other category.

Figure 9 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 9 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 stable 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 measure of non-tradables closer to the definition in Mian and Sufi (2014)—is also associated with lower subsequent growth, but the estimates are somewhat less statistically significant. The impulse response for transport and communication (H and J) also implies lower output, but is more uncertain.

In Figure 9 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 relationship between manufacturing credit innovations and medium term output is virtually unaffected by the inclusion of household debt.

These results highlight important sectoral heterogeneity. Overall, non-tradable sector credit broadly defined, along with household credit, is associated with growth slowdowns. But this is not purely driven by construction and real estate: we also find a role for other non-tradable services. Notably, tradable sector credit expansions are, if anything, associated with higher future growth.

5.3 Alternative Sector Classifications

So far, we have differentiated between firm credit by whether it predominantly finances tradable or non-tradable sectors in the economy. However, as we highlight in section 2.4, this distinction likely captures multiple underlying characteristics that may matter for understanding credit cycles. This suggests that an alternative approach for classifying sectors is to divide them based on these potentially important characteristics.

Table 5 presents the results of this alternative approach, where we consider how the characteristics of tradable and non-tradable sectors in Table 1 differ across nine non-financial industries.[24] We proceed in two steps. First, we ask whether an industry is on average above or below the median of a given characteristics in the United States, similar to Rajan and Zingales (1998). Second, we sum credit to the industries above and below the median, and create a measure of firm debt growth as the three-year change in the ratio of credit to GDP.

The results closely track our baseline distinction between tradable and non-tradable industries. Lending to sectors that score low in their export to value added ratio—or high in their dependence on final household demand, housing inputs, and mortgage collateral, or the share of small firms—predict a boom-bust pattern in real GDP growth. Other industries tend to exhibit a stable and positive relationship with growth. While it is difficult to disentangle the importance of each characteristic, this finding further supports the idea that differentiating between tradable and non-tradable sectors is a useful marker for understanding the link between firm credit expansions and the real economy.

[24] We focus on a slightly larger number of industries than in our baseline estimation to have more variation in sectoral characteristics. In particular, we include agriculture; mining; manufacturing; utilities; construction and real estate; wholesale and retail trade plus food and accommodation; transport and communication; business services; and personal and other services.

5.4 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 "twin crises." Indeed, growth in non-tradable and household credit are associated with a relative increase in non-tradable real activity (Table 6). Does slower growth after non-tradable credit expansions reflect an increase in the size of the non-tradable sector, or does it also reflect an increase in sectoral *leverage* and financial risks?

We use two approaches to address this question. First, Figure A11 panel (b) presents results from estimating (1) with additional controls for non-tradable and tradable sector value added shares. Second, Figure A11 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.[25] Both specifications suggest that the increase in credit to the non-tradable sector, not just an increase in sectoral real activity, matters for predicting future growth slowdown.

Additional controls Figure A12 panel (a) includes a variety of additional controls for the local projection specification (1).[26] 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 A12 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 A12 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 component, the impulse responses are slightly attenuated with year fixed effects, but the patterns remain similar to the baseline.

[25] 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.

[26] Figure A13 presents the same robustness checks using individual sectors as in equation (3).

Subsamples Panel (b) in Figure A12 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, 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 actually somewhat 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 contains a common country-specific component. Figure A14 presents impulse responses from local projections when individual sectors are included one-by-one. The qualitative dynamics of real GDP are similar to the multivariate local projections in Figure 8 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.

Recursive VAR evidence As an alternative to our baseline local projection impulse responses, Figure A15 presents impulse responses from a recursive VAR. The impulse responses of real GDP to credit shocks from the VAR are similar to the local projection responses. We also report the responses of the credit variables to their own shocks, which reveals that household credit is more persistent than both non-tradable and tradable corporate credit.

Long-difference regression robustness Table A1 presents a series of robustness exercises for the predictability of sectoral credit expansion over $t-3$ to t for medium-run growth from $t+1$ to $t+4$ from Table 4 column 5. The negative link between household and non-tradable sector credit and future growth is robust to controlling for a series of macroeconomic variables, including lagged GDP growth, inflation and short-term interest rates, house price growth, sectoral value added shares, and current account dynamics. The estimates are also similar, though in some cases smaller in magnitude, when controlling for year fixed effects, a common time trend, or country-specific time trends to account for global shocks or long-run trends in growth. Focusing on subsamples, both household and non-tradable credit expansion predict slower growth in the pre-2000 sample, but the estimates are weaker in the pre-1990 sample. The predictability for non-tradable credit is stronger in advanced than emerging economies.

5.5 Growth Around Major Credit Boom Events

An alternative approach to understanding whether the sectoral allocation of credit matters is to focus on the dynamics of growth following clearly defined credit boom events. To do this, we first detrend total private credit-to-GDP using the Hamilton (2018) filter with a horizon of four years. Next, we identify credit booms as the first year when detrended total credit-to-GDP exceeds 1.65 times its country-specific standard deviation, σ_i. We then separate these booms into (i) tradable biased and (ii) non-tradable biased booms, depending on whether the change in the share of tradable credit, $s_{it}^T = \frac{d_{it}^T}{d_{it}^T + d_{it}^{NT} + d_{it}^{HH}}$, over the previous five years is positive or negative. We denote these respective booms as $\mathbf{Boom}_{it}^T$ and $\mathbf{Boom}_{it}^{NT}$. We group household and non-tradables into the same group to obtain two disjoint sets of events based on theories discussed in section 2 and the empirical evidence above.

As a concrete example, we identify a credit boom in Spain in 2005 and mark this as a non-tradable biased boom based on the fact that s_{it}^T declined by 5.9 percentage points from 2000 to 2005. In total, we identify 25 tradable biased booms and 87 non-tradable biased booms in our sample, indicating that credit booms often, but not always, tend to be biased toward households and non-tradables.

We estimate the average dynamics of real GDP for five years around these booms relative to "normal" times using the following specification:

$$y_{t+h} - y_{t-1} = \alpha_i + \beta_T^h \mathbf{Boom}_{it}^T + \beta_{NT}^h \mathbf{Boom}_{it}^{NT} + \epsilon_{it+k}^h, \quad h = -5, ..., 5.$$

Figure 10 presents the sequence of estimates $\{\hat{\beta}_T^h, \hat{\beta}_{NT}^h\}$. During the boom phase from event time $t = -5$ to $t = 1$, cumulative real GDP increases faster than during normal times for both types of booms. Growth then diverges sharply starting at the top of the boom in $t = 0$ depending on the allocation of credit. Tradable biased booms see real GDP plateau about 4 percentage points higher after the boom relative to periods without a boom. In contrast, non-tradable biased booms see a sharp decline in growth that is statistically significantly different from tradable biased booms at the 5% level. From the peak in event time 0, GDP declines by about 5% relative to non-boom periods. Thus, the allocation of credit during clearly identified major credit booms helps distinguish whether these booms end badly.

6 Mechanisms

In this section, we explore three mechanisms we outlined in our discussion of credit cycle models above that might connect credit expansions to macroeconomic outcomes, depending on whether they are concentrated in the tradable, non-tradable, or household sectors. We first discuss the role of credit in fueling booms and busts in demand, then turn to asymmetries in the link between credit to different sectors and financial stability, and finally explore the role of different credit expansions in productivity growth.

6.1 What Happens During Sectoral Credit Expansions?

What happens to real economic activity during the boom period when credit expands to different sectors? Table 6 examines the correlation between sectoral credit expansions over three years and a range of macroeconomic outcomes over the same period. Column 1 shows that household credit booms are strongly associated with rising consumption as a share of GDP, suggesting that household credit expansions finance consumption booms. On the other hand, tradable and non-tradable corporate credit are associated with stronger investment-to-GDP, suggesting that rising credit to business sectors finances increased investment (column 2). Consistent with rapid demand growth, credit expansions, especially to households, are associated with a fall in the trade balance (column 3).

How do sectoral credit expansions interact with the sectoral allocation of real activity? Columns 4 and 5 examine the relation between sectoral credit expansions and growth in the ratio of non-tradable to tradable real value added and employment, respectively. Household and non-tradable credit expansions coincide with a reallocation of activity toward the non-tradable sector. This indicates that when households and non-tradables expand their borrowing, the domestic non-tradable sector expands to meet rising domestic demand. Credit expansion to these sectors are also periods of real exchange rate appreciation, as seen in column 6. Column 7 shows that house price increases are particularly correlated with credit to the non-tradable sector.

These patterns are consistent with household and non-tradable credit booms fueling demand booms that reallocate resources toward non-tradables, appreciate the real exchange rate, and thus worsen international competitiveness (Mian et al., 2020). Taken together, these correlations provide suggestive evidence that one reason for the negative predictability of household and non-tradable, but not tradable, credit for future growth is that in these booms credit is financing rising demand, rather than productive capacity. In the model of Schmitt-Grohé and Uribe (2016), such credit-induced demand booms are followed by busts when credit conditions revert, as the fall in demand from the elevated burden of debt depresses employment when wages are slow to adjust downward.

6.2 Sectoral Credit Expansions and Financial Crises

Why are some types of credit expansions associated with crises, while others are not? One potential channel could be that risks to financial stability vary with what credit is being used for. In the model of Ozhan (2020), for example, banks facing a higher cost of monitoring firms in the non-tradable sector. As a result, lending to firms in the non-tradable sector leads to higher financial fragility, as these firms are more sensitive to reversals in credit conditions. In Schneider and Tornell (2004) and Kalantzis (2015), the non-tradable sector borrows in foreign currency. The resulting currency mismatch can lead to a crisis in which many firms in the non-tradable sector default (also see Mendoza, 2002). Because financial crises are associated with large costs in terms of 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 a 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. (2016) 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 have a similar link with crises when interacted with house and equity prices, respectively. Here, we ask whether there are systematic differences in which types of credit growth tend to be followed by financial crises using much more granular data.

We start with a descriptive event-study analysis that examines how credit allocation changes around the precise start of such crises, as defined by Baron et al. (2020) and Laeven and Valencia (2018). Figure 11 plots the average one-year change in sectoral credit-to-GDP values for five years before and after a systemic banking crisis (as in Gourinchas and Obstfeld, 2012).[27] 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 firm credit to the non-tradable and tradable sectors. Non-tradable sector credit expands at more than twice the rate of tradable sector credit, surpassing the growth of household debt in the three years immediately before before crises.

Panels (b) and (c) in Figure 11 decompose these broad sectors into the by now familiar five industry groups. The growth rates of manufacturing, mining, and agriculture credit are, on average, muted in the run-up to financial crisis 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.

Importantly, credit to the non-tradable sector also declines more sharply after a crisis hits compared to the tradable sector. On one hand, this may reflect that lending in non-tradable industries was "excessive" before the crisis. However, it is also consistent with the idea that non-tradable sector firms may be particularly exposed to contractions in credit supply during crises (Ozhan,

[27]The results look almost equivalent if we de-mean the variables with respect to country averages. The results are also robust to using standardized changes in credit-to-GDP, which account for differences in volatility across sectors.

2020), as crises are known to affect firms more if they are highly dependent on external financing (Kroszner, Laeven, and Klingebiel, 2007).

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

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

where $\alpha_i^{(h)}$ is a country fixed effect and $\Delta_3 d_{it}^k$ the change in the credit-to-GDP ratio for sector k from $t-3$ to t. $Crisis_{it\ to\ it+h}$ is an indicator variable that equals one if country i experiences the start of a systemic banking crisis between year t 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 again use the crisis dates from Baron et al. (2020) 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 statistic is a given model's ability to classify the data into crisis and non-crisis periods, where an AUC of 0.5 is thought of as containing classification ability no better than a coin toss.[28]

Table 7 reports the results from estimation of equation (4). 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 5.8 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 3.4 percent. For households, the magnitude is around 5.3 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

[28]Note, however, that we are concerned with describing historical data patterns around crisis events, not a forecasting exercise.

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.

6.2.1 Robustness

In Table 8, 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 7. We focus on estimating equation (4) at 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 the predicted probability of a crisis 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 country fixed effects with averages of the dependent and independent variables. This circumvents the well-known incidental parameter bias issue and 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-to-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 at least two standard deviations above its mean, or alternatively in the top quintile of the distribution (as in Greenwood et al., 2020). Row (9) repeats the exercise in row (8) out-of-sample by only using backward-looking information on what constitutes a "boom". Again, these exercises yield similar conclusions.

Next, we consider alternative chronologies of financial crises. Row (10) uses the dates compiled by Reinhart and Rogoff (2009b); rows (11) and (12) only use the data from either Baron et al. (2020) or Laeven and Valencia (2018). These tests result in very different samples, because 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 (13) restricts the sample to the period before 2000, while rows (14) and (15) 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 control for the shares of value added in GDP (in row 16). The results suggest that it is expansions in non-tradable and household sector credit—not just changes in sector size—that are more closely associated with future crises.

Table A2 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, accommodation, and food services are robust predictors of crises similar to household debt. In Table A3, Table A4, and Table A5, 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.

6.2.2 Sectoral Defaults During Financial Crises

What ties sectoral credit expansions to a banking crisis that affects the economy as a whole? In open economy models such as Schneider and Tornell (2004), the mechanism are large-scale defaults in the non-tradable sector that drag down the economy. In Figure 12, we provide some evidence consistent with the idea that sectoral losses are important for understanding why the banking sector as a whole can end up in distress. To measure losses, we look at non-performing loans (NPLs), which a few countries' central banks or financial regulators report disaggregated by sector, although usually only starting in the mid-2000s. Here, we focus on the case of Spain and Portugal in the Eurozone crisis, which we touched on in Section 4.

The left panels of Figure 12 plot the ratio of sectoral NPLs to outstanding sectoral credit, a measure of how widespread default is in different sectors of the economy. This reveals that, both in Spain and Portugal, the ratio of distressed loans in the non-tradable sector was approximately double that of the tradable sector. At their peak, almost 30 percent of outstanding loans to the non-tradable sector were classified as non-performing in Spain, and around 20 percent in Portugal. With the exception of a wave of NPLs in 2008 and 2009, households were much less likely to default than firms, which is partly explained by strict household bankruptcy laws. The right panels show that sectoral differences are central to understanding why banks became distressed as well. In both countries, losses in the non-tradable sector accounted for more than half of total NPLs in the aftermath of the crisis. In contrast, the tradable sector made up only 8-9 percent of NPLs. While they can only be suggestive, these data highlight that financial fragility in non-tradable sectors of the economy can contribute to how credit booms lead to poor macroeconomic outcomes down the line.

6.2.3 Discussion

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 in a way that is systematically predicted by theory. Non-tradable sector and household credit expansions may pose greater financial stability risks than tradable sector credit expansions. Second, while household debt and construction/real estate play an important role, the run-up in credit before banking crises is 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, accommodation, and food services. On one hand, the link with non-tradable sector credit may be a reflection of a demand boom induced by higher credit supply to households (Mian and Sufi, 2018). But we also find a similar pattern of expansions in credit to the non-tradable and household sectors when controlling for changes in the share of different sectors in value added. This suggests a potential role for asymmetric financing constraints as emphasized in, for example, Schneider and Tornell (2004) or Kalantzis (2015). Third, this new evidence on sectoral credit helps in interpreting the mixed results of prior studies on the role of firm 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 on lending to the private sector.

6.3 Sectoral Credit Expansion and Productivity Growth

An additional channel that may connect credit growth in the non-tradable and household sectors to lower medium-run growth could be differences in sectoral productivity. As outlined in Section 2, both the level and growth rate of labor productivity is, on average, considerably higher in the tradable sector. Reis (2013) and Benigno and Fornaro (2014) take this as a starting point to show that, in an otherwise standard open economy framework, an increase in debt of the non-tradable and household sectors can lower aggregate productivity growth by reallocating resources away from the tradable sector. Conversely, higher credit growth to the tradable sector should be associated with stable or stronger productivity growth.

We test these predictions empirically by asking whether different types of sectoral credit expansions predict not only differences in future GDP growth but also productivity. To do so, we replace the dependent variable in equations (1) and (2) with (i) changes in labor productivity, the natural logarithm of output per worker, or (ii) changes in total factor productivity (TFP).[29]

Table 9 presents the results. The dependent variable is labor productivity growth in panel A and TFP growth in panel B. The results show that credit expansions in the non-tradable and household sectors are systematically associated with lower productivity growth. The opposite is true for lending to the tradable sector, which correlates with higher growth in labor productivity and TFP in the medium-run. Because these different credit expansions are also associated with a reallocation of value added and employment (see Section 6.1), this is consistent with the prediction that credit supply shocks can lead to economic slowdowns by misallocating resources across sectors (Benigno and Fornaro, 2014). This misallocation channel may also explain why Gorton and Ordoñez (2019) find that "bad booms" coincide with stagnant or falling productivity growth. It also adds nuance to the result in Borio et al. (2016) that growth in aggregate credit is accompanied by lower labor productivity growth in a sample of 21 advanced economies. Our findings suggest that whether credit finances expansions in the non-tradable or tradable sectors is important for differentiating between episodes of a potential misallocation of resources and periods where credit is linked to higher productivity growth, as emphasized in the literature on finance and growth (e.g., Levine, 2005).

7 Conclusion

There is increasing awareness that credit markets play a key role in macroeconomic fluctuations. However, a lack of detailed, comparable cross-country data on credit markets has left many questions unanswered.

Our paper shows that the sectoral allocation of credit—what credit is used for—plays an important role for understanding linkages between the financial sector and the real economy. There are predictable patterns in the future path of GDP, productivity, and the likelihood of systemic banking crises, depending on whether credit finances expansions in the tradable or non-tradable and household sectors. Our results suggest that previous work, which could not differentiate between different types of corporate credit, has missed an important margin of heterogeneity. Only credit growth in specific industries—construction and real estate, as well as other non-tradable sectors—predict a boom-bust pattern in output. Credit to the tradable sector, on the other hand, is associated with higher future productivity growth.

[29] We follow Gorton and Ordoñez (2019) and measure labor productivity using data from the Total Economy Database (TED). Results are similar for output per hours worked. We also use TED data for total factor productivity.

While we caution in making welfare statements based on our reduced form evidence, taken at face value, these findings have interesting policy implications. An ongoing policy debate has weighted whether financial regulation, including macroprudential policy, should have a stronger focus on sectoral risks (Basel Commitee on Banking Supervision, 2019). Our result suggest that such regulations could make sense, although there may be other concerns, e.g. about political economy constraints (Müller, 2019). However, the debate about risks in particular sectors has largely focused on household debt and housing. We find that lending within certain corporate sectors is important, including a clear role of non-housing non-tradable services in financial crisis episodes.

Some caveats are in order. First, the importance of non-tradable and household credit we document here may be a more recent phenomenon. While we cover a large fraction of economic downturns and crises since the 1950s, things may have been different in the era before World War II. Second, what we document are average dynamics. Understanding why there may be different patterns in some cases seems worth exploring.

Finally, we hope that our data will be useful to other researchers and, perhaps, for teaching purposes. Because of its disaggregated nature, we hope these data will be useful for many other applications bridging finance and macroeconomics.

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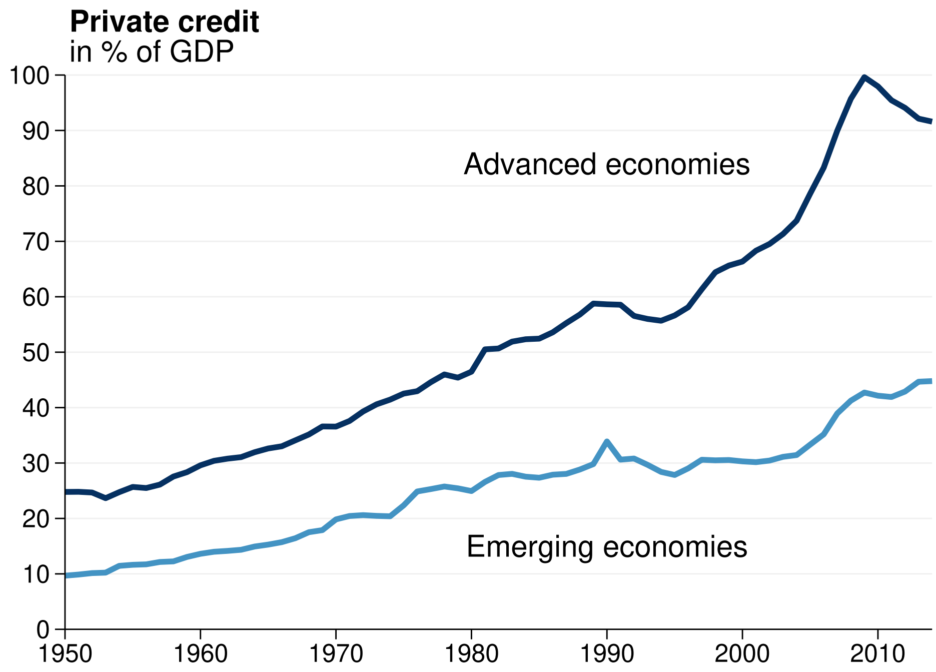
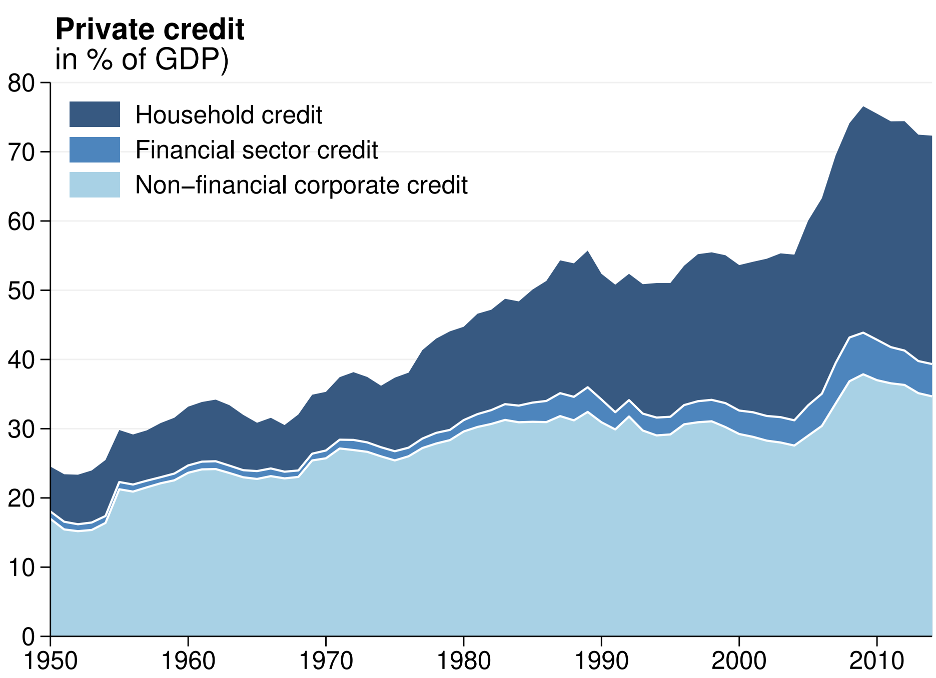
Figure 1: Private Credit to GDP (in %) by country group, 1950-2014



Sample: 52 advanced and 65 emerging economies, 1950-2014.
Notes: Average ratio of total private credit to GDP (unweighted).

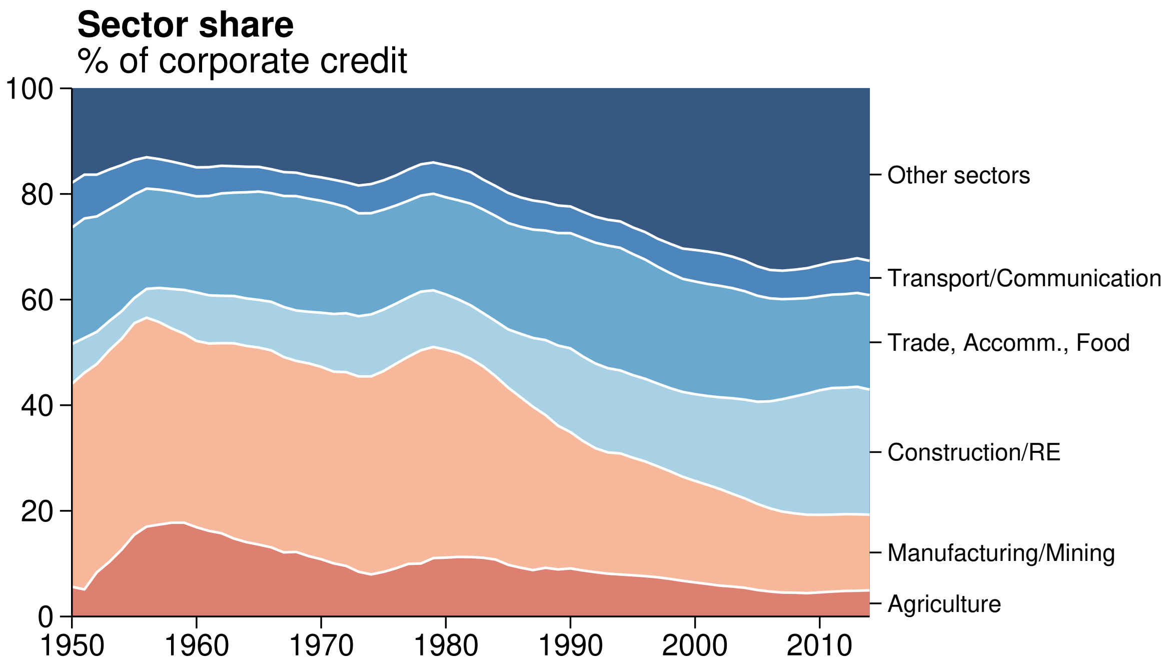
Figure 2: Private Credit to GDP, by Sector



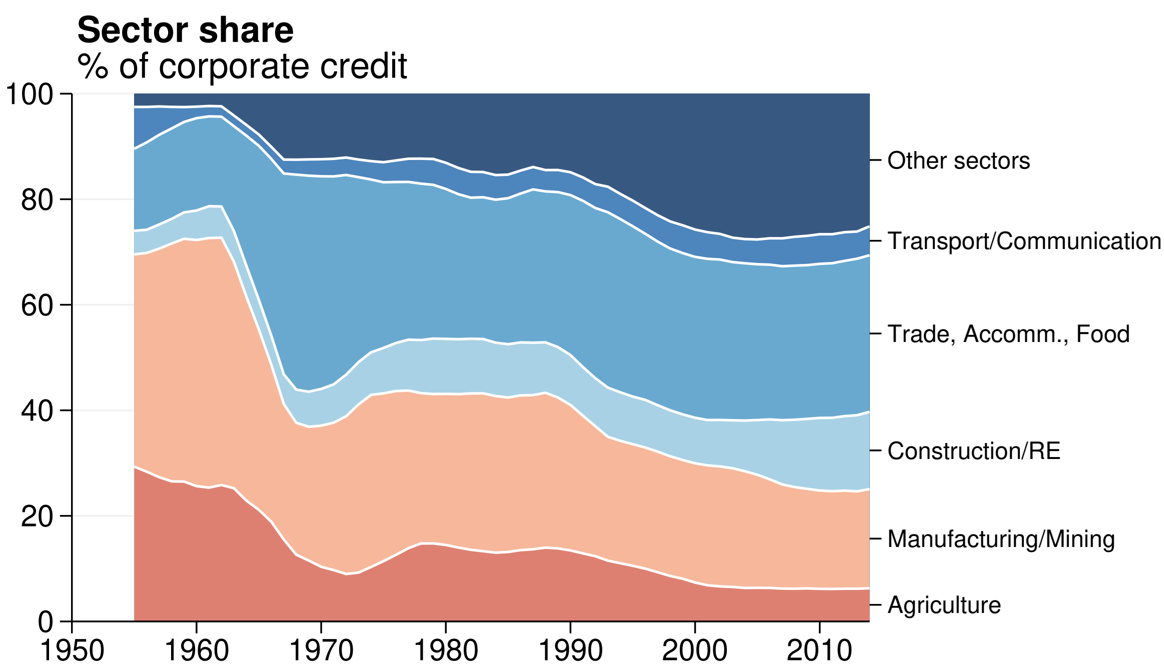
Sample: 51 advanced and 46 emerging economies, 1950-2014.
Notes: Average ratio of sectoral credit to GDP (unweighted).

Figure 3: Sector Shares in Corporate Credit

(a) Advanced economies



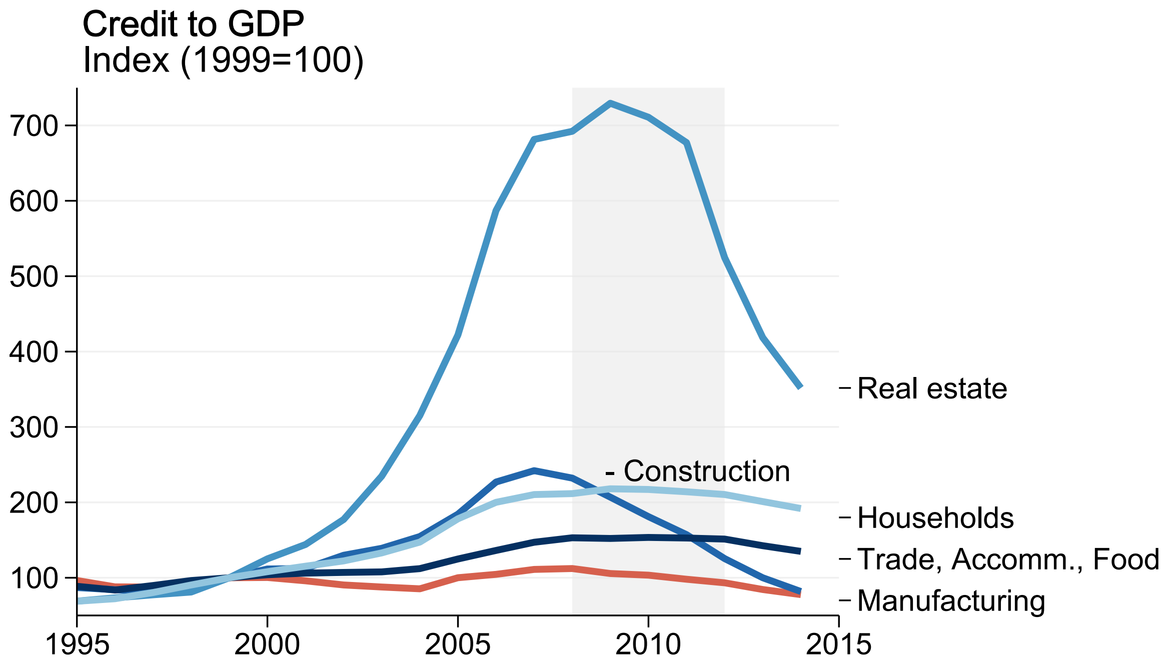
(b) Emerging economies



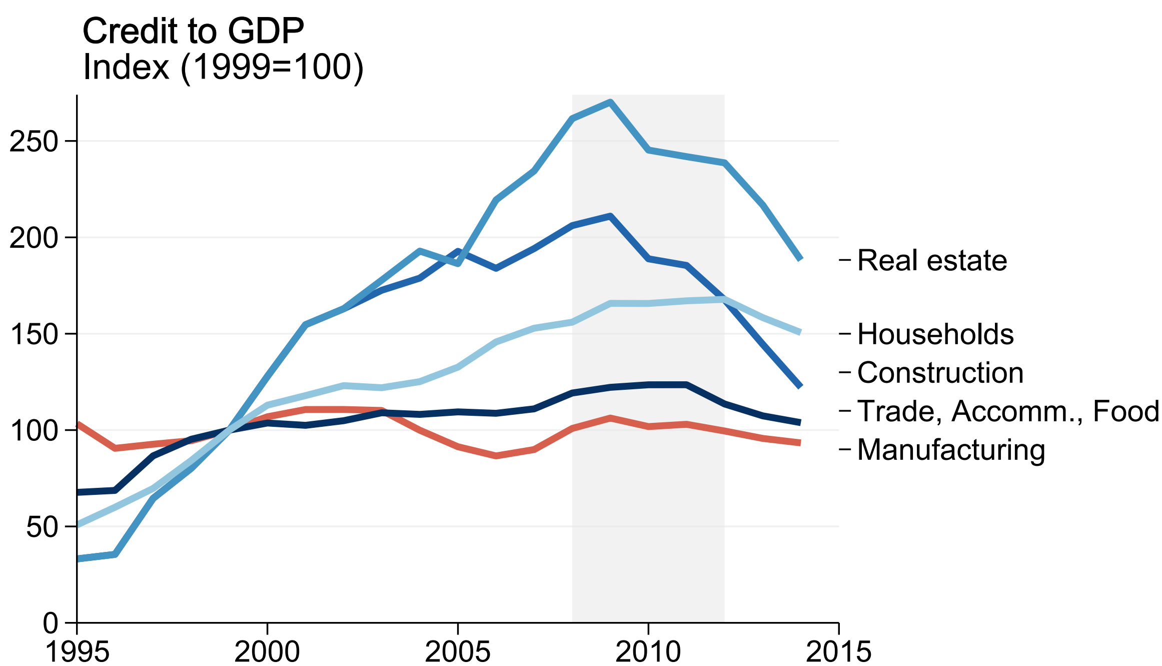
Sample: 35 advanced and 46 emerging economies.
Notes: Average ratio of individual sectors in total corporate credit.

Figure 4: The Spanish and Portuguese Financial Crises

(a) Spain



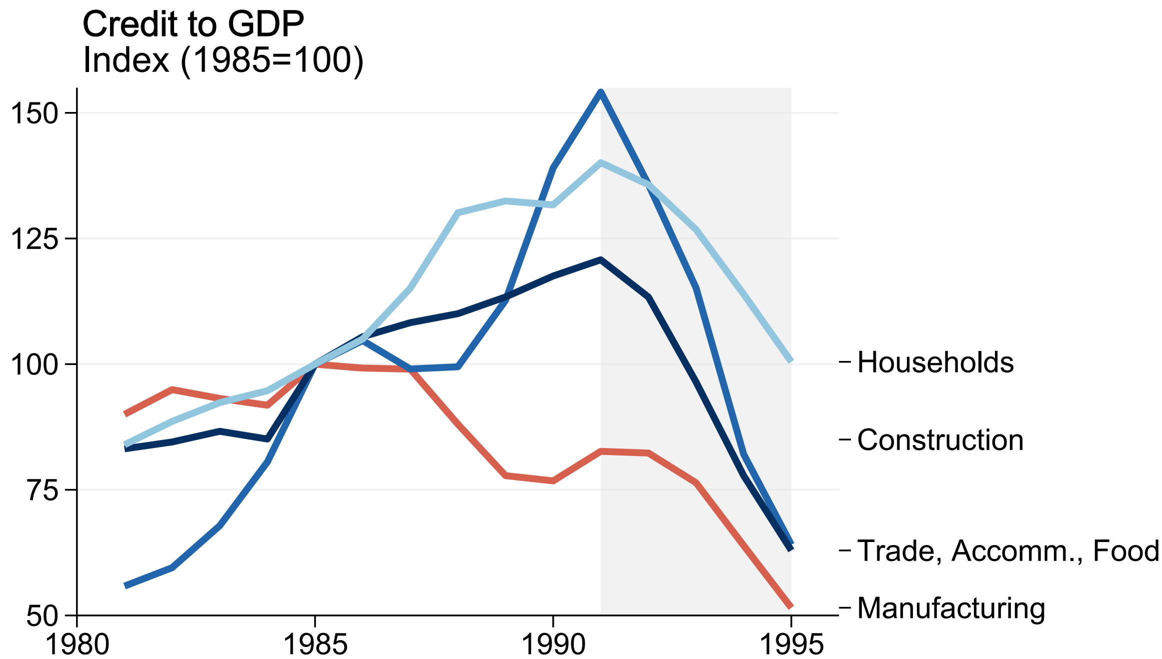
(b) Portugal



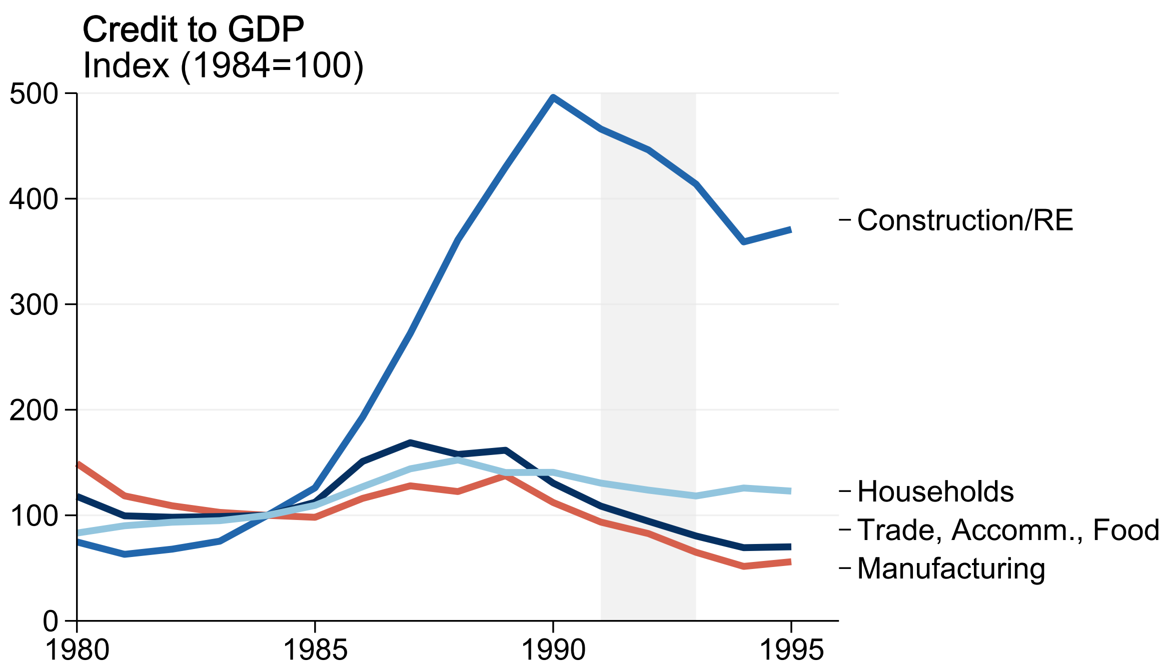
Notes: This figure plots the ratio of sectoral credit to value added for the construction (ISIC Rev. 4 section F), real estate (L), trade/accommodation/food (G + I), and manufacturing (C) industries around the time of the Eurozone crisis. We also plot data on household credit to GDP. The areas shaded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

Figure 5: The Finnish and Norwegian Financial Crises

(a) Finland



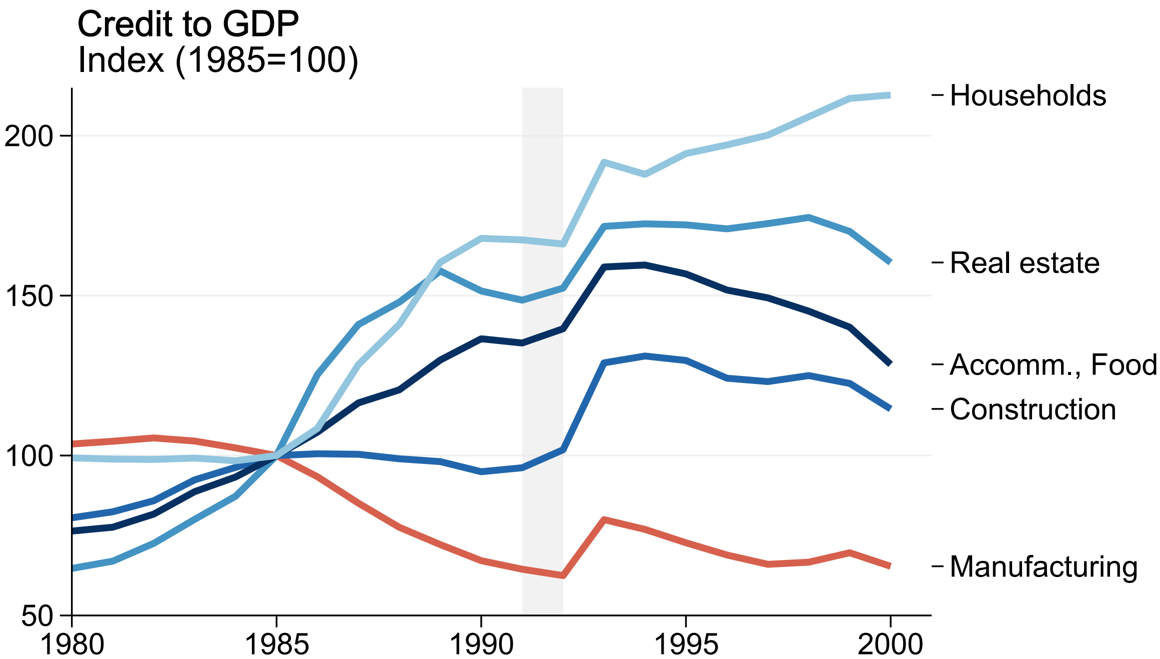
(b) Norway



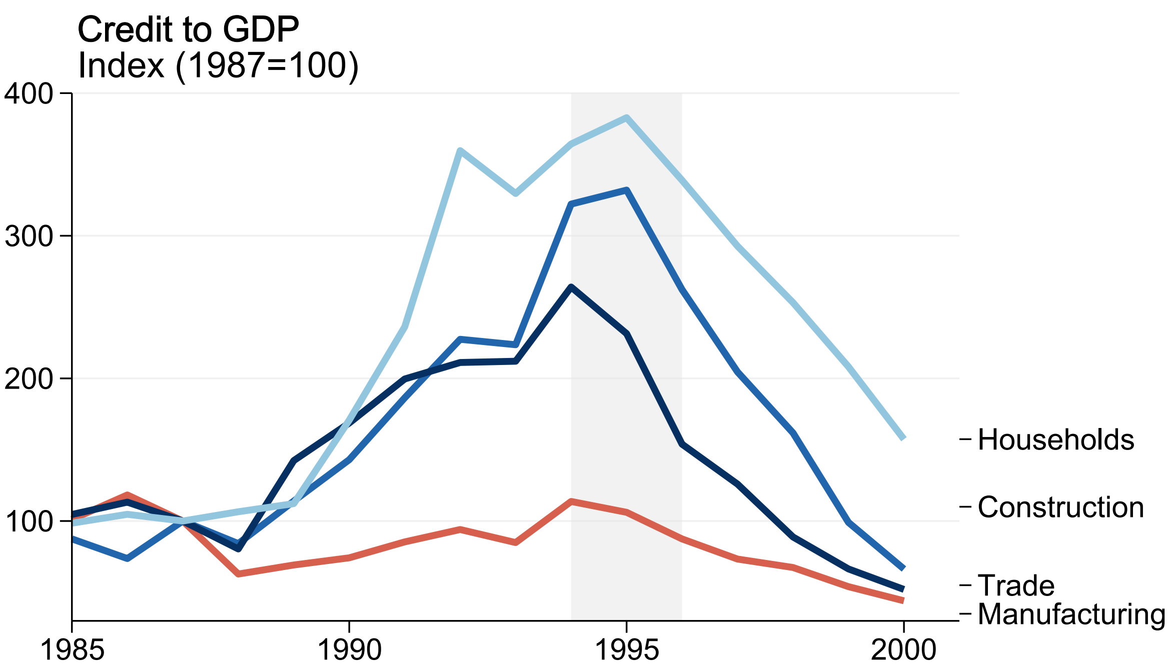
Notes: This figure plots the ratio of sectoral credit to value added for the construction (ISIC Rev. 4 section F), construction/real estate (F + L), trade/accommodation/food (G + I), and manufacturing (C) industries around the time of the Scandinavian banking crises. We also plot data on household credit 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 6: The 1991 Japanese and 1994 Mexican Financial Crises

(a) Japanese Crisis

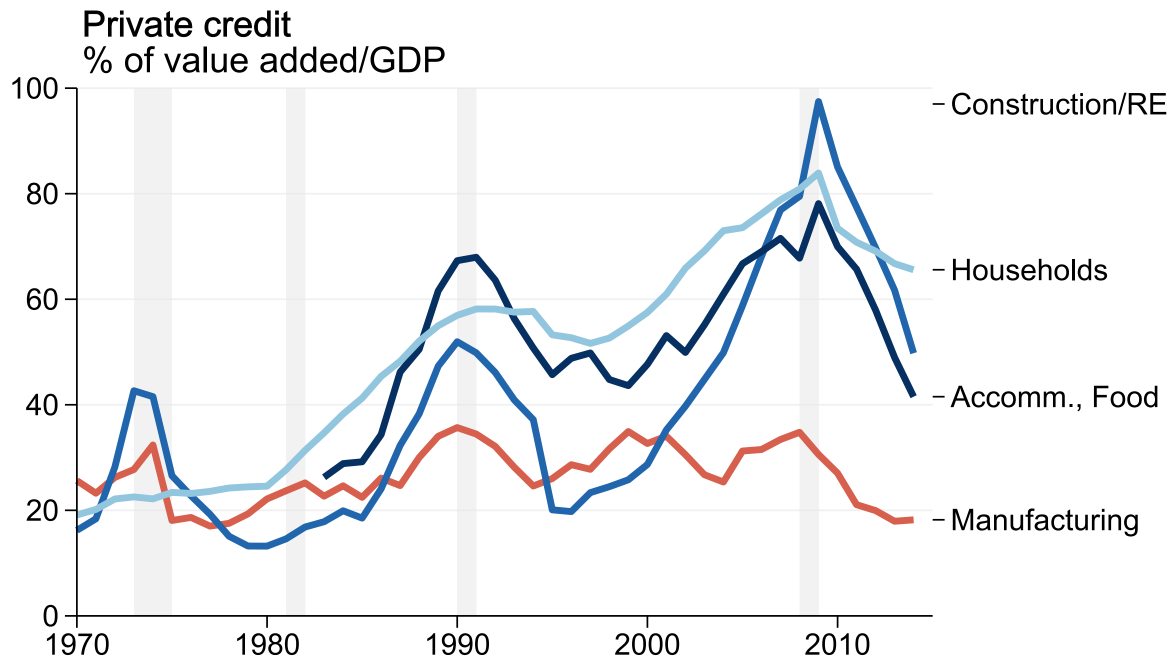


(b) Mexican Tequila Crisis



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).

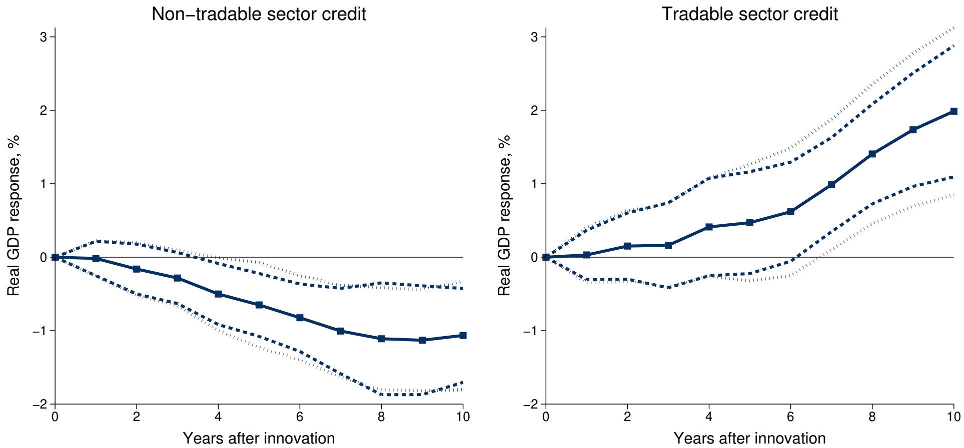
Figure 7: Industry Leverage and Household Debt Cycles in the United Kingdom



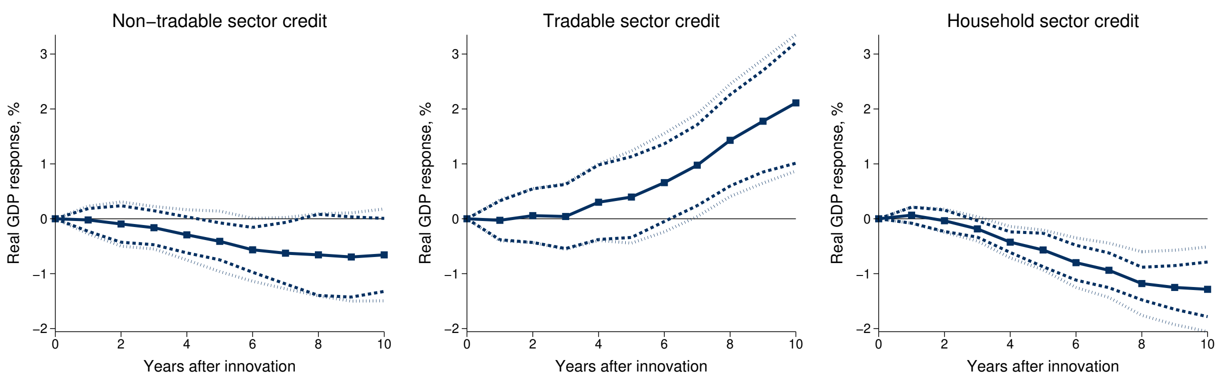
Notes: This figure plots the ratio of sectoral credit to value added for the construction/real estate (ISIC Rev. 4 sections F + L), accommodation/food (section I), and manufacturing (section C) industries between 1970 and 2014. We also plot data on household credit to GDP. The areas shaded in gray are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

Figure 8: 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:

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

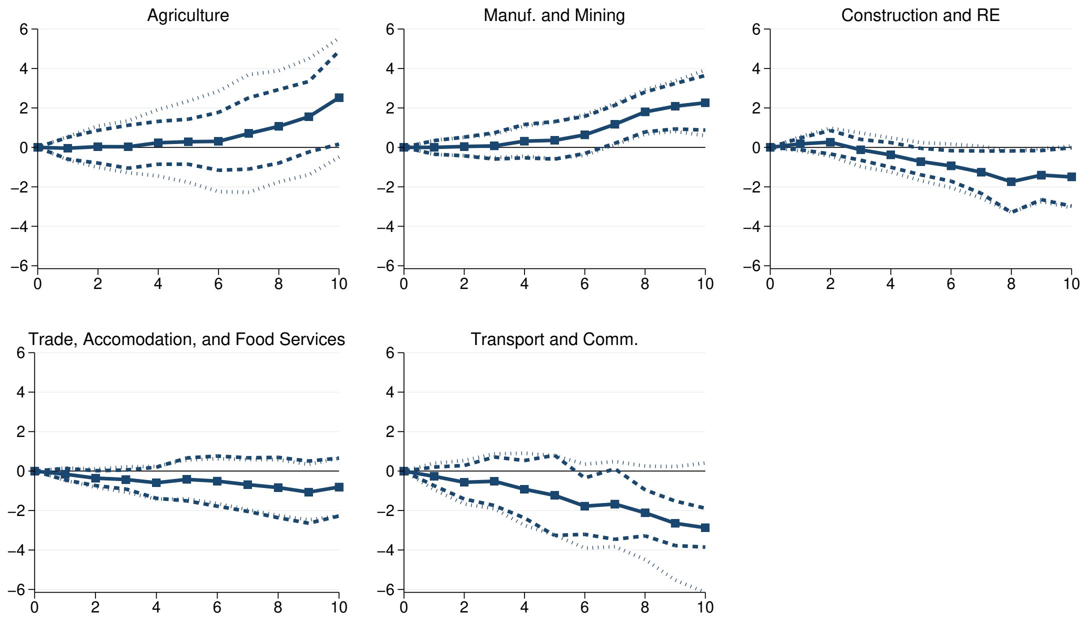
Panel (b) present the same specification but also includes household credit:

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

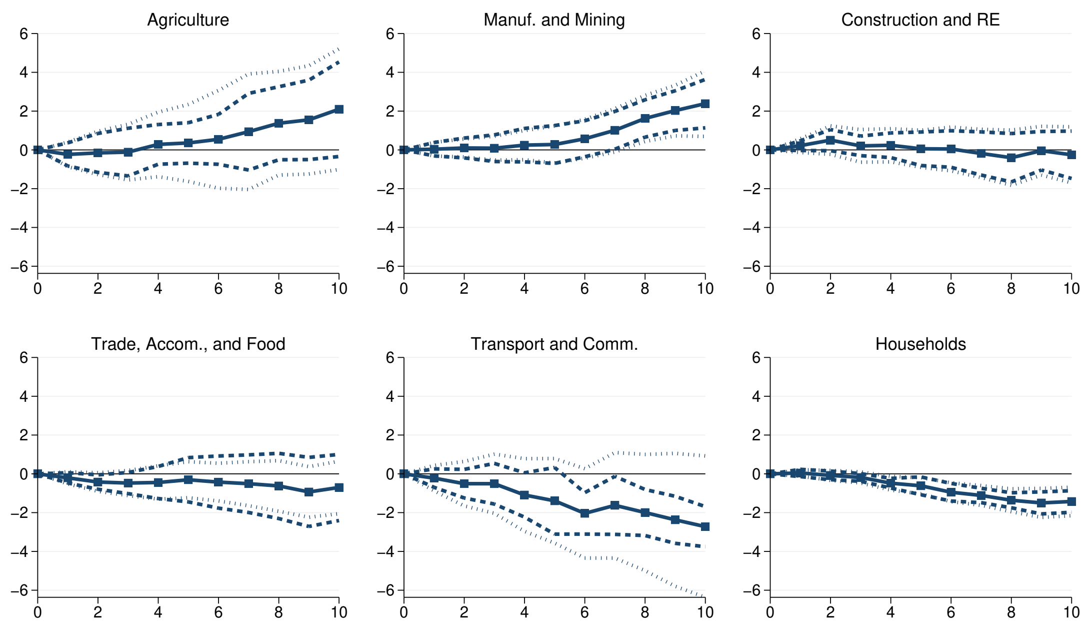
Dashed lines represent 95% confidence intervals computed using Driscoll-Kraay standard errors, and dotted lines represent 95% confidence intervals from standard errors two-way clustered on country and year.

Figure 9: Output Dynamics after Credit Expansions: Unpacking Corporate Sector Credit Expansions

(a) Non-financial Corporate Sectors

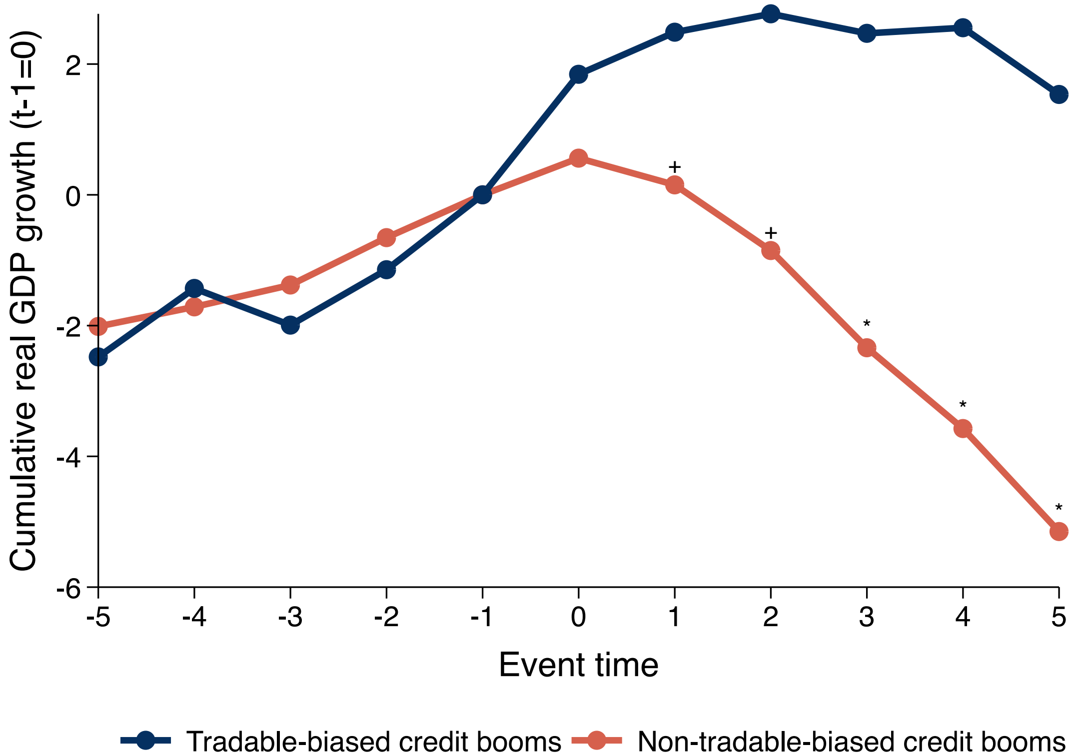


(b) Non-financial Corporate Sectors and Household Sector Credit



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 10: Output Dynamics around Credit Boom Events: Tradable vs. Non-tradable Biased Booms



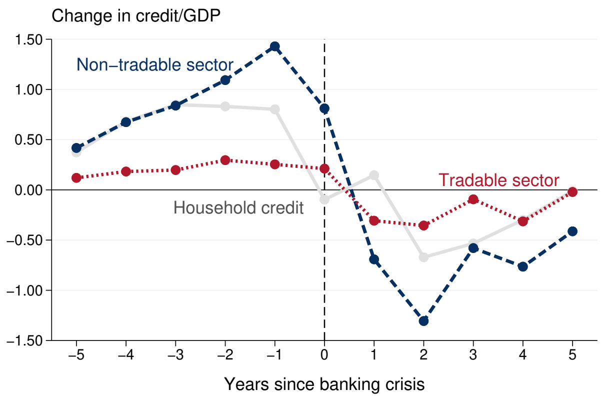
Notes: This figure plots estimates from

$$y_{t+h} - y_{t-1} = \alpha_i + \beta_T^h \mathbf{Boom}_{it}^T + \beta_{NT}^h \mathbf{Boom}_{it}^{NT} + \epsilon_{it+k}^h, \quad h = -5, ..., 5,$$

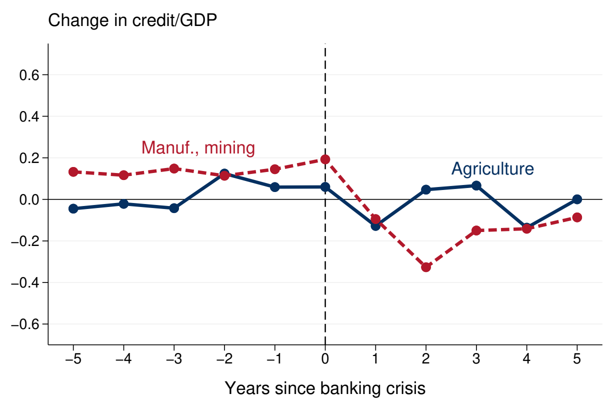
where $\mathbf{Boom}_{it}^s$ is an indicator for a credit boom with credit biased toward sector s. Time zero is defined as the first year in which the credit boom is identified. Tradable-biased (non-tradable biased) credit booms are defined as booms in which the share of tradable-sector credit (non-tradable and household sector credit) rises from time $t = -5$ to $t = 0$. The union of $\mathbf{Boom}_{it}^T$ and $\mathbf{Boom}_{it}^{NT}$ thus comprises all identified credit booms. +, * and ** indicate that the difference between the estimates, $\beta_T^h - \beta_{NT}^h$, is statistically significant at the 10%, 5% and 1% level.

Figure 11: Credit Dynamics Around Systemic Banking Crises

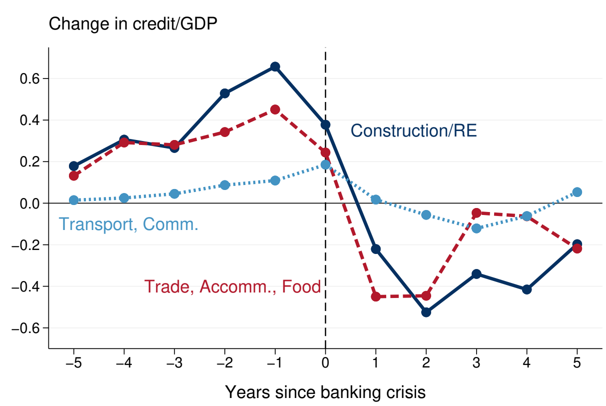
(a) Tradable vs. Non-Tradable Sector



(b) Tradable Sector Industries



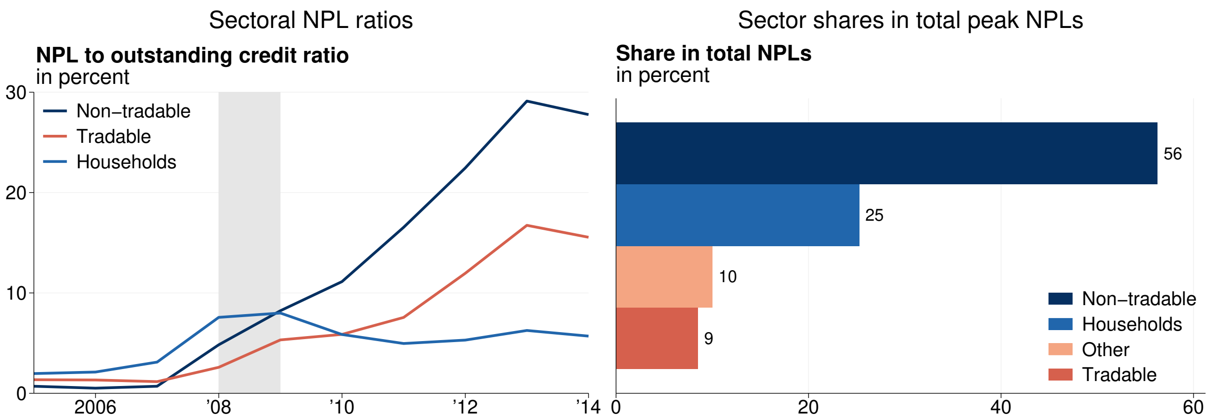
(c) Non-Tradable Sector Industries



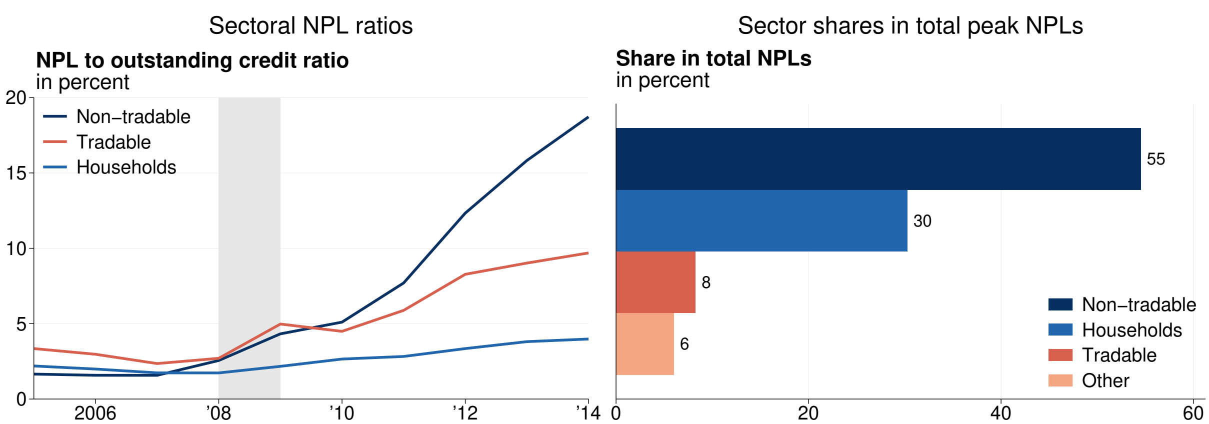
Notes: This figure plots average changes in the sectoral credit-to-GDP ratio around systemic banking crises in 83 countries between 1951 and 2009. The horizontal axis represents the number of years before and after a crisis.

Figure 12: Financial Crises and Sectoral Loan Losses – Eurozone Case Study

(a) Spain



(b) Portugal



Notes: These figures document sectoral differences in loan losses during the Spanish and Portuguese banking crises that started in 2008. The left panels plot the ratio of non-performing loans (NPLs) to outstanding loans separately for the non-tradable, tradable, and household sectors. Higher ratios mean a larger fraction of loans within a sector defaulted during the crisis. The right panels plot the share of the individual sectors in total non-performing loans in the year where the total NPL ratio reached its peak (2013 in Spain and 2014 in Portugal). The shares add up to 100%. Higher shares mean a sector contributed more to total loan losses during the crisis. The tradable sector is defined as agriculture, manufacturing, and mining; the non-tradable sector as construction, real estate, retail and wholesale trade, food, accommodation, transport, and communication.

Table 1: Comparing Non-Tradable and Tradable Sector Characteristics

	Tradable/Non-tradable			Key industries		
Country	T	NT	NT - T	Manuf.	Constr./RE	Food, Accomm.
Exports/value added	0.78	0.11	-0.67	0.95	0.01	0.06
IO proximity to HH	0.15	0.36	0.21	0.15	0.33	0.72
Housing input share	0.01	0.12	0.11	0.01	0.19	0.07
Small firm share	0.79	0.90	0.12	0.78	0.91	0.86
Mortgage share	0.19	0.36	0.17	0.18	0.67	0.56
Labor productivity	\$57,368	\$47,914	-\$9,454			
Labor productivity growth	3.7%	1.2%	-2.5%			

Notes: This table compares sectoral characteristics on non-tradable and tradable industries. The non-tradable sector is defined as comprising of construction (ISIC Rev. 4 section F), retail and wholesale trade (G), transport (H), communication (J), accommodation and food services (I), and real estate (L). The tradable sector is defined as agriculture (A), mining (B), and manufacturing (C).

For *Exports/value added*, *IO distance from HH*, and *Housing input share*, the source are the 2000-2014 versions of the World Input-Output Database, which covers 43 countries. *Exports/value added* is the weighted average ratio of exports to value added. *IO distance from HH* is defined as the weighted average ratio of domestic final household consumption to total output. *Housing input share* is defined as the weighted average ratio of inputs from the construction and real estate sectors (ISIC sections F and L68) to total intermediate consumption.

Small firm share is defined based on the OECD Structural and Demographic Business Statistics, which cover 43 countries. We compute, for each sector, the share of the total number of active businesses with less than 10 employees.

Mortgage share is the share of loans secured on real estate relative to all outstanding loans. We have data on five countries: Denmark, Latvia, Switzerland, Taiwan, and the United States; for the US, we use two sources. For Denmark, we define use the ratio of lending by mortgage banks in each sector relative to total lending by mortgage and commercial banks, using data for 2014-2020 from Danmarks Nationalbank. For Latvia, we use the share of loans secured by mortgages using data for 2006-2012 from the Financial and Capital Market Commission. For Switzerland, we use the share of mortgage lending in each sector using data for 1997-2020 from the Swiss National Bank. For Taiwan, we compute the share of lending for real estate purposes in each sector using data for 1997-2015 from the Central Bank of the Republican of China (Taiwan). For the United States, we construct the weighted average ratio of mortgages and other secured debt (dm) to total long-term debt ($dltt$) using Compustat Fundamentals data.

Labor productivity is defined as value added per engaged person in 2005 PPP USD from Mano and Castillo (2015), based on their "Goods-Producing" classification of tradable and non-tradable sectors. *Labor productivity growth* is the average yearly percent change in labor productivity.

Table 2: Comparison with Existing Data Sources on Private Credit

Dataset	Start	Freq.	Countries	Country-year obs.	Sectors	Total obs.
Panel A: Sectoral credit data						
Müller and Verner (2020)	1940	Y/Q/M	116	5,357	2–60 (mean=16)	476,555
BIS	1940	Q	43	1,220	2	9,501
Jordà et al. (2016)	1870	Y	17	1,697	3	3,913
IMF GDD	1950	Y	83	1,871	2	3,703
Panel B: Total credit data						
Müller and Verner (2020)	1910	Y/Q/M	189	10,262	—	93,839
IMF IFS	1948	Y/Q/M	182	8,483	—	86,892
Monnet and Puy (2019)	1940	Q	46	2,936	—	11,678
BIS	1940	Q	43	2,020	—	8,014
World Bank GFDD	1960	Y	187	7,745	—	7,745
IMF GDD	1950	Y	159	6,801	—	6,801
Jordà et al. (2016)	1870	Y	17	1,733	—	1,733

Notes: Panel A compares data that differentiate between different sectors of the economy (e.g. household vs. firm credit). Panel B compares different sources of data on total credit to the private sector. WB GFDD stands for the World Bank's Global Financial Development Database (Cihák, Demirgüç-Kunt, Feyen, and Levine, 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 (Mbaye et al., 2018), respectively. The data in Monnet and Puy (2019) is from historical paper editions of the IMF IFS. *Country-year obs.* refers to the number of country-year observations covered by the datasets. *Sectors* refers to the number of covered sectors; the mean refers to the average number of sectors in a country-year panel. *Total obs.* refers to country-sector-date observations. We count observations until 2014; the data will be updated to 2020 in a forthcoming revision.

Table 3: Descriptive Statistics

Panel A: Summary statistics					
	N	Mean	Std. dev.	10th	90th
Real GDP growth (t–3,t)	1,852	15.68	10.32	3.91	28.61
$\Delta_3 d_{it}^k$					
Non-tradables	1,852	0.81	3.70	-2.88	5.00
Tradables	1,852	0.04	2.26	-2.51	2.56
Household	1,852	2.10	4.13	-1.63	7.51
Agriculture	1,852	0.03	0.74	-0.64	0.65
Manuf. and Mining	1,852	0.01	1.87	-2.12	2.10
Construction and RE	1,852	0.52	2.09	-1.32	2.96
Trade, Accomodation, Food	1,852	0.18	1.73	-1.56	1.98
Transport, Comm.	1,852	0.13	0.75	-0.54	0.86

Panel B: Correlation matrix for credit expansion variables								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) NT	1							
(2) T	0.47	1						
(3) HH	0.43	0.15	1					
(4) Agr.	0.21	0.64	0.14	1				
(5) Man+Min	0.48	0.88	0.11	0.24	1			
(6) Con+RE	0.80	0.30	0.42	0.13	0.32	1		
(7) Trade etc.	0.79	0.44	0.27	0.21	0.44	0.37	1	
(8) Trans+Com	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.

Table 4: Sectoral Credit Expansion and GDP Growth

Panel A: Non-tradable and tradable sector credit

	Dependent var.: GDP growth over...					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 d_{it}^k$	(t-3,t)	(t-2,t+1)	(t-1,t+2)	(t,t+3)	(t+1,t+4)	(t+2,t+5)
Tradables	0.29*	0.30+	0.31	0.36	0.35	0.31
	(0.14)	(0.17)	(0.21)	(0.23)	(0.25)	(0.25)
Non-tradables	0.35**	0.051	-0.23*	-0.39**	-0.43**	-0.37**
	(0.11)	(0.12)	(0.11)	(0.10)	(0.12)	(0.12)
Observations	2,034	1,964	1,892	1,821	1,749	1,677
# Countries	74	74	74	74	74	74
R^2	0.04	0.01	0.01	0.02	0.03	0.02

Panel B: Including household credit

	Dependent var.: GDP growth over...					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 d_{it}^k$	(t-3,t)	(t-2,t+1)	(t-1,t+2)	(t,t+3)	(t+1,t+4)	(t+2,t+5)
Tradables	0.18	0.17	0.19	0.27	0.30	0.31
	(0.13)	(0.15)	(0.17)	(0.19)	(0.21)	(0.21)
Non-tradables	0.44**	0.18+	-0.062	-0.20**	-0.22**	-0.17*
	(0.075)	(0.099)	(0.094)	(0.067)	(0.055)	(0.078)
Households	-0.016	-0.12	-0.26**	-0.38**	-0.51**	-0.51**
	(0.093)	(0.088)	(0.072)	(0.075)	(0.12)	(0.13)
Observations	1,852	1,784	1,714	1,645	1,575	1,505
# Countries	73	73	73	73	73	73
R^2	0.05	0.01	0.02	0.05	0.08	0.07

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.

Table 5: Alternative Sector Classifications

$\Delta_3 d^k_{it}$	(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)
	Dependent var.: GDP growth over...					
Panel A: Sorting by exports-to-value added						
High export/VA	0.36**	0.27*	0.17	0.14	0.12	0.11
	(0.097)	(0.12)	(0.13)	(0.12)	(0.13)	(0.16)
Low export/VA	0.23+	-0.027	-0.26+	-0.38**	-0.39**	-0.30*
	(0.13)	(0.15)	(0.14)	(0.097)	(0.100)	(0.13)
Panel B: Sorting by proximity to household demand						
High proximity to HH	0.23*	-0.0097	-0.23*	-0.35**	-0.39**	-0.33**
	(0.100)	(0.11)	(0.10)	(0.083)	(0.075)	(0.077)
Low proximity to HH	0.39**	0.30**	0.20	0.19	0.22	0.26*
	(0.094)	(0.11)	(0.13)	(0.14)	(0.15)	(0.12)
Panel C: Sorting by housing input share						
High housing input share	0.32**	0.074	-0.16+	-0.29**	-0.34**	-0.33**
	(0.10)	(0.11)	(0.091)	(0.078)	(0.078)	(0.082)
Low housing input share	0.21	0.19	0.17	0.22	0.27	0.35
	(0.17)	(0.20)	(0.21)	(0.20)	(0.21)	(0.22)
Panel D: Sorting by small firm share						
High small firm share	0.21*	-0.048	-0.27*	-0.40**	-0.43**	-0.38*
	(0.087)	(0.099)	(0.11)	(0.13)	(0.15)	(0.15)
Low small firm share	0.38**	0.29*	0.17	0.16	0.15	0.17
	(0.083)	(0.11)	(0.15)	(0.17)	(0.19)	(0.19)
Panel E: Sorting by mortgage debt share						
High mortgage share	0.31*	0.067	-0.18	-0.30**	-0.32**	-0.27*
	(0.14)	(0.15)	(0.13)	(0.10)	(0.10)	(0.13)
Low mortgage share	0.31	0.21	0.13	0.12	0.10	0.12
	(0.19)	(0.22)	(0.21)	(0.19)	(0.21)	(0.26)

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

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

where $\alpha_i^{(h)}$ is a country fixed effect and $\Delta_3 d^k_{it}$ the change in the credit/GDP ratio for sector grouping k from $t-3$ to t. Each panel estimates a separate regression with two independent variables that capture firm credit growth. "High" refers to the three-year change in firm credit to GDP for sectors above the median in a given characteristics in the United States, and "low" to sectors below the median. See Table 1 for variable definitions and sources for these characteristics. 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.

Table 6: Correlates of Sectoral Credit Expansions

$\Delta_3 d_{it}^k$	$\Delta_3 \frac{Con}{Y}$ (1)	$\Delta_3 \frac{Inv}{Y}$ (2)	$\Delta_3 \frac{NX}{Y}$ (3)	$\Delta_3 \ln\left(\frac{Y^{NT}}{Y^T}\right)$ (4)	$\Delta_3 \ln\left(\frac{E^{NT}}{E^T}\right)$ (5)	$\Delta_3 \ln(RER)$ (6)	$\Delta_3 \ln(HPI)$ (7)
Tradables	0.015	0.12**	-0.23**	0.13	-0.18	-0.27	0.65
	(0.070)	(0.039)	(0.068)	(0.16)	(0.16)	(0.30)	(0.45)
Non-tradables	-0.039	0.19**	-0.14*	0.34**	0.44**	0.43+	0.96**
	(0.029)	(0.041)	(0.062)	(0.12)	(0.073)	(0.22)	(0.26)
Households	0.12**	0.066	-0.21**	0.32**	0.44**	0.30*	0.45
	(0.024)	(0.046)	(0.046)	(0.071)	(0.048)	(0.12)	(0.36)
Observations	1,838	1,838	1,852	1,431	992	1,755	868
# Countries	73	73	73	70	45	73	41
R^2	0.01	0.04	0.06	0.07	0.14	0.03	0.10

Notes: This table presents regressions of changes in various macroeconomic outcomes from $t-3$ to t on the expansion in tradable, non-tradable, and household credit-to-GDP over the same period. The outcome variables are the consumption-to-GDP ratio (column 1), investment-to-GDP ratio (column 2), net exports-to-GDP ratio (column 3), the log of the non-tradable to tradable real value added ratio (column 4), the log of the non-tradable to tradable employment ratio (column 5), the log of the real effective exchange rate (column 6), and the log real house index (column 7). All columns include country fixed effects. Driscoll and Kraay (1998) standard errors in parentheses with lag length of 6. +, * and ** denote significance at the 10%, 5% and 1% level.

Table 7: 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	-0.005	-0.007	-0.007	-0.004
	(0.004)	(0.005)	(0.005)	(0.005)
Non-tradables	0.013**	0.016**	0.017**	0.015**
	(0.003)	(0.002)	(0.003)	(0.005)
Households	0.005+	0.009**	0.011**	0.012**
	(0.003)	(0.003)	(0.003)	(0.004)
Observations	1,527	1,531	1,534	1,536
# Countries	70	70	70	70
# Crises	54	53	53	52
AUC	0.73	0.72	0.70	0.69
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	-0.000	-0.002	-0.003	-0.004
	(0.008)	(0.010)	(0.015)	(0.017)
Manuf. and Mining	-0.006	-0.009	-0.010	-0.007
	(0.006)	(0.008)	(0.007)	(0.007)
Construction and RE	0.019**	0.023**	0.021**	0.017**
	(0.006)	(0.006)	(0.005)	(0.006)
Trade, Accommodation, Food	0.014*	0.022**	0.028**	0.030**
	(0.005)	(0.006)	(0.008)	(0.009)
Transport, Communication	-0.007	-0.012	-0.013	-0.020
	(0.010)	(0.009)	(0.011)	(0.018)
Households	0.004	0.007*	0.009**	0.011**
	(0.003)	(0.003)	(0.003)	(0.003)
Observations	1,527	1,531	1,534	1,536
# Countries	70	70	70	70
# Crises	54	53	53	52
AUC	0.75	0.74	0.72	0.71
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.

Table 8: Sectoral Credit Expansions and Financial Crises – Multivariate Regressions

		N	# Countries	# Crises	AUC	Tradables		Non-tradables		Households	
						β	$[t]$	β	$[t]$	β	$[t]$
(1)	Baseline (LPM, country FE)	1,534	70	53	0.70	-0.01	-1.38	0.02	5.29**	0.01	3.33**
(2)	LPM, country + year FE	1,534	70	53	0.70	0.00	-0.61	0.01	2.70**	0.01	2.39*
(3)	Logit	1,534	70	53	0.70	0.00	-0.38	0.01	2.85**	0.01	2.54*
(4)	Logit, country FE	1,014	36	51	0.69	-0.01	-1.13	0.03	3.58**	0.02	4.57**
(5)	Logit, RE-Mundlak	1,534	70	53	0.83	0.00	-0.86	0.01	3.51**	0.01	2.38*
(6)	Lags of 1-year changes	1,530	70	53	0.70	-0.02	-1.36	0.05	5.34**	0.03	3.28**
(7)	Boom (>= Mean + 2 $\times$ SD)	1,534	70	53	0.59	0.02	0.18	0.26	3.49**	0.13	2.06*
(8)	Boom (>= 80th percentile)	1,534	70	53	0.71	0.00	-0.12	0.11	3.75**	0.19	4.13**
(9)	Boom (>= 80th percentile, OOS)	1,534	70	53	0.69	0.00	0.07	0.10	6.14**	0.10	3.64**
(10)	RR dates	1,038	42	131	0.62	-0.02	-1.51	0.03	2.81**	0.01	1.08
(11)	LV dates only	1,401	69	35	0.65	-0.01	-0.92	0.01	2.90**	0.01	1.76+
(12)	BVX dates only	992	35	39	0.74	0.00	-0.57	0.02	5.65**	0.01	3.15**
(13)	Pre-2000 only	908	46	27	0.65	-0.01	-2.49*	0.02	5.32**	0.01	3.85**
(14)	Advanced economies	876	31	33	0.73	-0.01	-1.58	0.02	3.80**	0.01	2.73**
(15)	Emerging economies	658	39	20	0.67	-0.01	-0.75	0.02	3.06**	0.01	4.10**
(16)	Value added controls	642	38	29	0.71	-0.01	-0.57	0.02	2.46*	0.00	1.26

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. (2020) 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) repeats the same exercise as in model (8) but only uses backward-looking information to construct booms. Model (10) uses the systemic banking crisis dates from Reinhart and Rogoff (2009b). Model (11) only uses crisis dates from Laeven and Valencia (2018), and model (12) only the dates from Baron et al. (2020). Model (13) restricts the sample to the years before 2000. Models (14) and (15) restrict the sample to countries classified as high-income and low-income/middle-income by the World Bank in 2019, respectively. Model (16) controls for three-year changes in sectoral value added/GDP.

Table 9: Sectoral Credit Expansions and Productivity

Panel A: Labor productivity

	Dependent variable: Labor productivity growth over...					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 d_{it}^k$	(t-3,t)	(t-2,t+1)	(t-1,t+2)	(t,t+3)	(t+1,t+4)	(t+2,t+5)
Tradables	0.188^{+}	0.177*	0.216*	0.219^{+}	0.183	0.141
	(0.094)	(0.075)	(0.088)	(0.119)	(0.148)	(0.169)
Non-tradables	0.098	-0.049	-0.162^{+}	-0.146^{+}	-0.073	0.002
	(0.141)	(0.127)	(0.090)	(0.075)	(0.057)	(0.059)
Households	-0.137*	-0.158*	-0.191**	-0.229**	-0.291**	-0.302**
	(0.064)	(0.066)	(0.055)	(0.061)	(0.074)	(0.067)
Observations	1,423	1,423	1,423	1,423	1,423	1,423
# Countries	67	67	67	67	67	67
R^2	0.01	0.01	0.02	0.03	0.03	0.03

Panel B: Total factor productivity

	Dependent variable: TFP growth over...					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 d_{it}^k$	(t-3,t)	(t-2,t+1)	(t-1,t+2)	(t,t+3)	(t+1,t+4)	(t+2,t+5)
Tradables	-0.059	-0.140	-0.156*	-0.015	0.159**	0.211*
	(0.173)	(0.143)	(0.072)	(0.046)	(0.040)	(0.094)
Non-tradables	-0.165^{+}	-0.324**	-0.382**	-0.317**	-0.212**	-0.117
	(0.094)	(0.098)	(0.102)	(0.076)	(0.055)	(0.093)
Households	-0.055	-0.077	-0.127^{+}	-0.205**	-0.282**	-0.246**
	(0.093)	(0.090)	(0.071)	(0.067)	(0.063)	(0.044)
Observations	805	805	805	805	805	805
# Countries	65	65	65	65	65	65
R^2	0.03	0.08	0.12	0.10	0.08	0.05

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

$$\Delta_3 Prod_{it+3+h} = \alpha_i^{(h)} + \sum_k^K \beta_k^{(h)} \Delta_3 d_{it}^k + u_{it}^{(h)}, \quad h = 0, ..., 5$$

where $\Delta_3 Prod_{it+3+h}$ is a measure of productivity growth from $t+h$ to $t+h+3$, $\alpha_i^{(h)}$ 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.

Credit Allocation and Macroeconomic Fluctuations
Online Appendix

Karsten Müller Emil Verner

This appendix supplements our paper *Credit Allocation and Macroeconomic Fluctuations*. The first part provides additional results for the stylized facts and empirical results in the main paper. The second 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.

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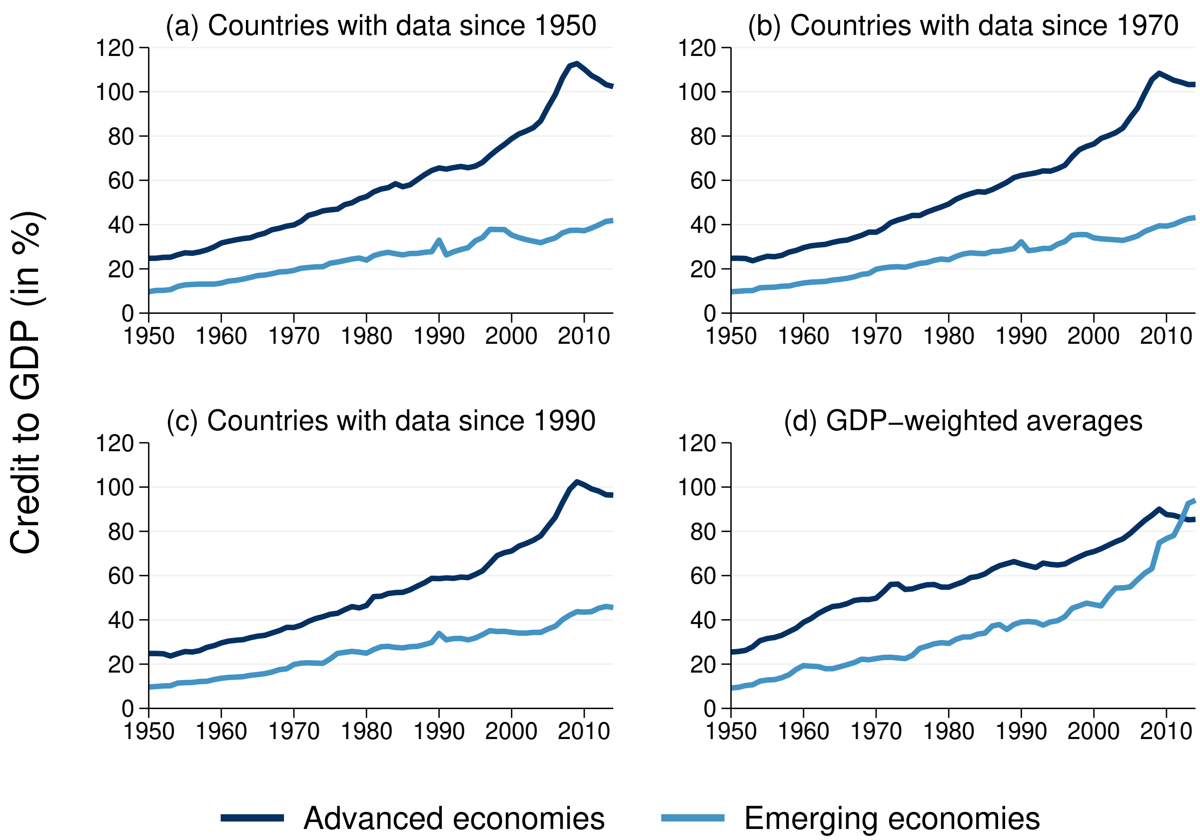
A Additional Results

A.1 Stylized facts

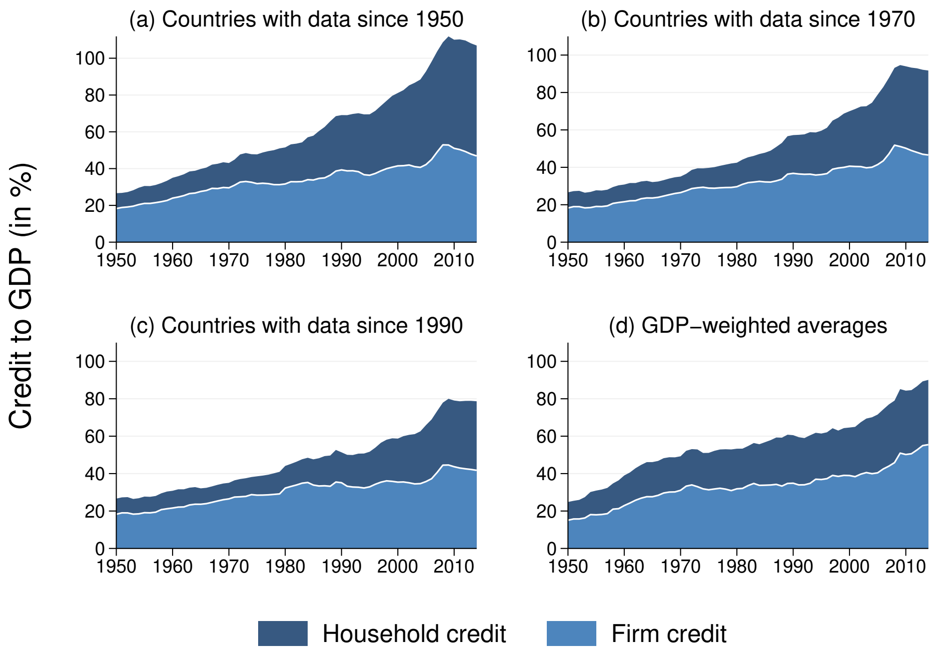
A.1.1 Aggregate Trends

Figure A1: Total Credit to GDP (in %), 1950-2014



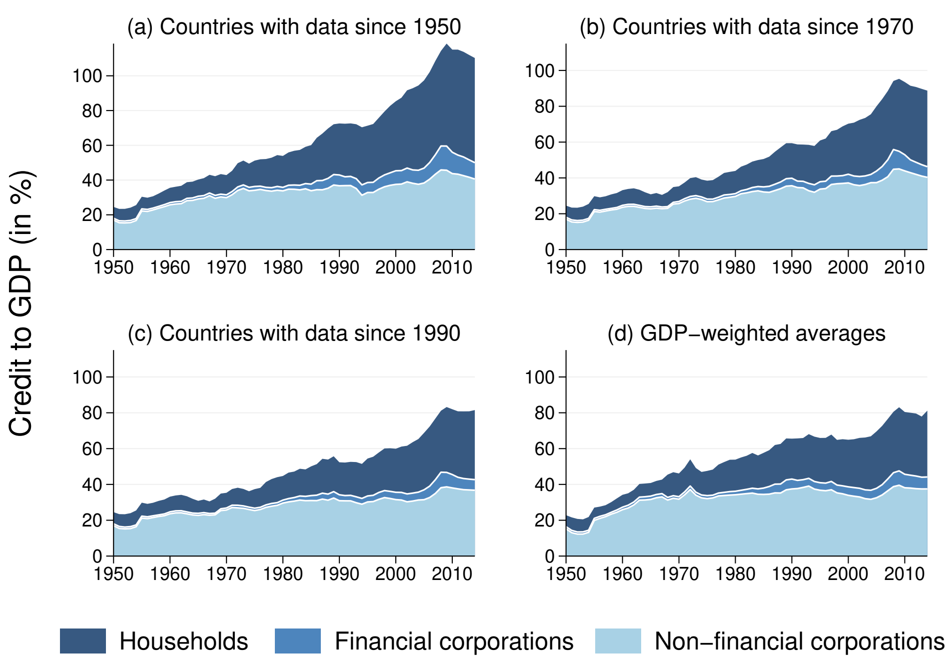
Sample: 26, 39, 46, and 52 advanced, and 24, 41, 53, and 65 emerging economies in panels (a), (b), (c), and (d), respectively.
Notes: Average ratio of total private credit to GDP (unweighted), except in panel (d).

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).

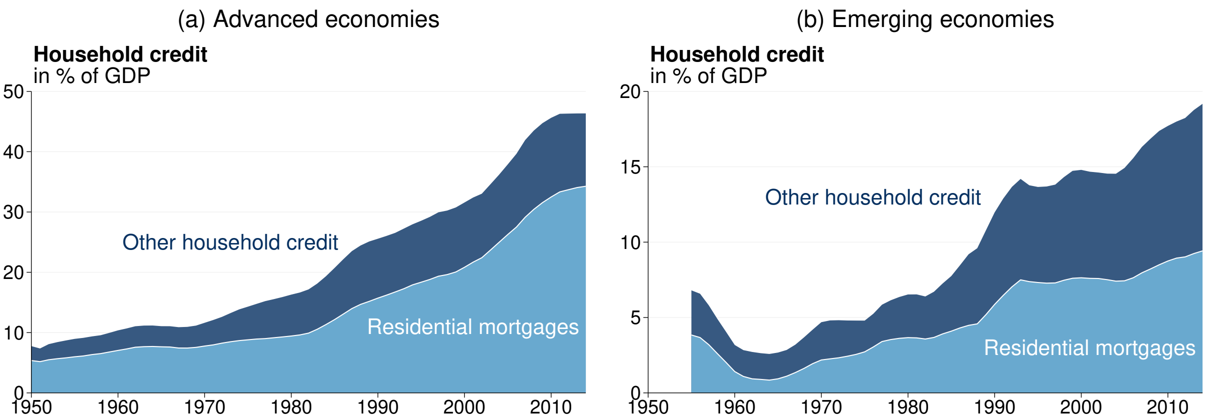
Figure A3: Total Credit Decomposition - Households, Non-Financial Firms, and Financial Sector



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

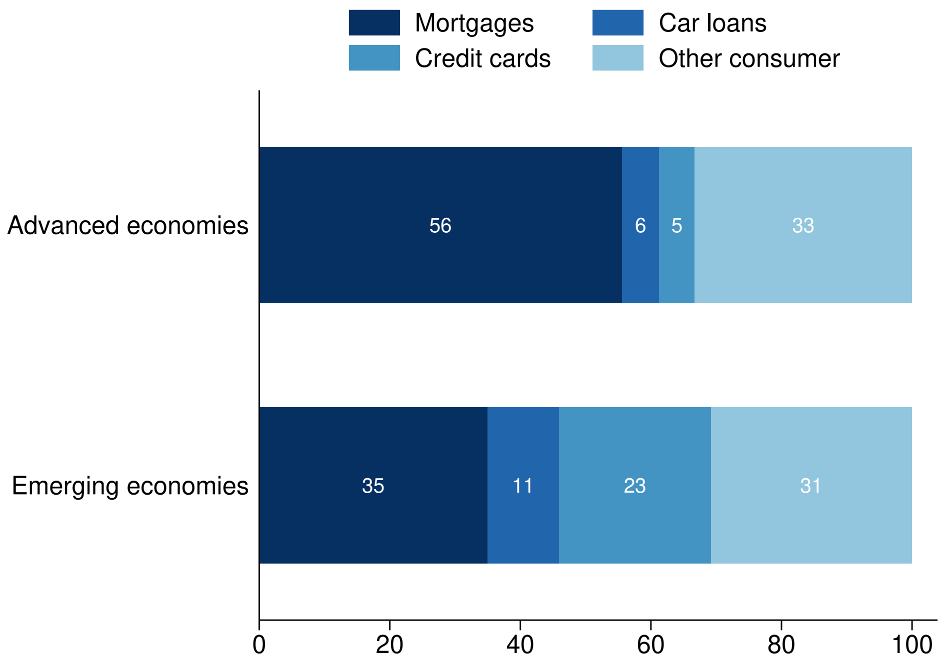
Figure A4: Household Credit to GDP, by Type and Country Group



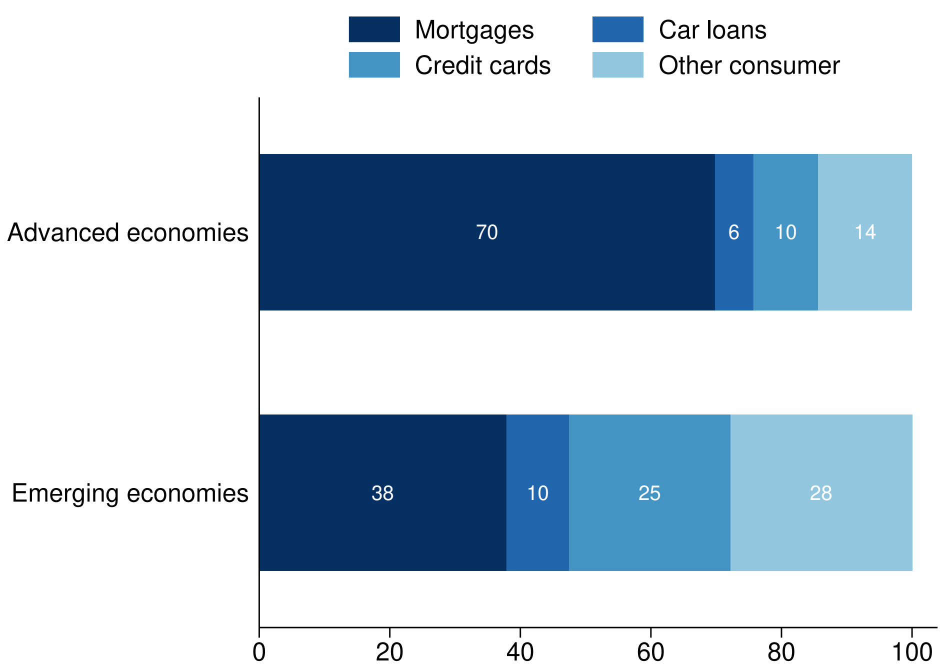
Sample: 49 advanced and 49 emerging economies, 1950-2014.
Notes: Average ratio of household credit to GDP (unweighted) split by type.

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

(a) Equal-weighted averages



(b) GDP-weighted averages

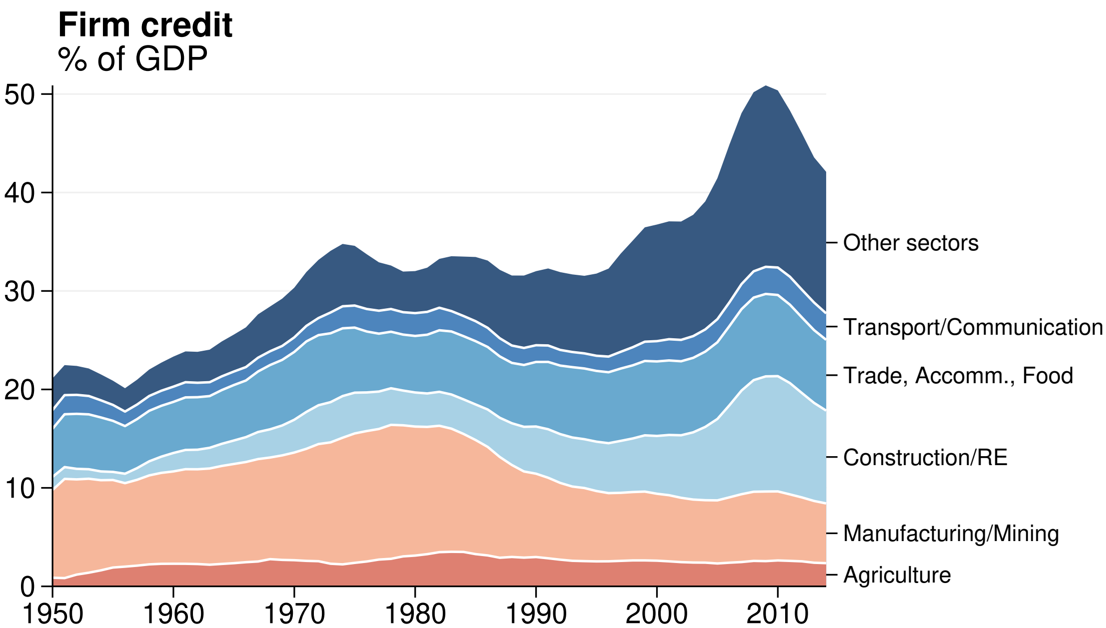


Sample: 10 advanced and 8 emerging economies with non-missing data for each loan purpose.
Notes: Average share of household credit by loan purpose during the period 2009-2014.

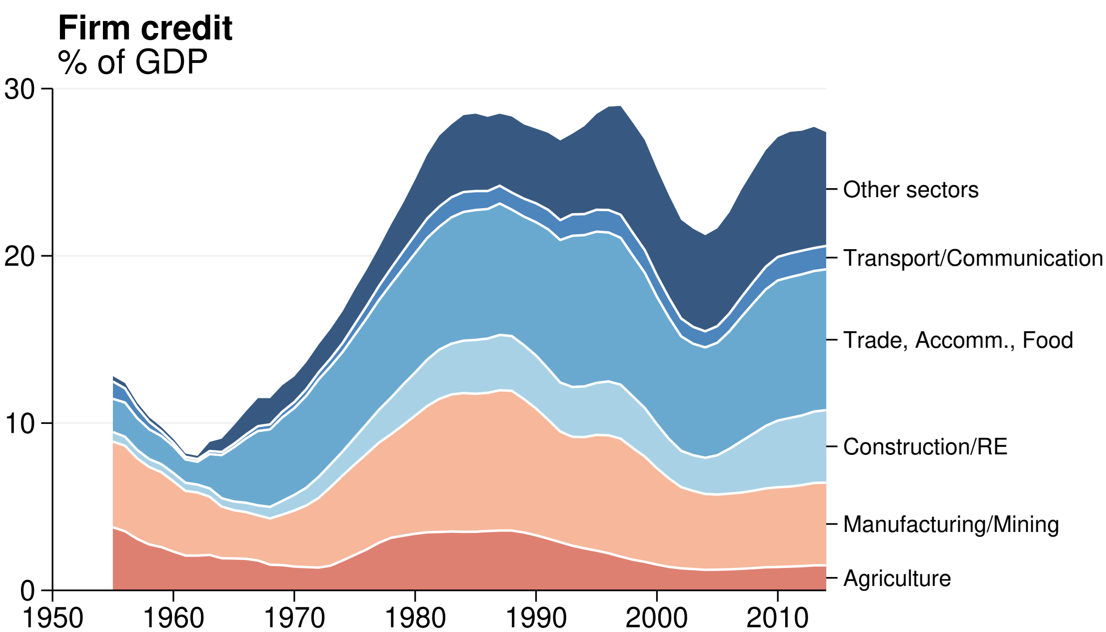
A.1.3 Structural Change in Corporate Credit

Figure A6: Corporate Credit Composition, by Country Group

(a) Advanced Economies



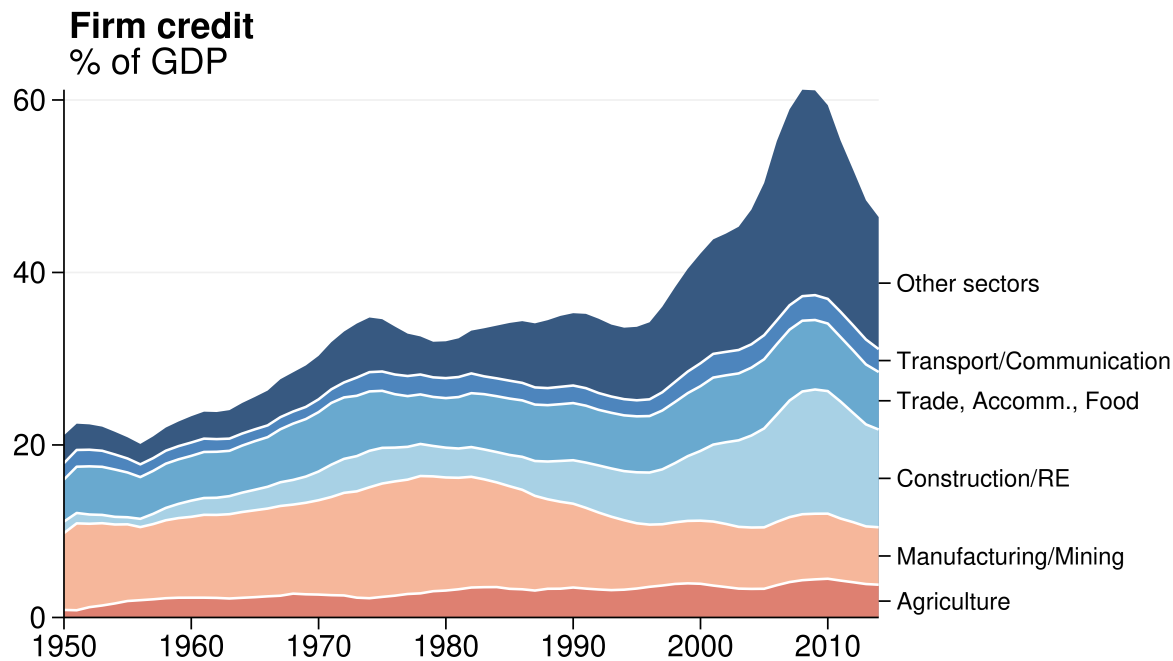
(b) Emerging Economies



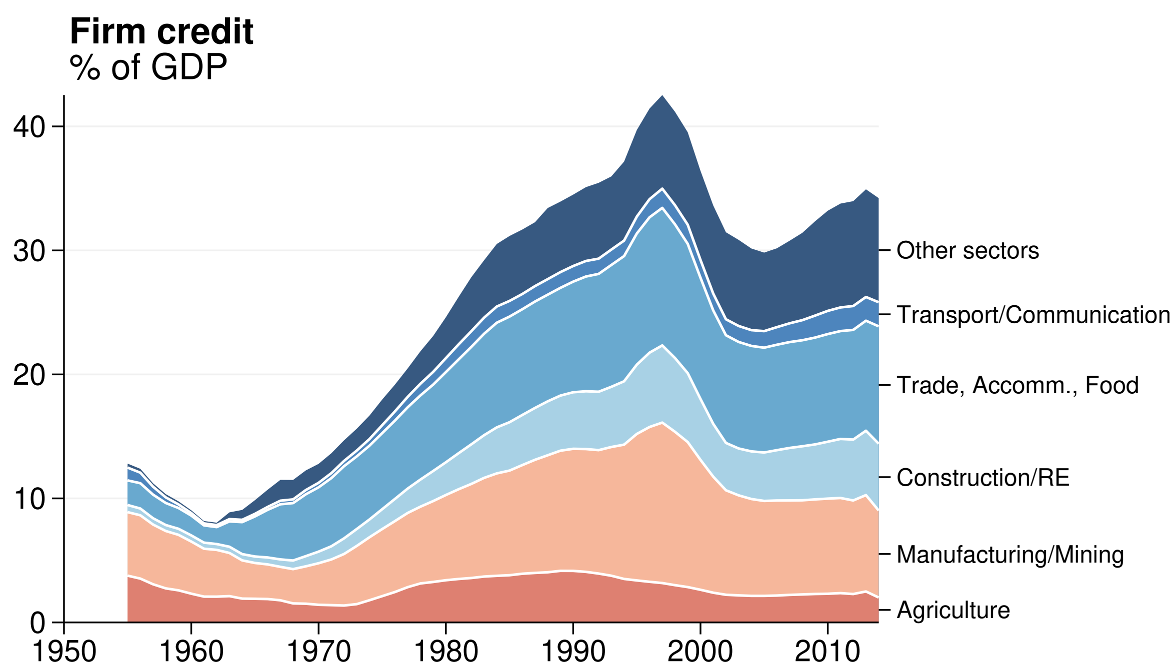
Sample: 35 advanced and 35 emerging economies, 1950-2014.
Notes: Panel A plots the average ratio of non-financial corporate credit to GDP (unweighted) for advanced economies, Panel B the average ratio for emerging economies.

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

(a) Advanced economies



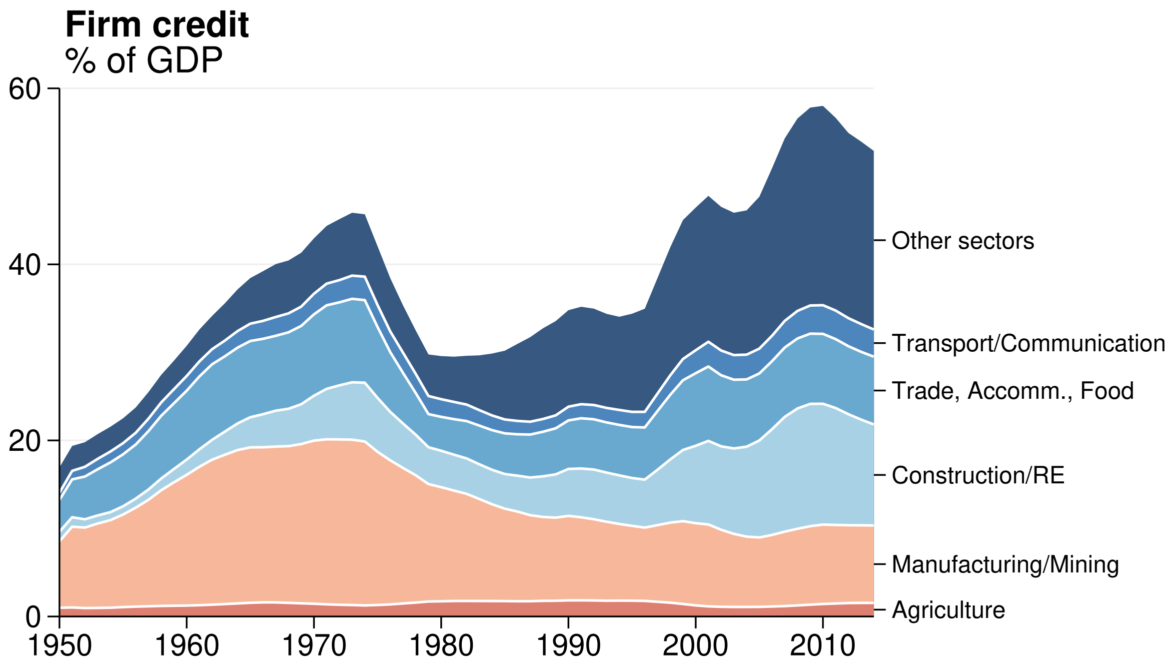
(b) Emerging economies



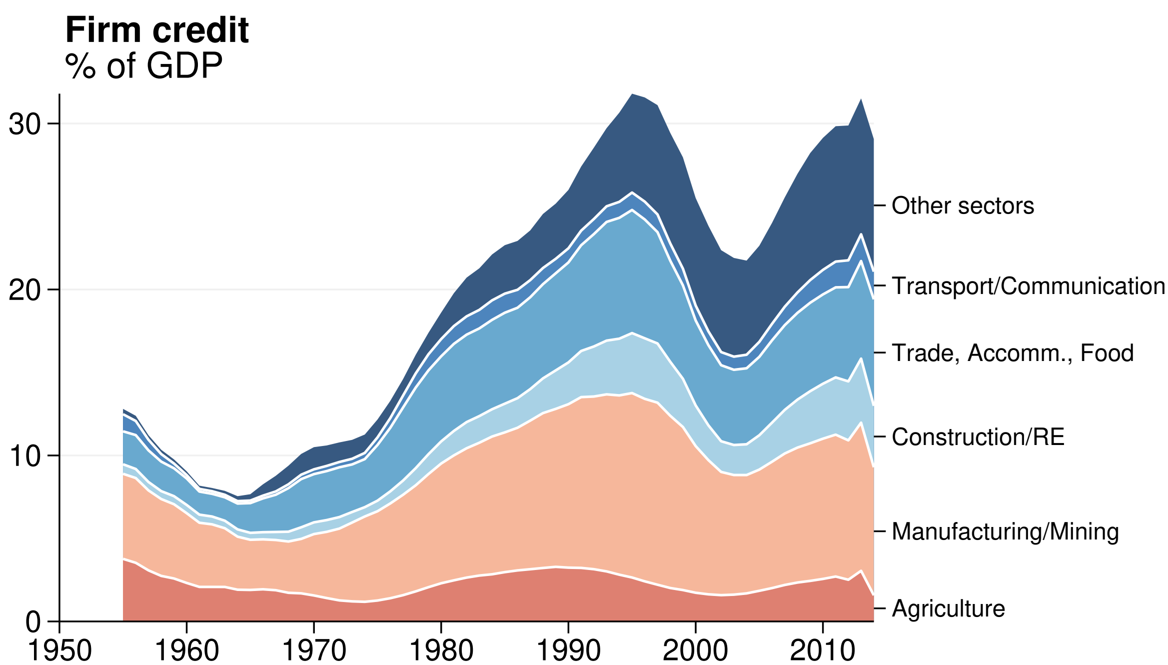
Sample: 13 advanced and 11 emerging economies.
Notes: Average ratio of corporate credit to GDP (unweighted) for countries with data since at least 1980.

Figure A8: Robustness – Corporate Credit to GDP Composition (GDP weighted)

(a) Advanced economies



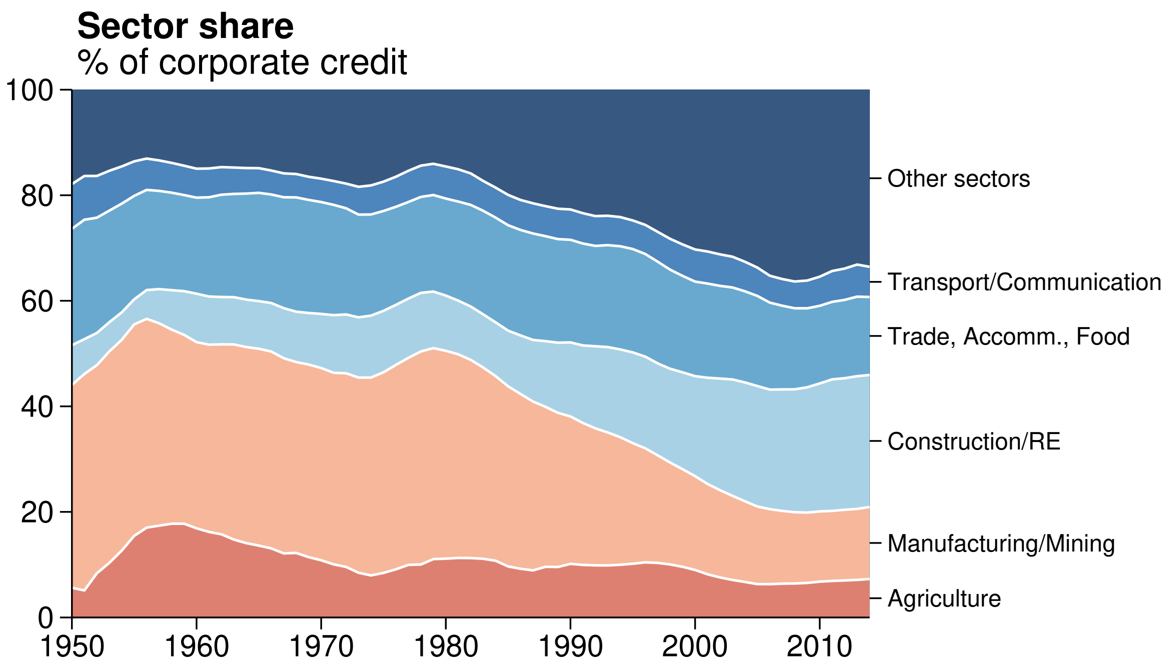
(b) Full sample (GDP weighted)



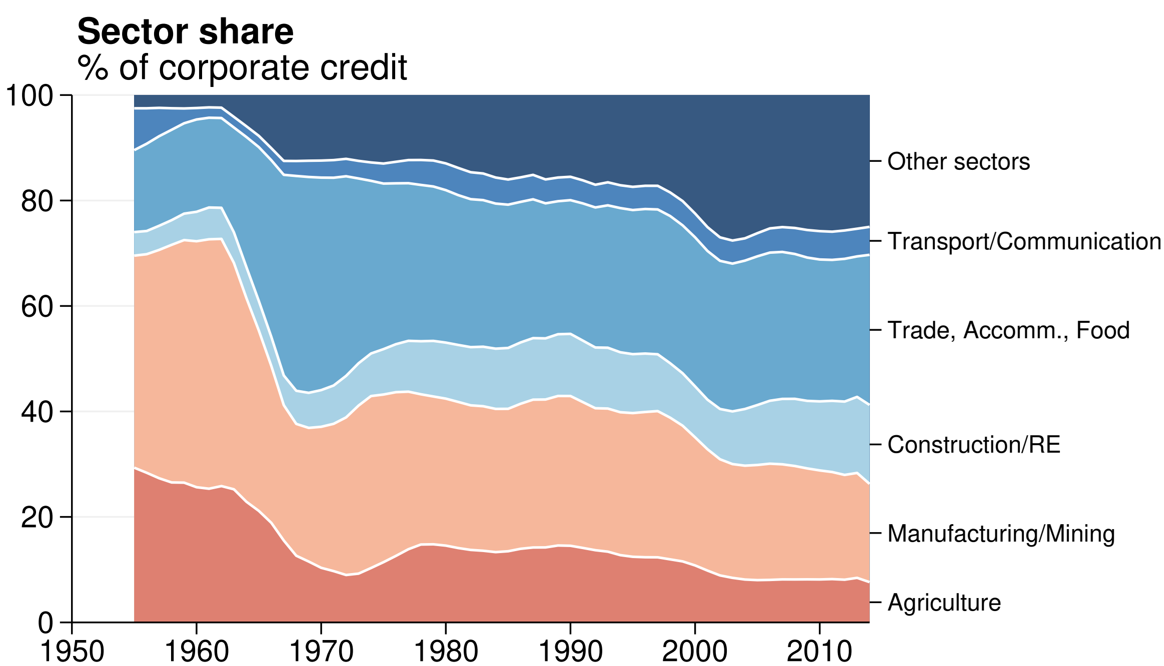
Sample: 35 advanced and 46 emerging economies.
Notes: Panel A plots the average ratio of corporate credit to GDP (GDP-weighted) for advanced economies, Panel B the average ratio for emerging economies.

Figure A9: Robustness – Sector Shares in Corporate Credit (Balanced Panel)

(a) Advanced economies



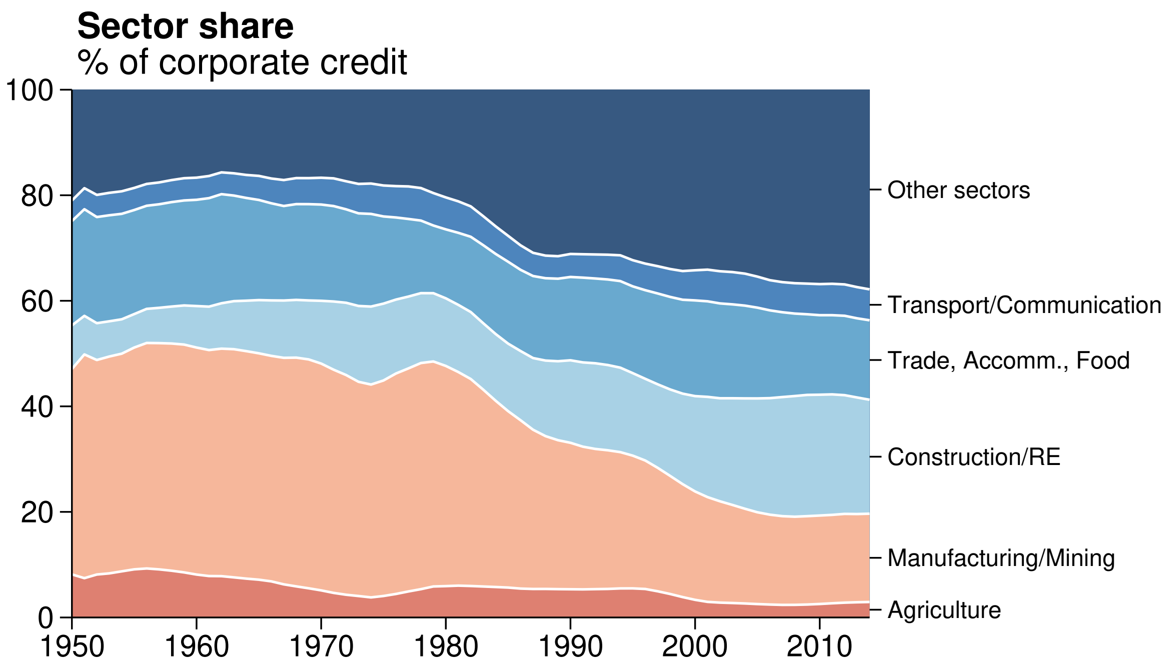
(b) Emerging economies



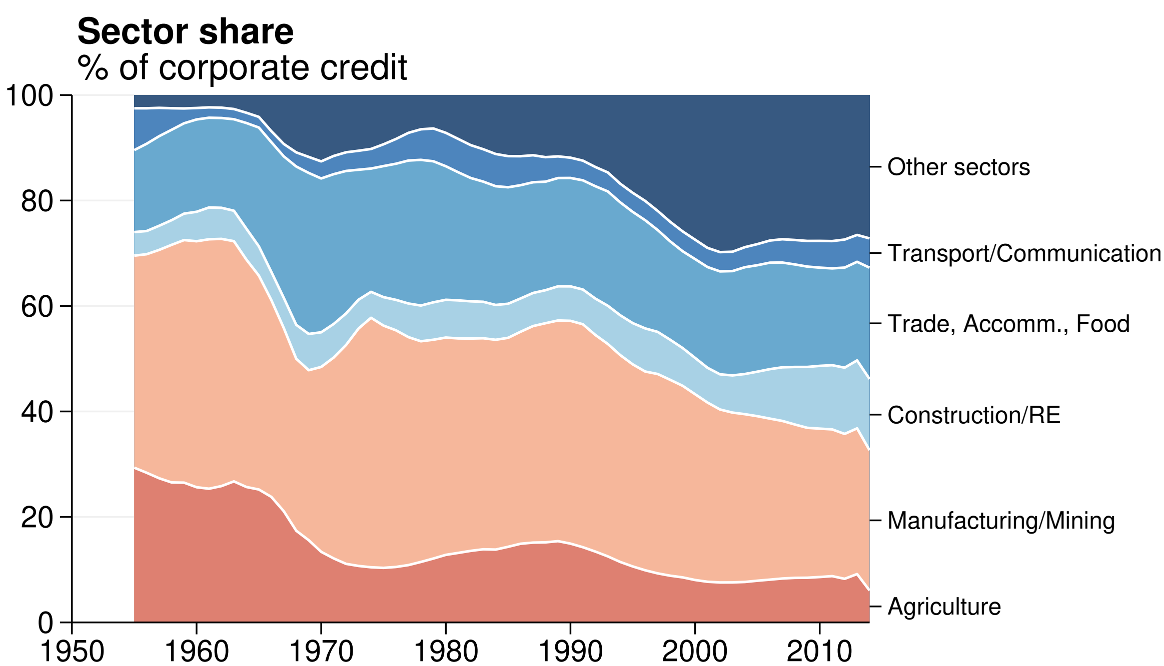
Sample: 13 advanced and 11 emerging economies.
Notes: Average ratio of individual sectors in corporate credit (unweighted) for countries with data since at least 1980.

Figure A10: Robustness – Sector Shares in Corporate Credit (GDP-weighted)

(a) Advanced economies



(b) Emerging economies

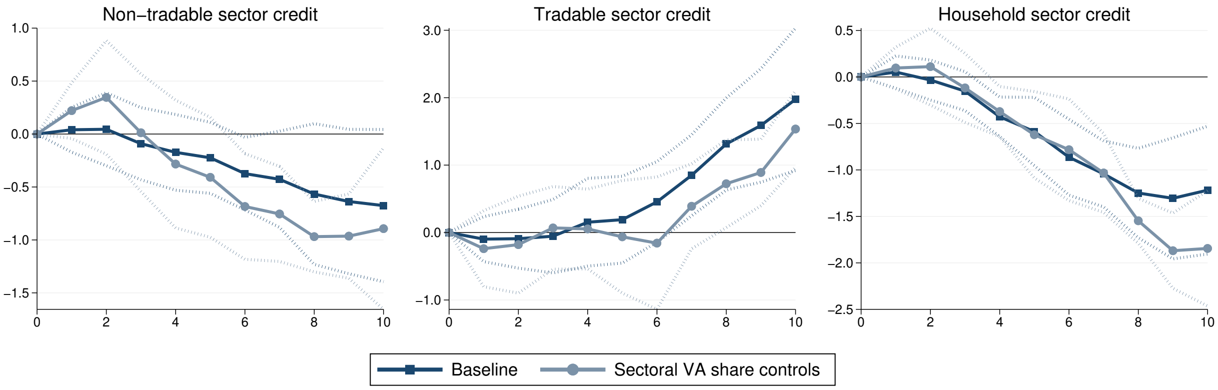


Sample: 35 advanced and 46 emerging economies.
Notes: Average ratio of individual sectors in corporate credit (GDP-weighted).

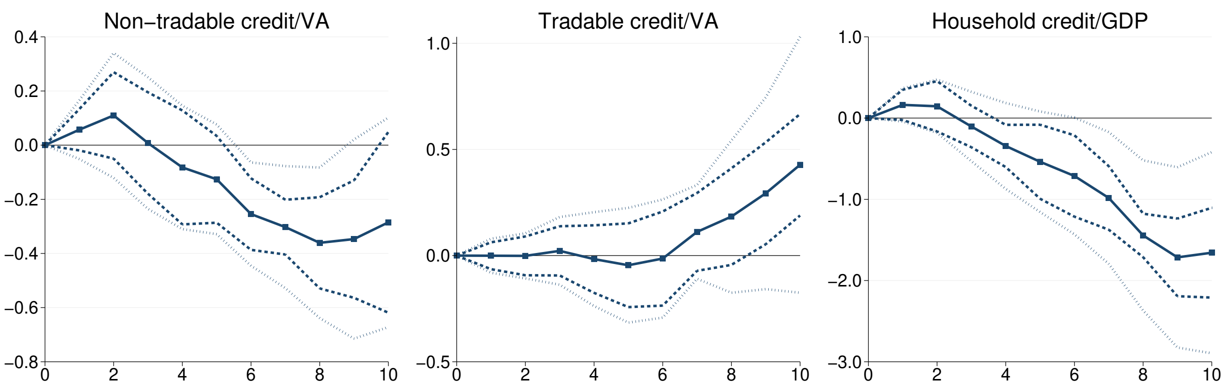
A.2 Local projections

Figure A11: 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:

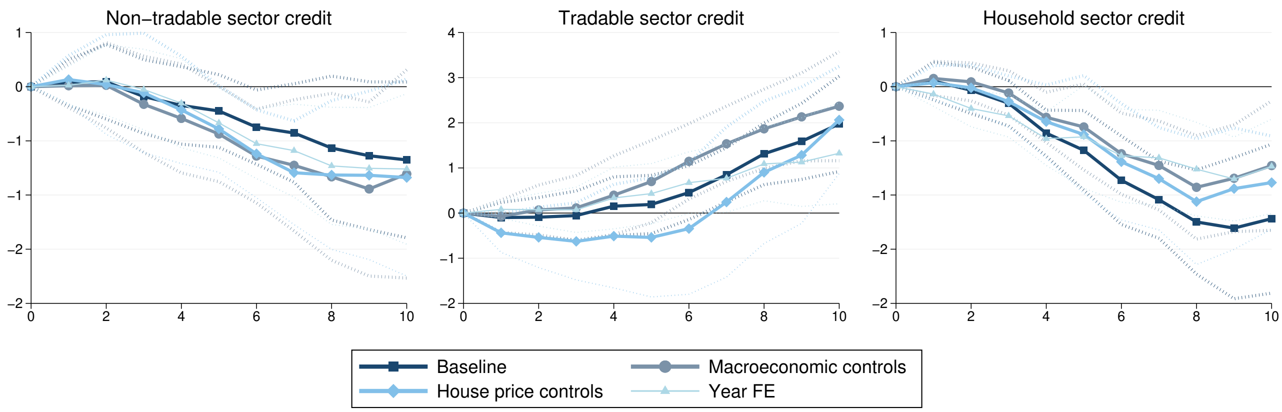
$$\Delta_h y_{it+h} = \alpha_i + \sum_{j=0}^{J} \beta_j^{NT} \Delta \tilde{d}_{it-j}^{NT} + \sum_{j=0}^{J} \beta_j^{T} \Delta \tilde{d}_{it-j}^{T} + \sum_{j=0}^{J} \beta_j^{HH} d_{it-j}^{HH} + \sum_{j=0}^{J} \gamma_j \Delta y_{it-j} + \epsilon_{it+h}, \quad h = 1, ..., H.$$

In contrast to our baseline results in Figure 8, credit in corporate sector k is scaled by value added in that sector, i.e., $\tilde{d}_{it}^{k} = 100 \cdot \frac{D_{it}^{k}}{VA_{it}^{k}}$.

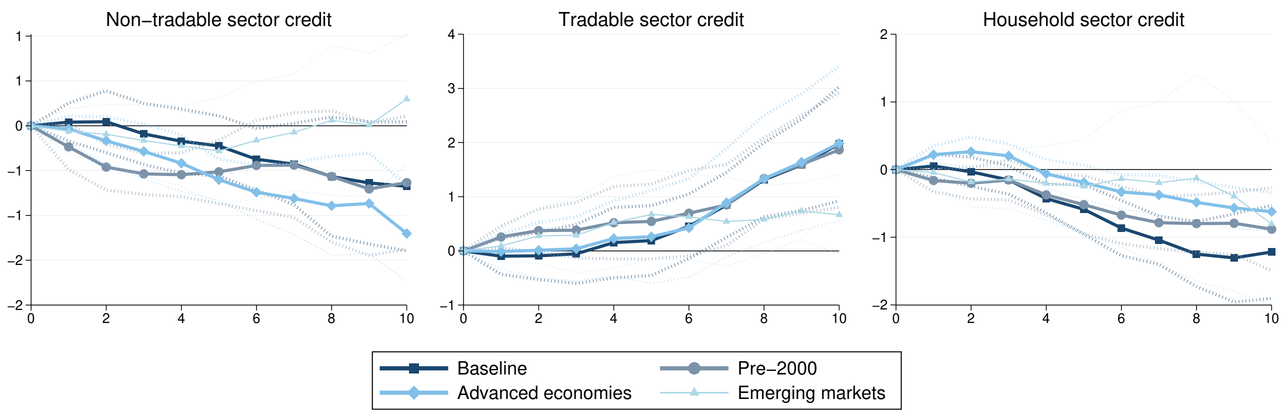
Panel (b) presets estimates of (1) using credit variables scaled by GDP with additional controls for changes in the non-tradable and tradable value added shares.
Dashed lines represent 95% confidence intervals computed using Driscoll-Kraay standard errors, and dotted lines represent 95% confidence intervals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

Figure A12: Robustness – Output Dynamics after Credit Expansions in Tradable, Non-Tradable, and Household Sectors

(a) Additional controls



(b) Subsamples



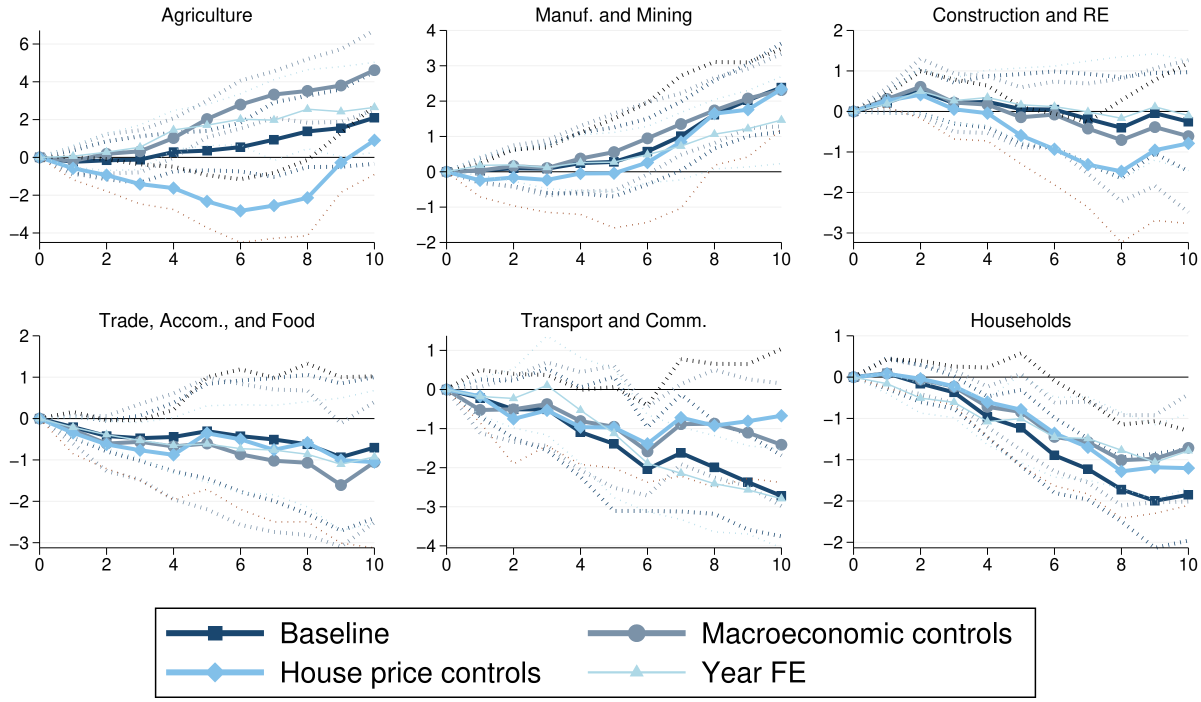
Notes: These figures presents local projection impulse responses of real GDP following innovations in tradable sector credit, non-tradable sector credit, and household credit (all measured relative to GDP):

$$\Delta_h y_{it+h} = \alpha_i + \sum_{j=0}^{J} \beta_j^{NT} \Delta d_{it-j}^{NT} + \sum_{j=0}^{J} \beta_j^{T} \Delta d_{it-j}^{T} + \sum_{j=0}^{J} \beta_j^{HH} d_{it-j}^{HH} + \sum_{j=0}^{J} \gamma_j \Delta y_{it-j} + \sum_{j=0}^{J} X'_{it-j} \kappa_j + \epsilon_{it+h}, \quad h = 1, ..., H.$$

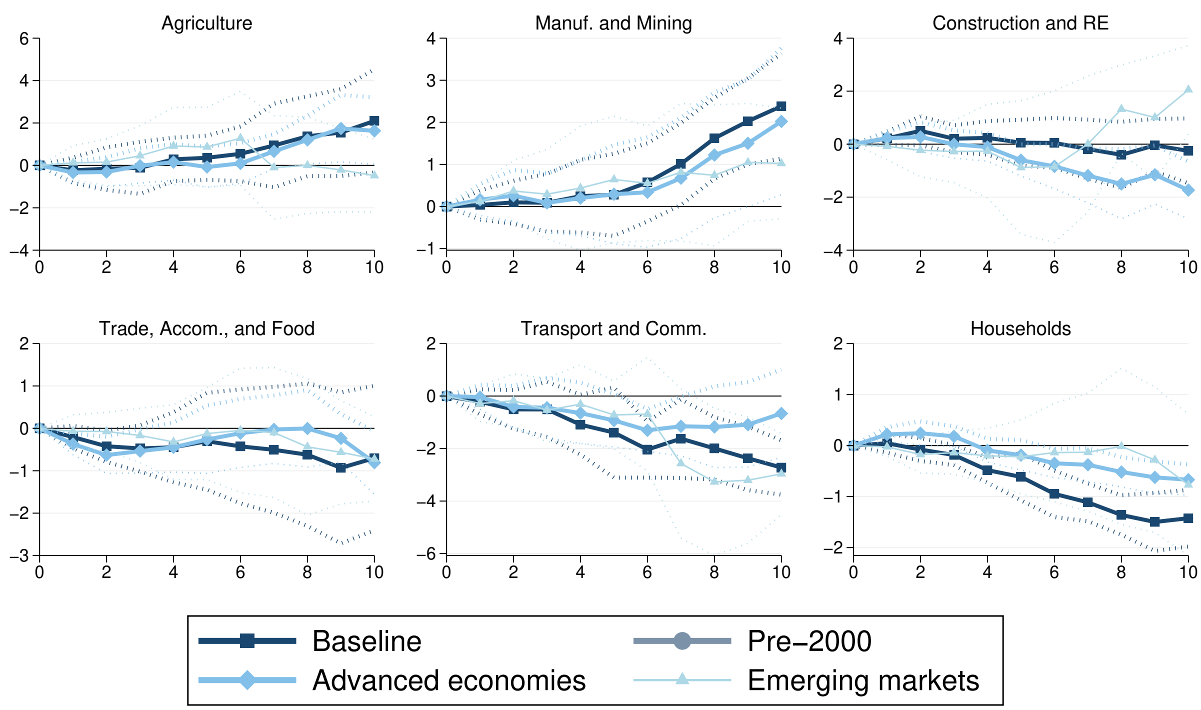
Panel (a) compares estimations with additional control variables to the baseline specification (X_{it-j}). Panel (b) considers subsamples. Dashed lines represent 95% confidence intervals computed using Driscoll-Kraay standard errors, and dotted lines represent 95% confidence intervals from standard errors two-way clustered on country and year.

Figure A13: Robustness – Output Dynamics after Credit Expansions: Unpacking Corporate Sector Credit Expansions

(a) Additional controls

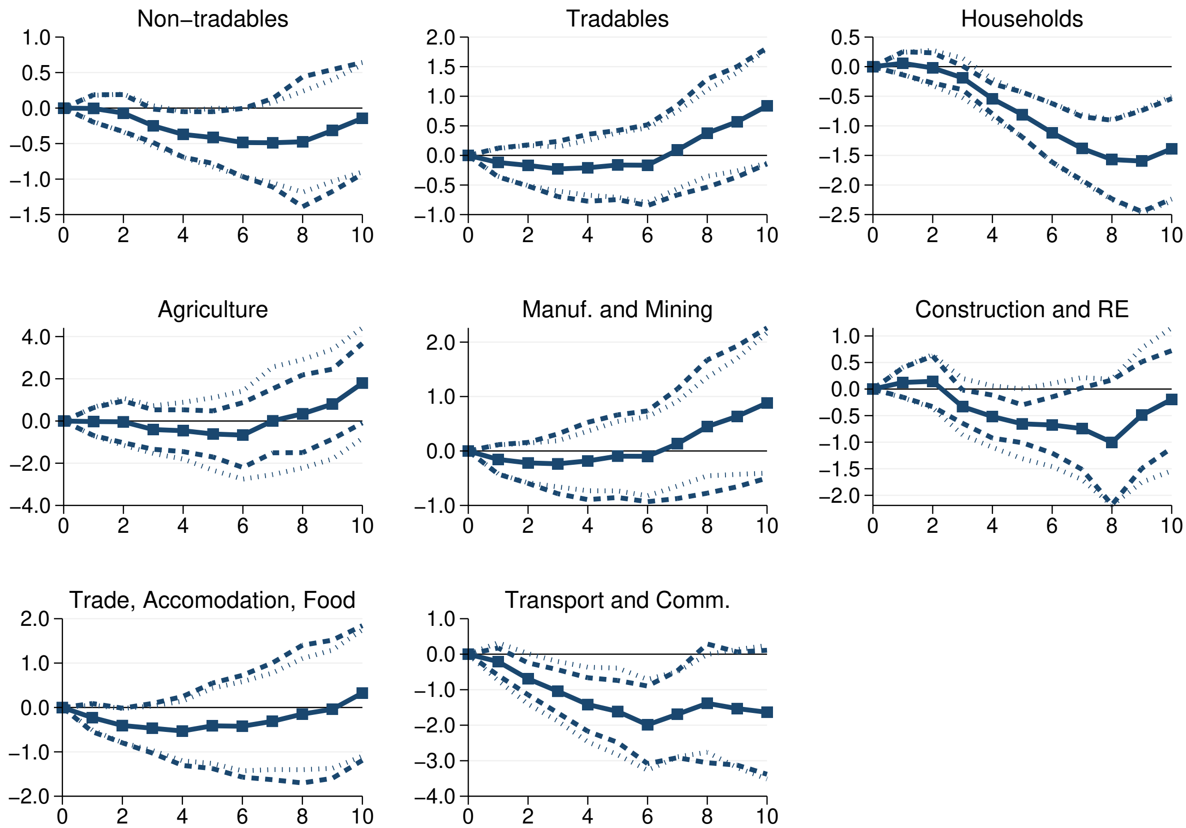


(b) Subsamples



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

Figure A14: Robustness – Output Dynamics after Credit Expansions: Sectors One-by-One

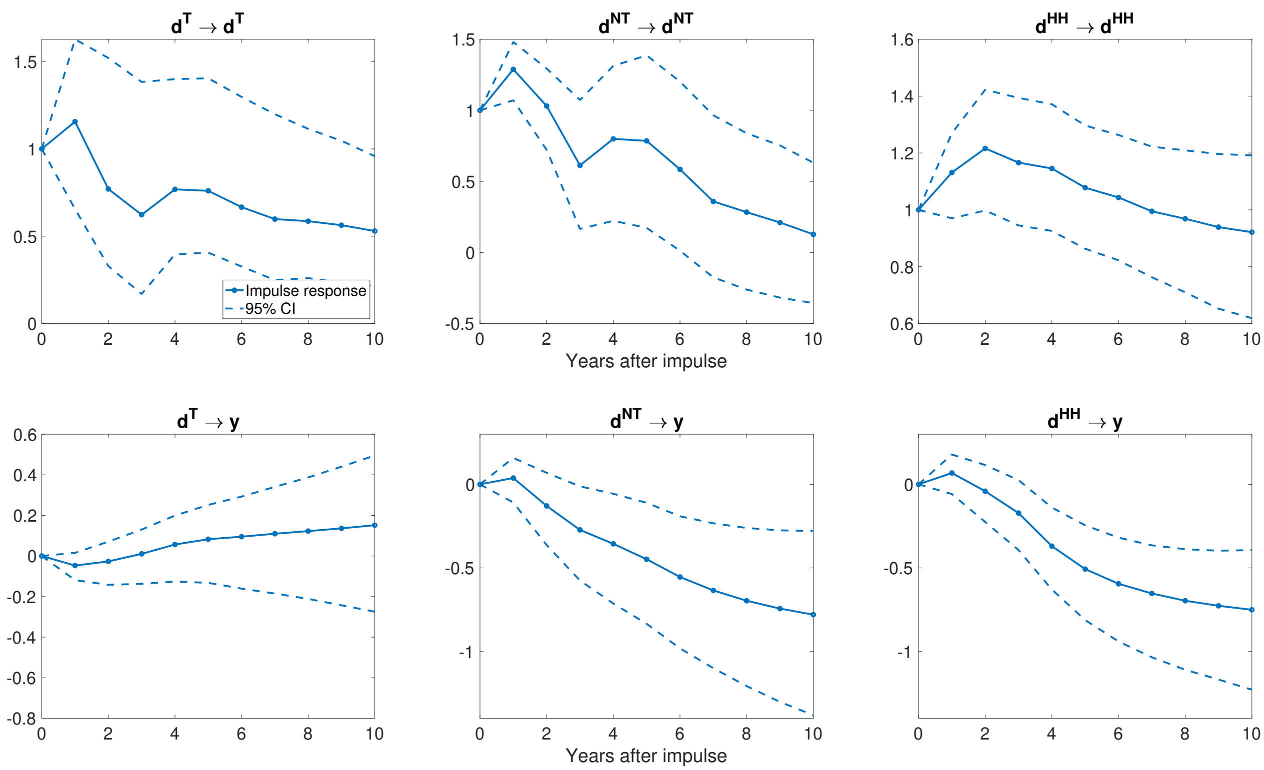


Notes: Each panel presents the impulse response of real GDP to an innovation in credit-to-GDP based on estimates from a separate local projection specification:

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

In contrast to our baseline results in Figure 8 and Figure 9, 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.

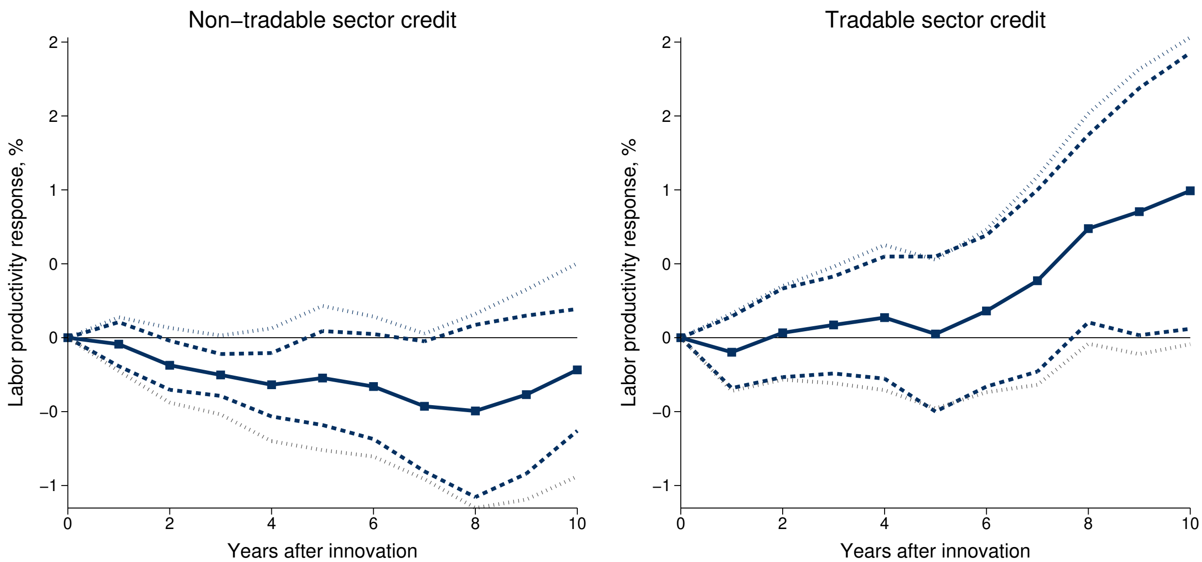
Figure A15: Impulse Responses from a Recursive VAR



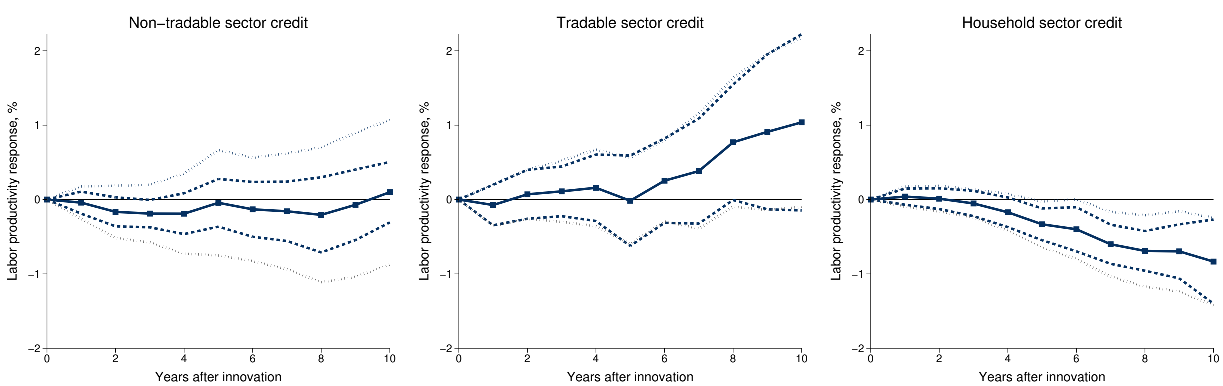
Notes: This figure presents impulse responses from a recursive panel VAR for log real GDP, household credit-to-GDP, tradable credit-to-GDP, and non-tradable credit-to-GDP. The VAR is estimate in levels with country fixed effects. The top panel presents responses of sectoral credit to their own shocks, and the bottom panels presents the response of real GDP to sectoral credit shocks. Dashed lines represent 95% bootstrapped confidence intervals.

Figure A16: Labor Productivity Dynamics after Credit Expansions

(a) Non-tradable and tradable credit



(b) Controlling for household debt



Notes: This figure presents local projection impulse responses of labor productivity to sectoral credit expansions. 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.

Table A1: Robustness Sectoral Credit Expansion and Medium-Run GDP Growth

		N	# Countries	R^2	Tradables		Non-tradables		Households	
					β_T	$[t]$	β_{NT}	$[t]$	β_{HH}	$[t]$
(1)	Baseline	1,575	73	0.08	0.30	1.42	-0.22	-3.89**	-0.51	-4.33**
(2)	Lagged GDP growth control	1,575	73	0.09	0.28	1.37	-0.26	-3.84**	-0.50	-4.19**
(3)	Year fixed effects	1,575	73	0.03	0.21	1.09	-0.16	-2.72**	-0.31	-3.82**
(4)	Common time trend	1,575	73	0.15	0.09	0.55	-0.20	-3.53**	-0.34	-3.58**
(5)	Country-specific trends	1,575	73	0.04	-0.18	-1.14	-0.18	-3.36**	-0.25	-3.03**
(6)	Macroeconomic controls	1,235	70	0.11	0.36	1.68+	-0.23	-3.10**	-0.47	-5.45**
(7)	House price growth control	716	36	0.11	0.43	1.69+	-0.38	-4.92**	-0.36	-4.52**
(8)	Value added controls	641	37	0.21	0.24	0.85	-0.63	-5.23**	-0.39	-4.41**
(9)	Current account control	1,344	71	0.07	0.26	1.24	-0.22	-2.96**	-0.45	-4.67**
(10)	Pre-2000 only	959	47	0.03	0.17	0.73	-0.22	-3.20**	-0.27	-3.14**
(11)	Pre-1990 only	625	29	0.01	0.08	0.28	-0.13	-1.37	-0.22	-1.75+
(12)	Advanced economies	915	34	0.12	0.17	0.68	-0.29	-4.47**	-0.54	-4.03**
(13)	Emerging economies	660	39	0.02	0.35	1.30	-0.04	-0.16	-0.38	-2.75**

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

$$\Delta_3 y_{it+4} = \alpha_i + \beta_T \Delta_3 d_{it}^T + \beta_{NT} \Delta_3 d_{it}^{NT} + \beta_{HH} \Delta_3 d_{it}^{HH} + \epsilon_{it+4}$$

where $\Delta_3 y_{it+4}$ is real GDP growth from $t+1$ to $t+4$, 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 $ceil(1.5(3+4)) = 11$ lags. +, * and ** denote significance at the 10%, 5% and 1% level.

Model (1) is our baseline specification, corresponding to column 5 in Table 4 Panel B. Model (2) controls for real GDP growth from $t-3$ to t. Model (3) includes year fixed effects. Model (4) includes a common time trend. Model (5) includes country-specific time trends. Macroeconomic controls in model (6) are three lags of inflation, the short-rate, and the change in the dollar exchange rate. Model (7) controls for house price growth from $t-3$ to t. Model (8) controls for the change in non-tradable and tradable value added shares from $t-3$ to t. Model (9) controls for the cumulative current account deficit over $t-2$, $t-1$, and t. Models (10) and (11) restrict the sample to the years $t \leq 2000$ and $t \leq 1990$, respectively. Models (12) and (13) restrict the sample to countries classified as high-income and low-income/middle-income by the World Bank in 2019, respectively.

A.3 Financial crisis prediction

Table A2: 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)	1,534	0.72	0.00	-0.20	-0.01	-1.39	0.02	3.83**	0.03	3.34**	-0.01	-1.10	0.01	3.31**
(2)	LPM, country + year FE	1,534	0.72	0.00	0.02	-0.01	-0.90	0.01	1.48	0.03	3.40**	-0.01	-1.29	0.01	2.12*
(3)	Logit	1,534	0.72	0.00	-0.16	0.00	-0.51	0.01	1.53	0.03	3.12**	0.00	-0.52	0.01	2.37*
(4)	Logit, country FE	1,014	0.72	0.01	0.26	-0.02	-1.74+	0.04	2.88**	0.07	3.85**	-0.04	-1.46	0.02	3.09**
(5)	Logit, RE-Mundlak	1,534	0.84	0.00	0.02	-0.01	-1.02	0.01	2.36*	0.03	4.17**	-0.01	-2.31*	0.01	1.52
(6)	Lags of 1-year changes	1,530	0.72	-0.01	-0.18	-0.03	-1.40	0.07	4.02**	0.08	3.06**	-0.04	-1.23	0.03	3.18**
(7)	Boom (>= Mean + 2 × SD)	1,534	0.59	0.04	0.80	0.06	0.55	0.16	3.31**	0.18	2.28*	-0.01	-0.14	0.16	2.86**
(8)	Boom (>= 80th percentile)	1,534	0.74	0.04	2.04*	-0.01	-0.34	0.09	3.05**	0.06	1.73+	-0.06	-2.49*	0.18	3.93**
(9)	Boom (>= 80th percentile, OOS)	1,534	0.70	0.04	1.63	-0.02	-0.47	0.06	2.99**	0.07	2.34*	-0.02	-1.21	0.10	3.38**
(10)	RR dates	1,038	0.62	0.00	0.18	-0.03	-1.84+	0.03	3.84**	0.03	1.93+	0.02	1.13	0.00	0.83
(11)	LV dates only	1,401	0.68	0.00	-0.05	-0.01	-0.92	0.01	2.93**	0.02	2.91**	-0.01	-1.23	0.01	1.89+
(12)	BVX dates only	992	0.75	0.02	0.72	-0.01	-0.90	0.03	4.43**	0.02	2.86**	-0.01	-0.48	0.01	2.20*
(13)	Pre-2000 only	908	0.69	-0.01	-1.02	-0.01	-2.00+	0.02	4.49**	0.03	2.46*	-0.01	-0.64	0.01	3.60**
(14)	Advanced economies	876	0.75	0.03	2.12*	-0.02	-2.34*	0.03	4.82**	0.02	1.65	0.00	-0.25	0.01	1.95+
(15)	Emerging economies	658	0.74	-0.05	-1.68+	0.01	0.52	0.00	0.30	0.04	4.08**	-0.05	-1.22	0.01	4.16**
(16)	Value added controls	642	0.72	0.03	1.99+	-0.03	-2.08*	0.02	2.37*	0.06	2.03*	0.00	-0.17	0.00	0.51

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

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

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. (2020) 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) repeats the same exercise as in model (8) but only uses backward-looking information to construct booms. Model (10) uses the systemic banking crisis dates from Reinhart and Rogoff (2009b). Model (11) only uses crisis dates from Laeven and Valencia (2018), and model (12) only the dates from Baron et al. (2020). Model (13) restricts the sample to the years before 2000. Models (14) and (15) restrict the sample to countries classified as high-income and low-income/middle-income by the World Bank in 2019, respectively. Model (16) controls for three-year changes in sectoral value added/GDP.

Table A3: 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)	0.01	1.65+	0.57	1,736	0.02	7.30**	0.66	1,674	0.02	10.08**	0.67	1,653
(2)	LPM, country + year FE	0.01	1.77+	0.57	1,736	0.01	3.15**	0.66	1,674	0.01	3.78**	0.67	1,651
(3)	Logit	0.01	1.64+	0.57	1,736	0.02	4.31**	0.66	1,674	0.01	5.03**	0.67	1,653
(4)	Logit, country FE	0.02	3.36**	0.58	1,227	0.04	6.75**	0.65	1,145	0.04	7.78**	0.68	1,197
(5)	Logit, RE-Mundlak	0.01	1.82+	0.80	1,736	0.01	4.60**	0.81	1,674	0.02	5.85**	0.81	1,653
(6)	Lags of 1-year changes	0.03	1.68+	0.57	1,731	0.05	7.34**	0.67	1,671	0.06	9.95**	0.67	1,653
(7)	Boom ($>=$ Mean + 2 $\times$ SD)	0.05	0.58	0.51	1,736	0.27	5.39**	0.55	1,674	0.27	5.72**	0.56	1,653
(8)	Boom ($>=$ 80th percentile)	0.04	1.41	0.54	1,736	0.15	6.46**	0.64	1,674	0.22	5.40**	0.66	1,653
(9)	Boom ($>=$ 80th percentile, OOS)	0.05	1.48	0.54	1,736	0.11	5.43**	0.64	1,674	0.13	4.62**	0.64	1,653
(10)	RR dates	0.00	-0.03	0.50	1,155	0.02	2.69**	0.60	1,101	0.02	3.09**	0.56	1,126
(11)	LV dates only	0.00	0.65	0.53	1,595	0.01	3.02**	0.62	1,540	0.01	3.06**	0.62	1,505
(12)	BVX dates only	0.01	2.26*	0.60	1,066	0.02	5.76**	0.69	1,031	0.02	7.55**	0.71	1,066
(13)	Pre-2000 only	0.00	0.43	0.53	1,052	0.02	4.38**	0.64	1,006	0.02	8.60**	0.61	980
(14)	Advanced economies	0.00	1.04	0.54	922	0.02	5.71**	0.66	896	0.02	5.70**	0.71	941
(15)	Emerging economies	0.01	1.49	0.60	814	0.02	3.60**	0.66	778	0.02	4.63**	0.63	712
(16)	Value added controls	0.02	3.13**	0.59	1,253	0.02	3.66**	0.69	671	0.02	10.08**	0.67	1,653

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. (2020) 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) repeats the same exercise as in model (8) but only uses backward-looking information to construct booms. Model (10) uses the systemic banking crisis dates from Reinhart and Rogoff (2009b). Model (11) only uses crisis dates from Laeven and Valencia (2018), and model (12) only the dates from Baron et al. (2020). Model (13) restricts the sample to the years before 2000. Models (14) and (15) restrict the sample to countries classified as high-income and low-income/middle-income by the World Bank in 2019, respectively. Model (16) controls for three-year changes in sectoral value added/GDP.

Table A4: 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	1.33	0.55	1,744	0.03	9.64**	0.63	1,722
(2)	LPM, country + year FE	.	.	.	.	0.01	1.50	0.55	1,744	0.02	2.83**	0.63	1,722
(3)	Logit	.	.	.	.	0.01	1.48	0.55	1,744	0.02	3.93**	0.63	1,722
(4)	Logit, country FE	.	.	.	.	0.02	2.21*	0.55	1,268	0.06	6.03**	0.63	1,246
(5)	Logit, RE-Mundlak	0.02	1.28	0.81	1,739	0.01	1.50	0.79	1,744	0.02	4.43**	0.80	1,722
(6)	Lags of 1-year changes	0.05	1.62	0.56	1,734	0.03	1.38	0.55	1,743	0.09	9.59**	0.64	1,720
(7)	Boom (>= Mean + 2 × SD)	0.05	1.24	0.50	1,739	0.07	0.66	0.51	1,744	0.22	5.75**	0.54	1,722
(8)	Boom (>= 80th percentile)	0.05	3.26**	0.54	1,739	0.02	0.63	0.53	1,744	0.14	4.74**	0.62	1,722
(9)	Boom (>= 80th percentile, OOS)	0.05	2.63*	0.54	1,739	0.03	0.73	0.53	1,744	0.08	2.94**	0.61	1,722
(10)	RR dates	0.01	0.64	0.50	1,158	0.00	-0.20	0.51	1,162	0.03	2.70**	0.56	1,142
(11)	LV dates only	0.01	0.79	0.54	1,598	0.00	0.50	0.51	1,603	0.02	3.21**	0.59	1,587
(12)	BVX dates only	0.04	2.27*	0.60	1,069	0.01	1.75+	0.58	1,072	0.04	7.90**	0.67	1,058
(13)	Pre-2000 only	0.01	0.62	0.51	1,055	0.00	0.30	0.54	1,056	0.03	6.90**	0.59	1,042
(14)	Advanced economies	0.04	2.43*	0.59	922	0.00	0.22	0.52	928	0.03	7.04**	0.66	911
(15)	Emerging economies	-0.01	-0.44	0.46	817	0.02	1.69+	0.59	816	0.03	2.12*	0.60	811
(16)	Value added controls	0.02	1.11	0.56	1,287	0.02	3.17**	0.60	1,260	0.03	4.36**	0.67	753

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. (2020) 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) repeats the same exercise as in model (8) but only uses backward-looking information to construct booms. Model (10) uses the systemic banking crisis dates from Reinhart and Rogoff (2009b). Model (11) only uses crisis dates from Laeven and Valencia (2018), and model (12) only the dates from Baron et al. (2020). Model (13) restricts the sample to the years before 2000. Models (14) and (15) restrict the sample to countries classified as high-income and low-income/middle-income by the World Bank in 2019, respectively. Model (16) controls for three-year changes in sectoral value added/GDP.

Table A5: 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)	0.03	3.59**	0.66	1,726	0.01	0.68	0.54	1,695	0.02	10.08**	0.67	1,653
(2)	LPM, country + year FE	0.03	3.37**	0.66	1,726	0.00	0.45	0.54	1,695	0.01	3.78**	0.67	1,651
(3)	Logit	0.03	4.17**	0.66	1,726	0.02	1.39	0.54	1,695	0.01	5.03**	0.67	1,653
(4)	Logit, country FE	0.07	5.31**	0.66	1,230	0.02	0.55	0.54	1,189	0.04	8.65**	0.68	1,197
(5)	Logit, RE-Mundlak	0.02	4.16**	0.81	1,726	0.01	0.76	0.80	1,695	.	.	.	.
(6)	Lags of 1-year changes	0.08	3.56**	0.67	1,724	0.02	0.79	0.56	1,694	.	.	.	.
(7)	Boom (>= Mean + 2 × SD)	0.13	1.65+	0.52	1,726	0.04	0.75	0.51	1,695	.	.	.	.
(8)	Boom (>= 80th percentile)	0.10	5.50**	0.59	1,726	-0.01	-0.72	0.48	1,695	.	.	.	.
(9)	Boom (>= 80th percentile, OOS)	0.10	4.10**	0.59	1,726	0.01	0.30	0.54	1,695	.	.	.	.
(10)	RR dates	0.02	1.76+	0.56	1,147	0.05	3.93**	0.53	1,115	.	.	.	.
(11)	LV dates only	0.02	2.63*	0.63	1,585	0.00	-0.09	0.50	1,555	.	.	.	.
(12)	BVX dates only	0.03	2.65**	0.67	1,064	0.02	1.59	0.58	1,044	.	.	.	.
(13)	Pre-2000 only	0.02	2.02*	0.67	1,043	0.01	0.46	0.53	1,020	.	.	.	.
(14)	Advanced economies	0.02	2.04*	0.62	917	0.01	0.92	0.57	912	.	.	.	.
(15)	Emerging economies	0.04	5.53**	0.72	809	-0.01	-0.21	0.50	783	.	.	.	.
(16)	Value added controls	0.04	4.05**	0.66	1,259	0.02	2.57*	0.57	1,231	.	.	.	.

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. (2020) 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) repeats the same exercise as in model (8) but only uses backward-looking information to construct booms. Model (10) uses the systemic banking crisis dates from Reinhart and Rogoff (2009b). Model (11) only uses crisis dates from Laeven and Valencia (2018), and model (12) only the dates from Baron et al. (2020). Model (13) restricts the sample to the years before 2000. Models (14) and (15) restrict the sample to countries classified as high-income and low-income/middle-income by the World Bank in 2019, respectively. Model (16) controls for three-year changes in sectoral value added/GDP.

B Database Overview

We construct a new database on the sectoral distribution of private credit for 189 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.

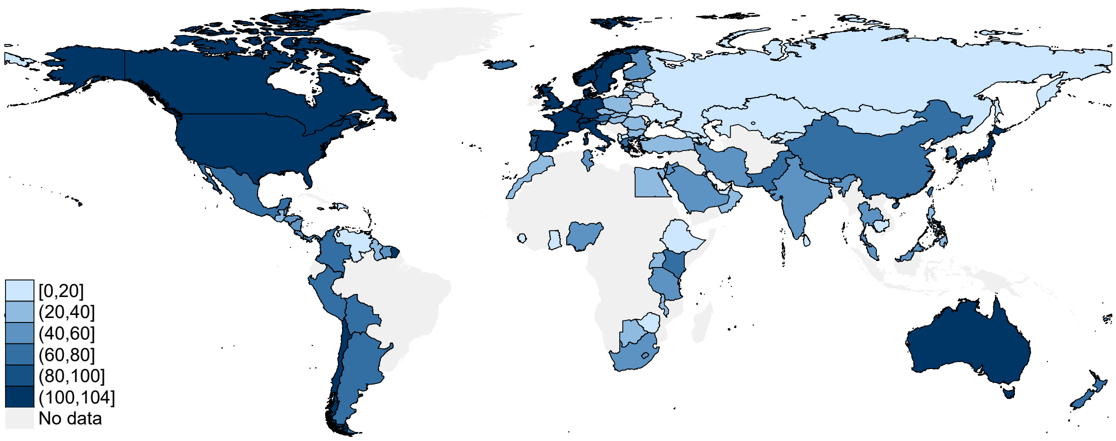
B.4 Database coverage

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.

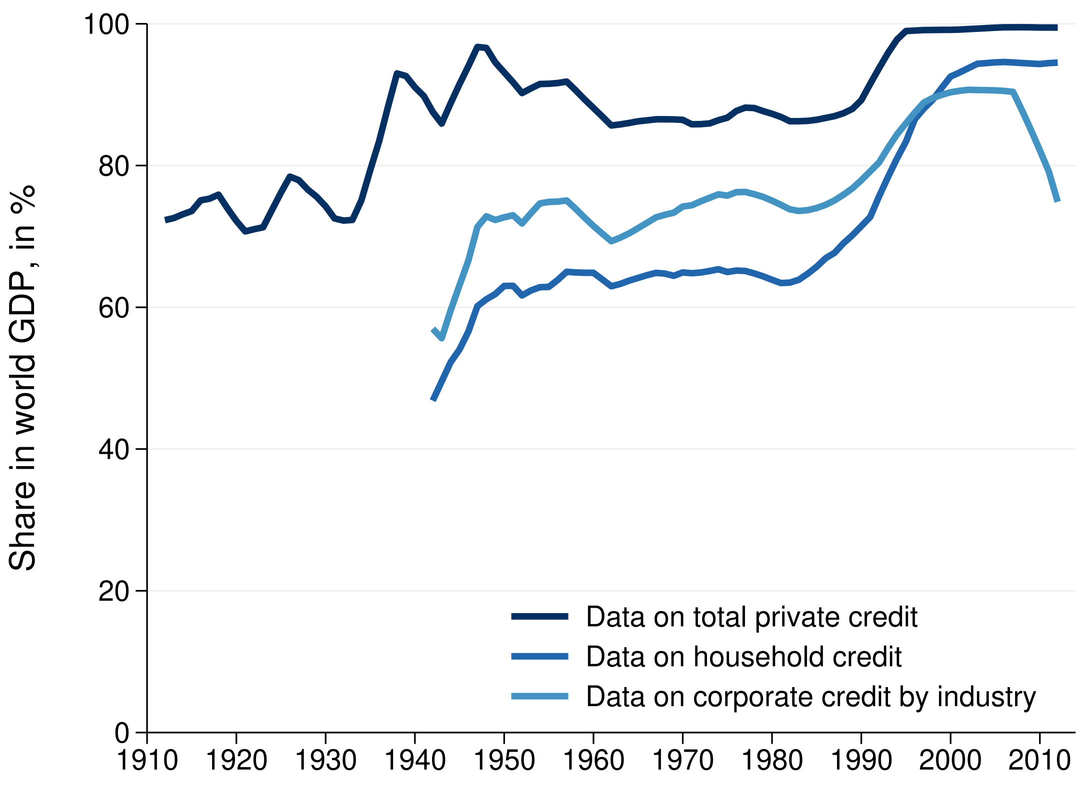
We add to this body of work by adding data on the sectoral allocation of credit and extending historical time series on household/firm and total private credit. The collection and dissemination of sectoral credit data by national authorities has largely moved in line with contemporary paradigms in central 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 A17: 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 1950 to 2014.

Table A6 compares our dataset with existing efforts (replicating Table 2 from the main paper). The database includes an unbalanced panel of credit data for 189 countries, starting in 1940, covering 2–60 sectors. The total number of unique country-sector-time observations is 93,839, with data frequency ranging from monthly to yearly. Overall, there are 10,262 country-year observations.

Table A6: Comparison with Existing Data Sources on Private Credit

Dataset	Start	Freq.	Countries	Country-year obs.	Sectors	Total obs.
Panel A: Sectoral credit data						
Müller and Verner (2020)	1940	Y/Q/M	116	5,357	2–60 (mean=16)	476,555
BIS	1940	Q	43	1,220	2	9,501
Jordà et al. (2016)	1870	Y	17	1,697	3	3,913
IMF GDD	1950	Y	83	1,871	2	3,703
Panel B: Total credit data						
Müller and Verner (2020)	1910	Y/Q/M	189	10,262	—	93,839
IMF IFS	1948	Y/Q/M	182	8,483	—	86,892
Monnet and Puy (2019)	1940	Q	46	2,936	—	11,678
BIS	1940	Q	43	2,020	—	8,014
World Bank GFDD	1960	Y	187	7,745	—	7,745
IMF GDD	1950	Y	159	6,801	—	6,801
Jordà et al. (2016)	1870	Y	17	1,733	—	1,733

Notes: Panel A compares data that differentiate between different sectors of the economy (e.g. household vs. firm credit). Panel B compares different sources of data on total credit to the private sector. 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 (Mbaye et al., 2018), respectively. The data in Monnet and Puy (2019) is from historical paper editions of the IMF IFS. *Country-year obs.* refers to the number of country-year observations covered by the datasets. *Sectors* refers to the number of covered sectors; the mean refers to the average number of sectors in a country-year panel. *Total obs.* refers to country-sector-date observations. We count observations until 2014; the data will be updated to 2020 in a forthcoming revision.

Figure A17a 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 A7 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 A17b plots the share of the countries for which we have data on total and household credit, or data on firm credit by industry, in world GDP. The data cover more than 80% of world GDP since at least 1935 and more than 95% today for total credit. Household credit is available for at least 60% of world GDP since around 1950 and hovers around 90% today. Firm credit by industry covers around 70% of world GDP since 1950.

Figure A18a 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 A19 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 A20 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 A21 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 2–60, with an average of 16.

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 A22a 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.

Table A7: 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 And 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	1952-2014	1960-2014	2003-2014	1999-2014	2003-2014	1964-2014	1964-2014	1964-2014	1952-2014
15	Botswana	1990-2014	1990-2014	1995-2014	1990-2014	1990-2014	1990-2014	1990-2014	1990-2014	1990-2014
16	Bulgaria	1995-2014	1995-2014	1995-2014	1995-2014	1995-2014	2000-2014	2000-2014	2000-2014	1995-2014
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	—	—	—
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 And Sint Maarten	1978-2014	1978-2014	—	—	1978-2014	—	1978-2014	1978-2014	1978-2014
24	Cyprus	1963-2014	1963-2014	2005-2014	2005-2014	2005-2014	1963-2007	1963-2007	1963-2007	1963-2014
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	1978-2014
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 A7: Sectoral Credit Data Coverage by Country (continued)

		Total	Household/	Residential	Major corporate sectors					
No.	Country	credit	firm credit	mortgages	Finance	NFC	Agriculture	Manuf., Mining	Construction	Other
29	Egypt, Arab Rep	1991-2014	1991-2014	—	—	—	1991-2014	1991-2014	—	1991-2014
30	Estonia	1993-2014	1993-2014	1997-2014	1993-2014	1993-2014	1995-2014	1995-2014	1995-2014	1993-2014
31	Ethiopia	2000-2014	—	—	—	—	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	1958-2014	1958-2014	1977-2014	1958-2014	1958-2014	1958-2014	1958-2014	1958-2014	1958-2014
34	France	1993-2014	1993-2014	1993-2014	1993-2012	1993-2014	2006-2014	2006-2014	2006-2014	1993-2014
35	Georgia	1995-2014	1995-2014	2006-2014	1995-2014	1995-2014	2003-2014	2003-2014	2003-2014	1995-2014
36	Germany	1949-2014	1949-2014	1949-2014	1968-2014	1968-2014	1949-2014	1949-2014	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	1990-2014	1990-2014	1993-2014	1990-2014	1993-2014	1993-2014	1993-2014	—	1990-2014
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 Sar, China	1965-2014	1965-2014	1978-2014	1965-2014	1965-2014	1965-2003	1965-2014	1965-2014	1965-2014
45	Hungary	1989-2014	1989-2014	2000-2014	1989-2014	1989-2014	1995-2014	1995-2014	1995-2014	1989-2014
46	Iceland	1950-2014	1958-2014	1958-2014	1970-2014	1970-2014	1950-2014	1955-2014	1970-2014	1950-2014
47	India	1972-2013	1972-2013	1973-2013	1973-2013	1973-2013	1972-2013	1972-2013	1972-2013	1972-2013
48	Iran, Islamic Rep	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	1948-2014	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	Korea, Rep	1952-2014	1952-2014	1967-2014	1954-2014	1967-2014	1952-2014	1952-2014	1952-2014	1952-2014

Table A7: 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	Kuwait	1972-2014	1972-2014	2000-2014	1972-2014	1972-2014	1972-2014	1972-2014	1972-2014	1972-2014
58	Kyrgyz Republic	1996-2014	1996-2014	2003-2014	—	—	1996-2014	1996-2014	1996-2014	1996-2014
59	Latvia	2000-2014	2000-2014	2003-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014
60	Lesotho	2002-2014	2002-2014	—	—	—	2008-2014	2002-2014	2002-2014	2002-2014
61	Lithuania	1993-2014	1993-2014	2004-2014	1993-2014	1993-2014	1995-2014	1995-2014	1995-2014	1993-2014
62	Luxembourg	1999-2014	1999-2014	1999-2014	1999-2014	1999-2014	—	—	—	1999-2014
63	Malawi	1990-2014	1990-2014	2013-2014	2013-2014	2013-2014	1990-2014	1990-2014	1990-2014	1990-2014
64	Malaysia	1968-2014	1971-2014	1971-2014	1996-2014	1996-2014	1968-2014	1968-2014	1968-2014	1968-2014
65	Maldives	1985-2014	1985-2014	—	—	—	1985-2014	1985-2014	1985-2014	1985-2014
66	Malta	1969-2014	1969-2014	1969-2014	1969-2014	1969-2014	1969-1992	1969-2014	1969-2014	1969-2014
67	Mauritius	1967-2014	1967-2014	1979-2014	1967-2014	1967-2014	1967-2014	1967-2014	1992-2014	1967-2014
68	Mexico	1942-2014	1984-2014	1942-2014	1979-2014	1984-2014	1942-2014	1969-2014	1969-2014	1942-2014
69	Mongolia	2000-2014	2000-2014	2008-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014
70	Montserrat	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014
71	Morocco	1977-2014	1993-2014	1993-2014	2001-2014	2001-2014	1977-2014	1977-2014	1977-2014	1977-2014
72	Nepal	1975-2014	2002-2014	—	1979-1987	—	1975-2014	1975-2014	2002-2014	1975-2014
73	Netherlands	1990-2014	1990-2014	1990-2014	1990-2014	1990-2014	2010-2014	2010-2014	2010-2014	1990-2014
74	New Zealand	1940-2014	1940-2014	1956-2014	1940-2014	1994-2014	1940-2014	1940-2014	1956-2014	1940-2014
75	Nicaragua	1960-2014	1995-2014	1960-2014	—	—	1960-2014	—	—	1960-2014
76	Nigeria	1960-2014	1966-1992	—	1960-2014	—	1960-2014	1960-2014	1960-2014	1960-2014
77	North Macedonia	2004-2014	2004-2014	2004-2014	2004-2014	2004-2014	2004-2014	2004-2014	2004-2014	2004-2014
78	Norway	1946-2014	1946-2014	1946-2014	1947-2014	1946-2014	1946-2014	1946-2014	1946-2014	1946-2014
79	Oman	1990-2014	1990-2014	—	1990-2014	1990-2014	1990-2014	1990-2014	1990-2014	1990-2014
80	Pakistan	1953-2014	1982-2014	2003-2014	1953-2014	1982-2014	1953-2014	1953-2014	1953-2014	1953-2014
81	Panama	1963-2014	1963-2014	1963-2014	1970-2014	1975-2014	1963-2014	1963-2014	1963-2014	1963-2014
82	Peru	1947-2014	1947-2014	2001-2014	1990-2014	1990-2014	1947-2014	1947-2014	1947-2014	1947-2014
83	Philippines	1980-2014	1981-2014	1997-2014	1999-2014	1999-2014	1980-2014	1980-2014	1980-2014	1980-2014
84	Poland	1996-2014	1996-2014	1996-2014	1996-2014	1996-2014	2002-2012	2002-2012	2002-2012	1996-2014

Table A7: Sectoral Credit Data Coverage by Country (continued)

		Total	Household/	Residential	Major corporate sectors					
No.	**Country**	**credit**	**firm credit**	**mortgages**	**Finance**	**NFC**	**Agriculture**	**Manuf., Mining**	**Construction**	**Other**
85	Portugal	1947-2014	1947-2014	1966-2014	1947-2014	1947-2014	1966-2014	1966-2014	1973-2014	1947-2014
86	Qatar	1977-2014	1977-2014	1977-2014	1980-2002	1980-2002	1977-2002	1977-2014	1977-2014	1977-2014
87	Romania	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014	2000-2014
88	Russian Federation	1995-2014	1998-2014	2005-2014	1995-2014	1998-2014	2002-2014	2002-2014	2002-2014	1995-2014
89	Saudi Arabia	1970-2014	1998-2014	1998-2014	1970-2014	1998-2014	1970-2014	1970-2014	1970-2014	1970-2014
90	Seychelles	1997-2014	1997-2014	—	1997-2014	1997-2014	1997-2014	1997-2014	1997-2014	1997-2014
91	Sierra Leone	1996-2014	2001-2014	—	2004-2014	—	1996-2014	1996-2014	1996-2014	1996-2014
92	Singapore	1962-2014	1980-2014	1991-2014	1963-2014	1980-2014	1962-2014	1962-2014	1962-2014	1962-2014
93	Slovak Republic	1992-2014	1992-2014	2003-2014	1992-2014	1992-2014	1992-2014	1992-2014	1992-2014	1992-2014
94	Slovenia	1991-2014	1991-2014	2004-2014	1991-2014	1991-2014	1994-2014	1994-2014	1994-2014	1991-2014
95	South Africa	1994-2013	1994-2013	—	1994-2013	1994-2013	1994-2013	1994-2013	1994-2013	1994-2013
96	Spain	1992-2014	1992-2014	1992-2014	1992-2014	1992-2014	1992-2014	1992-2014	1992-2014	1992-2014
97	Sri Lanka	1996-2014	1996-2014	2009-2014	—	—	1996-2014	2009-2014	1996-2014	1996-2014
98	St Kitts And Nevis	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014
99	St Lucia	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014
100	St Vincent And The Grenadines	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014	1991-2014
101	Suriname	1969-2014	1969-2014	1985-2014	—	—	1969-2014	1969-2014	1969-2014	1969-2014
102	Sweden	1975-2014	1975-2014	1975-2014	1975-2014	1975-2014	—	—	—	1975-2014
103	Switzerland	1977-2014	1977-2014	1985-2014	1977-2014	1977-2014	1997-2014	1985-2014	1985-2014	1977-2014
104	Taiwan	1953-2014	1953-2014	1988-2014	1997-2014	1997-2014	1956-2014	1956-2014	1997-2014	1953-2014
105	Tanzania	1967-2014	2003-2014	—	1967-2014	2003-2014	1967-2014	1967-2014	1967-2014	1967-2014
106	Thailand	1965-2014	1965-2014	1981-2014	1965-2014	1965-2014	1965-2014	1965-2014	1965-2014	1965-2014
107	Trinidad And Tobago	1946-2014	1954-2014	1987-2014	1963-2014	1963-2014	1946-2014	1946-2014	1963-2014	1946-2014
108	Tunisia	1962-2014	1962-2014	2002-2014	2007-2014	2007-2014	1962-2014	1962-2014	1962-2014	1962-2014
109	Turkey	1986-2014	1986-2014	2002-2014	1986-2014	1986-2014	2002-2014	2002-2014	2002-2014	1986-2014
110	Uganda	1991-2014	2004-2014	2010-2014	2004-2006	2004-2006	1991-2014	1991-2014	1991-2014	1991-2014
111	Ukraine	1995-2014	1995-2014	2006-2014	1995-2014	1995-2014	2000-2014	2000-2014	2000-2014	1995-2014
112	United Arab Emirates	1998-2014	1998-2014	—	1998-2014	1998-2014	1998-2014	1998-2014	1998-2014	1998-2014

Table A7: Sectoral Credit Data Coverage by Country (continued)

		Total	Household/	Residential	Major corporate sectors					
No.	**Country**	**credit**	**firm credit**	**mortgages**	**Finance**	**NFC**	**Agriculture**	**Manuf., Mining**	**Construction**	**Other**
113	United Kingdom	1946-2014	1946-2014	1963-2014	1946-2014	1946-2014	1946-2014	1946-2014	1946-2014	1946-2014
114	United States	1936-2014	1936-2014	1936-2014	—	—	1936-2014	—	—	—
115	Venezuela, Rb	1999-2014	2001-2014	2001-2014	1999-2014	—	2004-2014	2004-2014	2004-2014	1999-2014
116	Zimbabwe	2009-2014	2009-2014	—	2009-2014	2009-2014	2009-2014	2009-2014	2009-2014	2009-2014

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 A22 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

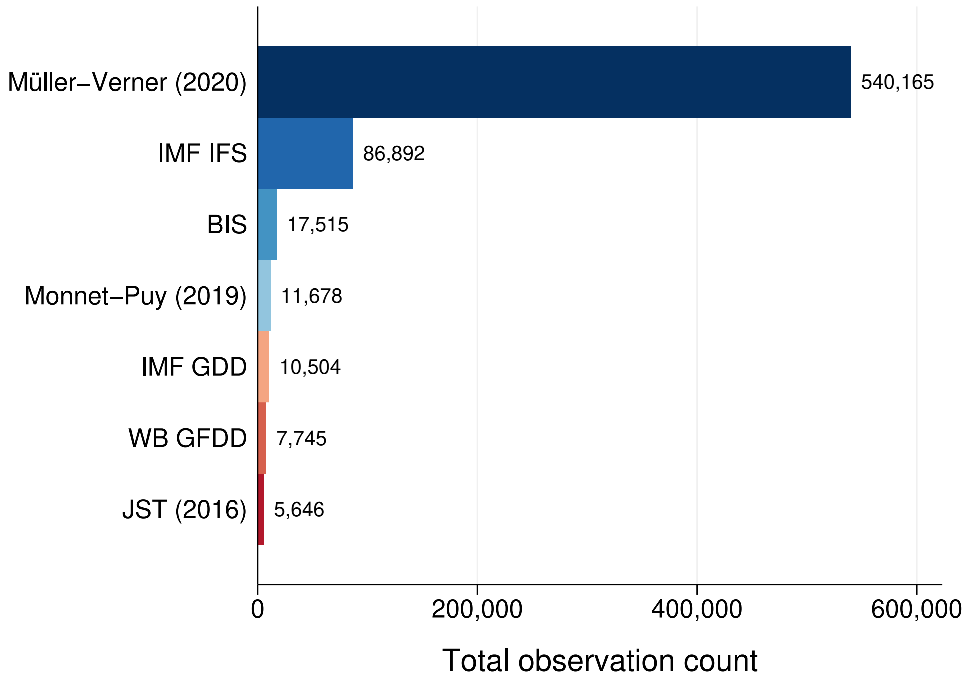
The principal data sources for this project were publications by national central banks and statistical offices. To identify the availability of detailed credit data, we followed four simple steps.

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.

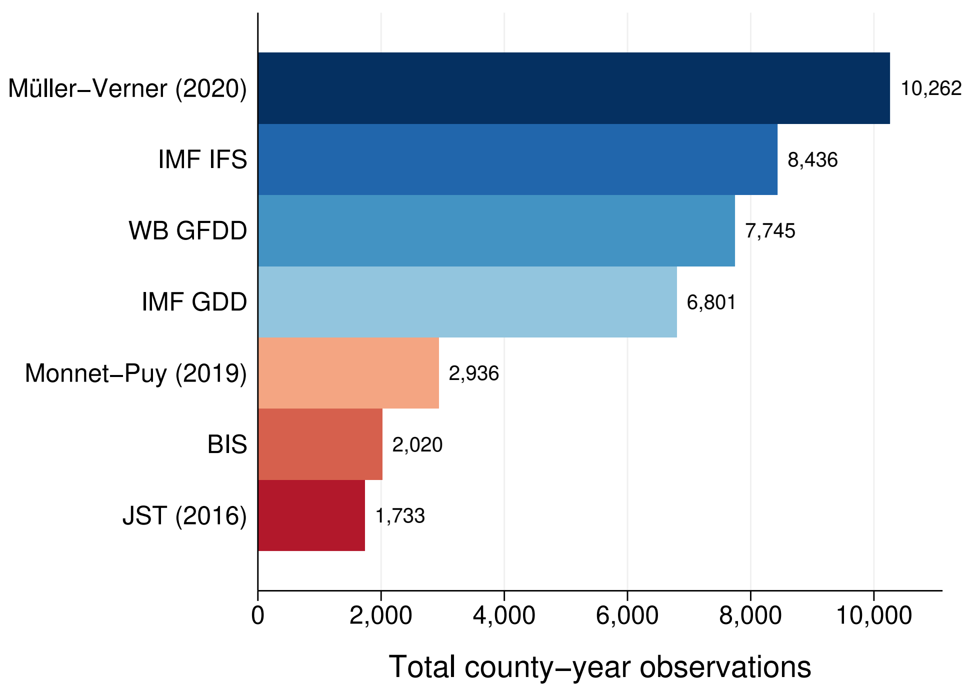
Step 2: Identifying data in PDF format or supervisory files Next, we turned to the source publications of the data, often only available in their original languages, especially for historical data. In many cases, these were the annual reports and statistical bulletins published by national central banks 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

Figure A18: Comparing the Observation Count of Datasets on Private Credit

(a) Total Observations



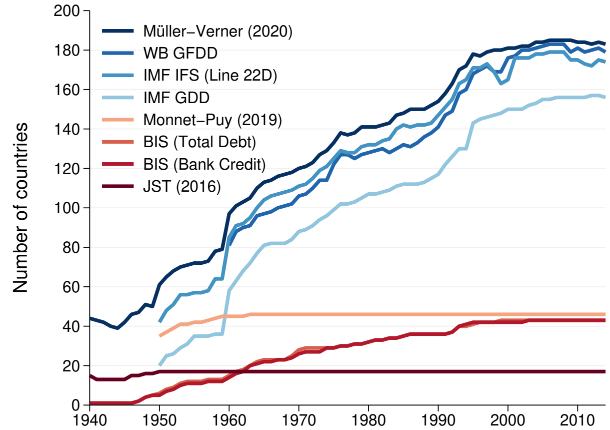
(b) Country-Year Observations



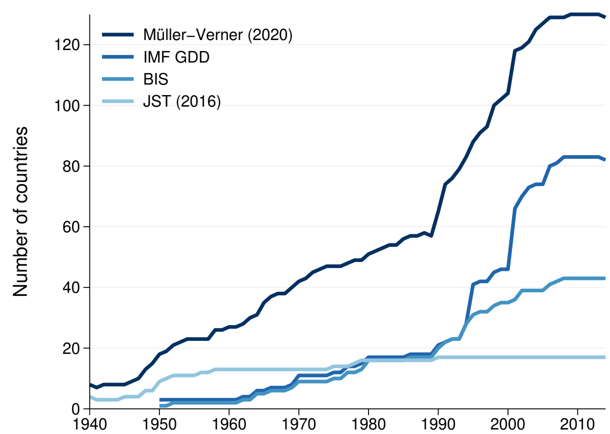
Notes: These figures compare the number of observations in different datasets on private credit. Panel (a) counts the total number of country-(sector)-time observations. Panel (b) counts country-year observations. For sources with sectoral data, these numbers are equal to the sum of total observations in panels A and B in Table 2/A6.

Figure A19: Comparing the Country Coverage of Different Sources on Private Credit Data

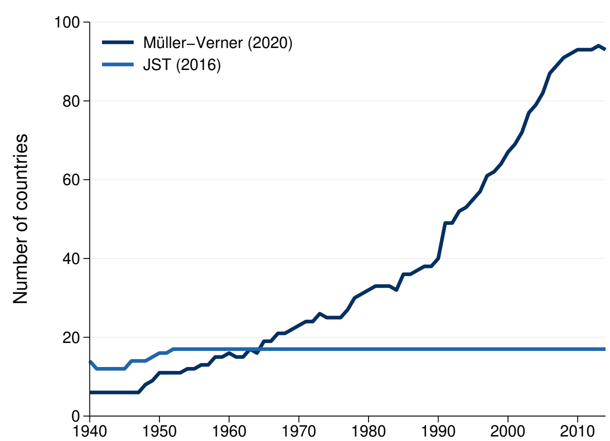
(a) Countries with Total Credit Data



(b) Countries with Household/Firm Credit Data

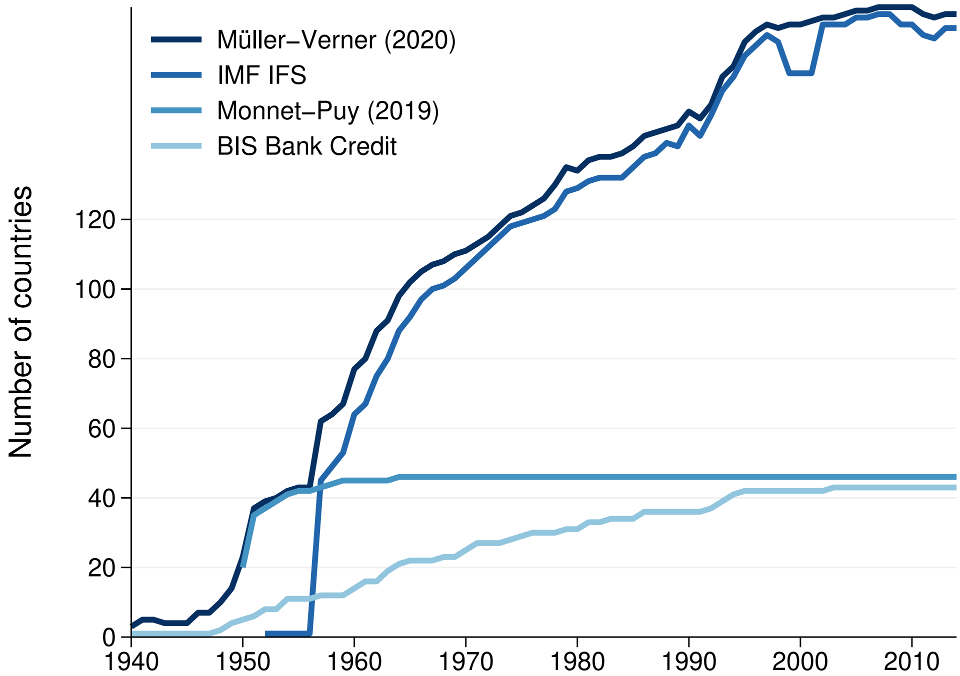


(c) Countries with Mortgage Credit Data



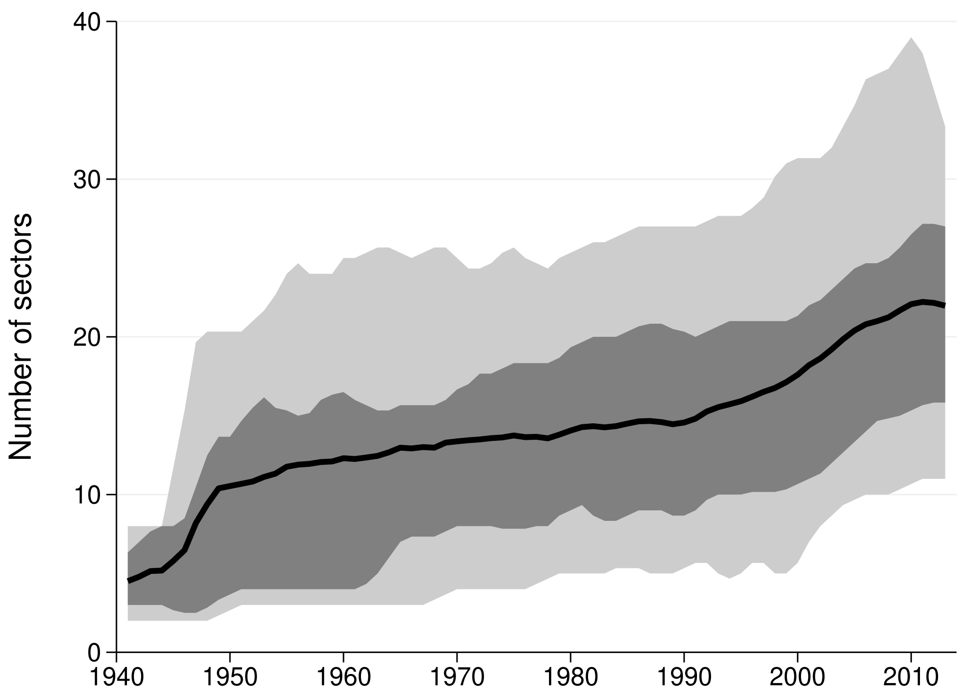
Notes: These graphs compare the coverage of different datasets on total credit (panel a), household/firm credit (panel b), and mortgage credit (panel c) over time. We compare our data to that compiled by the IMF IFS and GDD (Mbaye et al., 2018), BIS (Dembiermont et al., 2013), Jordà et al. (2016), Monnet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

Figure A20: 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.

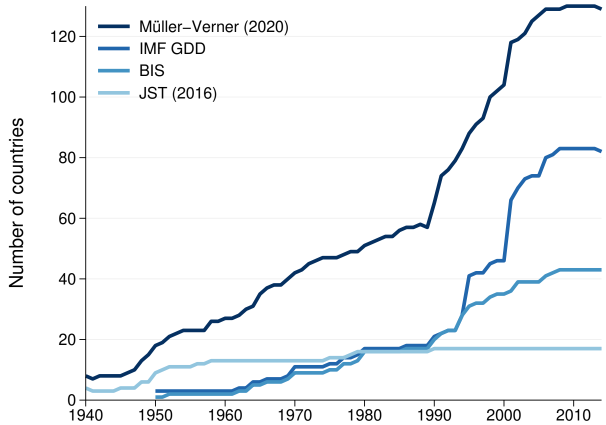
Figure A21: Numbers of Sectors per Country-Year Observation



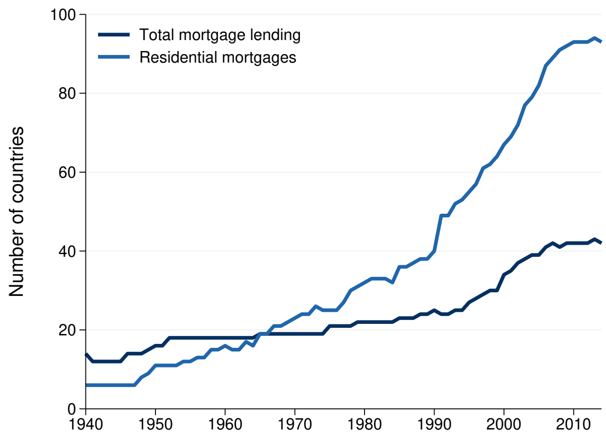
Notes: This graph plots the average number of sectors per country-year observation. The shaded areas represent the 10th, 25th, 75th, and 90th percentiles.

Figure A22: Country Coverage for Special Aggregates

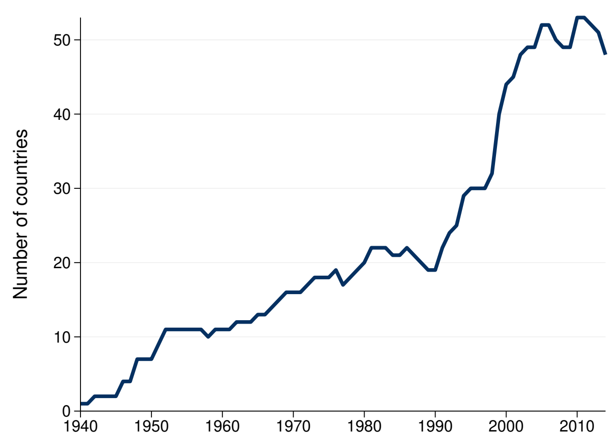
(a) Number of Sample Countries with Mortgages/Non-Mortgage Household Credit



(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).

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 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 A23 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 regarding (1) the type of lending institutions, and (2) what constitutes "credit".

Figure A23: 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.

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, investment 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, Lopez-De-Silanes, and Shleifer, 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).[30] 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 60 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 16 different sectors, the median country for 14. 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).

[30] 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.

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 A8 shows a full outline of the sectoral structure of the data.

Table A8: Sector Classification

Sector	Description
Households	Credit to households, incl. non-profit organizations and sole proprietors.
Residential mortgages	Credit to households secured by a mortgage; usually refers specifically to the purchase or construction of real estate.
Non-mortgage household credit	Credit to households that is not secured by a mortgage.
Consumer credit	Credit to households for the purchase of durable and non-durable goods and services except real estate.
Credit cards	Credit to households extended on credit cards.
Car loans	Credit to households for the purchase of any type of automobile.
Other consumer	Other credit to households for consumption.
Other non-mortgage	Other household credit not secured by a mortgage.
Total mortgages	Credit to households and corporations secured by a mortgage.
Commercial mortgages	Credit to corporations secured by a mortgage; often calculated as residual of total mortgage credit and residential mortgages.
Residential mortgages	Credit to households secured by a mortgage; usually refers specifically to the purchase or construction of real estate.
Non-bank financial corporations	Credit to non-bank financial corporations in ISIC section K (Financial and insurance activities).
K64	Financial service activities, except insurance and pension funding
K65	Insurance, reinsurance and pension funding, except compulsory social security
K66	Activities auxiliary to financial service and insurance activities
Non-financial corporations	Credit to non-financial corporations.
A	Agriculture, forestry and fishing
A1	Crop and animal production, hunting and related service activities
A2	Forestry and logging
A3	Fishing and aquaculture
B	Mining and quarrying
B05	Coal and lignite
B06	Crude petroleum and natural gas
B07	Metal ores
B08-09	Other mining and quarrying + Support service activities
C	Manufacturing
C10	Food
C11	Beverages
C12	Tobacco

Table A8: Sector Classification (continued)

Sector		Description
	C13	Textiles
	C14	Wearing Apparel
	C15	Leather
	C16	Wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
	C17	Paper and paper products
	C18	Printing and reproduction of recorded media
	C19	Coke and refined petroleum products
	C20	Chemicals and chemical products
	C21	Pharmaceuticals, medicinal chemical and botanical products
	C22	Rubber and plastics products
	C23	Other non-metallic mineral products
	C24	Basic metals
	C25	Fabricated metal products, except machinery and equipment
	C26	Computer, electronic and optical products
	C27	Electrical equipment
	C28	Machinery and equipment
	C29	Motor vehicles, trailers and semi-trailers
	C30	Other transport equipment
	C31	Furniture
	C32-33	Other
D		Electricity, gas, steam and air conditioning supply
E		Water supply; sewerage, waste management and remediation activities
F		Construction
G		Wholesale and retail trade; repair of motor vehicles and motorcycles
H		Transportation and storage
J		Information and communication
I		Accommodation and food service activities
L		Real estate activities
M		Professional, scientific and technical activities
N		Administrative and support service activities
O		Public administration and defence; compulsory social security
P		Education
Q		Human health and social work activities
R		Arts, entertainment and recreation
S		Other service activities
Z		All other categories

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.[31] 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

[31] 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.[32] 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.[33] 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 A8 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)

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

[33] 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 189 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.[34] 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 A24 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,

[34]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.[35] 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.

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

Figure A24: 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.[36] 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

[36] 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).[37]

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.

[37] 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

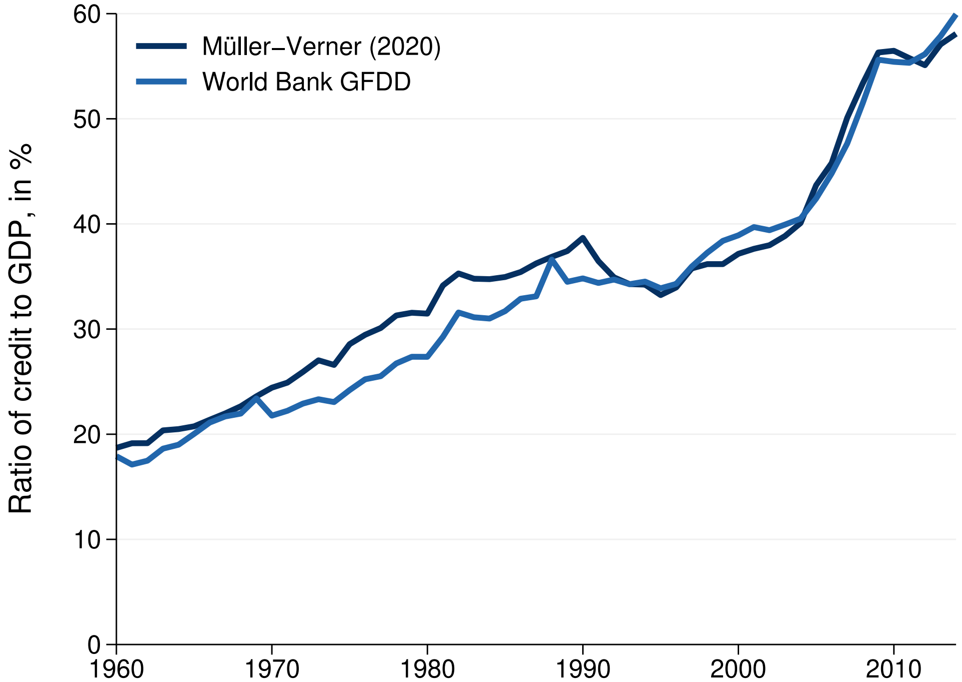
In Table 2 above, we already plotted the coverage of existing sources on credit market data as well as our database. Before comparing the six alternative resources with the newly compiled data, it is important to highlight important classification differences. Apart from differences in the available 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).

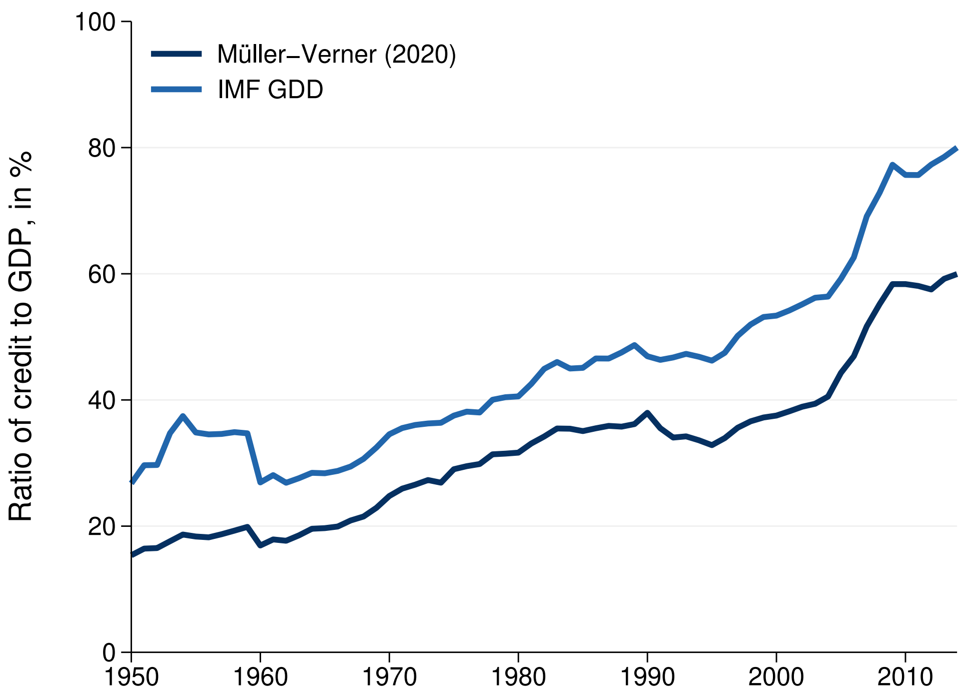
Figure A25 starts by plotting our data side-by-side with the total values on credit to the private sector from the World Bank's Global Financial Development database starting from 1960, when the World Bank data become available. The sample here are 180 countries for which there is data for both sources. 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 A25: Comparison with World Bank Data



Sample: 180 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 A26: Comparison with IMF Global Debt Database



Sample: 158 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 A26 shows that the broader coverage of lending institutions yields higher ratios of credit to GDP in their dataset in a sample of 158 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 A27 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 A28 shows that the data track each other almost one to one in the overlapping sample of 45 countries.

Next, we compare our dataset with the data compiled by the BIS (Dembiermont et al., 2013). Figure A29 plots the average values for a sample of 43 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.

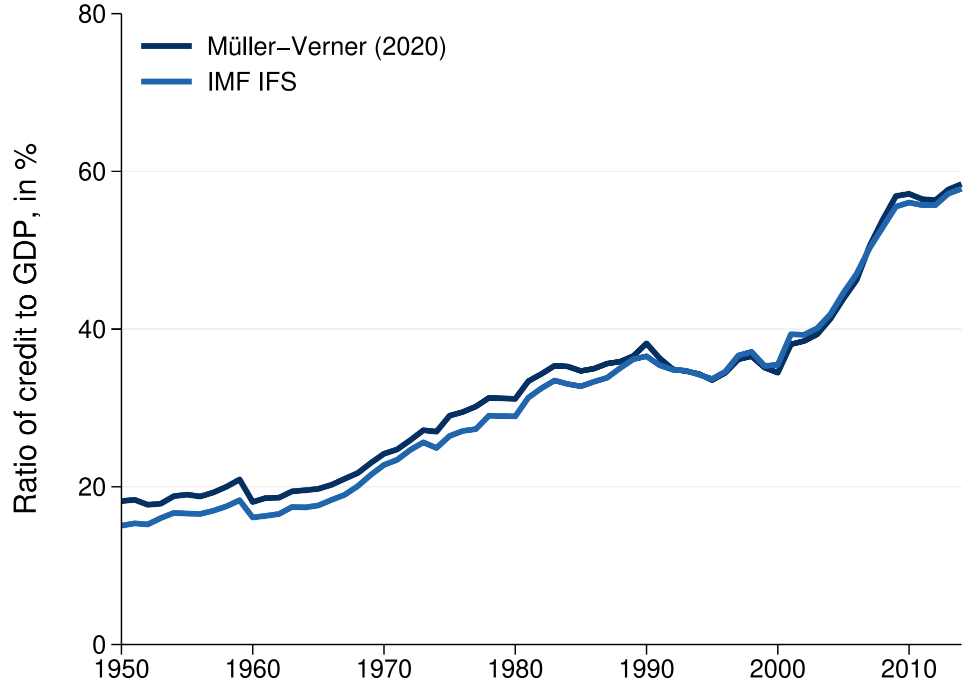
As a last exercise, we compare our data with the values compiled in the "Jordà-Schularick-Taylor Macrohistory Database" (Jordà et al., 2016). Again, we restrict the sample to the overlapping country-years in both data sources and plot the result in Figure A30. For the 17 overlapping countries, the picture 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

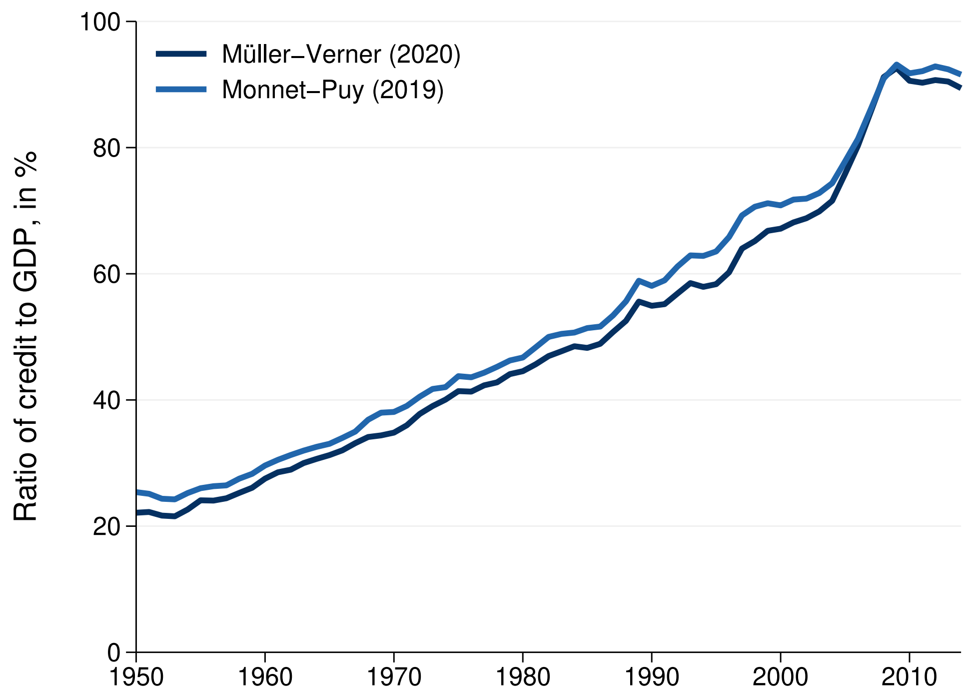
To get a closer look at the individual countries, we plot total credit for a panel of 43 countries where our database overlaps with the IMF GDD, IMF IFS, World Bank, and BIS datasets in Figure A31.

Figure A27: Comparison with IMF International Financial Statistics



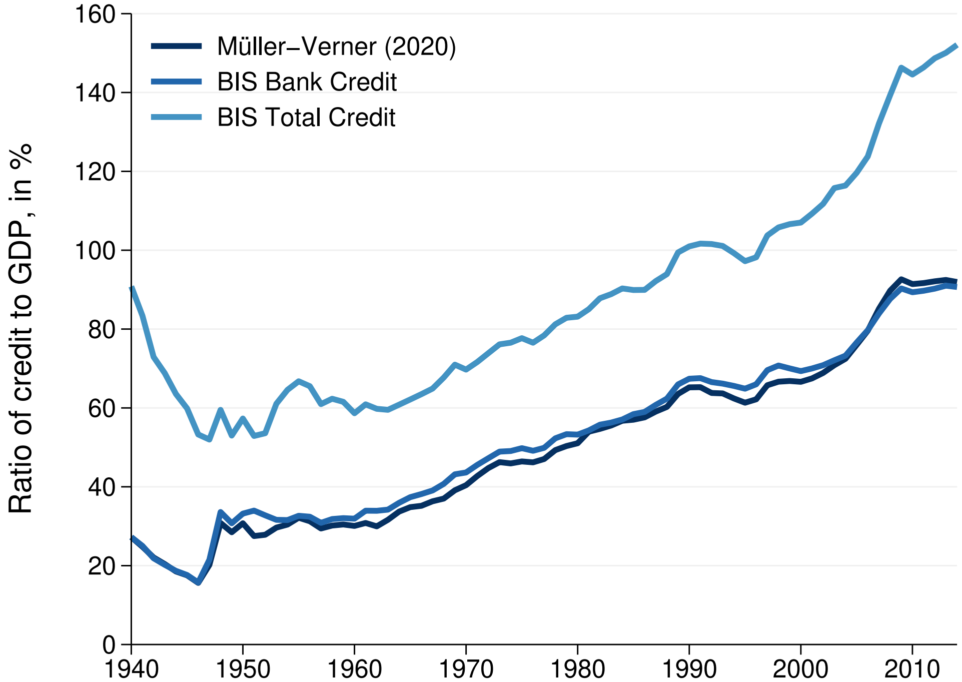
Sample: 184 countries in our dataset and the IMF's International Financial Statistics, 1948-2014.
Notes: Average total private credit to GDP (unweighted). IFS variables *FOSAOP* and *22D* (Claims on Private Sector).

Figure A28: Comparison with IMF data from Monnet and Puy (2019)



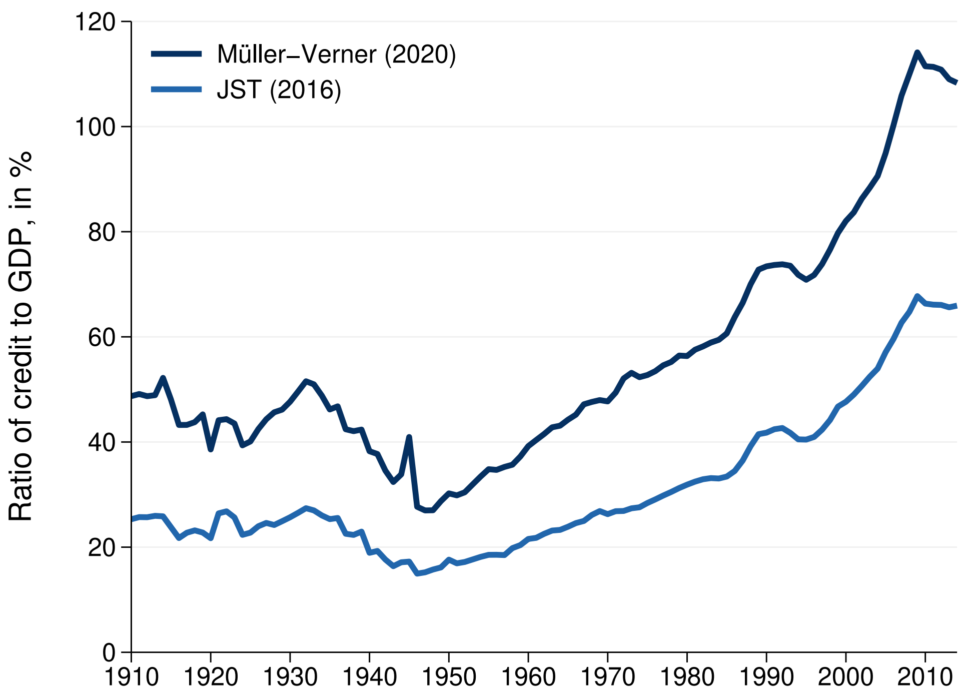
Sample: 45 countries in our dataset and the IMF data digitized and harmonized by Monnet and Puy (2019), 1950-2014.
Notes: Average ratio of total private credit to GDP (unweighted).

Figure A29: Comparison with BIS Total and Bank Credit Data



Sample: 43 countries in our dataset and the BIS private credit data, 1940-2014.
Notes: Average ratio of total private credit to GDP (unweighted).

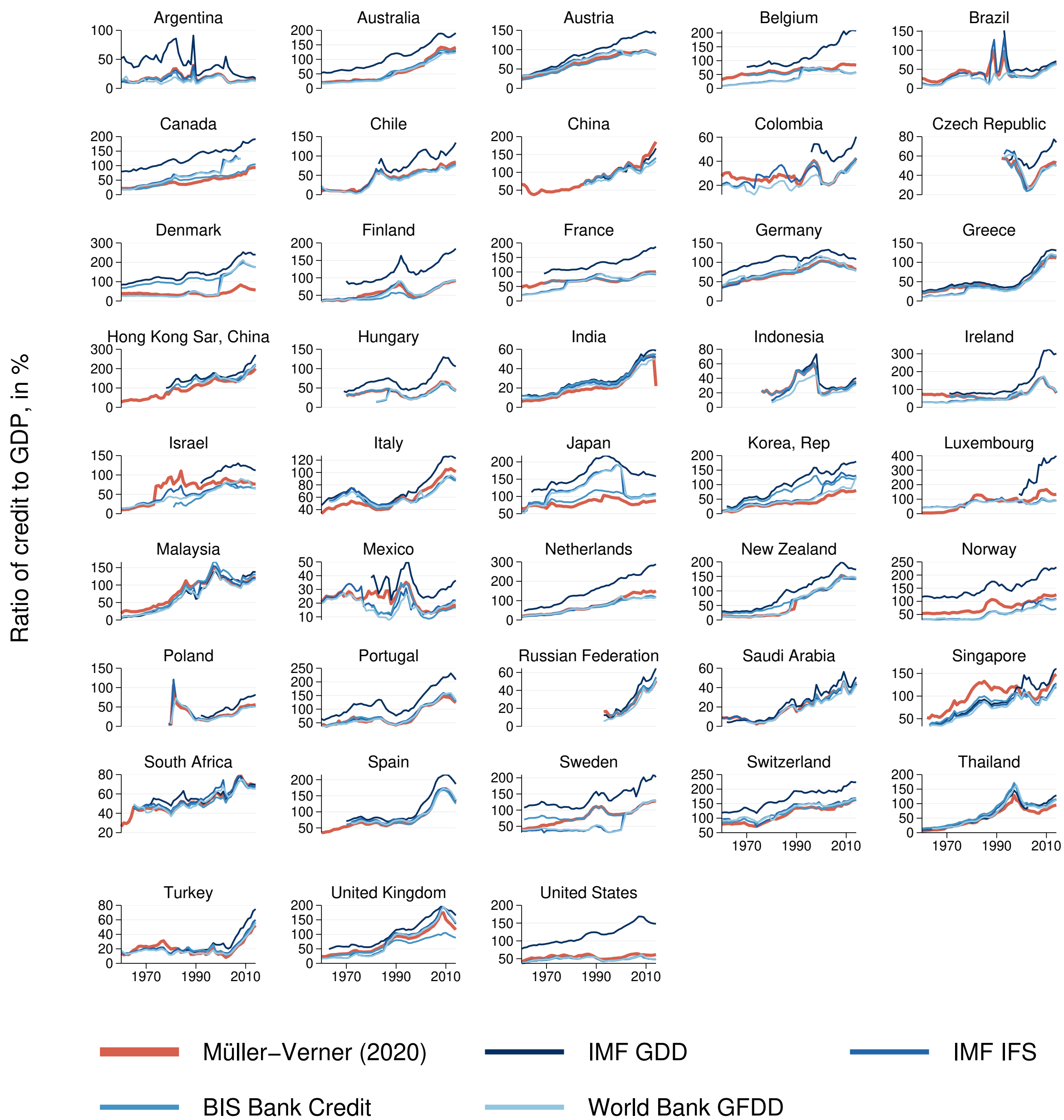
Figure A30: Comparison with Jordà et al. (2016) Data



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.

Figure A31: Comparison with IMF, World Bank, and BIS Data, by Country



Sample: 43 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).

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 A32a shows the evolution of BIS household credit and the newly compiled data over time in a sample of 43 countries. Note that these series have substantially different creditor coverage: as we could see above in Figure A29, 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.

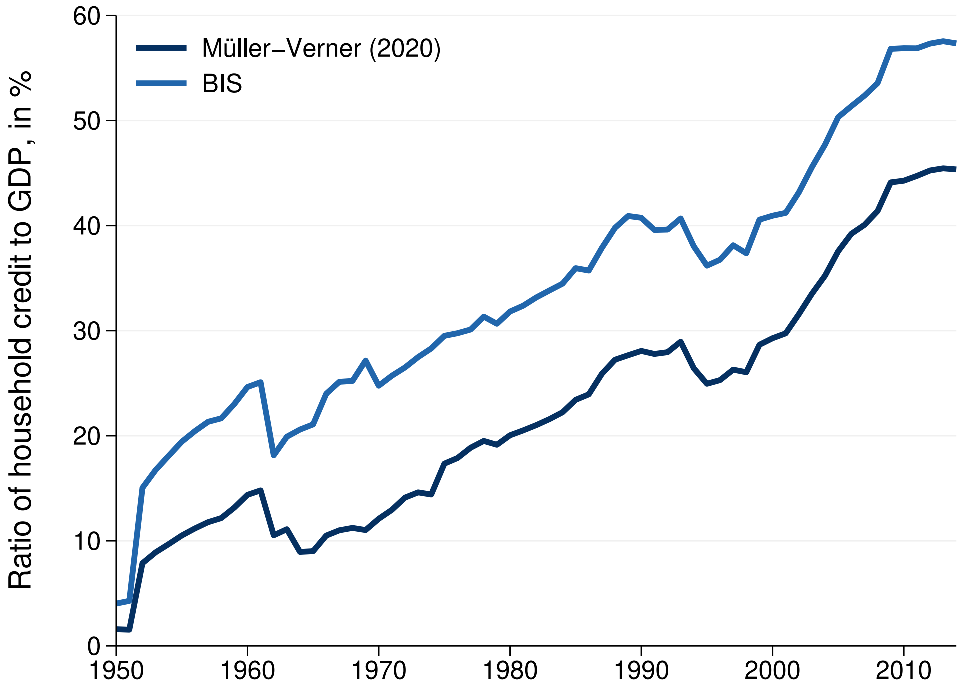
Next, we compare the new data with the IMF Global Debt Database on outstanding household credit scaled over GDP, which yields an overlapping sample of 83 countries. Given the slightly broader coverage in the IMF GDD data, it is unsurprising that the values there are slightly higher. Apart from this minor 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).

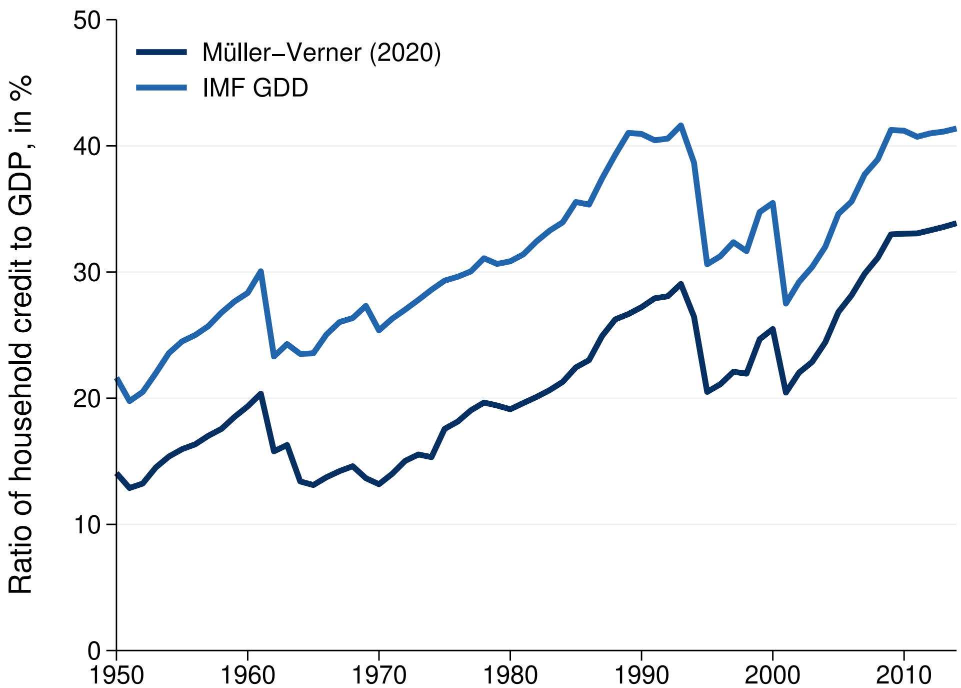
Another unique feature of our data is that we can differentiate between total mortgages and residential mortgages. In a final check, we thus also compare our total mortgage data with that in Jordà et al. (2016). Again, the time series closely track each other for the 17 overlapping countries, but our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

Figure A32: Comparison with BIS and IMF GDD Household Credit Data

(a) BIS Data

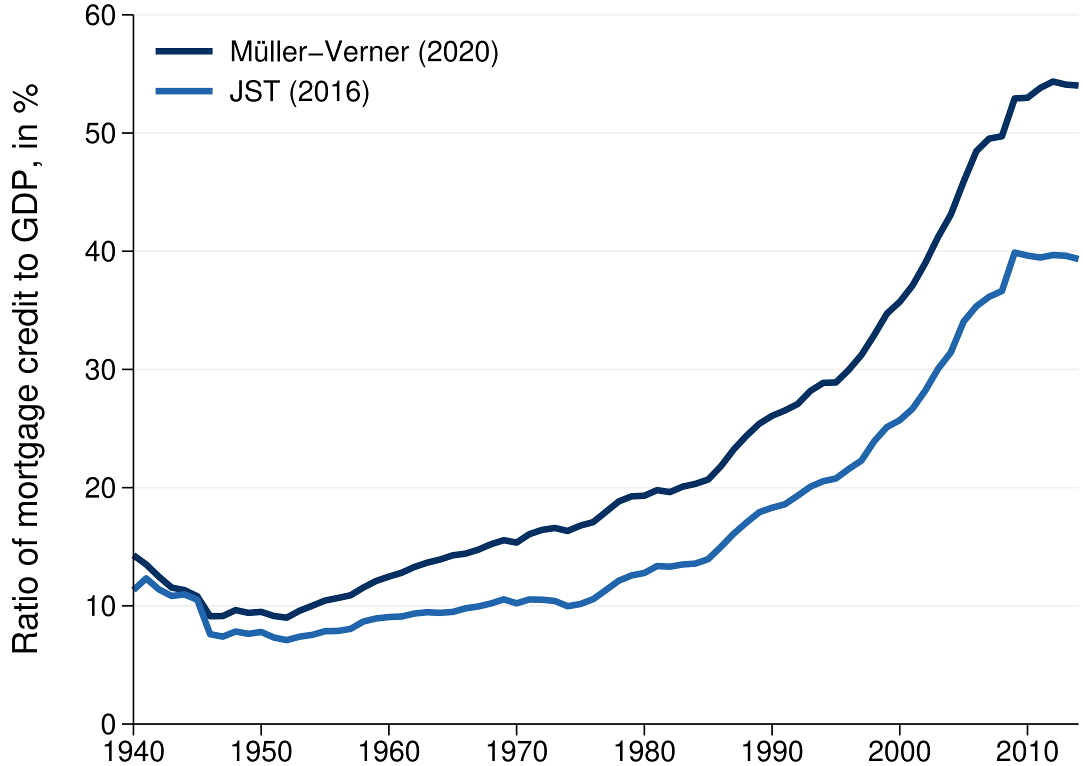


(b) IMF Global Debt Database



Sample: In panel (a), 43 countries in our dataset and the BIS data on credit to the non-financial private sector, 1940-2014. In panel (b), 83 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 A33: 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).

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