# 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 117 countries since 1940. We document that, during credit booms, credit flows disproportionately to the non-tradable sector. Credit expansions to the non-tradable sector, in turn, systematically predict subsequent growth slowdowns and financial crises. In contrast, credit expansions to the tradable sector are associated with sustained output and productivity growth without a higher risk of a financial crisis. To understand these patterns, we show that firms in the non-tradable sector tend to be smaller, more reliant on loans secured by real estate, and more likely to default during crises. Our findings are consistent with models in which credit booms to the non-tradable sector are driven by easy financing conditions and amplified by collateral feedbacks, contributing to increased financial fragility and a boom-bust cycle.

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# 1 Introduction

Rapid expansions in private credit are often, but not always, followed by recessions and financial crises (Schularick and Taylor, 2012; Jordà et al., 2013; Mian et al., 2017; Greenwood et al., 2020). However, important questions about how private credit interacts with the business cycle remain poorly understood. Why do some credit booms end badly, while others do not? What are the mechanisms behind "good" from "bad" booms (Gorton and Ordoñez, 2019)? Does it matter who takes on debt during these booms?

In this paper, we argue that the allocation of credit across sectors is important for answering these questions. Our analysis is motivated by models of credit cycles with sectoral heterogeneity and credit frictions (e.g., Schneider and Tornell, 2004; Reis, 2013; Benigno and Fornaro, 2014; Kalantzis, 2015; Ozhan, 2020; Benigno et al., 2020). These models distinguish between firms in the tradable and non-tradable sectors. Firms in the non-tradable sector are assumed to be more financing constrained and more exposed to feedbacks through collateral values and domestic demand linkages. This model set-up yields two predictions about the link between the sectoral allocation of credit and macroeconomic fluctuations. First, times of "easy credit" will lead to disproportionate lending growth to firms in the non-tradable sector. Second, credit booms concentrated in the non-tradable sector may lead to slower economic growth through increased financial fragility. In contrast, lending to the tradable sector is more likely to coincide with strong growth without increased financial fragility.

To examine the link between sectoral credit allocation and macroeconomic outcomes empirically, we construct a novel database on private credit for 117 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. 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]

Equipped with this database, we start by documenting that credit booms are systematically associated with a reallocation of credit toward the non-tradable sector, especially to the construction and real estate industries, alongside rapid growth in household credit. Lending toward non-tradable firms and households accounts for about 70% of total lending growth during major credit booms. As a result, the share of credit allocated to the non-tradable and household sectors rises in four out of

[1]We discuss details of the data construction at length below and in the data appendix. Our approach builds on best practices in the construction of national accounts used by the United Nations (e.g., United Nations, 2009, 2018) and other data sources on private credit (e.g., Dembiermont et al., 2013). 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.

five credit booms. This reallocation rejects the view that credit booms are equally likely to increase leverage in all sectors of the economy.

What explains this systematic reallocation of credit during booms? We document that firms in the non-tradable sector are smaller and more reliant on debt secured by real estate collateral relative to firms in the tradable sector. This suggests that non-tradable firms are more financially constrained and exposed to collateral feedbacks. Therefore, the systematic reallocation of credit is consistent with an important role for credit supply and asset price feedbacks in driving these kinds of booms. Further, credit to the non-tradable sector is reinforced by demand feedbacks, as non-tradable sector firms are more sensitive to booming domestic demand.

The allocation of credit during the boom predicts whether the boom ends in a bust. While all credit booms coincide with strong output growth, only credit booms concentrated toward non-tradable sector firms and households result in sharp growth reversals. The magnitude of the difference in economic outcomes is sizeable. Five years after they start, credit booms that are biased toward the non-tradable sector and households are associated with 6 percentage points lower real GDP relative to credit booms biased toward the tradable sector. As a result, there is significant heterogeneity in the unconditional predictability of credit expansions for future GDP growth. Expansion in credit to the non-tradable sector predicts subsequent GDP growth slowdowns, defined as a significant decline in growth relative to the previous trend. In contrast, tradable sector credit expansion is associated with stable or, in some specifications, higher growth in the medium run. Our analysis thus highlights that heterogeneity within the corporate sector is important for understanding the aftermath of credit expansions.

The patterns we document are robust to the inclusion of macroeconomic controls, excluding the 2008 financial crisis, focusing solely on advanced or emerging markets, controlling for year fixed effects or growth trends, and controlling for measures of the riskiness of firm debt issuance based on the proxies used by Greenwood and Hanson (2013). The results also hold after controlling for changes in sectoral value added, showing that credit matters over and above variation in sectoral real activity. Further, while our sectoral credit data generally do not systematically include bond market debt, various tests incorporating information on bond issuance reinforce our findings.

Why does credit expansion to the non-tradable sector, but not to the tradable sector, foreshadow lower future economic growth?[2] Guided by theory, we present several pieces of evidence that increased financial fragility and the risk of financial crisis explain the poor growth performance after non-tradable credit booms. At the outset, we emphasize that causal identification of the exact mech-

[2]Given the established role of household credit expansions in predicting growth slowdowns documented by Mian et al. (2017) and Jordà et al. (2020), among others, we focus most of our discussion on the role of heterogeneity within the corporate sector. However, we always report results that control for household credit, and, in the process, confirm the importance of household credit for predicting growth slowdowns and crises in a larger sample than previous work.

anisms is challenging in such a broad and long macro panel. Instead, our goal is to understand which theories are most consistent with the empirical patterns.

First, credit expansion to the non-tradable sector is associated with a considerably higher likelihood of a future systemic banking crisis. In contrast, lending to the tradable sector, if anything, predicts a slightly lower probability of a banking crisis. The occurrence of a banking crisis statistically accounts for the majority of the growth slowdown in the aftermath of non-tradable credit expansions. Lending to the non-tradable sector also falls dramatically after the onset of crises, indicating that this sector is more adversely affected by credit contractions.

Second, loan losses during banking crises are concentrated in the non-tradable sector. We collect data on non-performing loans by sector for ten major crisis episodes. When non-performing loans reach their peak after banking crises, the share of non-performing loans is 50% higher in the non-tradable compared to the tradable sector. Because credit growth before crises is usually concentrated in non-tradable industries, the non-tradable sector accounts for the majority of loan losses during banking sector meltdowns. In contrast, the tradable and household sectors make up a much smaller fraction of losses. Thus, defaults among firms in the non-tradable sector are key for understanding losses during banking crises, as emphasized by the models of Schneider and Tornell (2004) and Kalantzis (2015).

Third, non-tradable credit expansions are more strongly associated with real estate price growth and subsequent busts. This pattern is consistent with greater financial fragility from exposure to collateral feedbacks (Kiyotaki and Moore, 1997). Fourth, GDP growth forecasts from the International Monetary Fund (IMF) are over-optimistic during non-tradable and household credit expansions, but not during tradable credit expansions. Professional forecasters appear to neglect the financial fragility risks of credit booms concentrated among non-tradables and households, consistent with theories emphasizing over-optimism during these booms (Kindleberger, 1978; Minsky, 1986; Bordalo et al., 2018).

Finally, non-tradable credit expansions coincide with an appreciation of the real exchange rate and a reallocation of labor and value added toward the non-tradable sector, suggesting rising sectoral imbalances. At the same time, these booms predict lower future productivity growth, consistent with the lower productivity in the non-tradable sector (Reis, 2013; Benigno and Fornaro, 2014; Borio et al., 2016; Benigno et al., 2020). Lending to the tradable sector, on the other hand, is associated with higher productivity growth and a stable real exchange rate.

This paper contributes to a growing literature on credit cycles. Previous studies find that rapid growth in total private credit is associated with future growth slowdowns and an increased risk of a financial crisis (Schularick and Taylor, 2012; Jordà et al., 2013). Several studies examine the relative role of household and corporate credit during credit expansions. Mian et al. (2017) find that credit expansion to households is associated with a boom and subsequent bust in output, while there is less evidence for such a link for firm credit (see also Drehmann et al., 2018; Jordà et al., 2020). In related work, Jordà et al. (2016b) find that mortgage debt is associated with more severe recessions, compared to non-mortgage debt, but that mortgage and non-mortgage debt have similar predictability for financial crises. In contrast, Greenwood et al. (2020) find that credit booms coupled with elevated asset prices, both in the household and corporate sectors, strongly predict financial crises (see also Giroud and Mueller, 2020). Related studies find that elevated credit market sentiment—proxied by times of increased lending to lower credit quality firms—is correlated with credit expansions and predicts subsequent reversals in credit market conditions and output (Greenwood and Hanson, 2013; López-Salido et al., 2017).

We provide several contributions to this literature. Our novel sectoral credit database considerably extends existing datasets in terms of the sectors, countries, and time span it covers. These data allow for new insights into the nature of credit booms that are relevant for models featuring firm heterogeneity in financing constraints. Sufi and Taylor (2021) argue that understanding financial crises requires investigating the boom that precedes them. Our finding of a reallocation of credit toward non-tradable firms before banking crises points to the role of credit supply and collateral feedbacks as an important factor. This finding complements previous evidence on the importance of credit supply based on credit spreads (Krishnamurthy and Muir, 2017; Mian et al., 2017) and debt issuance by risky firms (Greenwood and Hanson, 2013).

Our new evidence on the importance of heterogeneity *within* the corporate sector clarifies the mixed results about the link between corporate credit and macroeconomic downturns. Beyond comparing household and firm debt, differentiating between different types of firm credit is important. Our data allow us to explore the mechanisms for why some credit booms end badly. Our new evidence on sectoral loan losses directly links pockets of rapid firm credit growth to subsequent financial instability, supporting the view that many financial crises are credit booms gone bust. In addition, our evidence speaks to the tension between the literature emphasizing the benefits of credit for growth (Levine, 2005) and studies linking credit booms to subsequent economic downturns. Differentiating between different types of credit may not only matter for understanding downturns, but also for longer-run growth outcomes.

Finally, our paper also contributes to the literature on capital inflows (Calvo et al., 1996). Benigno et al. (2015) document that episodes of large capital inflows are associated with booms and busts, along with a reallocation of labor out of manufacturing (see also Tornell and Westermann, 2002; Schneider and Tornell, 2004). Diebold and Richter (2021) document that much of the increase in credit-to-GDP has been financed by foreign capital and that credit booms financed with capital inflows are likely to be followed by growth slowdowns. Many of the credit booms we examine also stem from capital inflows.

The paper proceeds as follows. Section 2 describes our novel sectoral credit database and presents new stylized facts about the evolution of credit markets around the world. Section 3 discusses our conceptual framework for why credit expansion in certain sectors may be linked to boom-bust cycles. Sections 4 to 6 present the main results and explore mechanisms, and Section 7 provides concluding remarks.

# 2 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 challenges involved in constructing these data. We address additional technical details and comparisons with other data sources in much greater detail in a dedicated data appendix (Online Appendix C).

## 2.1 Data Coverage

Existing datasets on private credit at best differentiate between household and firm credit. These aggregated data, however, are not suitable for testing theories that link sectoral credit expansions to economic fluctuations. We construct a new database on the sectoral allocation of private credit covering the period 1940 to 2014.[3] We assembled data on credit by sector for 117 countries, which account for around 90% of world GDP today, and include 53 advanced and 64 emerging economies. The number of sectors ranges from 2–60, with an average of 16. We also considerably extended the coverage of data on total private credit, for which we cover up to 189 countries.

Table 1 compares our database to existing datasets on private credit. Panel A highlights the difference in our approach. The most disaggregated available data in Jordà et al. (2016a) differentiates between household, firm, and mortgage credit for 18 advanced economies. Our database contains a more detailed sectoral breakdown for many more countries. It covers more than three times the country-year observations in Jordà et al. (2016a) 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 of our data, it contains a total of 89,019 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 on total credit is also more comprehensive than existing work.

## 2.2 Data Sources

Most countries have collected sectoral credit data for several decades. However, historical data are often not available in digitized form and are not reported on a harmonized basis. We draw

[3] The data are available at http://www.globalcreditproject.com.

**Table 1:** Comparison with Existing Data Sources on Private Credit

| Dataset | Start | Freq. | Countries | Country-year obs. | Sectors | Country-sector-year obs. |
|---|---|---|---|---|---|---|
| **Panel A: Sectoral credit data** | | | | | | |
| Müller-Verner | 1940 | Y | 117 | 5,436 | 2–60 (mean=16) | 89,019 |
| Jordà et al. (2016a) | 1870 | Y | 18 | 1,764 | 3 | 4,103 |
| IMF GDD | 1950 | Y | 83 | 1,871 | 2 | 3,703 |
| BIS | 1940 | Q | 43 | 1,220 | 2 | 2,417 |
| **Panel B: Total credit data** | | | | | | |
| Müller-Verner | 1910 | Y | 189 | 10,272 | — | 10,272 |
| IMF IFS | 1948 | Y/Q/M | 182 | 8,458 | — | 8,458 |
| World Bank GFDD | 1960 | Y | 187 | 7,745 | — | 7,745 |
| IMF GDD | 1950 | Y | 159 | 6,802 | — | 6,802 |
| Monnet and Puy (2019) | 1940 | Q | 46 | 2,936 | — | 2,936 |
| BIS | 1940 | Q | 43 | 2,020 | — | 2,020 |
| Jordà et al. (2016a) | 1870 | Y | 18 | 1,816 | — | 1,816 |

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. *Country-sector-year obs.* refers to country-sector-year observations. We count observations until 2014.

on hundreds of scattered sources to construct these time series. The main sources are statistical publications and data appendices published by central banks and statistical offices. 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 untapped sources of total credit to the private sector that allow us to extend existing time series.

We complement our newly collected data with existing time series from the BIS (Dembiermont et al., 2013), Jordà et al. (2016a), the International Monetary Fund (IMF)'s International Financial Statistics (IFS) and Global Debt Database (GDD, Mbaye et al., 2018), and additional data from the print versions of the IFS digitized by Monnet and Puy (2019). These existing sources track broad credit aggregates such as total private credit or household credit for a subset of the countries we consider. We also build on scholarship on individual countries, such as Barnett (1982), De Bonis et al. (2013), and Abildgren (2007).

## 2.3 Concepts and Methods

We are interested in the sectoral distribution of outstanding credit to the private sector. Ideally, the data should 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 adjustments. To harmonize data from a wide range of sources, we draw on the metadata in historical publications and consulted with 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 covers loans, including foreign currency loans. We also include the bond exposures recorded on financial institutions' balance sheets wherever they are reported. In practice, however, domestic credit is almost entirely accounted for by loans, while bonds are often held by foreign financial institutions.

We try to cover the entire financial system wherever possible. In most countries, the data predominantly measures 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 the IMF IFS or BIS data on bank credit to the non-financial private sector. At times, we find somewhat larger values than the data in Jordà et al. (2016a), which largely covers 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, we differentiate between the broad sectors "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 data, including on credit. In most countries, we can differentiate between credit to the major "sections" in ISIC parlance (Agriculture, Mining, Manufacturing, and so forth).

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 include lending to state-owned firms. We do not include direct lending to general or local governments.

A key issue when dealing with time series data covering long time periods is how to deal with level shifts (or "breaks"). 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 financial institutions covered). To address this issue, we coded country-specific classification changes based on a reading of the metadata and additional methodological publications, as well as exchanges with the national authorities.

We adjusted breaks due to methodological changes using chain-linking, following methods used in previous datasets on private credit (Dembiermont et al., 2013; Monnet and Puy, 2019). To guarantee internal consistency of the data, we rescale chain-linked time series to match an aggregate such as "total credit to non-financial corporations" when needed, in line with the United Nations' recommendation on backcasting national accounts (United Nations, 2018).

## 2.4 Variable and Sample Construction

For the analysis in this paper, we construct a country-year panel dataset by merging the new credit data with macroeconomic outcomes, house prices, and value added by sector. For our main analysis, we restrict the sample to 75 countries with a population greater than one million in 2000 to avoid the results being influenced by large fluctuations in very small countries. Table A.1 reports the countries and years used in our main analysis. The sample includes broad coverage of both advanced and emerging market economies. We winsorize variables at the 1% and 99% level to mitigate the influence of outliers, although our results are similar without winsorizing. Table 2 reports summary statistics for key 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 and C); construction and real estate (sections F and L); wholesale and retail trade, accommodation, and food services (sections G and I); as well as transport and communication (sections H and J). We further group together agriculture with manufacturing and mining as the "tradable sector" and the other three industry groups as the "non-tradable sector," similar to other studies in international macroeconomics (e.g., Kalantzis, 2015).

To investigate the characteristics of different sectors, we use data on firm size from the OECD's Structural Business Statistics (SBS) and compute the share of firms with less than 10 employees for each industry. We also collect data on the type of collateral posted in different sectors, which we could identify for five countries (Denmark, Latvia, Switzerland, Taiwan, and the United States). These data come from the national central banks or banking regulators, with the exception for the United States, where we use data from Compustat.

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 et al., 2015), IMF IFS, GGDC (Inklaar et al., 2018), Jordà et al. (2016a), Mitchell (1998), and the UC Davis Nominal GDP Historical Series. For a few countries, we use data from national sources: Taiwan (National Statistics), the United States (FRED), and Saudi Arabia (Saudi Arabian Monetary Authority). For labor and

**Table 2:** Descriptive Statistics

| Panel A: Summary statistics | | | | | |
|---|---|---|---|---|---|
| | N | Mean | Std. dev. | 10th | 90th |
| Real GDP growth (t–3,t) | 1,890 | 15.71 | 10.35 | 3.89 | 28.68 |
| $\Delta_3 d_{it}^k$ | | | | | |
| Non-tradables | 1,890 | 0.83 | 3.83 | -2.92 | 5.16 |
| Tradables | 1,890 | 0.03 | 2.26 | -2.55 | 2.57 |
| Household | 1,890 | 2.12 | 4.18 | -1.63 | 7.58 |
| Agriculture | 1,890 | 0.02 | 0.73 | -0.66 | 0.66 |
| Manuf. and Mining | 1,890 | 0.01 | 1.87 | -2.14 | 2.08 |
| Construction and RE | 1,890 | 0.54 | 2.20 | -1.32 | 3.01 |
| Trade, Accomodation, Food | 1,890 | 0.19 | 1.73 | -1.58 | 2.03 |
| Transport, Comm. | 1,890 | 0.11 | 0.75 | -0.55 | 0.84 |

| Panel B: Correlation matrix for credit expansion variables | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\Delta_3 d_{it}^k$ | | | | | | | | |
| (1) Non-tradables | 1 | | | | | | | |
| (2) Tradables | 0.46 | 1 | | | | | | |
| (3) Household | 0.45 | 0.15 | 1 | | | | | |
| (4) Agriculture | 0.21 | 0.64 | 0.15 | 1 | | | | |
| (5) Manuf. and Mining | 0.47 | 0.88 | 0.11 | 0.25 | 1 | | | |
| (6) Construction and RE | 0.81 | 0.29 | 0.45 | 0.13 | 0.30 | 1 | | |
| (7) Trade, Accomodation, Food | 0.79 | 0.44 | 0.28 | 0.22 | 0.44 | 0.37 | 1 | |
| (8) Transport, Comm. | 0.55 | 0.29 | 0.22 | 0.084 | 0.32 | 0.29 | 0.33 | 1 |

Notes: Panel A shows summary statistics for the main estimation sample. Panel B plots Pearson correlation coefficients for three-year changes in the credit-to-GDP ratio $\Delta_3 d_{it}^k$ for all sectors $k$ used in the analysis.

total factor productivity, we use data from the Total Economy Database (TED). Data on effective real exchange rates comes from the World Bank, BIS, and Bruegel (Darvas, 2012).

We construct data on sectoral value added and inflation from EU KLEMS, the Groningen Growth and Development Centre (GGDC) 10-sector database (Marcel Timmer, 2015), United Nations, UNIDO, OECD STAN, World Input-Output Database (WIOD), and the Economic Commission for Latin America and the Caribbean (ECLAC). We evaluate each source on a country-by-country 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.

We use data on the onset of systemic banking crises from Baron et al. (2021), who classify banking crises with data on bank equity crashes and narrative information on the occurrence of panics and widespread bank failures. For countries not covered by Baron et al. (2021), we use data from Laeven and Valencia (2018). For robustness, we also use banking crisis start dates from Reinhart and Rogoff (2009b). For house prices, we use data from the BIS residential property price series, OECD, Dallas Fed International House Price Database (Mack and Martínez-García, 2011), and Jordà et al. (2016a). Finally, to measure changes in firm borrowing in the bond market, we draw on gross bond issuance data from SDC Platinum.

## 2.5 Stylized Facts About Private Credit Around the World

In this section, we discuss three stylized facts about long-term trends in 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. The novelty of our data here is mainly the extension of long-run credit series to the period before 1960. Figure 1a plots the average credit-to-GDP ratio for advanced and emerging economies. This figure confirms the "hockey stick" pattern of rising private debt in advanced economies documented by Schularick and Taylor (2012), but it also reveals that the rise in credit is less pronounced in emerging economies.

**Fact #2: Household debt has boomed globally, while firm credit 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 1b plots averages of household and firm credit-to-GDP over time. This shows that most of the growth in credit-to-GDP since the early 1980s is accounted for by a rise in household debt. Relative to GDP, the rise in lending to firms has been modest. This reinforces previous evidence in Jordà et al. (2016b), who showed a similar pattern for a smaller sample of 17 advanced economies.

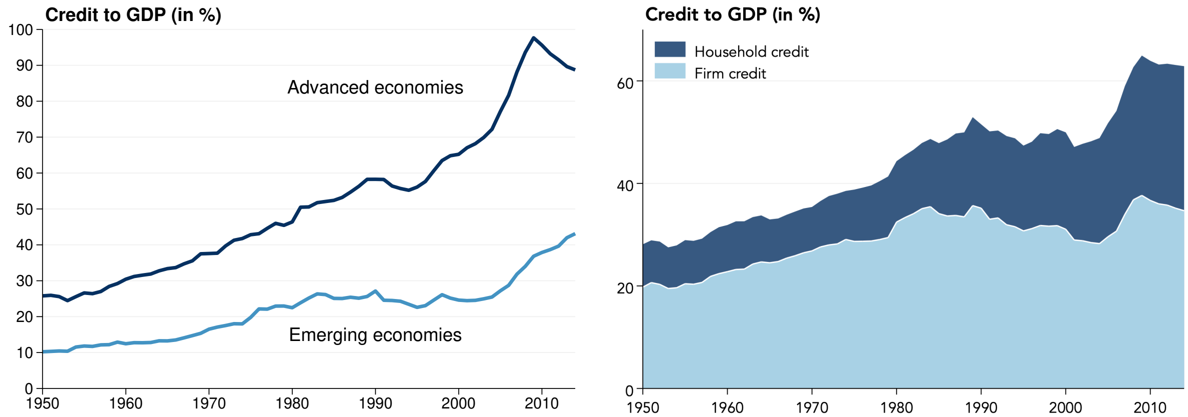
**Fact #3: Firm credit has shifted from tradable sectors to construction, real estate, and other non-tradable sectors.**

It is a well-known phenomenon that countries undergo structural change as they develop, away from primary sectors towards manufacturing and then service sectors. One may expect to find similar trends in corporate credit. At the same time, 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 1:** Private Credit-to-GDP (in %) by Country Group and by Sector, 1950-2014

**(a)** By country group

**(b)** By sector




Notes: Panel (a) shows the unweighted cross-country average of the ratio of total private credit-to-GDP. The average is estimated on the full sample of 58 advanced and 127 emerging economies over the period 1950-2014. Advanced economies refer to the World Bank's 2019 classification of "high income countries", and emerging economies refers to all others. Panel (b) plots the unweighted cross-country average of sectoral credit-to-GDP. The average is estimated on the full sample of 54 advanced and 76 emerging economies, 1950-2014.

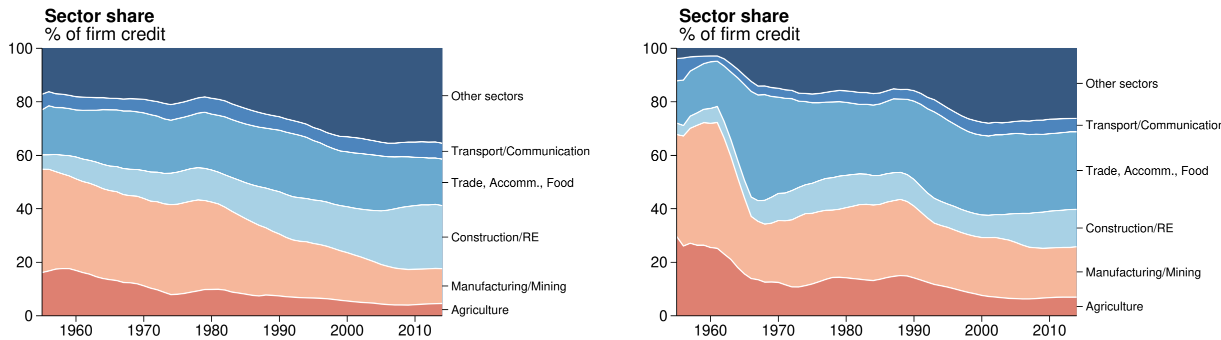
Figure 2 plots the share of six subsectors in total corporate credit: agriculture; mining and manufacturing; construction and real estate; trade, accommodation, and food services; transport and communication; and other sectors. Consistent with structural change in the credit market, the share of lending to agriculture and industry has declined, particularly since around 1980. This trend appears in both advanced and emerging economies.

The second major trend is that construction and real estate lending has 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 around 24 percent. This shift is large and cannot be fully accounted for by an increase in construction value added. While the housing boom of the 2000s has clearly played a role, the share had already grown in the 1990s. Strikingly, a similar pattern also holds true in developing countries. In 1960, lending to industry and agriculture accounted for more than 73 percent of corporate financing. Today, the ratio is closer to 26 percent. At the same time, construction and real estate has increased from around 5 percent to 14 percent. The loan portfolio of emerging markets has thus also seen a profound shift.

Other services have also seen a substantial increase in their lending share. In advanced economies, other services have increased from around 18 percent in 1960 to around 35 percent in recent years. Emerging economies have seen an increase from around 3 percent to 26 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 minor role for understanding modern credit markets.

**Figure 2:** Sector Shares in Corporate Credit

**(a)** Advanced economies **(b)** Emerging economies




Notes: This figure plots the average ratio of individual sectors in total corporate credit separately for advanced and emerging economies. The plots are based on a sample of 46 advanced and 54 emerging economies. "Other sectors" is the residual of total firm credit and the sectors we use in our main analysis. This residual mainly comprises other (largely non-tradable) service sectors. Countries differ significantly in the detail of credit data reported for service sectors. To maximize the number of countries for this exercise, we grouped these together into "other sectors."

# 3 Conceptual Framework

This section lays out a conceptual framework that motivates our empirical analysis. We address the following questions. Which factors cause credit booms? What leads credit booms to be concentrated in particular sectors of the economy? Does the sectoral allocation of credit matter for whether a credit boom increases financial fragility and triggers a subsequent output decline? We organize the discussion around two hypotheses about credit expansions: the *easy credit hypothesis* and the *productivity-enhancing credit hypothesis*. Given the nature of our dataset, we focus on theories of heterogeneity across industries, but we note that heterogeneity within sectors is also likely to matter (see, e.g., Gopinath et al., 2017). Moreover, given the prior evidence on household debt in credit cycles (Mian et al., 2017; Jordà et al., 2020), we focus our discussion on heterogeneity within the corporate sector.

## 3.1 Easy Credit Hypothesis

**Credit supply expansion and credit allocation** The easy credit hypothesis starts with an expansion in credit supply. Lenders provide cheaper credit and increase their willingness to lend to risky borrowers. The expansion in credit supply can be driven by a variety of factors, including optimism following a period of good fundamentals, loose monetary policy, rapid capital inflows, or financial deregulation.

How does credit supply affect the allocation of credit across sectors in the economy? Easy credit should particularly affect sectors that are more financing constrained, as well as those more exposed to feedbacks through collateral values and their reliance on domestic demand. Our main measure of sensitivity to changes in credit conditions is to differentiate between non-tradable and tradable sectors using our sectoral credit data.

Lending to the non-tradable sector is especially exposed to changes in credit conditions for three reasons. First, firms in the non-tradable sector are likely to be more financing constrained. To support this idea, Table 3 shows that the share of firms with less than 10 employees is considerably higher in the non-tradable sector. Small firms are often more financing constrained than large firms because they are more likely to be opaque, bank-dependent, and have low net worth (Gertler and Gilchrist, 1994; Chodorow-Reich, 2014). This is consistent with a large literature in international macroeconomics that assumes that non-tradable sector firms are more financially constrained than firms in the tradable sector.[4]

Second, firms in the non-tradable sector are nearly twice as reliant on credit secured by real estate (see Table 3). This implies that non-tradable sector firms are more sensitive to asset price feedbacks through a collateral channel. Greater reliance on secured debt also provides additional evidence that these firms are more financially constrained (Berger et al., 2016; Luck and Santos, 2019; Benmelech et al., 2020; Rampini and Viswanathan, 2022). Firms in the non-tradable sector are particularly reliant on secured debt because they are often small, risky, opaque, and low net worth, partially because they are limited to serving domestic markets.

Third, non-tradable sector firms are more sensitive to feedbacks from domestic demand. A credit boom that increases domestic demand will increase demand for both tradable and non-tradable goods. While tradables can be imported, non-tradables must be produced domestically. This leads to a further increase in output and, potentially, credit in the non-tradable sector (Mian et al., 2020; Ozhan, 2020).[5]

**Does the sectoral allocation of credit matter for financial fragility?** An expansion of credit supply may result in a reallocation of credit toward firms in the non-tradable sector. But does the allocation of credit across sectors matter for whether the boom increases financial fragility?

The same factors that lead non-tradable sector firms to disproportionately benefit from an expansion in credit can also explain why such credit booms increase financial fragility and are more likely to end in a bust. More severe financing frictions in the non-tradable sector imply a greater sensitivity to a reversal in credit supply following a negative real or financial shock. Reliance on lending secured by real estate allows non-tradable sector firms to lever up during the boom, but also exposes

[4]See, for example, Tornell and Westermann (2002), Schneider and Tornell (2004), Reis (2013), Kalantzis (2015), Bleck and Liu (2018), Brunnermeier and Reis (2019), and Ozhan (2020).

[5]Ozhan (2020) refers to the financing constraint and demand mechanisms as the "banking" and "trade" channels of sectoral reallocation. Mian and Sufi (2014) and Mian et al. (2020) use a narrower definition of the non-tradable sector (restaurant and retail sectors) to capture the demand (or "trade") channel. A distinct prediction for the relevance of financial frictions, which we test below, is that non-tradable sector *leverage* (e.g., credit-to-output) rises during credit expansions and predicts subsequent output slowdowns.

them to tightening borrowing constraints and the possibility of fire sales in the bust (Kiyotaki and Moore, 1997).[6] Furthermore, firms in the non-tradable sector are often less productive, so lending to the non-tradable sector can shift resources to less productive firms that are more likely to default, as in the models of Reis (2013), Benigno and Fornaro (2014), and Bleck and Liu (2018). The higher fragility of non-tradable sector firms can lead to large-scale defaults that cause a banking crisis, depressing credit supply and output. If borrowers and lenders do not fully anticipate the downside risks during non-tradable credit booms, this can lead to disappointed expectations following an increase in defaults, as in behavioral models of credit cycles (Bordalo et al., 2018; Maxted, 2019).

**Table 3:** Comparing Non-Tradable and Tradable Sector Characteristics

| | Tradable/Non-tradable | | | Key industries | | |
|---|---|---|---|---|---|---|
| Country | T | NT | NT - T | Manuf. | Constr./RE | Food, Accomm. |
| 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 growth | 5.03 | 2.65 | -2.38 | 4.82 | 2.52 | 2.74 |
| Total factor productivity growth | 2.02 | 0.51 | -1.51 | 2.19 | -0.20 | 1.07 |

Notes: This table compares sectoral characteristics on non-tradable and tradable industries. *Small firm share* is defined based on the OECD Structural and Demographic Business Statistics, which covers 43 countries. For each sector, we compute the share of active businesses with less than 10 employees. *Mortgage share* is the share of loans secured on real estate relative to all outstanding loans based on data from five countries: Denmark, Latvia, Switzerland, Taiwan, and the United States. 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 Republic 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. *Labor productivity growth* is defined as the average yearly percentage growth in value added per engaged person in 2005 PPP USD, calculated based on data from EU KLEMS, WIOD, and OECD STAN, as well as data on sectoral relative prices from GGDC. The estimates are based on data from 39 countries. *Total factor productivity growth* is from EU KLEMS and is based on data from 18 countries.

## 3.2 Productivity-enhancing Credit Hypothesis

**Productivity and credit** Credit growth could also reflect higher anticipated productivity and output growth. In basic permanent income hypothesis models, households and firms demand more credit to finance consumption and investment in response to higher expected future income or productivity, so expansions in credit should be associated with stronger future growth (e.g., Aguiar and

[6] A related form of financial fragility due to high leverage and falling asset prices arises from currency mismatch through foreign currency debt in the non-tradable sector, especially in emerging markets (Mendoza, 2002; Schneider and Tornell, 2004; Kalantzis, 2015). However, the empirical patterns we document below are broadly similar in advanced and emerging economies, suggesting that foreign currency debt is not the only channel that can lead to financial fragility.

Gopinath, 2007; Arezki et al., 2016). In Coimbra and Rey (2017), a positive productivity shock leads to an increase in credit without endangering financial stability. In their model, "productivity driven leverage booms are not a concern for financial stability in the same way that credit supply driven ones are."

Credit growth could also drive sustained output growth. One example is a financial reform that increases the ability of the financial sector to channel resources to productive but constrained firms. The finance and growth literature treats credit depth as a marker of financial development, so rising credit could contribute to stronger long-run growth (Levine, 2005).[7]

**Does the sectoral allocation of credit matter for growth?** Productivity-enhancing credit growth could occur in all sectors, but it may be more likely when credit is financing the tradable sector, especially manufacturing. This is because manufacturing has a high level of productivity and has seen high productivity growth. Table 3 shows that annual labor productivity growth has been over 2 percentage points higher in the tradable compared to the non-tradable sector. Growth in TFP has been 1.5 percentage points higher in the tradable relative to the non-tradable sector. Moving resources to manufacturing may have a positive effect on aggregate growth rates, making manufacturing an "engine of growth" (Rodrik, 2012, 2016). Tradable sectors are more likely to learn about foreign knowledge through trade and foreign competition, and productivity gains in the tradable sector may be associated with positive spillovers to other firms in the economy (e.g., Benigno and Fornaro, 2014). The tradable sector also accounts for a disproportionate share of investments in innovation, which can contribute to long-run growth (Benigno et al., 2020). Lending growth biased toward tradables may thus capture times of strong subsequent productivity and output growth without an elevated risk of a financial crisis.

# 4 The Allocation of Credit During Credit Booms

In this section, we examine the dynamics of credit growth across sectors during credit booms. We first discuss several prominent case studies and then turn to more systematic evidence.

## 4.1 Case Studies

To motivate our empirical analysis and showcase our novel credit data, we begin by investigating two case studies of prominent credit booms.[8] The first is the case of Greece, Spain, and Portugal in the

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

[8] Appendix B provides additional case study evidence.

run-up to the Eurozone Crisis. The peripheral countries of the Eurozone experienced a major boom-bust cycle over the period 2000-2012. The creation of the European Monetary Union eliminated currency risk, which led to a large reduction in country spreads and large capital flows from core to peripheral economies (Baldwin and Giavazzi, 2015). These capital inflows financed rapid loan growth.

Which sectors of the economy were financed by this credit expansion? Panels (a) through (c) in Figure 3 reveal a large increase in lending to real estate firms, construction firms, and households. In relative terms, lending to the real estate sector grew the fastest in Portugal and Spain, while the absolute increase in debt was largest for the household sector in all three countries. 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 tradable 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). The Global Financial Crisis of 2008 led to a reversal of inflows, a sharp contraction in credit, falling asset prices, severe recessions, and banking crises.

The second case is that of Japan in the 1980s. 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 and loose monetary policy (Cargill, 2000). The boom was characterized by surging stock and urban real estate prices, which reinforced speculative investment in housing by real estate finance companies (Ueda, 2000).

Panel (d) in Figure 3 shows that the Japanese credit boom was associated with significant credit reallocation across sectors. Real estate and household credit increased by over 50 percent between 1985 and 1990. Credit to the accommodation and food service sectors also boomed. In contrast, manufacturing credit declined during this period.

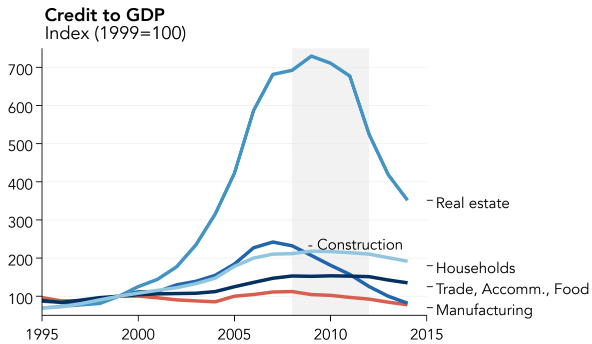
## 4.2 Credit Booms and Credit Allocation: Systematic Evidence

We next turn to a more systematic investigation. We start by defining major credit booms as periods when private credit-to-GDP expands rapidly relative to its previous trend. To operationalize this definition, we first detrend total private credit-to-GDP using the Hamilton (2018) filter with a horizon of four years. Then, we identify credit booms as the first year when detrended total credit-to-GDP exceeds its country-specific standard deviation.[9] This captures periods when credit is particularly high relative to a slow-moving trend. With this procedure, we obtain 113 credit boom episodes in our sample.

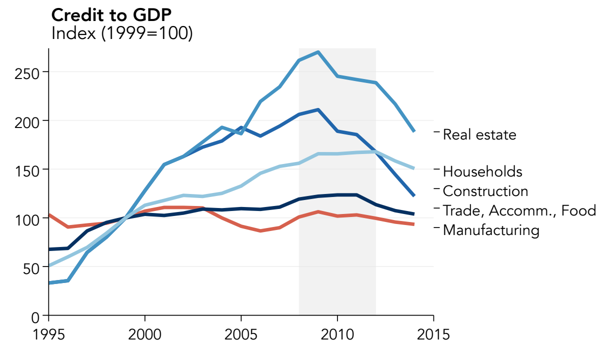
[9]The results are similar using an HP-filter or identifying credit booms as periods when the three-year expansion in credit-to-GDP is in its top quintile.

**Figure 3:** Case Studies: The Eurozone and Japanese Crises

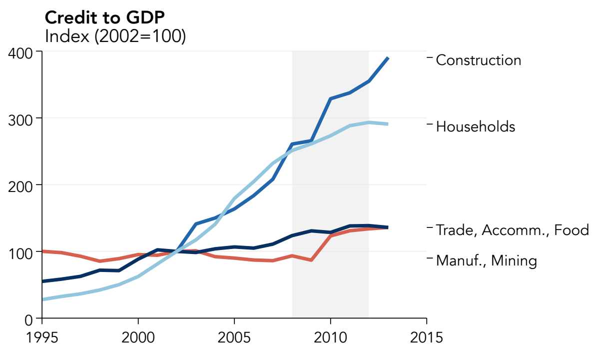
**(a)** Eurozone Crisis: Spain



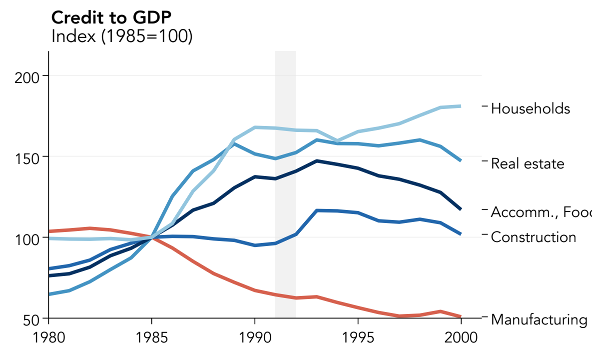

**(b)** Eurozone Crisis: Portugal




**(c)** Eurozone Crisis: Greece




**(d)** Japanese Financial Crisis




Notes: Panels (a)-(c) plot the ratio of sectoral credit-to-GDP for construction (ISIC Rev. 4 section F), real estate (L), trade/accommodation/food (G + I), manufacturing (C), and households in Spain, Portugal, and Greece around the time of the Global Financial Crisis and Eurozone crisis. Values for Spain and Portugal are indexed to 100 in 1999 (the year the euro was introduced), while Greece is indexed to 100 in 2002, as construction credit data only start in that year. Panel (d) plots the ratio of sectoral credit-to-GDP for construction (ISIC Rev. 4 section F), real estate (L), trade/accommodation/food (G + I), manufacturing (C), and households around the Japanese banking crisis of the early 1990s. The areas shaded in gray mark years the countries were in a systemic banking crisis as defined by Laeven and Valencia (2018).

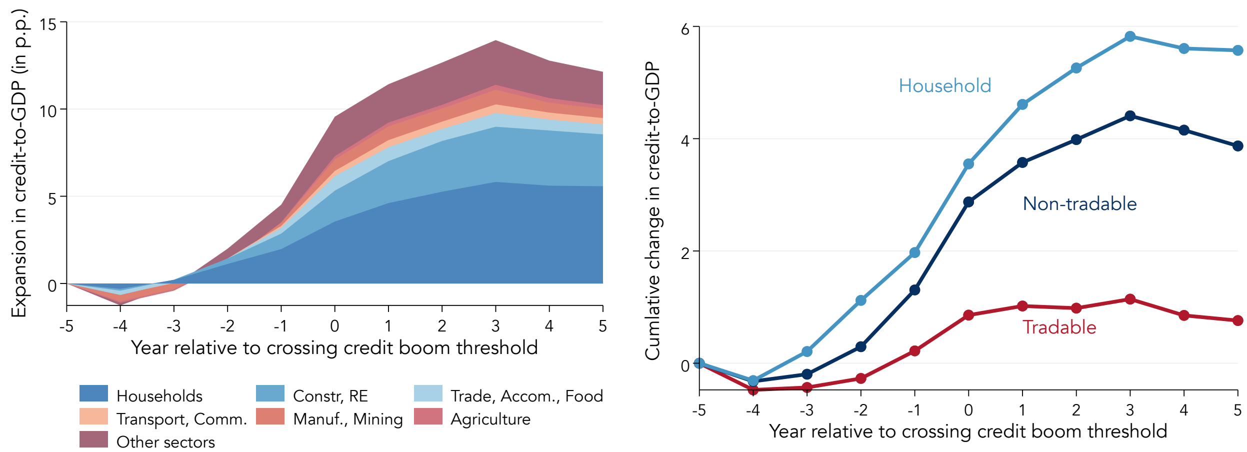
Which sectors account for the increase in private credit during credit booms? Figure 4 presents an event study of the average cumulative increase in credit-to-GDP during major booms and breaks this down by sectors. Panel (a) plots the contribution of individual corporate sectors and the household sector to the total increase in private credit-to-GDP, while panel (b) reports the cumulative change for the non-tradable, tradable, and household sectors. Event time $t = 0$ refers to the year in which the boom starts. We de-mean the change in credit-to-GDP for each sector within each country to abstract from longer-term structural trends in sectoral credit documented in section 2.

Figure 4 shows substantial heterogeneity in the importance of different sectors for the credit expansion during credit booms. The largest increase in absolute terms is accounted for by household credit. This is followed by credit to construction and real estate and the trade, accommodation, and food services sectors. These sectors account for roughly 70% of the total increase in private credit.

Thus, credit booms are largely a story of lending to the real estate sector, other non-tradable sectors, and households. The outsized role played by construction and real estate, other non-tradables, and households also stands out in case studies of many prominent credit booms and crises (see Appendix B). Among tradable sectors, manufacturing and mining represent the largest increase relative to GDP, while the expansion in lending to agriculture is small.

**Figure 4:** The Allocation of Credit During Credit Booms

**(a)** Sectoral breakdown of aggregate credit expansion **(b)** Non-tradable, tradable, and household sectors




Notes: This figure plots an event study of the cumulative change in private credit-to-GDP around credit booms, broken down by sectors. Panel (a) presents the disaggregated industries, and panel (b) shows the non-tradable, tradable, and household sector aggregates. The credit boom events are defined as periods of large deviations from a Hamilton (2018) filter with a horizon of four years. The change in credit-to-GDP in each sector is demeaned at the country level to abstract from longer-term trends in credit over time within countries. "Other sectors" is a residual category that includes services not included in the remaining industries.

## 4.3 Which Characteristics Shape Credit Allocation During Booms?

Which characteristics shape the allocation of credit across corporate sectors during credit booms? We investigate this question by estimating versions of the following specification in a country-sector-year panel:

$$\Delta_3 \ln(d_{i,s,t}) = \alpha_i + \beta_1 \mathbf{Boom}_{i,t} + \beta_2(\mathbf{Boom}_{i,t} \times \text{High Characteristic}_s) + \epsilon_{i,s,t}, \tag{1}$$

where $\Delta_3 \ln(d_{i,s,t})$ is the three-year growth in credit-to-GDP in country $i$ and sector $s$, $\mathbf{Boom}_{i,t}$ is an indicator for when the credit boom is identified, and $\text{High Characteristic}_s$ is an indicator for a sector being above the median in non-tradability (the inverse of exports-to-value added), the share of small firms, or the reliance on real estate collateral. We estimate this for the five corporate sectors for which we have a broad and consistent panel. We use the percentage growth in credit to capture a sector's sensitivity to a boom; this ensures that the reallocation documented in Figure 4 is not solely the product of differences in sectoral size.

Table 4 presents the estimates of equation (1). Credit booms are associated with 23% higher three-year sectoral credit growth compared to other periods. However, there is important heterogeneity across sectors. During credit booms, the three-year growth rate in credit is 6.4% higher in the non-tradable sector, 7.3% higher in sectors with a high share of small firms, and 6.1% higher in sectors with a high mortgage share.

The estimates in Table 4 are robust to the inclusion of country-year and country-industry fixed effects. Country-year fixed effects absorb aggregate shocks to countries and can be viewed as a "difference-in-differences" estimate of the reallocation of credit toward more constrained sectors during credit booms. Country-industry fixed effects absorb country-specific trends in sectoral credit growth.

In sum, credit booms feature a large reallocation of credit toward the non-tradable sector, and, related to this, industries that are more financially constrained and exposed to collateral feedbacks. Given that financially constrained firms and those relying on real estate collateral are particularly sensitive to a relaxation in financing conditions, this points to an important role for credit supply expansion during credit booms. These patterns are in line with the predictions of open-economy models of credit cycles discussed in section 3.

# 5 Credit Allocation and Business Cycles

Does the sectoral allocation of credit matter for whether a credit boom ends in a subsequent bust? Existing studies show that credit booms predict growth slowdowns and financial crises. The previous section documented that credit booms are associated with a reallocation of credit toward non-tradable sector firms and households. This section shows that these two facts are related: credit booms that feature reallocation toward non-tradable firms and households are more likely to end in growth slowdowns.

## 5.1 Growth Around Major Credit Boom Episodes

We start with the sample of credit boom events constructed in the previous section. We then divide these booms into two groups based on the sectoral allocation of credit. Specifically, we define "tradable-biased" and "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

**Table 4:** Credit Booms and Credit Reallocation

| | Dependent var.: $100 \times \Delta_3 \ln(D_{i,s,t}/GDP_{i,t})$ | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| $\text{Boom}_{i,t}$ | 23.0** | 18.8** | | 18.7** | | 19.9** | |
| | (1.73) | (2.57) | | (1.95) | | (2.42) | |
| $\text{Boom}_{i,t} \times \text{Non-tradable}_s$ | | 7.08* | 7.04** | | | | |
| | | (3.15) | (2.57) | | | | |
| $\text{Boom}_{i,t} \times \text{HighSmallFirmShare}_s$ | | | | 7.12** | 6.96** | | |
| | | | | (2.15) | (1.83) | | |
| $\text{Boom}_{i,t} \times \text{HighMortShare}_s$ | | | | | | 5.10* | 5.33* |
| | | | | | | (2.32) | (2.01) |
| Country FE | ✓ | ✓ | | ✓ | | ✓ | |
| Industry FE | ✓ | ✓ | | ✓ | | ✓ | |
| Country×Year | | | ✓ | | ✓ | | ✓ |
| Country×Industry FE | | | ✓ | | ✓ | | ✓ |
| Observations | 10,529 | 10,529 | 10,526 | 10,529 | 10,526 | 10,529 | 10,526 |
| # Countries | 76 | 76 | 76 | 76 | 76 | 76 | 76 |
| $R^2$ | 0.11 | 0.11 | 0.59 | 0.11 | 0.59 | 0.11 | 0.59 |

Notes: This table presents estimates of equation (1) in a country-sector-year panel, where the dependent variable is the percentage change in sectoral credit-to-GDP over the previous three years. There are five sectors: agriculture; manufacturing and mining; construction and real estate; wholesale and retail trade, accommodation, and food services; and transport and communication. Non-tradable industries are: construction and real estate; wholesale and retail trade, accommodation, and food services; and transport and communication. Non-tradable industries are classified based on the inverse of the exports to value-added ratio in the United States. Industries with a high small firm share are: agriculture; construction and real estate; and transport and communication. The small firm share is based on the share of active businesses in the United States with less than 10 employees from the OECD Structural and Demographic Business Statistics. High mortgage share industries are agriculture; construction and real estate; and wholesale and retail trade, accommodation, and food services. The industry mortgage share is based on the average mortgage share across five countries: Denmark, Latvia, Switzerland, Taiwan, and the U.S. See Table 3 for details on the industry characteristics. Driscoll and Kraay (1998) standard errors with six lags in parentheses. +, * and ** denote significance at the 10%, 5% and 1% level.

these booms as $\mathbf{Boom}_{it}^{T}$ and $\mathbf{Boom}_{it}^{NT}$, respectively. We group households and non-tradables to obtain two disjoint sets of events.[10]

As a concrete example, we identify a credit boom in Spain in 2004 and mark this as a non-tradable-biased boom based on the fact that $s_{it}^{T}$ declined by 6.6 percentage points from 1999 to 2004. In total, we identify 25 tradable-biased booms and 88 non-tradable-biased booms in our sample. The preponderance of non-tradable-biased booms is consistent with the systematic credit reallocation toward non-tradables documented in the previous section.

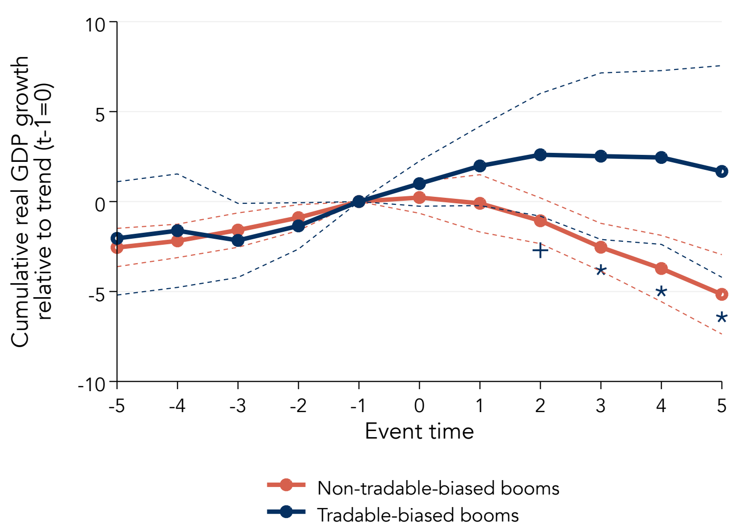
[10]Figure A.1 shows the results are similar when separating booms based on the non-tradable share, excluding household debt.

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

$$y_{t+h} - y_{t-1} = \alpha_i^h + \beta_T^h \mathbf{Boom}_{it}^T + \beta_{NT}^h \mathbf{Boom}_{it}^{NT} + \epsilon_{it+k}^h, \quad h = -5, ..., 5. \tag{2}$$

The inclusion of country fixed effects, $\alpha_i$, allows for different trend growth rates across countries. Figure 5 presents the sequence of estimates $\{\hat{\beta}_T^h, \hat{\beta}_{NT}^h\}$. During the boom phase from event time $t = -5$ to $t = 0$, cumulative real GDP increases faster than during normal times for both types of booms. Growth then diverges 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 are followed by major growth slowdowns.

**Figure 5:** Output Dynamics around Tradable and Non-tradable Biased Credit Booms




Notes: This figure plots results from estimating equation (2). 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. Dashed lines represent 90% confidence intervals based on Driscoll and Kraay (1998) standard errors with lag length $ceiling(1.5(3 + h))$. +, * and ** indicate that the difference between the estimates, $\hat{\beta}_T^h - \hat{\beta}_{NT}^h$, is statistically significant at the 10%, 5% and 1% level, respectively.

## 5.2 Growth Following Sectoral Credit Expansions

Do sectoral credit expansions have differential unconditional predictive content for business cycles? To answer this, we estimate the path of real GDP following innovations in sectoral credit-to-GDP using Jordà (2005) local projections. The specification we estimate is:

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

where $\Delta_h y_{it+h}$ is real GDP growth from year $t$ to $t+h$, $\alpha_i^h$ is a country fixed effect, and $\Delta d_{it}^k$ 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 evidence in the previous section that credit expansions and subsequent busts often play out over longer periods. Standard errors are computed using the methods in Driscoll and Kraay (1998) with a lag length of $ceiling(1.5 \cdot h)$, to allow for residual correlation within countries, as well residual correlation across countries in proximate years. We also report standard errors two-way clustered on country and year, which tend to be slightly more conservative in our application.

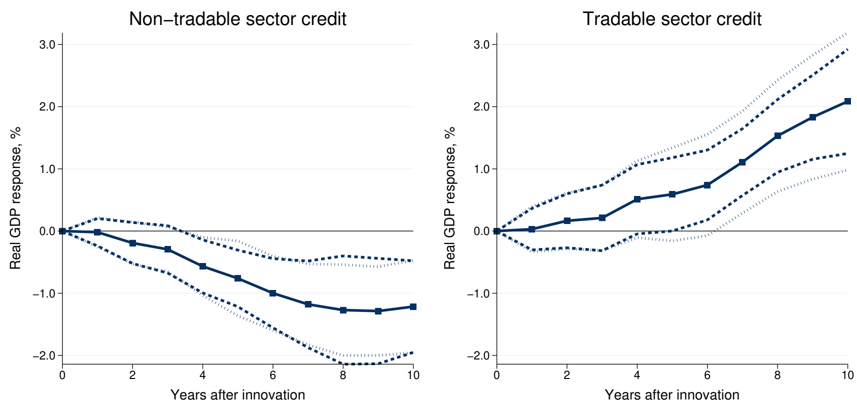
Figure 6 presents the impulse responses of real GDP to innovations in non-tradable sector credit, tradable sector credit, and household credit given by the estimated sequence of coefficients $\{\hat{\beta}_{h,0}^k\}$ for $k \in \{NT, T, HH\}$. Panel (a) presents results from an estimation that includes the tradable and non-tradable corporate sectors, and panel (b) presents results that add household credit to the specification. 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 growth in other sectors.

The left panel in Figure 6a reveals that an innovation 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 0.8% lower cumulated GDP growth over the next five years. In contrast, the right panel in Figure 6a shows that expansion in tradable sector credit is not associated with lower GDP growth. The predictive relation is positive in the medium-term after five years. A one percentage point innovation in tradable credit-to-GDP predicts 0.6% stronger cumulated growth over the next five years and 2.1% cumulated over ten years.

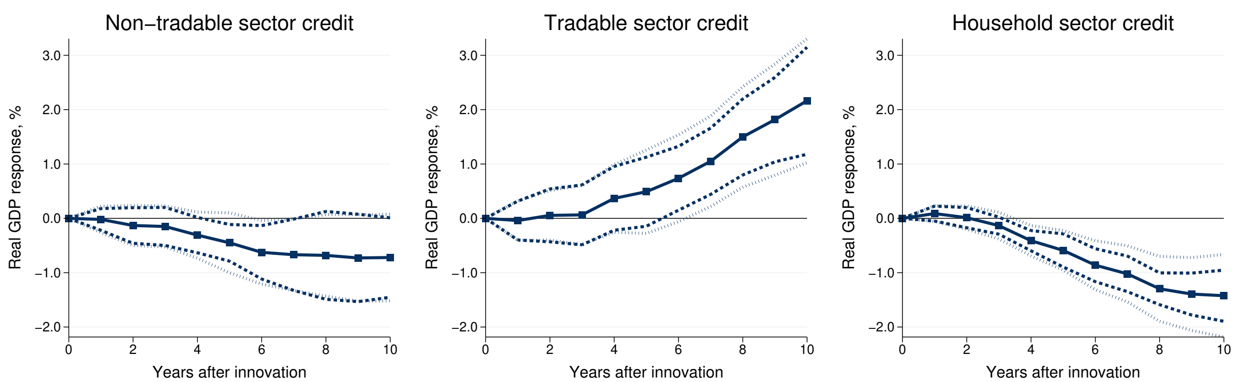
Panel (b) adds household credit to the estimation of equation (3). Household credit-to-GDP innovations are a strong predictor of lower GDP after three to four years. This confirms the result in Mian et al. (2017) with a sample that is more than twice as large. The patterns implied by the estimates on $\Delta d_{it}^{NT}$ and $\Delta d_{it}^{T}$ are similar to panel (a), but slightly more muted. As non-tradable and household credit are relatively strongly correlated (see Table 2), the estimates for non-tradable sector credit fall by about one-third 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 easy credit conditions and to collateral and demand feedbacks.

**Figure 6:** 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). The impulse responses are based on estimation of (3). Panel (a) includes non-tradable and tradable firm credit, while panel (b) presents results from the same specification that also includes household credit. Dashed lines represent 95% confidence intervals computed using Driscoll and Kraay (1998) standard errors, and dotted lines represent 95% confidence intervals from standard errors two-way clustered on country and year.

Table 5 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 $h = 0, ..., 5$:

$$\Delta_3 y_{i,t+h} = \alpha_i^h + \beta_h^{NT} \Delta_3 d_{it}^{NT} + \beta_h^T \Delta_3 d_{it}^T + \beta_h^{HH} \Delta_3 d_{it}^{HH} + \epsilon_{it+h}, \tag{4}$$

where the left-hand-side is the change in log real GDP from year $t - 3 + h$ to $t + h$, $\alpha_i^h$ is a country fixed effect, and $\Delta_3 d_{it}^k$ is the three-year change in sector $k$ credit-to-GDP. We use the three-year change in credit-to-GDP based on the observation from Figure 4 that credit expands rapidly over three to four years during credit booms (see also Mian et al., 2017).

Panel A in Table 5 presents the estimates of (4) for tradable and non-tradable credit, and Panel B adds household credit. Non-tradable credit expansions are positively correlated with GDP growth contemporaneously (column 1). In the medium run, however, the sign reverses (columns 4-6). 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 0.70 percentage points lower growth from $t$ to $t + 3$. The pattern for household credit is similar, though household credit has a weaker contemporaneous correlation with growth (column 1) and stronger negative predictability further into the future (columns 4-6). The estimate for the $h = 3$ horizon implies that a one standard deviation increase in $\Delta_3 d_{it}^{HH}$ is associated with 1.60 percentage points lower growth from $t$ to $t+3$. 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.

## 5.3 Additional Results and Robustness

This section presents additional results and robustness for the predictive relation between sectoral credit expansions and subsequent real economic outcomes.

**Sector size or sector leverage?** Credit booms often involve a reallocation of *real activity* from the tradable to the non-tradable sector.[11] Is slower growth after non-tradable credit expansions merely driven by an increase in the size of the non-tradable sector, or is it driven by an increase in sectoral *leverage*?

We use two approaches to address this question. First, Appendix Figure A.2a presents results from estimating (3) with additional controls for the share of the non-tradable and tradable sectors in value added, which hold constant any reallocation of output to the non-tradable sector (see also Appendix Table A.3). Second, Appendix Figure A.2b presents estimates of impulse responses from (3) where we replace sectoral credit-to-GDP with credit scaled by *sectoral value added*. Credit-to-

[11] See the discussion of Table 9 below, as well as Kalantzis (2015) and Mian et al. (2020). Kalantzis (2015) finds that an increase in non-tradable relative to tradable value added predicts "twin" crises (banking crisis and sudden stop).

**Table 5:** 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 | 0.087 | 0.11 | 0.19 | 0.30 | 0.38 | 0.39 |
| | (0.15) | (0.18) | (0.18) | (0.19) | (0.24) | (0.26) |
| Non-tradables | 0.46** | 0.15 | -0.18+ | -0.38** | -0.47** | -0.43** |
| | (0.088) | (0.11) | (0.10) | (0.11) | (0.14) | (0.16) |
| Observations | 1,890 | 1,820 | 1,748 | 1,677 | 1,605 | 1,533 |
| # Countries | 75 | 75 | 75 | 75 | 75 | 75 |
| $R^2$ | 0.05 | 0.01 | 0.01 | 0.02 | 0.03 | 0.03 |

**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 | 0.086 | 0.095 | 0.16 | 0.26 | 0.33 | 0.34 |
| | (0.14) | (0.17) | (0.17) | (0.17) | (0.20) | (0.23) |
| Non-tradables | 0.47** | 0.21+ | -0.045 | -0.19* | -0.23** | -0.19* |
| | (0.075) | (0.11) | (0.100) | (0.079) | (0.069) | (0.091) |
| Households | -0.0070 | -0.11 | -0.25** | -0.39** | -0.53** | -0.55** |
| | (0.090) | (0.088) | (0.075) | (0.071) | (0.10) | (0.13) |
| Observations | 1,890 | 1,820 | 1,748 | 1,677 | 1,605 | 1,533 |
| # Countries | 75 | 75 | 75 | 75 | 75 | 75 |
| $R^2$ | 0.05 | 0.01 | 0.02 | 0.05 | 0.08 | 0.08 |

Notes: This table presents the results from estimating (4). The dependent variable in column $h$ is the change in log real GDP (times 100) from year $t-3+h$ to $t+h$. The right-hand-side variables, $\Delta_3 d_{it}^k$, are the changes in the credit/GDP ratio (in percentage points) 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.

value-added captures an increase in sectoral leverage. Both approaches reveal that the increase in credit to the non-tradable sector, not just an increase in sectoral real activity, matters for predicting future growth slowdowns. This is consistent with models that emphasize differences in financing constraints across sectors.

**Sectoral allocation and credit risk** Recent studies find that increased lending to riskier firms in the economy is associated with a subsequent tightening in credit market conditions and macroeconomic downturns (Greenwood and Hanson, 2013; López-Salido et al., 2017). Are our sectoral credit expansion measures simply picking up variation captured by existing credit risk measures?

To address this question, we construct two proxies for credit risk based on the measures introduced by Greenwood and Hanson (2013) for the United States. The first measure, $ISS$, is the average riskiness of firms with high debt issuance minus the average riskiness of firms with low debt issuance, where riskiness is measured as either the expected default probability or leverage. We construct the $ISS$ measure for an international panel using firm-level data from Worldscope following Brandao-Marques et al. (2019). The second measure, $HYS$, is the share of bond issuance by high-yield firms, constructed by Kirti (2018).[12] These measures are only available for approximately one-third of the country-years in our baseline sample, highlighting the broad coverage of our sectoral credit database.

Table A.2 in the Appendix shows that these credit risk measures are positively correlated with credit expansion in all sectors. However, Appendix Table A.3 (rows 15-16) shows that controlling for firm credit risk has little impact on our results on GDP growth. These results imply that the allocation of credit to non-tradables and households contains distinct information over and above the credit risk measures. While credit risk moves hand in hand with credit expansions, it is the sectoral allocation of credit in particular that helps differentiate between booms that end badly and those that do not.

**Accounting for bond issuance** Because our credit data are based on the asset side of financial institutions, they primarily capture loans. In most cases, the data do not include bond market financing.[13] Appendix Table A.3 shows that our results are similar when accounting for bond issuance using two adjustments to specification (4). First, we add gross bond issuance to GDP during years $t-2, t-1$, and $t$ from SDC Platinum to the credit expansion variables (row 10). Second, we control for changes in outstanding international bonds relative to GDP (row 11). Both exercises indicate that bond issuance does not explain the differential importance of non-tradable versus tradable sector credit.

**Alternative sector classifications** To explore the role of underlying sector characteristics, we examine two alternative sectoral classifications: the share of small firms and the reliance on real estate collateral. As we discussed in section 3, these are two important characteristics motivating the non-tradable/tradable distinction. Figure A.4 and Table A.4 reveal that credit expansion to sectors that score high in the share of small firms and the mortgage share predict a boom-bust pattern in real

[12] Kirti (2018) has generously posted his international panel of high-yield share estimates on his webpage.

[13] Figure A.3 in the Appendix uses data on outstanding debt securities from the BIS to show that bonds make up around 14% of non-financial firm debt in advanced economies and around 9% in emerging economies. Thus, the importance of international bond issues has increased over time but remains a relatively small share of non-financial corporate debt.

GDP growth. These findings are similar to the pattern for lending booms to non-tradables, which is not surprising since credit expansions based on all three sector characteristics are strongly positively correlated (see Table A.5).

**Sectoral credit expansions and unemployment** We also ask whether sectoral credit expansions also differentially predict slack in the labor market, as measured by the unemployment rate. Appendix Figure A.5 presents local projection impulse responses from estimating (3) with the unemployment rate as the dependent variable. Non-tradable credit expansions have particularly strong predictive power for a future rise in the unemployment rate.

**Additional controls** Appendix Figure A.6 panel (a) presents results from adding a variety of additional controls to the local projection specification (3).[14] First we add the following macroeconomic controls: CPI inflation, short-term interest rates, and the change in the log US dollar exchange rate. These variables help account for changes in monetary policy, which Brunnermeier et al. (2019) show can drive both credit and output dynamics. The impulse responses with these controls are similar to the baseline results.

Second, in a separate test reported in Appendix Figure A.6a, we control for house price growth. Credit expansions, especially in the household, construction, and real estate sectors, are closely connected to house price dynamics, as we discuss further below. Here, we simply test whether credit contains information over and above changes in house prices. The impulse responses with house price controls are similar to the baseline findings, which suggests that credit, not just asset prices, is informative about future growth.

Third, Appendix Figure A.6a also shows that the results are similar when controlling for sectoral price inflation to account for relative price changes that could shift credit demand. Fourth, Figure A.6a reports estimates that include year fixed effects in order to account for common shocks and time trends. Given that credit cycles have an important global component (Miranda-Agrippino and Rey, 2021), the impulse responses are attenuated with year fixed effects, but the patterns remain similar.

**Subsamples** Appendix Figure A.6b estimates impulse responses from equation (3) 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 2008 Global Financial Crisis. Figure A.6b 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 somewhat stronger in advanced than emerging economies (see also Table A.3).

[14] Table A.3 presents a series of similar robustness exercises for the predictability of sectoral credit expansion over $t-3$ to $t$ for medium-run growth from $t+1$ to $t+4$ based on estimation of (4), corresponding to Table 5 column 5.

# 6 The Role of Financial Fragility

Why are some types of credit expansions associated with economic slowdowns, while others are not? One potential channel could be that risks to financial stability vary with what credit is financing in the economy. This section explores the role of financial crises, concentrated banking sector losses, house price reversals, over-optimistic beliefs, and sectoral imbalances in contributing to downturns in the aftermath of sectoral credit expansions.

## 6.1 Financial Crises

Models of financial crises with sectoral heterogeneity suggest that credit growth to non-tradables and households can increase financial fragility, as these sectors are more sensitive to expansions and reversals in credit supply and the price of assets used as collateral (Mendoza, 2002; Schneider and Tornell, 2004; Kalantzis, 2015; Coimbra and Rey, 2017; Ozhan, 2020). Because financial crises are associated with large costs in terms of permanently lost output (Reinhart and Rogoff, 2009a), this may create a link between sectoral credit expansions and future macroeconomic performance.

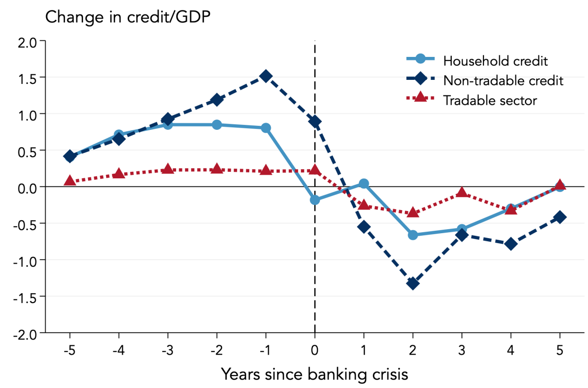
**Credit dynamics around financial crises** We start with a descriptive event-study analysis that examines how credit evolves across sectors around the start of financial crises. Figure 7 plots the average yearly change in sectoral credit-to-GDP values for five years before and after a systemic banking crisis, relative to non-crisis times. The sample includes 59 crises. Panel (a) shows that non-tradable firm and household credit tend to expand more rapidly than the sample average in the run-up to crises. Non-tradable sector credit expands more than twice as rapidly relative to GDP as tradable sector credit, surpassing the growth of household debt in the three years immediately before crises.

Panels (b) and (c) in Figure 7 decompose the broad firm sectors into five industry groups. The expansion in credit to agriculture, manufacturing/mining, and transport/communication is muted in the run-up to financial crises. In contrast, there is a strong expansion in credit to trade, accommodation, and food services and to construction and real estate. This evidence shows that the reallocation of credit during credit booms identified in section 4 also occurs in the run-up to financial crises. For individual case studies illustrating these patterns, see Appendix B.

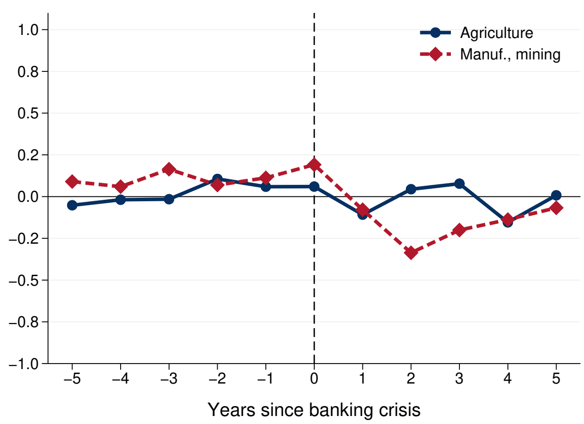
Once the crisis occurs, credit to the non-tradable sector declines more compared to the tradable sector. This may reflect that lending in non-tradable industries was "excessive" before the crisis, leading to debt overhang (Myers, 1977). It is also consistent with models where non-tradable sector firms are particularly exposed to contractions in credit supply and tightening collateral constraints during crises (Ozhan, 2020), as crises are known to disproportionately affect smaller firms and firms that are highly dependent on external financing (Kroszner et al., 2007).

**Figure 7:** Credit Dynamics around Systemic Banking Crises

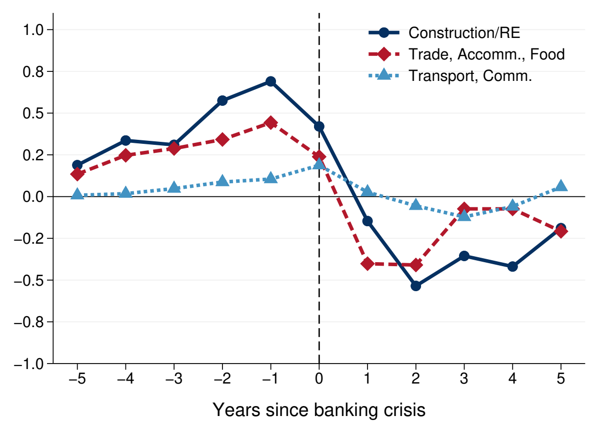
**(a)** Tradable vs. Non-Tradable Sector




**(b)** Tradable Sector Industries




**(c)** Non-Tradable Sector Industries




Notes: This figure plots average annual percentage point changes in sectoral credit-to-GDP ratios around 59 systemic banking crises in 90 countries between 1951 and 2009. The horizontal axis represents the number of years before and after a crisis. Crisis dates are from Baron et al. (2021), supplemented with dates from Laeven and Valencia (2018) for countries where they report no data.

**Sectoral credit expansion and financial crisis predictability** Next, we examine the predictability of financial crises based on expansions in credit to different sectors. We run predictive panel regressions of the following form:

$$Crisis_{it+1 \ to \ it+h} = \alpha_i^h + \sum_{k \in K} \beta_k^h \Delta_3 d_{it}^k + \epsilon_{it+h}, \tag{5}$$

where $Crisis_{it+1 \ to \ it+h}$ is an indicator variable that equals one if country $i$ experiences the start of a systemic banking crisis between year $t+1$ and $t+h$, $\alpha_i^h$ is a country fixed effect, and $\Delta_3 d_{it}^k$ the change in the credit-to-GDP ratio for sector $k$ from year $t-3$ to $t$. We thus estimate the predictive content of different credit expansions for cumulative crisis probabilities.

Table 6 reports the results from estimating equation (5). Panel A examines the predictive content

**Table 6:** Sectoral Credit Expansions and Financial Crises

**Panel A: Non-tradable, tradable, and household sector credit**

| | *Dependent variable: Crisis within...* | | | |
|---|---|---|---|---|
| $\Delta_3 d_{it}^k$ | 1 year | 2 years | 3 years | 4 years |
| Tradables | -0.004+ | -0.007* | -0.007+ | -0.004 |
| | (0.002) | (0.004) | (0.003) | (0.004) |
| Non-tradables | 0.006** | 0.010** | 0.011** | 0.008+ |
| | (0.002) | (0.002) | (0.003) | (0.004) |
| Household | 0.004* | 0.008* | 0.010* | 0.012** |
| | (0.002) | (0.003) | (0.004) | (0.004) |
| Observations | 1,557 | 1,557 | 1,557 | 1,557 |
| # Countries | 72 | 72 | 72 | 72 |
| # Crises | 47 | 47 | 47 | 47 |
| Mean Crisis Prob. | 0.03 | 0.06 | 0.09 | 0.12 |
| $\Delta$Prob. if 2 SD higher $\Delta_3 d_{it}^{NT}$ | 0.05 | 0.08 | 0.08 | 0.06 |
| AUC | 0.73 | 0.70 | 0.69 | 0.67 |
| SE of AUC | 0.04 | 0.03 | 0.03 | 0.02 |

**Panel B: Individual corporate sectors**

| | *Dependent variable: Crisis within...* | | | |
|---|---|---|---|---|
| $\Delta_3 d_{it}^k$ | 1 year | 2 years | 3 years | 4 years |
| Agriculture | -0.007 | -0.008 | -0.010 | -0.010 |
| | (0.004) | (0.009) | (0.016) | (0.017) |
| Manuf. and Mining | -0.003 | -0.008 | -0.007 | -0.003 |
| | (0.003) | (0.005) | (0.005) | (0.006) |
| Construction and RE | 0.008** | 0.012** | 0.011** | 0.008 |
| | (0.003) | (0.005) | (0.004) | (0.005) |
| Trade, Accomodation, Food | 0.009** | 0.020** | 0.026** | 0.028** |
| | (0.003) | (0.005) | (0.008) | (0.008) |
| Transport, Comm. | -0.008 | -0.018* | -0.032** | -0.044* |
| | (0.006) | (0.007) | (0.010) | (0.019) |
| Household | 0.004* | 0.007* | 0.010** | 0.012** |
| | (0.002) | (0.003) | (0.003) | (0.003) |
| Observations | 1,557 | 1,557 | 1,557 | 1,557 |
| # Countries | 72 | 72 | 72 | 72 |
| # Crises | 47 | 47 | 47 | 47 |
| Mean Crisis Prob. | 0.03 | 0.06 | 0.09 | 0.12 |
| AUC | 0.75 | 0.74 | 0.72 | 0.71 |
| SE of AUC | 0.04 | 0.03 | 0.02 | 0.02 |

Notes: This table presents the results from estimating (5). In Panel A, we differentiate between credit to the tradable, non-tradable, and household sectors. In Panel B, we use individual corporate sectors. Crisis dates are from Baron et al. (2021), supplemented with dates from Laeven and Valencia (2018) for countries not covered by Baron et al. (2021). Driscoll and Kraay (1998) standard errors with lag length $ceiling(1.5(3 + h))$ are in parentheses. +, * and ** denote significance at the 10%, 5% and 1% level.

of tradable, non-tradable, and household credit. Non-tradable and household credit expansions predict an elevated probability of a financial crisis at one to four-year horizons. In terms of magnitudes, a two standard deviation higher three-year change in non-tradable sector credit-to-GDP is associated with a 5% higher crisis probability over the next year. This is sizeable relative to the unconditional probability of a crisis of around 3%. For households, the magnitude is around 4%. In contrast, tradable sector credit expansion predicts a slightly *lower* probability of a subsequent financial crisis. The estimates on tradable sector credit are negative and mostly statistically significant at the 10% level.

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

We evaluate the performance of sectoral credit expansion in predicting crises through the lens of the Area Under the Curve (AUC) statistic. The AUC is the integral of a classifier's true positive rate against its false positive rate for varying classification thresholds (usually referred to as receiver operating characteristic curve, or ROC curve). The AUC statistic measures a model's ability to classify the data into crisis and non-crisis periods. An AUC of 0.5 is thought of as containing classification ability no better than a coin toss.

The in-sample AUC in column 1 is 0.73, consistent with the informativeness of credit expansion for predicting crises. In a rolling out-of-sample estimation, the corresponding AUC is 0.75 (unreported). These AUC values are similar or slightly higher than the AUCs from other studies using linear or logit models of crisis prediction. For example, in a longer sample with fewer countries, Schularick and Taylor (2012) report AUCs of 0.67 to 0.72. Using only total private credit rather than sectoral credit on the same sample as in Table 6 column 1, we obtain an AUC of 0.70, compared to 0.73 (panel A) or 0.75 (panel B) with sectoral credit measures.[15]

The increased likelihood of banking crises is central to understanding the slowdown in real GDP growth in the aftermath of credit expansions toward non-tradable sectors. To illustrate this, Appendix Figure A.7 presents local projection impulse responses of real GDP growth to sectoral credit expansions separately for periods with a banking crisis within the next three years and periods outside of banking crises. The real GDP response to a non-tradable credit expansion is close to zero and insignificant outside of banking crises, but large and significant for credit expansions that are followed by banking crises. As an interesting contrast, the aftermath of household credit expansions is as severe when excluding banking crises, consistent with theories emphasizing depressed household demand from household debt overhang (Mian et al., 2021).

[15] The AUCs are, however, considerably lower than those using more sophisticated machine learning predictions (e.g. Fouliard et al., 2021).

**Robustness of crisis predictability results** Appendix Table A.6 shows that the results on crisis predictability are robust to a wide array of different model specifications. These include: controlling for year fixed effects; estimating the probability of a crisis using nonlinear estimators; replacing three-year changes of credit-to-GDP ($\Delta_3 d_{it}^k$) with three lags of one-year changes ($\Delta d_{it}^k$); defining "credit booms" as periods where the three-year change in credit-to-GDP is at least two standard deviations above its mean or in the top quintile of its distribution; using only backward-looking information on what constitutes a "boom"; controlling for the shares of value added in GDP; using sectoral credit scaled by sectoral value added to capture increases in leverage; using alternative financial crisis chronologies from either Reinhart and Rogoff (2009b) or Laeven and Valencia (2018); and reestimating the model on the sample before 2000, the sample of advanced economies, and the sample of emerging markets. Furthermore, Table A.6 shows the results are robust to controlling for the $ISS$ and $HYS$ credit risk variables discussed in section 5.3, changes in cross-border loans, or the real effective exchange rate.

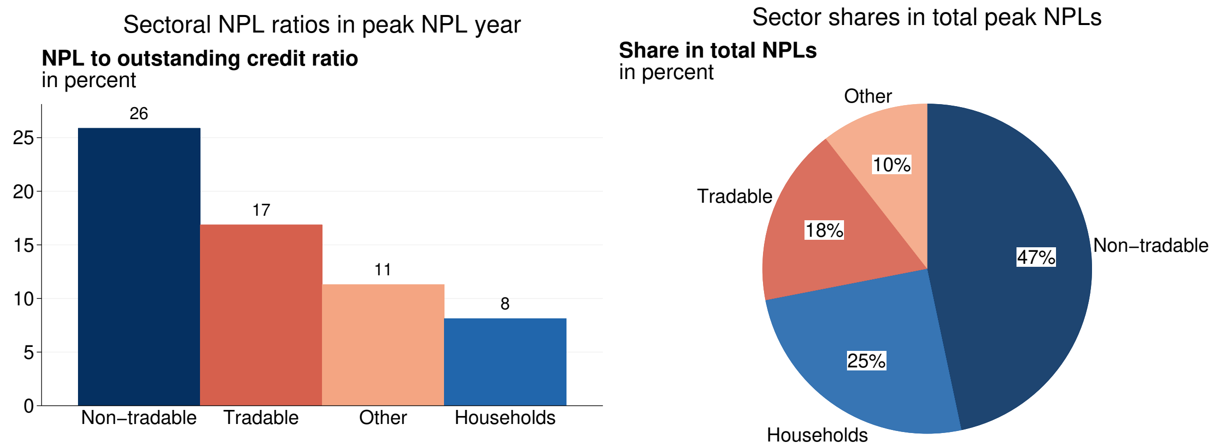
**Cross tabulation of non-tradable vs. tradable booms** As a further illustration of the heterogeneity in crisis predictability, Appendix Table A.7 reports the frequency of crises at the one to four year horizons across periods of low versus high growth in two credit variables: tradable sector credit versus non-tradable plus household credit. Periods of high credit growth are defined as country-years in the top quartile of the three-year change in sectoral credit-to-GDP. Across all horizons, moving from the bottom 75$^{\text{th}}$ percentile to the top 25$^{\text{th}}$ percentile of non-tradable and household credit is associated with economically large and statistically significant increases in the probability of a financial crisis. For example, at the 4-year horizon, the probability of a crisis goes from 7% to 23% when moving from low to high credit growth in non-tradables and households, even when tradable credit expansion is low. On the other hand, moving from low to high growth in tradable sector credit is associated with negligible increases or even a decrease in crisis probability.

## 6.2 Sectoral Defaults During Financial Crises

What ties sectoral credit expansions to a banking crisis that affects the economy as a whole? In Figure 8, we provide evidence that sectoral losses are important for understanding why the banking sector can end up in distress following credit expansion to non-tradable sectors. 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. We focus on ten financial crisis episodes for which we were able to identify sectoral NPL data (see the note in Figure 8 for the list of episodes).

The left panel in Figure 8 plots the NPL rates of different sectors, and the right panel shows a sector's share in total NPLs. Banking crises tend to be followed by default rates that are concentrated

**Figure 8:** Financial Crises and Sectoral Loan Losses: Evidence from Ten Banking Crises




Notes: This figure documents sectoral differences in loan losses and the composition of non-performing loans (NPLs) following ten systemic banking crises. The included crisis episodes (based on data availability) are Mexico (1994), Thailand (1997), Indonesia (1997), Turkey (2000), Argentina (2001), Italy (2008), Latvia (2008), Croatia (2008), Spain (2008), and Portugal (2008). Note that Laeven and Valencia (2018) do not classify Croatia as experiencing a crisis in 2008, but Croatia did experience a long-lasting recession following a period of rapid capital inflows and growth in corporate debt. The left panel shows the median ratio of NPLs to outstanding loans separately for the non-tradable, tradable, and household sectors in the peak NPL year. The right panel plots the median share of the individual sectors in total non-performing loans in the year where the total NPL ratio reached its peak (within ten years after each crisis).

among firms in the non-tradable sector. Moreover, loans to non-tradables and households account for nearly three-quarters of total bank NPLs post-crisis, as shown in the right panel. Losses on loans to the non-tradable sector account for nearly half of total NPLs in the aftermath of crises, while households account for a quarter of NPLs.

These results have three important implications. First, they link the pockets of rapid credit growth in the boom to banking sector distress in the crisis. This reinforces the view that banking crises are often the consequence of loan losses following rapid credit growth. Second, the evidence highlights that firms in the non-tradable sector are particularly fragile following credit expansions, resulting in banking sector losses and poor macroeconomic outcomes down the line. Third, the high rate of NPLs in the non-tradable sector compared to the household sector suggests that banking sector distress is important for explaining the slow growth after non-tradable sector credit booms, whereas other channels such as weak household demand matter more for household credit booms.

## 6.3 House Price Booms and Busts

Credit expansions often coincide with strong growth in real estate prices. This connection may be particularly strong for credit to non-tradables and households, as these sectors rely heavily on loans collateralized by real estate (see Table 3). By relaxing collateral constraints, increases in real estate prices can lead to increased borrowing by non-tradable sector firms and households. In addition, an increase credit supply can itself boost real estate prices (e.g., Greenwald and Guren, 2019). The aftermath of credit expansions, in turn, often coincides with real estate price declines, generating feedback loops between credit contraction and falling asset prices.

**Table 7:** Sectoral Credit Expansions and House Price Growth

| | Dependent var.: Real house price 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 | 0.70 | $0.99^{+}$ | $1.28^{*}$ | $1.16^{*}$ | $1.20^{**}$ | $0.91^{**}$ |
| | (0.48) | (0.53) | (0.57) | (0.52) | (0.42) | (0.25) |
| Non-tradables | $1.02^{**}$ | 0.23 | $-0.61^{+}$ | $-1.11^{**}$ | $-1.32^{**}$ | $-1.04^{**}$ |
| | (0.28) | (0.37) | (0.37) | (0.34) | (0.21) | (0.19) |
| Households | 0.41 | 0.075 | -0.27 | $-0.70^{**}$ | $-0.98^{**}$ | $-0.92^{**}$ |
| | (0.37) | (0.37) | (0.23) | (0.16) | (0.16) | (0.21) |
| Observations | 890 | 877 | 861 | 845 | 828 | 809 |
| # Countries | 42 | 42 | 42 | 42 | 42 | 42 |
| $R^2$ | 0.11 | 0.02 | 0.03 | 0.09 | 0.14 | 0.10 |

Notes: This table presents the results from estimating (4) with $\Delta_3 \ln(HPI)_{it+h}$ (the three-year change in log real house prices) as the dependent variable. All columns include country fixed effects. 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 7 investigates the dynamic relation between real estate price growth and sectoral credit expansions by estimating equation (4) with real house price growth as the dependent variable. Column 1 shows that house price growth over $t-3$ to $t$ is positively correlated with credit expansions over the same three-year period. The correlation is positive for all sectors and strongest for credit to the non-tradable sector.[16]

The subsequent columns in Table 7 reveal that non-tradable and household credit predict a sizeable fall in *future* house price growth. A one standard deviation increase in non-tradable credit expansion predicts 4.9 percentage points lower house price growth from $t$ to $t+3$. A one standard deviation increase in household credit expansion predicts 3.3 percentage points lower house price growth over the same period. In contrast, tradable credit expansions are associated with stronger future house price growth. This evidence is consistent with heightened financial fragility through falling real estate prices following expansions in non-tradable and household credit.

[16]Appendix Figure A.8 confirms these patterns also hold in a local projection framework by estimating (3) with log real house prices as the outcome variable.

## 6.4 Sectoral Credit Booms and GDP Growth Forecast Errors

Are credit expansions associated with overoptimistic expectations? Over-optimism and neglect of downside risk can help explain why credit expands rapidly during booms and thereby increases financial fragility (Minsky, 1977; Kindleberger, 1978; Bordalo et al., 2018). To test whether such neglected risks differ across credit expansions, Table 8 examines the relation between GDP growth forecast errors from the IMF's *World Economic Outlook* and credit growth in different sectors.

We first document that non-tradable and household credit expansions are preceded by positive growth surprises. Credit expansion from $t-3$ to $t$ is positively correlated with the forecast error of GDP growth from $t-6$ to $t-3$ based on the IMF's forecast in $t-6$ (column 1). Similarly, credit expansions are positively correlated with upside growth surprises from $t-3$ to $t$ (column 2). However, growth forecasts in the aftermath of rapid non-tradable and household credit expansions are systematically too optimistic. Column 3 reveals that credit expansion in the non-tradable and household sector predicts negative forecast errors of growth from $t$ to $t+3$. Forecasts are less overoptimistic following tradable credit expansions.

**Table 8:** Sectoral Credit Expansions and GDP Growth Forecast Errors

| | Dependent var.: GDP growth forecast errors | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $\Delta_3 d_{it}^k$ | $\Delta_3 y_{i,t-3} - F_{t-6}\Delta_3 y_{i,t-3}$ | $\Delta_3 y_{i,t} - F_{t-3}\Delta_3 y_{i,t}$ | $\Delta_3 y_{i,t+3} - F_t\Delta_3 y_{i,t+3}$ |
| Tradables | -0.016 | -0.13 | -0.15 |
| | (0.22) | (0.19) | (0.26) |
| Non-tradables | 0.50** | 0.14* | -0.52* |
| | (0.098) | (0.055) | (0.24) |
| Households | 0.22** | 0.22** | -0.27** |
| | (0.066) | (0.067) | (0.087) |
| Observations | 1,103 | 1,061 | 931 |
| # Countries | 73 | 73 | 74 |
| $R^2$ | 0.13 | 0.03 | 0.14 |

Notes: This table presents regressions of GDP growth forecast errors on the expansion in tradable, non-tradable, and household credit. $F_{t-k}\Delta_3 y_{t-k+3}$ is the forecast of real GDP growth from $t-k$ to $t-k+3$ made in year $t-k$. Columns 1, 2, and 3 are forecast errors based on forecasts made in year $t-6$, $t-3$, and $t$, respectively. The right-hand-side variables are the three-year change in sectoral credit-to-GDP from $t-3$ to $t$. Forecasts are from the IMF World Economic Outlook Fall Issue. 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.

## 6.5 Sectoral Reallocation, Real Appreciation, and Productivity Dynamics

Credit expansion to the non-tradable sector can lead to sectoral imbalances and real exchange rate overvaluation. This can increase financial fragility in the preseence of asymmetric financing frictions (e.g., Schneider and Tornell, 2004; Kalantzis, 2015). In models with sectoral heterogeneity in productivity dynamics (Reis, 2013; Benigno and Fornaro, 2014; Benigno et al., 2020), sectoral imbalances further lead to lower productivity. Low productivity growth is a direct source of low GDP growth and can also increase the risk of a financial crisis (Gorton and Ordoñez, 2019). In contrast, credit expansion to the tradable sector, often seen as an engine of growth, could finance productivity improvements.

**Table 9:** Sectoral Credit Expansions, Sectoral Real Activity, and the Real Exchange Rate

| $\Delta_3 d_{it}^k$ | (1)<br>$\Delta_3 \ln\left(\frac{Y^{NT}}{Y^T}\right)$ | (2)<br>$\Delta_3 \ln\left(\frac{E^{NT}}{E^T}\right)$ | (3)<br>$\Delta_3 \ln(RER)$ |
|---|---|---|---|
| Tradables | 0.29 | -0.30 | -0.32 |
| | (0.23) | (0.19) | (0.29) |
| Non-tradables | 0.70** | 0.43** | 0.43* |
| | (0.16) | (0.076) | (0.20) |
| Households | 0.41** | 0.27** | 0.31* |
| | (0.10) | (0.058) | (0.12) |
| Observations | 1,638 | 846 | 1,793 |
| # Countries | 69 | 36 | 75 |
| $R^2$ | 0.09 | 0.14 | 0.03 |

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 log of the non-tradable to tradable value added ratio (column 1), the log of the non-tradable to tradable employment ratio (column 2), and the log of the real effective exchange rate (column 3). The real effective exchange rate is defined such that an increase signifies real appreciation. 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 9 investigates how sectoral credit expansions correlate with the sectoral allocation of real activity and the real exchange rate. Columns 1 and 2 reveal that non-tradable credit expansions coincide with a reallocation of real activity toward the non-tradable sector, both in terms of output and employment. Credit expansion to the non-tradable sector also correlates with a real exchange rate appreciation (column 3).[17] While these patterns are not necessarily causal, they are consistent

[17] Household credit expansions also contribute to a reallocation of real activity to non-tradables and real exchange rate appreciation, consistent with a household demand channel of credit expansion (Mian et al., 2020).

**Table 10:** Sectoral Credit Expansions and Productivity

| **Panel A: Labor productivity** | | | | | | |
|---|---|---|---|---|---|---|
| | *Dependent variable*: Labor productivity growth over... | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\Delta_3 d^k_{it}$ | (t-3,t) | (t-2,t+1) | (t-1,t+2) | (t,t+3) | (t+1,t+4) | (t+2,t+5) |
| Tradables | $0.186^{+}$ | $0.173^{*}$ | $0.208^{*}$ | $0.219^{+}$ | 0.199 | 0.169 |
| | (0.093) | (0.081) | (0.086) | (0.113) | (0.150) | (0.179) |
| Non-tradables | 0.066 | -0.072 | $-0.168^{*}$ | $-0.147^{*}$ | -0.080 | -0.009 |
| | (0.142) | (0.125) | (0.082) | (0.067) | (0.054) | (0.059) |
| Households | $-0.147^{*}$ | $-0.183^{**}$ | $-0.226^{**}$ | $-0.261^{**}$ | $-0.312^{**}$ | $-0.308^{**}$ |
| | (0.061) | (0.061) | (0.057) | (0.067) | (0.076) | (0.068) |
| Observations | 1,451 | 1,451 | 1,451 | 1,451 | 1,451 | 1,451 |
| # Countries | 69 | 69 | 69 | 69 | 69 | 69 |
| $R^2$ | 0.01 | 0.01 | 0.03 | 0.03 | 0.03 | 0.03 |
| **Panel B: Total factor productivity** | | | | | | |
| | *Dependent variable: TFP growth over...* | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\Delta_3 d^k_{it}$ | (t-3,t) | (t-2,t+1) | (t-1,t+2) | (t,t+3) | (t+1,t+4) | (t+2,t+5) |
| Tradables | -0.079 | -0.182 | $-0.204^{*}$ | -0.016 | $0.193^{**}$ | $0.263^{**}$ |
| | (0.164) | (0.159) | (0.088) | (0.037) | (0.040) | (0.083) |
| Non-tradables | $-0.212^{*}$ | $-0.348^{**}$ | $-0.391^{**}$ | $-0.333^{**}$ | $-0.240^{**}$ | -0.144 |
| | (0.090) | (0.086) | (0.083) | (0.060) | (0.053) | (0.096) |
| Households | -0.073 | -0.113 | $-0.174^{*}$ | $-0.247^{**}$ | $-0.310^{**}$ | $-0.260^{**}$ |
| | (0.090) | (0.086) | (0.077) | (0.077) | (0.066) | (0.049) |
| Observations | 829 | 829 | 829 | 829 | 829 | 829 |
| # Countries | 67 | 67 | 67 | 67 | 67 | 67 |
| $R^2$ | 0.04 | 0.10 | 0.14 | 0.11 | 0.09 | 0.05 |

Notes: This table presents the results from estimating equation (4) with the three-year change in the log of either labor or total factor productivity. 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.

with the predictions of multi-sector open economy models. Real appreciation could arise from strong domestic demand that increases the scarcity of non-tradables (Mendoza, 2002; Schneider and Tornell, 2004; Kalantzis, 2015; Mian et al., 2020). It could also be driven by misallocation that leads to a higher cost per unit of produced non-tradable output (Reis, 2013). In contrast, credit expansion to the tradable sector is not associated with significant sectoral reallocation or real exchange rate appreciation.

Table 10 examines whether credit expansions to different sectors predict differences in future productivity. To do so, we replace the dependent variable in equation (4) with (i) changes in labor productivity, measured as the natural logarithm of output per worker, or (ii) changes in total factor productivity (TFP). The results in Table 10 show that credit expansions to the non-tradable sector 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 both the short and medium run.

# 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 about the relation between credit cycles and the macroeconomy unanswered. By introducing a new worldwide database on sectoral credit, this paper shows that heterogeneity in the allocation of credit across sectors—what credit is used for—plays an important role for understanding linkages between the financial sector and the real economy.

We document that credit expansions lead to disproportionate credit growth toward non-tradable sector firms and households. This pattern is in line with theories in which these sectors are more sensitive to relaxations in financing conditions and to feedbacks through collateral values and domestic demand. The sectoral allocation of credit, in turn, has considerable predictive power for the future path of GDP and the likelihood of systemic banking crises. Credit growth to non-tradable industries predicts a boom-bust pattern in output and elevated financial fragility. Credit to the tradable sector, on the other hand, is less prone to large booms and is associated with higher future productivity growth. Our evidence rejects the view that growth in private debt or leverage is uniformly associated with subsequent downturns. It suggests that previous work, which could not differentiate between different types of corporate credit, has missed an important margin of heterogeneity.

While we are cautious about making welfare claims based on our reduced-form evidence, these findings have interesting policy implications if taken at face value. An ongoing policy debate has weighed whether financial regulation, including macroprudential policy, should have a stronger focus on sectoral risks (Basel Commitee on Banking Supervision, 2019b,a; European Banking Authority, 2020). Our results 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 focused mainly on household debt and housing. We find that lending to certain corporate sectors also matters.

Some caveats are in order. First, the importance of non-tradable and household credit that we document here may be a more recent phenomenon. While we cover a large proportion of economic downturns and crises since the 1950s, things may have been different in the pre-World War II period.

Second, while we point to a number of potentially relevant sources of heterogeneity across industries, we cannot precisely identify the exact underlying mechanisms. Third, the predictive patterns we document in this paper are not necessarily causal. We hope that future work will find creative ways to identify shocks to credit in different sectors, which could then be linked to economic outcomes.

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# Credit Allocation and Macroeconomic Fluctuations

# **Online Appendix**

Karsten Müller* Emil Verner†

This appendix supplements the paper *Credit Allocation and Macroeconomic Fluctuations* by Karsten Müller and Emil Verner.

- Appendix A presents additional empirical results.
- Appendix B presents case studies of the sectoral dimension of major credit booms.
- Appendix C provides information on the methodology and coverage of the new database on sectoral credit.

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# A Additional Tables and Figures

**Table A.1:** Sample of Countries for Main Analysis

| Country | Years | Country | Years |
|---|---|---|---|
| Albania | 2001-2014 | Malawi | 1990-2014 |
| Argentina | 1952-2014 | Malaysia | 1971-2014 |
| Armenia | 1999-2014 | Mauritius | 1998-2014 |
| Australia | 1948-1983 | Mexico | 1994-2014 |
| Austria | 1963-2014 | Mongolia | 2002-2014 |
| Belgium | 1976-2014 | Morocco | 1993-2014 |
| Botswana | 1990-2014 | Nepal | 2002-2014 |
| Bulgaria | 2000-2014 | New Zealand | 1956-2014 |
| Chile | 1993-2014 | Nigeria | 1966-1992 |
| Colombia | 1998-2014 | Norway | 1946-2014 |
| Costa Rica | 1987-2014 | Oman | 1990-2014 |
| Czech Republic | 1992-2014 | Pakistan | 1982-2014 |
| Denmark | 1986-2014 | Panama | 2002-2014 |
| Dominican Republic | 1996-2014 | Peru | 1990-2014 |
| Estonia | 1995-2014 | Philippines | 1981-2014 |
| Finland | 1958-2014 | Portugal | 1973-2014 |
| Georgia | 2003-2014 | Russia | 2002-2014 |
| Germany | 1968-2014 | Saudi Arabia | 1998-2014 |
| Ghana | 2005-2014 | Sierra Leone | 2001-2014 |
| Greece | 2002-2014 | Singapore | 1980-2014 |
| Guatemala | 2003-2014 | Slovak Republic | 1992-2014 |
| Haiti | 1999-2014 | Slovenia | 1994-2014 |
| Honduras | 1968-2014 | South Africa | 1994-2013 |
| Hong Kong | 1965-2003 | South Korea | 1953-2014 |
| Hungary | 1995-2014 | Spain | 1992-2014 |
| India | 1972-2013 | Switzerland | 1997-2014 |
| Ireland | 1985-2014 | Taiwan | 1997-2014 |
| Israel | 1974-2014 | Tanzania | 2003-2014 |
| Italy | 1948-2014 | Thailand | 1970-2014 |
| Jamaica | 1977-2014 | Trinidad & Tobago | 1963-2014 |
| Japan | 1948-2014 | Tunisia | 1962-2014 |
| Jordan | 1964-2014 | Turkey | 2002-2014 |
| Kazakhstan | 1997-2014 | Uganda | 2004-2014 |
| Kenya | 1965-2014 | Ukraine | 2000-2014 |
| Kyrgyz Republic | 1996-2014 | United Arab Emirates | 1998-2014 |
| Latvia | 2000-2014 | United Kingdom | 1946-2014 |
| Lithuania | 1995-2014 | Venezuela | 2004-2014 |
| Macedonia | 2004-2014 | | |

Notes: This table reports the 75 countries and years covered in the main estimation sample. See Section 2.4 for a description of the criteria used to construct the sample used in the main analysis.

**Table A.2:** Correlation between Credit Risk Measures and Sectoral Credit Expansion

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| **Panel A: Correlation with $ISS_{i,t}^{EDF}$** | | | | | |
| | $\Delta_3 d_{it}^{T}$ | $\Delta_3 d_{it}^{NT}$ | $\Delta_3 d_{it}^{HH}$ | $\Delta_3$NT sh.$_{it}$ | $\Delta_3$NT+HH sh.$_{it}$ |
| $ISS_{it}^{EDF}$ (Worldscope) | 0.616** | 1.448** | 0.892** | 0.518+ | -0.025 |
| | (0.179) | (0.324) | (0.277) | (0.284) | (0.327) |
| Observations | 662 | 662 | 662 | 662 | 662 |
| # Countries | 40 | 40 | 40 | 40 | 40 |
| $R^2$ | 0.06 | 0.07 | 0.02 | 0.01 | 0.00 |
| **Panel B: Correlation with $ISS_{i,t}^{Leverage}$** | | | | | |
| | $\Delta_3 d_{it}^{T}$ | $\Delta_3 d_{it}^{NT}$ | $\Delta_3 d_{it}^{HH}$ | $\Delta_3$NT sh.$_{it}$ | $\Delta_3$NT+HH sh.$_{it}$ |
| $ISS_{it}^{Leverage}$ (Worldscope) | 0.839** | 2.143** | 0.943** | 0.595 | -0.071 |
| | (0.154) | (0.161) | (0.313) | (0.363) | (0.340) |
| Observations | 665 | 665 | 665 | 665 | 665 |
| # Countries | 40 | 40 | 40 | 40 | 40 |
| $R^2$ | 0.10 | 0.13 | 0.02 | 0.01 | 0.00 |
| **Panel C: Correlation with $HYS$ from Kirti (2021)** | | | | | |
| | $\Delta_3 d_{it}^{T}$ | $\Delta_3 d_{it}^{NT}$ | $\Delta_3 d_{it}^{HH}$ | $\Delta_3$NT sh.$_{it}$ | $\Delta_3$NT+HH sh.$_{it}$ |
| High yield share$_{it}$(Kirti) | -0.002 | -0.006 | -0.040 | -0.024 | -0.027* |
| | (0.010) | (0.032) | (0.041) | (0.023) | (0.012) |
| Observations | 516 | 516 | 516 | 516 | 516 |
| # Countries | 28 | 28 | 28 | 28 | 28 |
| $R^2$ | 0.00 | 0.00 | 0.01 | 0.01 | 0.02 |

Notes: This table presents the correlation between credit risk and sectoral credit expansion variables. The $ISS^{EDF}$ measure is defined as the average decile of expected default frequency (EDF) of firms in the top quintile of debt issuance minus the average decile of firms in the bottom quintile of debt issuance: $ISS_{i,t} = \frac{\sum_{f \in TopIssuers} Decile_{f,i,t}}{N_{it}^{TopIssuers}} - \frac{\sum_{f \in BottomIssuers} Decile_{f,i,t}}{N_{it}^{BottomIssuers}}$. $TopIssuers$ ($BottomIssuers$) refers to the top (bottom) quintile of the change in debt-to-assets in a country-year and $Decile$ refers to firm $f$'s decile in the distribution of EDF across public firms within a country-year. $ISS^{Leverage}$ is defined analogously using firm leverage as the measure of credit risk. The NT sh.$_{it}$ is defined as the share of non-tradable credit relative to non-tradable and tradable credit. The NT+HH sh.$_{it}$ is defined as the share of non-tradable and household credit relative to non-tradable, tradable, and household credit. 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 A.3:** Robustness – Sectoral Credit Expansion and Medium-Run GDP Growth

| | | | | | Tradables | | Non-tradables | | Households | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | N | # Countries | $R^2$ | $\beta_T$ | $[t]$ | $\beta_{NT}$ | $[t]$ | $\beta_{HH}$ | $[t]$ |
| (1) | Baseline | 1,605 | 75 | 0.08 | 0.33 | 1.62 | -0.23 | -3.29** | -0.53 | -5.06** |
| (2) | Lagged GDP growth control | 1,605 | 75 | 0.09 | 0.31 | 1.54 | -0.27 | -3.54** | -0.52 | -4.90** |
| (3) | Year fixed effects | 1,605 | 75 | 0.04 | 0.26 | 1.36 | -0.17 | -2.20* | -0.32 | -4.37** |
| (4) | Common time trend | 1,605 | 75 | 0.16 | 0.12 | 0.75 | -0.21 | -3.00** | -0.36 | -4.43** |
| (5) | Country-specific trends | 1,605 | 75 | 0.04 | -0.14 | -0.93 | -0.18 | -3.69** | -0.28 | -3.99** |
| (6) | Macroeconomic controls | 1,265 | 72 | 0.12 | 0.38 | 1.77+ | -0.25 | -3.05** | -0.49 | -5.51** |
| (7) | House price growth control | 734 | 37 | 0.14 | 0.41 | 1.72+ | -0.40 | -4.77** | -0.41 | -5.51** |
| (8) | Value added controls | 1,373 | 69 | 0.11 | 0.25 | 1.35 | -0.28 | -4.39** | -0.53 | -5.65** |
| (9) | Current account control | 1,374 | 73 | 0.08 | 0.30 | 1.41 | -0.24 | -2.51* | -0.48 | -5.34** |
| (10) | Add sectoral bond issuance | 838 | 46 | 0.12 | -0.01 | -0.29 | -0.12 | -2.53* | -0.47 | -7.16** |
| (11) | Bond issuance control | 1,100 | 61 | 0.14 | -0.04 | -0.30 | -0.21 | -3.57** | -0.46 | -5.58** |
| (12) | Pre-2000 only | 972 | 48 | 0.03 | 0.18 | 0.83 | -0.18 | -2.49* | -0.33 | -3.70** |
| (13) | Advanced economies | 938 | 35 | 0.13 | 0.17 | 0.73 | -0.30 | -4.37** | -0.55 | -4.84** |
| (14) | Emerging economies | 667 | 40 | 0.03 | 0.40 | 1.40 | 0.00 | 0.01 | -0.45 | -2.83** |
| (15) | Control for $ISS^{EDF}$ | 508 | 37 | 0.19 | -0.17 | -0.89 | -0.30 | -3.69** | -0.34 | -7.08** |
| (16) | Control for $HYS$ | 409 | 28 | 0.23 | -0.53 | -2.80** | -0.30 | -2.65* | -0.29 | -9.54** |
| (17) | Cross-border loan control | 1,217 | 75 | 0.10 | -0.01 | -0.08 | -0.27 | -3.56** | -0.44 | -5.48** |
| (18) | Real exchange rate control | 1,508 | 75 | 0.09 | 0.19 | 0.95 | -0.21 | -2.50* | -0.49 | -4.95** |

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 $t+4$, $\alpha_i$ 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 (in percent) 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 5 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 $t$. Model (10) adjusts $d_{it}^T$ and $d_{it}^{NT}$ to include the cumulative sum of gross bond issuance in the tradable and non-tradable sector, based on data from SDC Platinum. Model (11) controls for the change in outstanding bonds issued in international markets relative to GDP from $t-3$ to $t$, based on BIS data on debt securities. Model (12) restricts the sample to years $t \leq 2000$. Models (13) and (14) restrict the sample to countries classified as high-income and low-income/middle-income by the World Bank in 2019, respectively. Model (15) controls for the $ISS^{EDF}$ issuer quality measure of Greenwood and Hanson (2013), constructed using Worldscope data. Model (16) controls for the high yield share measure of Greenwood and Hanson (2013) constructed by Kirti (2018). Model (17) controls for the 3-year change in cross-border loans/GDP based on BIS data. Model (18) controls for the three-year change in the log of the real effective exchange rate.

**Table A.4:** Sectoral Credit Expansions and Growth: Alternative Sector Classifications

**Panel A: High vs low mortgage share industries**

| | 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) |
| High mortgage share | 0.42** | 0.15 | -0.16 | -0.34* | -0.41* | -0.35 |
| | (0.13) | (0.15) | (0.15) | (0.14) | (0.19) | (0.22) |
| Low mortgage share | 0.20 | 0.10 | 0.11 | 0.20 | 0.23 | 0.23 |
| | (0.19) | (0.21) | (0.18) | (0.20) | (0.28) | (0.33) |
| $R^2$ | 0.05 | 0.01 | 0.00 | 0.02 | 0.02 | 0.02 |

**Panel B: High vs low small firm share industries**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| High small firm share | 0.27* | -0.073 | -0.37* | -0.59* | -0.67* | -0.62* |
| | (0.11) | (0.13) | (0.15) | (0.24) | (0.30) | (0.29) |
| Low small firm share | 0.41** | 0.33** | 0.23 | 0.27 | 0.28 | 0.29 |
| | (0.083) | (0.094) | (0.14) | (0.22) | (0.28) | (0.27) |
| $R^2$ | 0.05 | 0.01 | 0.01 | 0.03 | 0.04 | 0.03 |

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

$$\Delta_3 y_{it+h} = \alpha_i^h + \beta_h^{High} \Delta_3 d_{it}^{High} + \beta_h^{Low} \Delta_3 d_{it}^{Low} + u_{it+h}, \quad h = 0, ..., 5$$

where $\Delta_3 y_{it+h}$ is the change in log real GDP (times 100) from $t - 3 + h$ to $t + h$, $\alpha_i^h$ is a country fixed effect, and $\Delta_3 d_{it}^{Low}$ and $\Delta_3 d_{it}^{High}$ are the changes in the credit/GDP ratio (in percentage points) for a specific sector grouping 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 A.5:** Correlation of Credit Expansion Variables Based on Industry Traits

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| $\Delta_3 d_{it}^k$ | | | | | | | |
| (1) Non-tradables | 1 | | | | | | |
| (2) High mortgage share | 0.95 | 1 | | | | | |
| (3) High small firm share | 0.90 | 0.88 | 1 | | | | |
| (4) Tradables | 0.51 | 0.57 | 0.50 | 1 | | | |
| (5) Low mortgage share | 0.62 | 0.55 | 0.56 | 0.90 | 1 | | |
| (6) Low small firm share | 0.73 | 0.73 | 0.52 | 0.85 | 0.86 | 1 | |
| (7) Household | 0.52 | 0.53 | 0.53 | 0.18 | 0.19 | 0.26 | 1 |

Notes: This table presents the correlation matrix of various credit expansion variables. All variables are three-year changes in credit, scaled by GDP. "High" and "low" refers to firm credit split by sectors, depending on whether they are above or below the median of a given characteristic. The table shows that the expansion in credit to non-tradable sectors is strongly positively correlated with credit expansion to sectors that have a high mortgage share and high small firm share. See the data description in section 2 for the exact definitions of sector splits.

**Table A.6:** Sectoral Credit Expansions and Financial Crises – Robustness

| | | N | # Countries | # Crises | AUC | Tradables | | Non-tradables | | Households | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | $\beta$ | $[t]$ | $\beta$ | $[t]$ | $\beta$ | $[t]$ |
| (1) | Baseline (LPM, country FE) | 1,557 | 72 | 47 | 0.73 | -0.004 | -1.82+ | 0.006 | 3.85** | 0.004 | 2.03* |
| (2) | LPM, country + year FE | 1,557 | 72 | 47 | 0.73 | -0.002 | -1.20 | 0.004 | 2.34* | 0.004 | 3.67** |
| (3) | Logit | 1,557 | 72 | 47 | 0.72 | -0.001 | -0.60 | 0.004 | 2.70** | 0.002 | 2.60** |
| (4) | Logit, country FE | 1,026 | 37 | 47 | 0.72 | -0.028 | -1.32 | 0.042 | 2.74** | 0.024 | 2.56* |
| (5) | Boom (>= Mean + 2 $\times$ SD) | 1,557 | 72 | 47 | 0.62 | 0.017 | 0.49 | 0.098 | 2.87** | 0.063 | 1.68+ |
| (6) | Boom (>= 80th percentile) | 1,557 | 72 | 47 | 0.73 | -0.013 | -0.91 | 0.054 | 2.93** | 0.052 | 2.12* |
| (7) | Boom (>= 80th percentile, OOS) | 1,557 | 72 | 47 | 0.71 | -0.014 | -0.88 | 0.038 | 2.64* | 0.035 | 2.42* |
| (8) | RR crisis dates | 1,112 | 44 | 39 | 0.71 | -0.003 | -0.81 | 0.007 | 2.80** | 0.003 | 1.32 |
| (9) | LV crisis dates only | 1,403 | 71 | 37 | 0.67 | -0.003 | -1.38 | 0.004 | 1.98+ | 0.003 | 0.99 |
| (10) | BVX crisis dates only | 1,015 | 36 | 38 | 0.75 | -0.002 | -0.97 | 0.007 | 3.72** | 0.004 | 2.37* |
| (11) | Pre-2000 only | 913 | 47 | 26 | 0.70 | -0.005 | -2.10* | 0.006 | 3.53** | 0.005 | 3.11** |
| (12) | Advanced economies | 897 | 32 | 27 | 0.74 | -0.003 | -1.45 | 0.005 | 2.85** | 0.004 | 2.14* |
| (13) | Emerging economies | 660 | 40 | 20 | 0.74 | -0.008 | -1.62 | 0.011 | 2.74** | 0.004 | 1.54 |
| (14) | Value added controls | 1,334 | 66 | 45 | 0.74 | -0.004 | -1.50 | 0.007 | 4.11** | 0.004 | 1.73+ |
| (15) | Credit/value added | 1,334 | 66 | 45 | 0.72 | -0.000 | -0.65 | 0.002 | 2.97** | 0.005 | 1.93+ |
| (16) | Control for $ISS^{EDF}$ | 504 | 36 | 22 | 0.76 | 0.003 | 0.76 | 0.006 | 2.68* | 0.002 | 0.84 |
| (17) | Control for $HYS$ | 409 | 28 | 20 | 0.69 | 0.001 | 0.23 | 0.006 | 1.91+ | 0.004 | 1.57 |
| (18) | Control for cross-border loan growth | 1,179 | 72 | 45 | 0.71 | -0.004 | -1.07 | 0.007 | 4.20** | 0.004 | 1.53 |
| (19) | Control for real exchange rate | 1,466 | 72 | 47 | 0.72 | -0.004 | -1.55 | 0.006 | 3.80** | 0.004 | 1.92+ |

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

$$Crisis_{it+1} = \alpha_i + \beta_1 \Delta_3 d_{it}^T + \beta_2 \Delta_3 d_{it}^{NT} + \beta_3 \Delta_3 d_{it}^{HH} + \epsilon_{it+3}$$

where $Crisis_{it+1}$ is a dummy variable that equals one for the start of a systemic banking crisis in country $i$ over the next year, $\alpha_i$ 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 as in the first column of Table 6, Panel A. Model (2) adds year FE to the model. Model (3) is a logit model with standard errors clustered by country. Model (4) reports results from a conditional/FE logit model. Model (5) 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 (6) creates a 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 (7) repeats the same exercise as in model (6) but only uses backward-looking information to construct booms. Models (8)-(10) use alternative systemic banking crisis dates from Reinhart and Rogoff (2009b), Laeven and Valencia (2018), and Baron et al. (2021), respectively; note that this results in very different samples. Model (11) restricts the sample to the years before 2000. 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. Model (14) controls for three-year changes in sectoral value added/GDP. Model (15) uses $d_{it}^T$ and $d_{it}^{NT}$ with credit scaled over sectoral value added instead of GDP. Model (16) controls for the $ISS^{EDF}$ issuer quality measure of Greenwood and Hanson (2013), constructed using Worldscope data. Model (17) controls for the high yield share measure of Greenwood and Hanson (2013) constructed by Kirti (2018). Model (18) controls for the 3-year change in cross-border loans/GDP based on BIS data. Model (19) controls for the three-year change in the log of the real effective exchange rate.

**Table A.7:** Financial Crisis Likelihood by Type of Credit Expansion

**Frequency of financial crisis within 1 year**

| *Non-tradable and household credit expansion* $(t-3,t)$ | *Tradable credit expansion* $(t-3,t)$ Bottom 75% | Top 25% |
|---|---|---|
| Bottom 75% | 0.02 | $0.00^{+}$ |
| Top 25% | 0.06 | $0.09^{*}$ |

**Frequency of financial crisis within 2 years**

| *Non-tradables and households* | *Tradables* Bottom 75% | Top 25% |
|---|---|---|
| Bottom 75% | 0.04 | 0.02 |
| Top 25% | $0.13^{+}$ | $0.14^{**}$ |

**Frequency of financial crisis within 3 years**

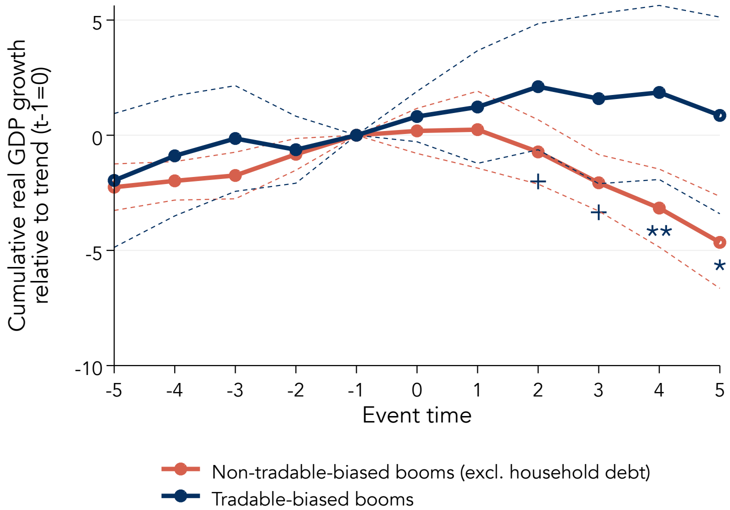
| *Non-tradables and households* | *Tradables* Bottom 75% | Top 25% |
|---|---|---|
| Bottom 75% | 0.05 | 0.06 |
| Top 25% | $0.19^{*}$ | $0.19^{**}$ |

**Frequency of financial crisis within 4 years**

| *Non-tradables and households* | *Tradables* Bottom 75% | Top 25% |
|---|---|---|
| Bottom 75% | 0.08 | 0.10 |
| Top 25% | $0.23^{*}$ | $0.24^{**}$ |

Notes: This table reports the frequency of financial crises following credit expansions and normal times across bins of sectoral credit expansion. Top 25% is defined as country-years when the three-year change in sectoral credit-to-GDP from $t-3$ to $t$ is above the $75^{\text{th}}$ percentile. The table groups together non-tradable and household credit expansion. The "Frequency of financial crisis within 1 year" in the top panel is computed as the probability of a crisis occurring in year $t+1$. The remaining panels report the probability of a crisis occurring between years $t+1$ and $t+h$, with $h=2,3,4$. +, * and ** indicate whether the mean in a cell is statistically significantly different from the top left cell in each panel (bottom 75% of credit expansion in both sectors) at the 10%, 5% and 1% level based on Driscoll and Kraay (1998) standard errors with lag length $ceiling(1.5(3+h))$.

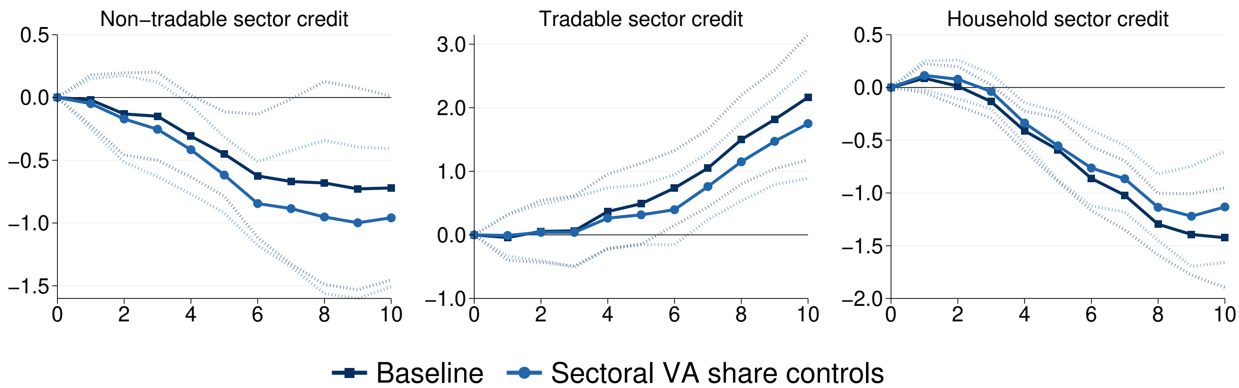
**Figure A.1:** Output Dynamics around Credit Boom Episodes: Non-tradable versus Tradable Biased Booms, Excluding Household Debt



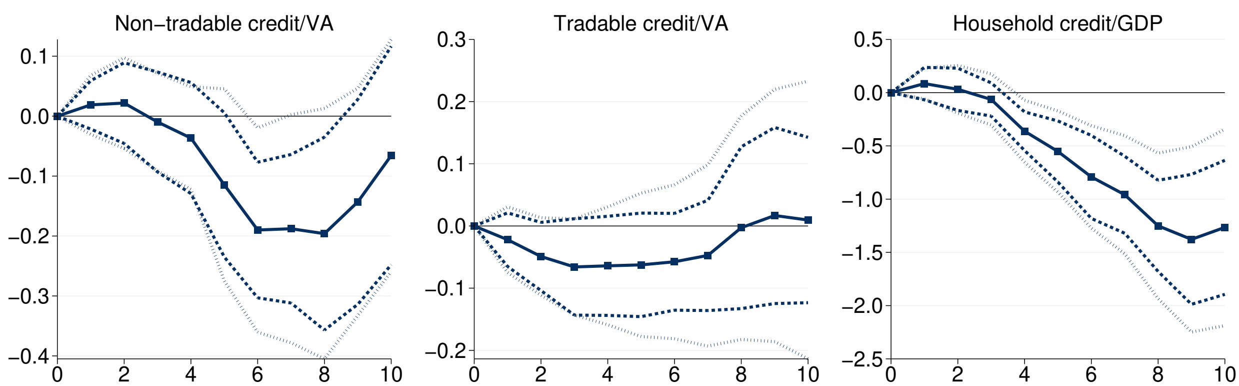

Notes: This figure is similar to Figure 5 but splits sectors by non-tradable vs. tradable, excluding household debt. Dashed lines represent 90% confidence intervals based on Driscoll and Kraay (1998) standard errors with lag length $ceiling(1.5(3+h))$. +, * and ** indicate that the difference between the estimates, $\hat{\beta}^h_T - \hat{\beta}^h_{NT}$, is statistically significant at the 10%, 5% and 1% level.

**Figure A.2:** Output Dynamics after Credit Expansions: Sector Size vs Sector Leverage

**(a)** Controlling for sectoral value added shares




**(b)** Corporate Sectoral Credit Scaled by Value Added



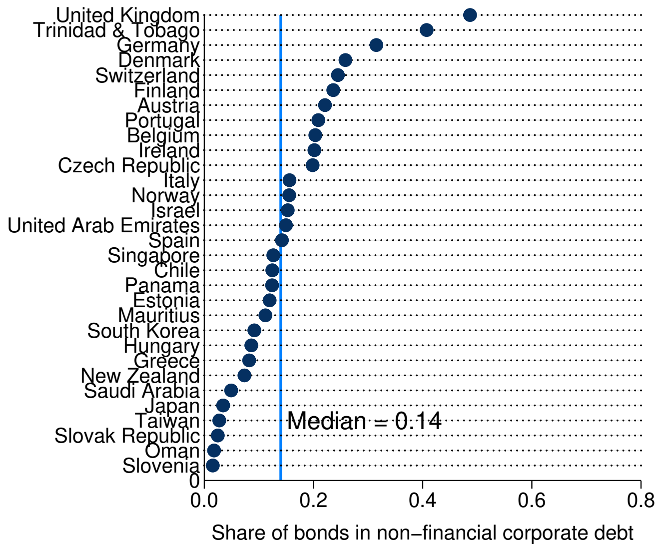

Notes: This figure presents two tests to disentangle the role of sectoral leverage from changes in sector size. Panel (a) presents estimates of (3) using credit variables scaled by GDP with additional controls for changes in the non-tradable and tradable value added shares. We include the same lags ($j = 0, ..., 5$) for the value added share controls. Panel (b) presents the impulse response of real GDP to an innovation in sectoral credit from the following local projection specification for $h = 1, ..., H$:

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

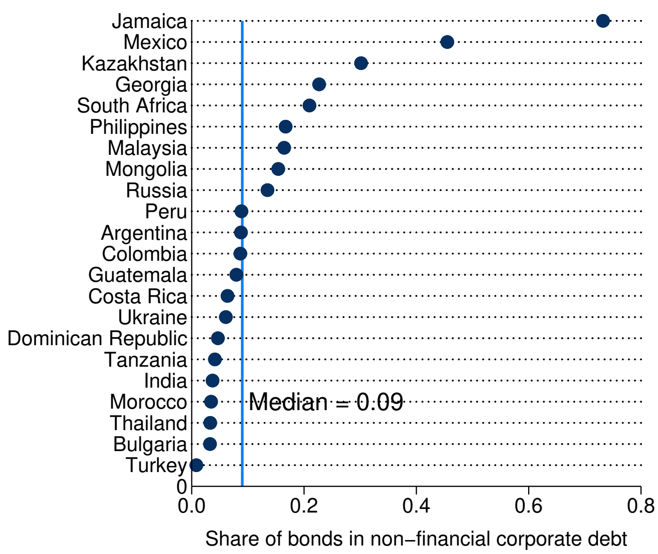
In contrast to our baseline results in Figure 6, credit in corporate sector $k$ is scaled by value added in that sector, i.e., $\tilde{d}_{it}^k = 100 \cdot \frac{D_{it}^k}{VA_{it}^k}$. We note that the number of observations in these regressions fall by approximately 15% because of missing sectoral value added data for some countries and time periods. Dashed lines represent 95% confidence intervals computed using Driscoll and Kraay (1998) standard errors, and dotted lines represent 95% confidence intervals from standard errors two-way clustered on country and year.

**Figure A.3:** Share of Bonds in Non-financial Corporate Debt (Average, 2010-2014)

**(a)** Advanced economies



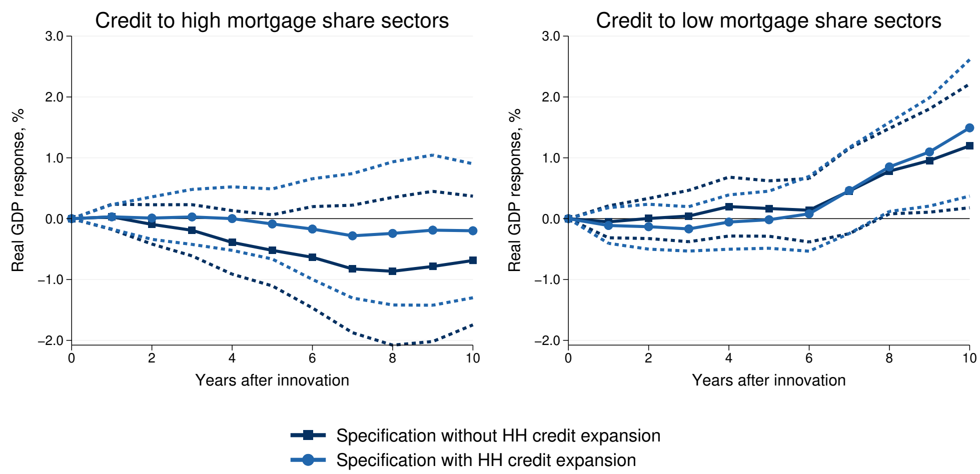

**(b)** Emerging economies



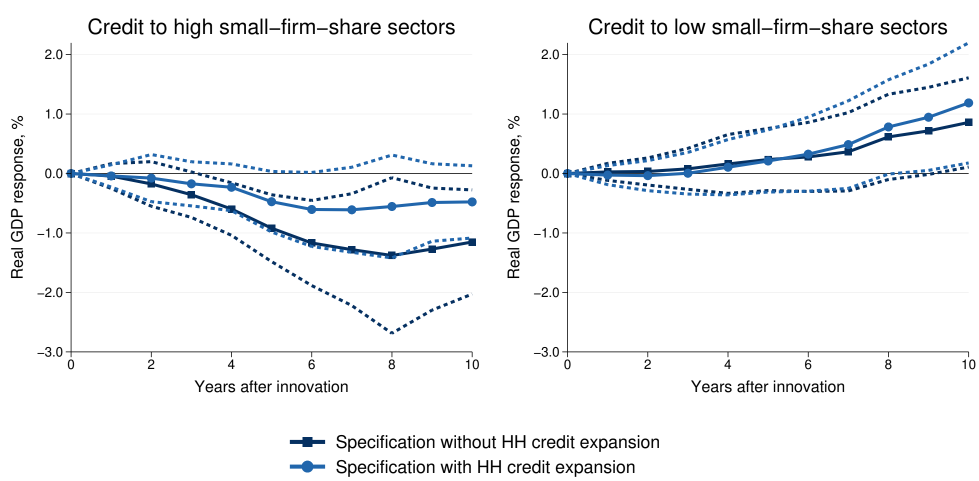

Sample: 31 advanced economies in Panel A and 22 emerging economies in Panel B.
Notes: We plot the average ratio of outstanding international debt securities of non-financial corporations to the sum of outstanding debt securities and outstanding credit to non-financial corporations for 2010-2014. Data on bonds is from the BIS Debt Securities dataset, data on credit to non-financial corporations from the data used in this paper.

**Figure A.4:** Output Dynamics after Credit Expansions: Alternative Sector Classifications

**(a)** High vs. low mortgage share sectors

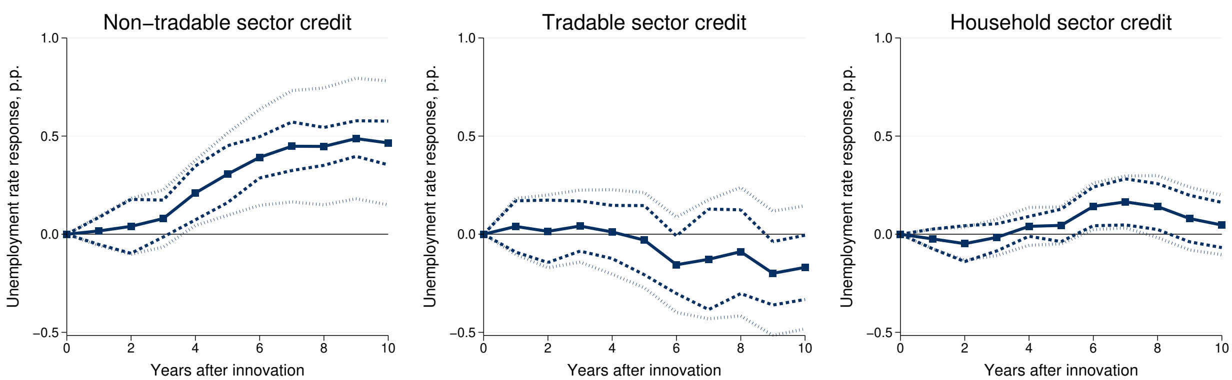



**(b)** High vs. low small-firm-share sectors




Notes: This figure presents local projection impulse responses of real GDP following innovations in sectoral credit based on alternative sector splits. Panels (a) and (b) split corporate sectors based on the mortgage share and the small firm share, respectively. Impulse responses are reported for local projection specifications that exclude and include household credit-to-GDP. Dashed lines represent 95% confidence intervals computed using Driscoll and Kraay (1998) standard errors.

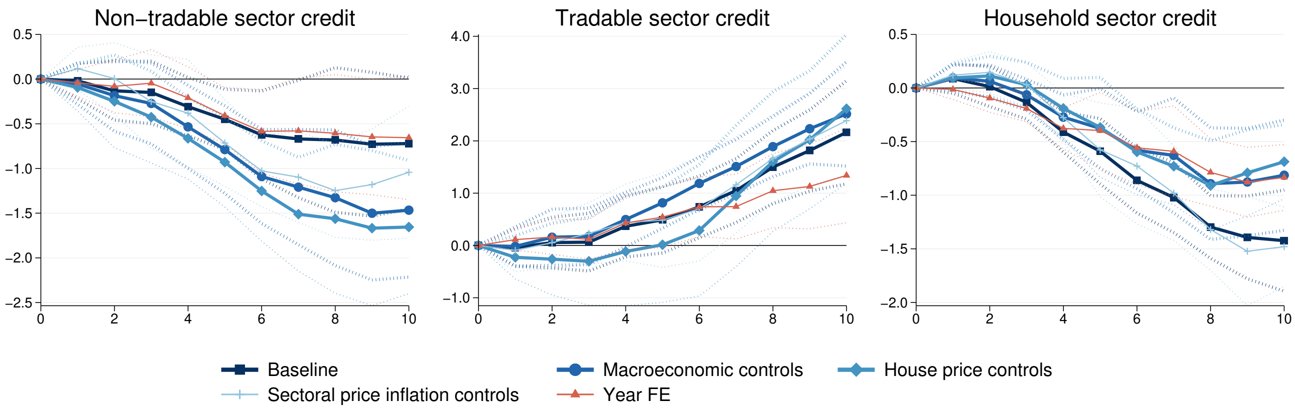
**Figure A.5:** Unemployment Dynamics after Credit Expansions



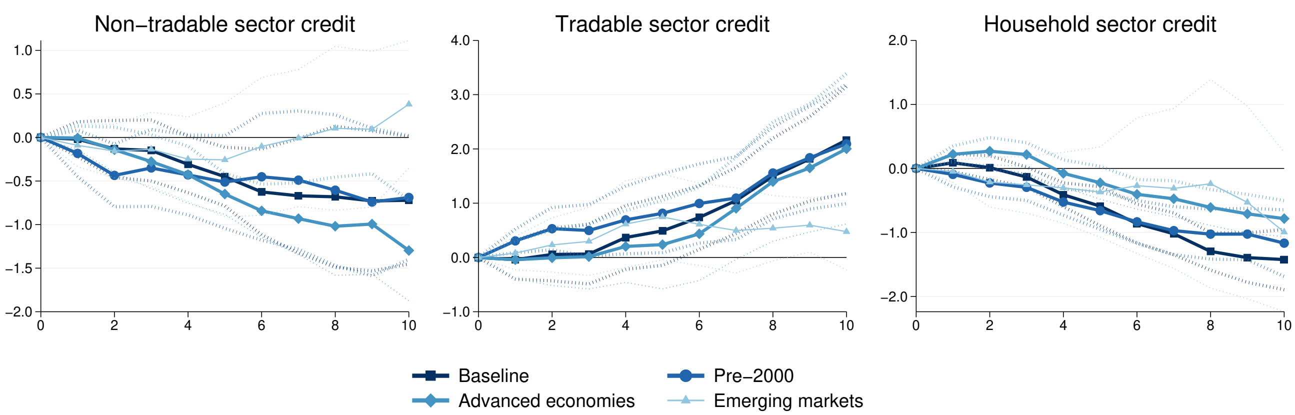

Notes: This figure presents local projection impulse responses of the unemployment rate to sectoral credit expansions. Dashed lines represent 95% confidence intervals computed using Driscoll and Kraay (1998) standard errors, and dotted lines represent 95% confidence intervals from standard errors two-way clustered on country and year.

**Figure A.6:** Output Dynamics after Sectoral Credit Expansions: Robustness to Additional Controls and Subsamples

**(a)** Additional controls




**(b)** Subsamples

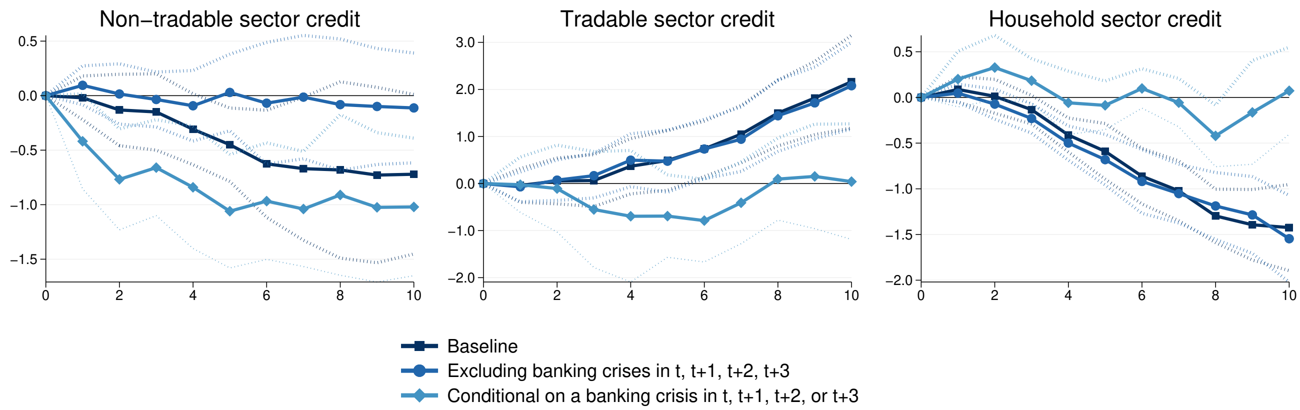



Notes: These figures present local projection impulse responses of real GDP following innovations in tradable sector credit, non-tradable sector credit, and household credit (all measured relative to GDP):

$$\Delta_h y_{it+h} = \alpha_i^h + \sum_{j=0}^{J} \beta_{h,j}^{NT} \Delta d_{it-j}^{NT} + \sum_{j=0}^{J} \beta_{h,j}^{T} \Delta d_{it-j}^{T} + \sum_{j=0}^{J} \beta_{h,j}^{HH} d_{it-j}^{HH} + \sum_{j=0}^{J} \gamma_{h,j} \Delta y_{it-j} + \sum_{j=0}^{J} X_{it-j}' \kappa_{h,j} + \epsilon_{it+h}, \quad h = 1, ..., H.$$

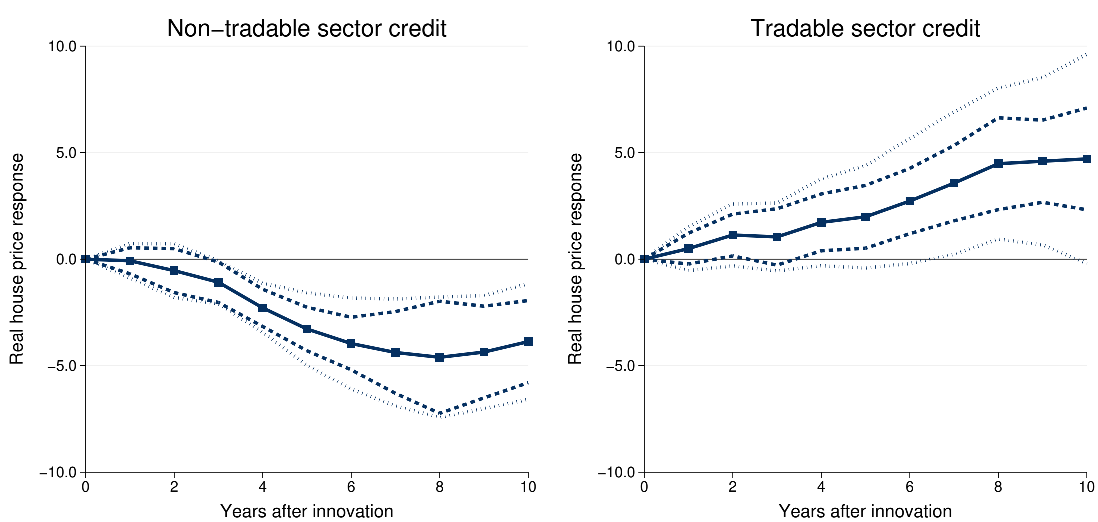
Panel (a) compares estimations with additional control variables to the baseline specification ($X_{it-j}$). Panel (b) considers other subsamples. Dashed lines represent 95% confidence intervals computed using Driscoll and Kraay (1998) standard errors, and dotted lines represent 95% confidence intervals from standard errors two-way clustered on country and year.

**Figure A.7:** Output Dynamics after Sectoral Credit Expansions: Excluding Banking Crises




Notes: These figures present 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). We estimate the impulse responses separately for observations with and without a banking crisis in year $t$, $t+1$, $t+2$, or $t+3$. Dashed lines represent 95% confidence intervals computed using Driscoll and Kraay (1998) standard errors, and dotted lines represent 95% confidence intervals from standard errors two-way clustered on country and year.

**Figure A.8:** House Price Dynamics after Credit Expansions




Notes: This figure presents local projection impulse responses of real house prices to sectoral credit expansions. Dashed lines represent 95% confidence intervals computed using Driscoll and Kraay (1998) standard errors, and dotted lines represent 95% confidence intervals from standard errors two-way clustered on country and year.

# B Case Studies

This appendix provides case studies illustrating sectoral credit dynamics during prominent credit expansions and crises. This serves to further showcase our sectoral credit data, support the quantitative evidence in the paper, and highlight commonalities and differences across credit booms. Our discussion is brief and selective, focusing on insights offered by the sectoral credit data.

Before discussing the individual cases, we highlight two important insights about the nature of major credit booms gleaned from these cases.

*First, what are the proximate causes of credit growth during major credit booms?* In the case studies we consider, credit expansions often follow financial liberalizations, increased competition in the financial sector, capital inflows from abundant foreign liquidity, or periods of loose monetary policy. Some credit expansions also come on the heels of exchange rate stabilizations that reduce inflation and country risk premia. Narrative accounts suggest that, during the boom, market participants are overoptimistic about future asset price valuations and cash flows, which reinforces lending growth. These observations are consistent with the narratives in Kindleberger (1978), Minsky (1977), Demirgüç-Kunt and Detragiache (1998), Diaz-Alejandro (1985), and Reinhart and Rogoff (2009b).

*Second, what is the sectoral composition of major credit booms?* A key finding is that many prominent credit booms which ended in financial crises involved substantial intersectoral reallocation of credit. Lending to the non-tradable and household sectors expand rapidly, while primary and manufacturing sector credit often stagnate. Once a crisis occurs, credit to the previously booming non-tradable and household sectors contracts, often dramatically, with less of a contraction in the tradable sector. On the other hand, the case study of Korea's financial reforms in the 1960s and subsequent growth "miracle" provides an example of an episode where credit growth mainly financed tradable sector firms and was associated with benign macroeconomic outcomes.

### Case Studies around the 2008 Global Financial Crisis

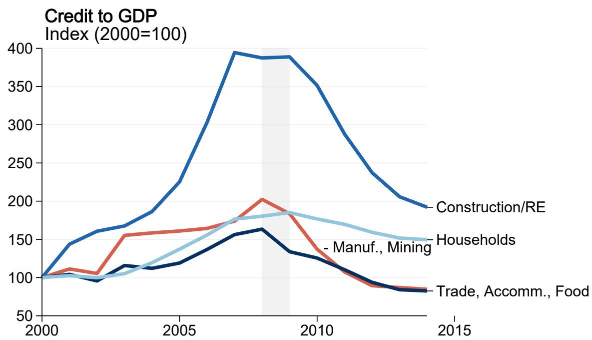
**Denmark** Denmark experienced strong credit growth in the run-up to the 2008 financial crisis. Total private credit-to-GDP increased by over 40 percentage points from 2000 to 2008. Figure B.1a illustrates that lending expanded fourfold to construction/real estate. In absolute terms, household lending also increased significantly. Lending to manufacturing also grew, though significantly less than lending to the property sector. These patterns are consistent with narrative evidence of a boom in lending and prices in commercial and residential real estate markets, including rapid lending growth to these markets by many small and medium-sized banks (Rangvid et al., 2013).

At the onset of the crisis in 2008, the banking sector had large and concentrated exposure to the property market, especially through risky commercial real estate loans Rangvid et al. (2013). These exposures translated into large bank losses from impairments and write-downs (IMF, 2014). Lending was financed by international wholesale funding, exposing banks to funding pressure during the crisis.

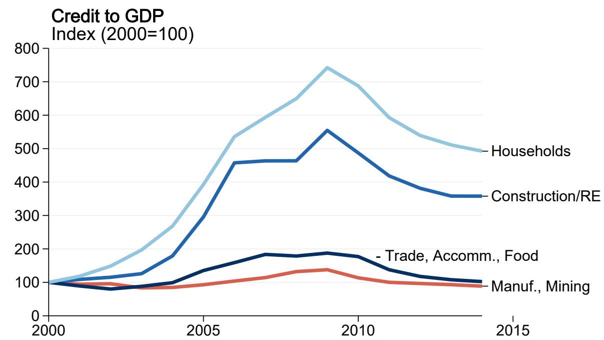
The crisis resulted in a consolidation of the banking system. Fifteen banks were closed and many others were acquired. The government implemented a blanket guarantee for creditors and government equity injections. The banking crisis was associated with, and contributed to, a severe real economic downturn (Jensen and Johannesen, 2017). Real GDP declined by over 5% from 2007 to 2009.

**Figure B.1:** Additional Cases in the Run-up to the 2008 Global Financial Crisis

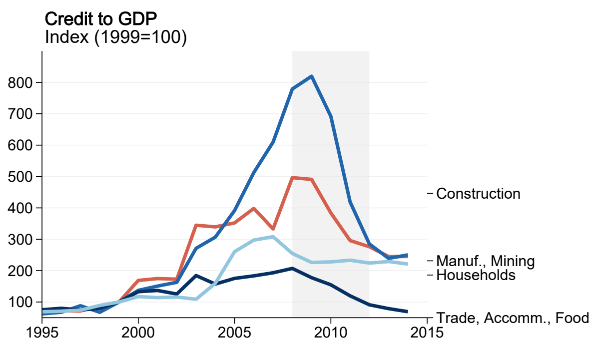
**(a)** Denmark



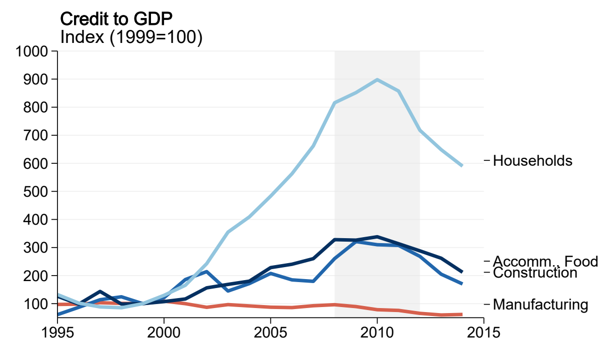

**(b)** Estonia



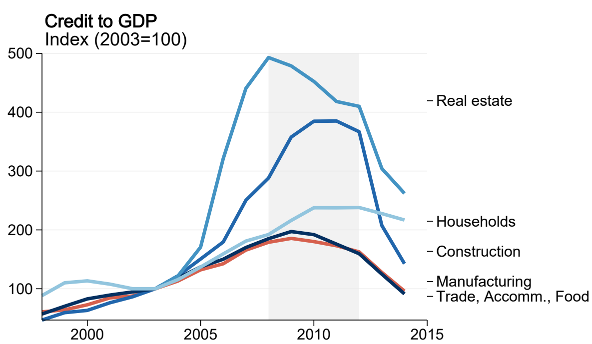

**(c)** Iceland



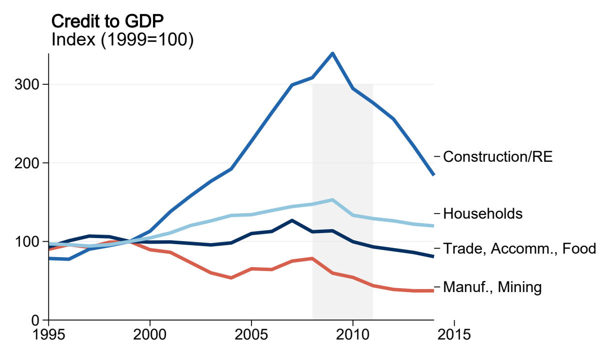

**(d)** Hungary




**(e)** Slovenia




**(f)** United Kingdom




Notes: These figures plot the ratio of sectoral credit-to-GDP for various countries in the run-up to the 2008 Global Financial Crisis. We also plot data on household credit-to-GDP. The shaded in gray mark the years of a banking crisis according to Laeven and Valencia (2018).

**Estonia** Estonia saw a large housing boom and bust during the 2000s. Abundant global liquidity combined with a currency board, an open capital account, and the prospect of EU entry stimulated large capital inflows, reflected in large current account deficits over 2000-07 (IMF, 30 Jul. 2007). Foreign-owned banks competing for market share expanded lending aggressively at low rates (Brixiova et al., 2010).

Figure B.1b shows that these inflows financed rapid lending growth. Credit to households increased seven times faster than GDP, fuelling and reinforced by rising house prices. Credit to construction and real estate also grew quickly. Lending to manufacturing, meanwhile, stagnated.

The Estonian case provides an example of a credit boom and economic bust *without* a clear-cut banking crisis (bank failures or widespread banking panic). Nevertheless, capital outflows, a contraction in credit supply, and elevated household debt contributed to an extremely severe recession.[18] Real GDP declined by 19% from 2007 to 2009.

**Iceland** The privatization and deregulation of the Icelandic banking system in the early 2000s was followed by extremely rapid banking sector asset growth, driven by domestic and international expansion of the three largest banks (Landsbanki, Glitnir, and Kaupthing) (IMF, 2012a). This growth was financed by massive current account deficits, which surpassed 15% from 2004 to 2007.

Figure B.1c plots the growth in domestic lending across sectors in Iceland. The figure shows that, in relative terms, lending expanded most rapidly toward construction, followed by lending to manufacturing/mining, driven by investment in energy and energy-intensive industries. Lending to households also expanded significantly in absolute terms, by nearly 40 percentage points from 2000 to 2007. Lending growth fueled a boom in the valuations of a range of domestic asset classes, including real estate and the stock market. In October 2008, the three largest banks failed, plunging Iceland into a severe recession. Real GDP declined by over 10% cumulatively, while asset prices and the exchange rate also plummeted IMF (2012a).

**Hungary** Hungary built up substantial vulnerabilities during the 2000s and, subsequently, experienced a major recession, a large exchange rate depreciation, and a banking crisis with a large increase in private sector non-performing loans. In Hungary, the entry of foreign banks led to increasing competition in the credit markets. This resulted in a boom in mortgage and consumer lending, much of which was denominated in foreign currency (Verner and Gyöngyösi, 2020).

Figure B.1d shows that credit growth was strongest for households, followed by construction and other non-tradables. Credit to the manufacturing sector, meanwhile, was flat. When the crisis arrived in 2008, the consequence was a sharp depreciation, a 7% cumulative decline in real GDP (Bakker and Klingen, 2012), severe household financial distress, and significant credit losses for banks.

**Slovenia** Slovenia experienced a rapid expansion in credit starting in the mid 2000s. The boom was financed by capital inflows from abroad. It followed Slovenia's entry into the EU and ERM II in 2004 and adoption of the euro in 2007 (IMF, 2012b). Slovenia is a case where credit expansion was concentrated mostly in the non-tradable corporate sector, rather than households. In particular, the lending boom financed a construction boom. Credit to real estate and construction more than quadrupled during this period, as shown in Figure B.1e. Employment growth was also concentrated in construction and service sectors, reflecting the domestic boom (IMF, 2009). Credit to manufacturing grew slower compared to lending to property-related sectors. The boom coincided with a rise in wages and a real exchange rate appreciation, which worsened competitiveness (IMF, 2009).

The aftermath of the boom resulted in a rise in non-performing loans, which created large losses for the domestic banking sector. By 2013, the banking sector was insolvent and required a govern-

[18] Other important factors in the severity of the recession include large negative external shocks, lack of monetary policy flexibility, and fiscal austerity.

ment bail-out in December 2013. This prolonged Slovenia's slump, resulting in a second recession in 2012-13 (IMF, 2017).

**United Kingdom** The United Kingdom experienced a lending boom and real estate price bubble during the 2000s. The lending boom occurred in an environment of loose credit conditions and a booming housing market. Figure B.1f shows that lending to construction/real estate surged from 1999 to 2008. This resulted in high leverage in the real estate sector, as noted by (IMF, 03 Aug. 2011). Household credit-to-GDP also increased significantly, rising by over 23 percentage points from 2000 to 2008. Growth in lending to trade/accommodation/food service was more modest, while credit to manufacturing declined relative to GDP. Starting in 2007, the disruption in global financial markets and the correction in UK house prices plunged the UK into a recession. Real GDP fell by nearly 4.5% from 2007 to 2009.

### 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).[19] The credit expansion in both countries came after substantial deregulation of banking markets and capital flows.

Figure B.2 panels (a) and (b) show the evolution of sectoral credit in Finland and Norway during this period. In Finland, household credit saw by far the largest absolute increase, 15 percentage points 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 started in 1990, non-tradables and households saw the sharpest credit contractions.

Similarly, in Norway, 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, followed 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.

### The 1994-95 Mexican "Tequila Crisis"

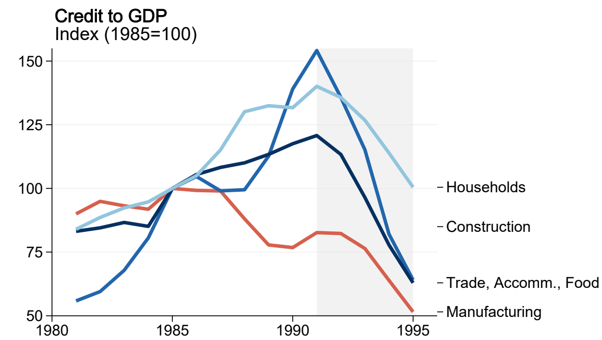
The 1994-95 Mexican crisis illustrates the role of the sectoral allocation of credit in the run-up to a prominent emerging market "sudden stop" episode.[20] Mexico experienced rapid capital inflows, large current account deficits, and real exchange rate appreciation following the capital account liberalization 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).

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

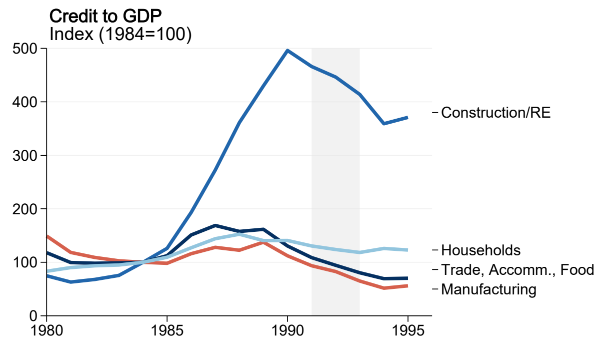
[20] Appendix B contains additional examples of sectoral credit allocation around emerging market crises.

**Figure B.2:** The Nordic and Mexican Financial Crises

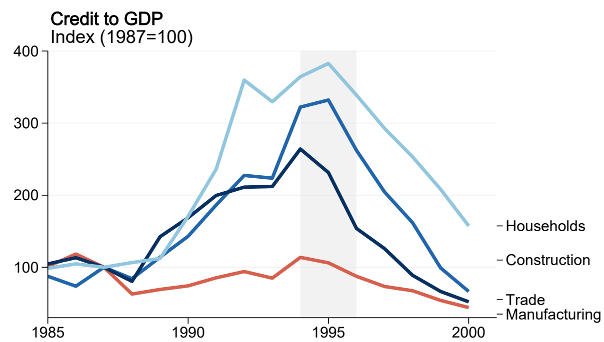
**(a)** Finnish Financial Crisis




**(b)** Norwegian Financial Crisis




**(c)** Mexican Tequila Crisis




Notes: This figure plots the ratio of sectoral credit-to-GDP 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 Nordic, Japanese, and Mexican financial crises. We also plot 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 B.2c shows the dynamics of sectoral credit resemble the experience of other major crises. From 1988 to 1994, the credit to households, the construction sector, and wholesale and retail trade grew rapidly, as inflows financed strong growth in consumption (Dornbusch and Werner, 1994). For example, household credit-to-GDP increased nearly fourfold from 1988 to 1994. Meanwhile, manufacturing credit remained stable relative to GDP during the boom.

### The Asian Financial Crisis

The 1997 Asian Financial Crisis was precipitated by the devaluation of the Thai baht in July 1997, which initiated a cascade of financial crises in Korea, Malaysia, Indonesia, and the Philippines. The Asian Crisis was preceded by a credit boom starting in the early 1990s, on the heels of domestic financial liberalization (Glick, 1998). Lending growth was financed by large capital inflows, a high proportion of which was denominated in foreign currency. Credit expansion inflated property and stock market valuations and increased banks' exposure to real estate, especially in Thailand and Malaysia. During the boom, the quality of bank loan portfolios deteriorated, leading to rising non-performing loans as the crisis unfolded (Glick, 1998).

Figure B.3 plots credit growth for various sectors in Thailand, Malaysia, Korea, and the Philippines.[21] In Malaysia and the Philippines, lending growth was skewed toward construction and other non-tradables. Lending to households also increased rapidly, financing a consumption boom (see also Graciela L. Kaminsky, 2001).

In Thailand, our data show that, unlike previous cases, manufacturing credit also increased rapidly. Yet narrative accounts emphasize that real estate and non-tradables, not manufacturing, were the central source of financial distress in Thailand (Corsetti et al., 1999). The discrepancy in part reflects a limitation of our data that is worth discussing. Lending by non-bank intermediaries is not always captured by our credit aggregates.[22] In the case of Thailand, non-bank intermediaries lent heavily to property and real estate sectors, as they were subject to less stringent regulation on credit quantities (Corsetti et al., 1999).[23]

Korea, in contrast, is a case where financial distress was concentrated in *tradable* sector conglomerates (Glick, 1998; Noland, 2000). Thus, while the thesis of our paper is that bad credit booms are often characterized by lending toward non-tradables and households, there are interesting exceptions. Nevertheless, even Korea experienced a deterioration of real estate markets and significant losses to real estate companies (Corsetti et al., 1999).[24]

### Additional Case Studies of Pre-2008 Crises

**Malaysia's 1985-88 Crisis** Malaysia experienced a banking crisis over 1985-88. The crisis followed a credit expansion, fraud and speculation in real estate and stock markets, and a sharp decline in Malaysia's terms of trade in 1985 (World Bank, 1993; Sheng, 1989).

Total private credit-to-GDP increased from 51% in 1979 to 97% in 1985. Over this period, Malaysia ran large current account deficits that coincided with real exchange rate appreciation (Sheng, 1989). Figure B.4b shows that lending to households and construction/real estate surged over this period, increasing four-fold. Credit to tradable sectors (agriculture and manufacturing/mining) and to other non-tradables (trade/accommodation/food) grew more slowly.

The credit boom was followed by financial distress at banks and finance companies. Property prices fell sharply in 1985. Depositor fears led to runs on 32 (out of 35) deposit-taking cooperatives (World Bank, 1993). The NPL ratio of commercial banks reached 30% in 1987 and 1988, mainly from exposure to the property sector (Athukorala, 2010). Real GDP growth per capita fell from 6.2% in 1983 and 7.7% in 1984 to -1.0% in 1985 and 1.2% in 1986. The unemployment rate increased from 3.8% in 1983 to 7.4% in 1986.

**Colombia's 1998 Crisis** Colombia undertook significant structural reforms in the early 1990s, including a liberalization of its financial system (IMF, 2000; Barajas et al., 2000). The liberalization included a relaxation of interest rate restrictions; a relaxation of entry requirements, opening banking system to greater competition; and privatization of state-owned banks, which controlled nearly half of bank assets (Uribe and Vargas, 2002). These reforms coincided with strong capital inflows.

Credit expanded rapidly following the financial and economic reforms. Total private credit-to-GDP increased from 19% in 1991 to 41% in 1997. As seen in Figure B.4a, credit growth was

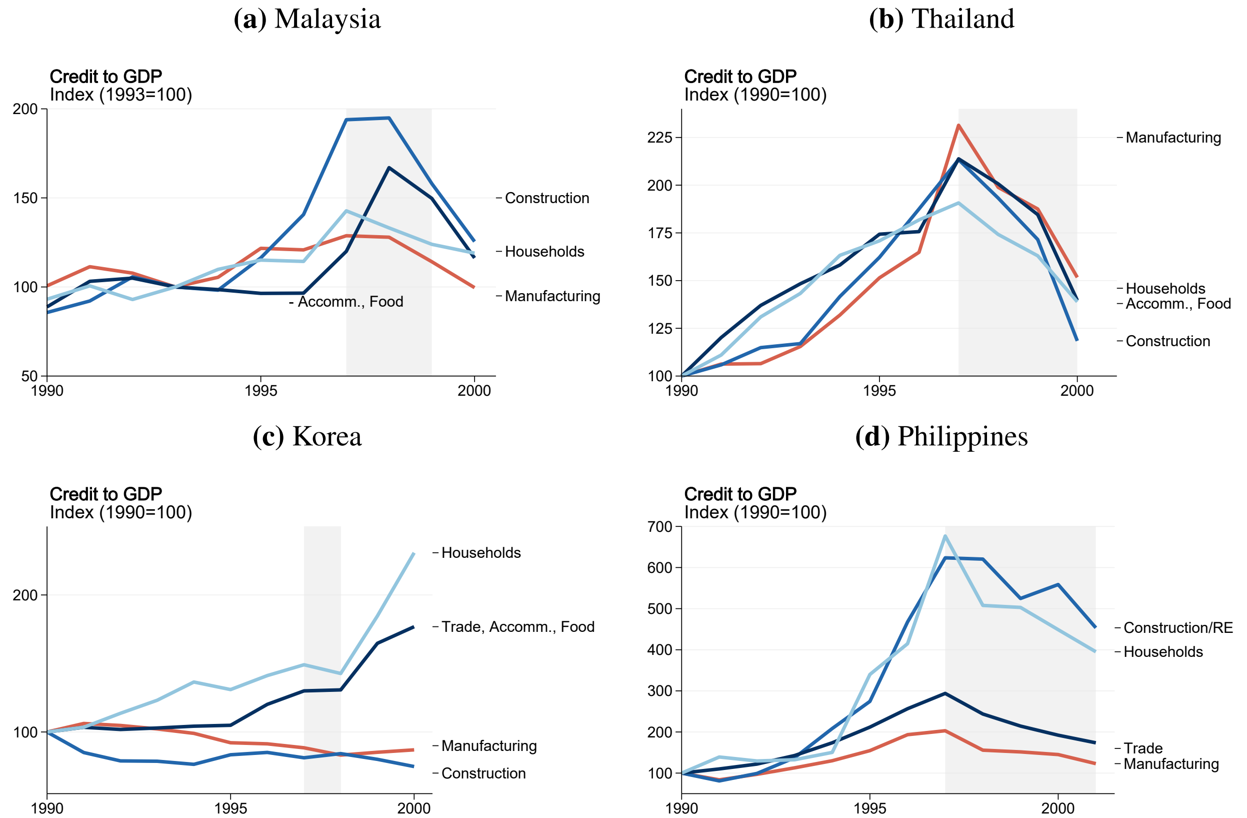
[21] Our sectoral dataset does not contain data for Indonesia during this period.

[22] See the data appendix for a detailed discussion of the coverage of lending institutions.

[23] Corsetti et al. (1999) report that 40% of Thai finance companies' loan portfolios consisted of loans to the real estate sector, compared to 25% for commercial banks.

[24] For example, share prices of Korean property companies fell by roughly 30% from 1995 to 1996 (Glick, 1998).

**Figure B.3:** The Asian Financial Crisis




Notes: These figures plot the ratio of sectoral credit-to-GDP for various sectors around the 1997 Asian Financial Crisis. Our dataset covers four of the five major countries that were severely affected by the crisis (Indonesia is not covered for this period). We also plot household credit-to-GDP. The areas shaded in gray mark the years of systemic banking crisis according to Laeven and Valencia (2018).

strongest for lending to households, construction, and other non-tradables. Meanwhile, real estate prices grew quickly and credit quality deteriorated (Uribe and Vargas, 2002). In contrast lending to agriculture and manufacturing remained roughly constant relative to GDP.

Turmoil in international financial markets in 1998, a reversal of capital flows, and worsening terms of trade produced a financial crisis and credit contraction (Uribe and Vargas, 2002). Banks saw rising non-performing loans and a deterioration in their solvency. Real GDP growth slowed to 1% in 1998 and fell to -4% in 1999, the first contraction in Colombia since the 1930s (Uribe and Vargas, 2002).

**UK's 1973 Crisis** The removal of credit controls and liberalization of the banking system in the early 1970s was followed by the worst banking crisis in the United Kingdom since the 19$^{\text{th}}$ century. Prior to 1971, the credit controls were used both for macroeconomic stabilization and to influence allocation of credit toward high-priority industries (Hodgman, 1973; Needham, 2015). The 1971 Act on Competition and Credit Control (CCC) replaced lending ceilings with monetary policy based on targeting interest rates. The policy was introduced to increase competition in deposit and lending markets, to phase out credit ceilings, and in response to regulatory arbitrage of lending ceilings through non-bank lending. Banks responded to the CCC by raising deposit rates and reducing lending rates to compete for customers. The CCC was accompanied by a period of highly expansive monetary policy (Reid, 1982).

Figure B.4c shows that lending growth accelerated from 1971, following the implementation of the CCC.[25] Much of the new lending was by secondary (fringe) banks to firms in the construction and real estate sectors, "one of the least recommended categories of lending before 1971" (Reid, 1982, p. 59, quoting a property developer). These banks financed much of their lending through the rapidly expanding short-term wholesale funding markets. Lending growth to the property sector was accompanied by booming real estate prices, buoyant demand, and expansive fiscal policy (the "Barber Boom"). On the other hand, lending to tradables such as manufacturing hardly kept up with aggregate GDP growth.

"In the euphoria of the time, the increasingly prevalent view was that property values could only go up" (Reid, 1982, pp. 62-63). However, when interest rates rose sharply and property prices started declining in 1973, the boom was followed by the "Secondary Banking Crisis." This crisis involved the failure or rescue of dozens fringe banks involved in lending to the property market (Reid, 1982). The UK economy went into recession with real GDP growth of -2.5% in 1974.

**The Korean Growth Miracle**

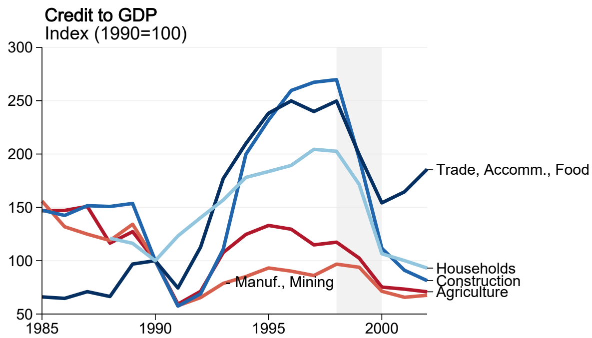
We conclude this section by discussing Korea's growth "miracle," which provides an example of a credit expansion that accompanied sustained high economic growth and that was not followed by a slowdown in growth or a financial crisis. An interest rate reform in 1965 increased real deposit rates, which boosted and reallocated savings from the informal to the formal financial sector (McKinnon, 1973; Shaw, 1973). As part of its export-led development strategy, the government-controlled banking sector directed lending at preferential rates toward export activities, mostly in the manufacturing sector (Cho, 1989).

Figure B.5 shows the large rise in credit starting in 1965. The rise is concentrated in lending to manufacturing. At the same time, loans to non-tradable firms and households remained low, an explicit policy choice. The expansion in bank credit toward manufacturing coincided with the initial phase of Korea's sustained rapid economic growth. Manufacturing credit remained elevated during Korea's Heavy and Chemicals Industry drive, launched in 1973.

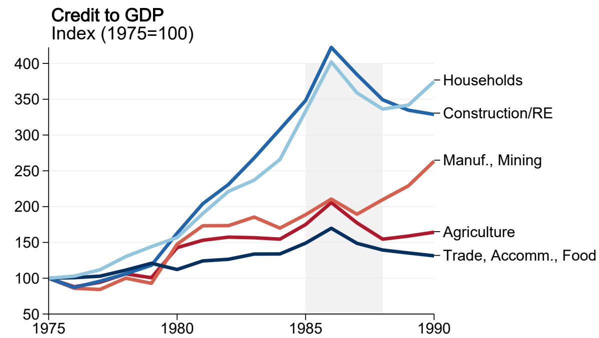
[25] Reid (1982) directly connects the CCC with the lending boom: "The [CCC] scheme thus provided a framework within which a money boom of remarkable proportions was able to blow up, under expansive economic policies, in the succeeding two-and-a-half years, contributing strongly to the massive growth in the secondary banking sector which preceded the crisis" (pp. 32-33).

**Figure B.4:** Additional Case Studies of Pre-2008 Crises

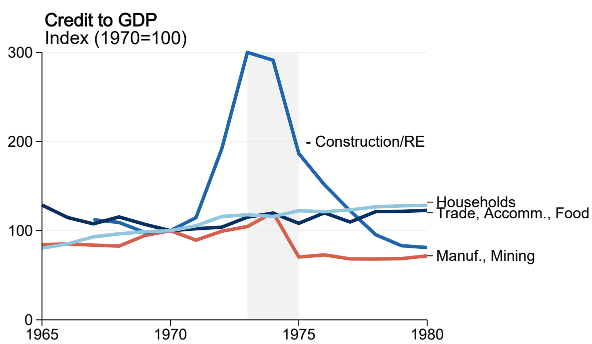
**(a)** Colombia's 1998 Crisis



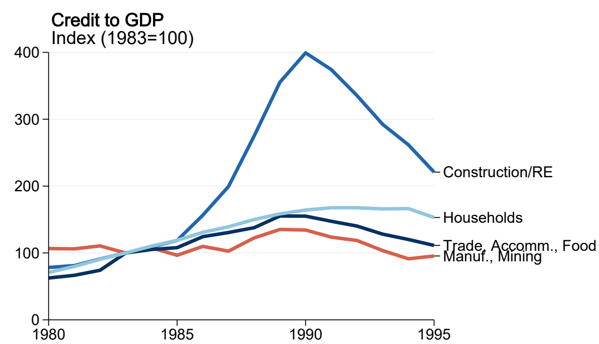

**(b)** Malaysia's 1985 Crisis




**(c)** UK 1973 Crisis

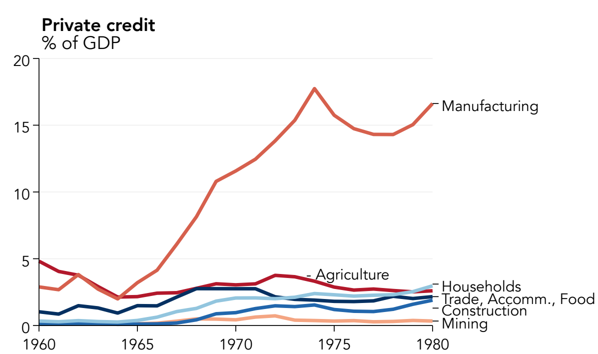



**(d)** UK 1991 Recession




Notes: These figures plot the ratio of sectoral credit-to-GDP during major credit booms in the run-up to various banking crises and recessions. We also plot data on household credit-to-GDP. The shaded in gray mark the years of a banking crisis according to Laeven and Valencia (2018) or Baron et al. (2021).

**Figure B.5:** The Korean Growth Miracle




Notes: This figure plots the ratio of sectoral credit-to-GDP for the following industries: agriculture (ISIC Rev. 4 section A), mining (section B), manufacturing (section C), construction (section F), and trade/accommodation/food (section GI) for Korea between 1960 and 1980. We also plot household credit-to-GDP.

# C Data Appendix: Sectoral Credit Database

This data appendix describes the construction of the database on total private credit and the sectoral distribution of private credit introduced in Müller and Verner (2023). These data cover 117 countries from 1940 to 2014. We also extend existing data sources on total credit for a total of 189 countries. To do so, we draw on more than 600 country-specific sources, many of which were digitized for the first time. In this appendix, we focus the discussion on the construction of new annual series for total credit, household/corporate credit, and sectoral credit for broad sectoral aggregates.[26] The remainder of this appendix provides more details on how to access the data, the conceptual issues involved in constructing sectoral credit data, and how the data compare to existing sources.

## C.1 Acknowledgements

This database is the result of a multi-year process of data collection, retrieval, and harmonization that is still ongoing. We were only able to undertake this project because of the support of many organizations and people whom we would like to thank.

We would like to gratefully acknowledge financial support from the Institute for New Economic Thinking, the Governor's Woods Foundation, the National Science Foundation (NSF Award 1949504), as well as our home institutions. Without their support, this project would not have been possible.

We would also like to thank our current and former research assistants who helped us turn a haphazardly put together PhD chapter into a useful database. In particular, we would like to thank, in no particular order, Adamson Bryant, Paul Dai, Michelle Girouard, Sarah Guo, Wei Chin Ho, Nils Hübel, Mengrui Jiang, Julien Maire, Gudrun Müller, Jason Ng, Sungho Park, Yash Roy, Niels Ruigrok, Flemming Slok, Ziyu Su, Brendan Tan, Yuxuan Tang, Aissata Thiam, Yevhenii Usenko, Hui Yi Yap, and Yi Fei Zou for their excellent work.

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[26] In ongoing work, we are expanding the data to a higher frequency and to more disaggregated sectors (both for corporate and household credit).

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). All remaining errors are ours.

## C.2 Downloading the Data

Users can download the data on http://www.globalcreditproject.com.

Most users will be interested in the ready-to-use annual cross-country panel, which contains harmonized total credit data for 189 countries and sectoral data for 117 countries starting in 1940.

For users interested in the details of data construction for specific countries, we provide spreadsheets for each country that contain the raw data and documentation upon request. These files show precisely which source was used in each time period and contains notes about the raw data and adjustments.

The data are provided under the terms of a Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License; more information is on the website. All users may use and/or share the licensed material, in whole or in part, provided that it is for non-commercial purposes, properly cited with credit to the authors, and only shared under identical license terms. Commercial data providers are forbidden to sell all or parts of this dataset.

When using the data, please use the following citation:

Müller, Karsten and Verner, Emil (2023). *Credit Allocation and Macroeconomic Fluctuations*.

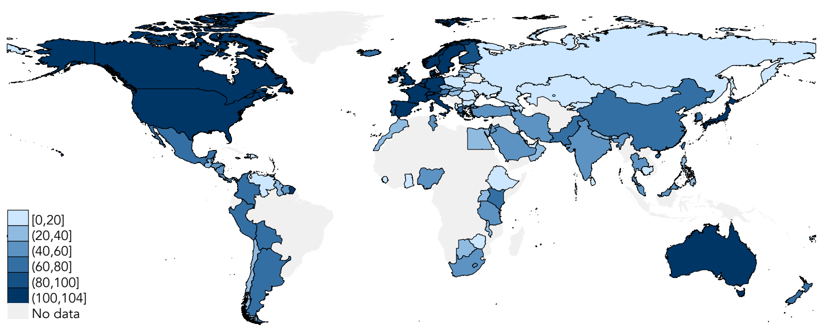
## C.3 Database Coverage

The Global 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 line of work by Óscar Jordà, Moritz Schularick, and Alan Taylor has resulted in the *Jordà-Schularick-Taylor Macrohistory Database* (Jordà et al., 2016a). 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.

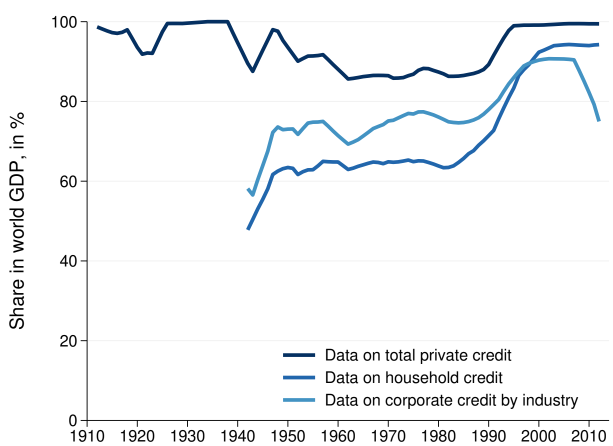
We build on this body of work by (i) *adding data on the sectoral allocation of credit* and (ii) *extending historical time series on household/firm and total private credit*. The collection and dissemination of sectoral credit data by national authorities has largely moved in line with contemporary 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 C.1:** 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.

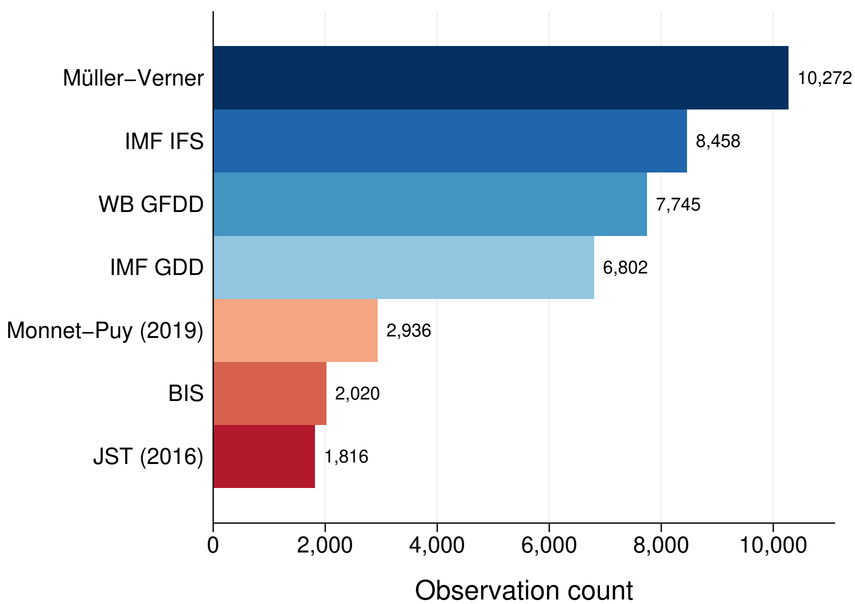
Table 1 in the main paper compares our dataset with existing efforts. The database includes an unbalanced panel of credit data for 189 countries, starting in 1940, covering 2–60 sectors. The total number of unique country-sector-year observations is 89,019. Overall, there are 10,272 country-year observations.

Figure C.1a 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 C.1 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? Figure C.1b 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 C.2 shows that the total number of country-year observations in our dataset is higher than that in datasets from the BIS, IMF International Financial Statistics (IFS) and Global Debt Database (GDD), World Bank Global Financial Development Database (GFDD), Jordà et al. (2016a), and Monnet and Puy (2019). Figure C.3 compares the number of countries in the sample by their availability of total and household/firm credit. Our database more than doubles the number of countries with data on household credit since 1970 compared to existing sources.

**Figure C.2:** Country-Year Observations




Notes: This figure compares the number of country-year observations in different datasets on private credit.

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 C.4 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.

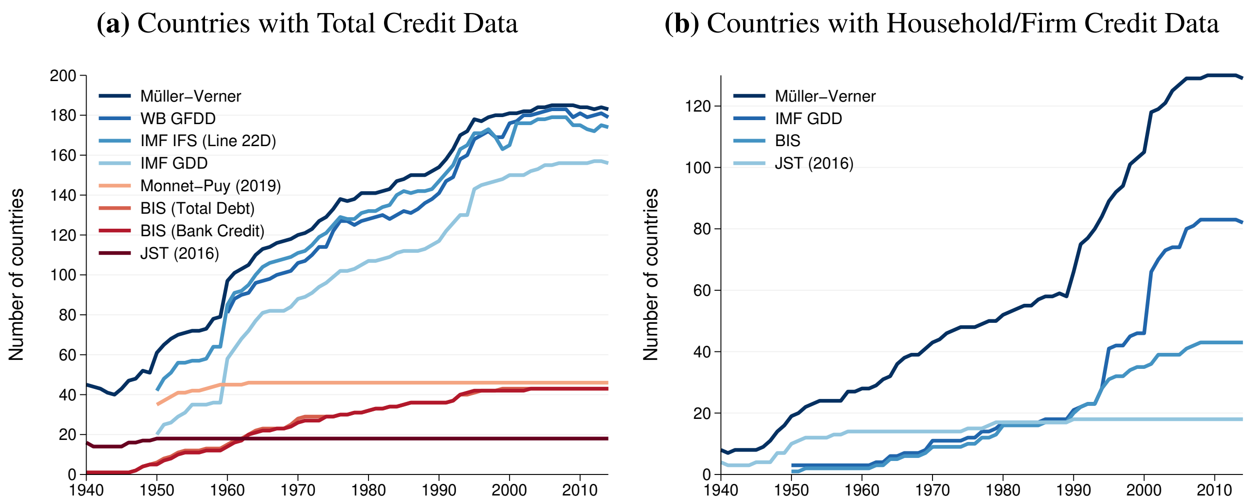
**Table C.1:** Credit Data Coverage by Country

| | | | | Major corporate sectors | | | | |
|---|---|---|---|---|---|---|---|---|
| **No.** | **Country** | **Total credit** | **Household/ firm credit** | **Agriculture** | **Manuf., Mining** | **Constr., RE** | **Trade etc.** | **Transp., Comm.** |
| 1 | Albania | 2000-2014 | 2000-2014 | 2000-2014 | 2000-2014 | 2000-2014 | 2000-2014 | 2000-2014 |
| 2 | Anguilla | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 |
| 3 | Antigua & Barbuda | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 |
| 4 | Argentina | 1952-2014 | 1952-2014 | 1952-2014 | 1952-2014 | 1952-2014 | 1952-2014 | 1952-2014 |
| 5 | Armenia | 1998-2014 | 1998-2014 | 1998-2014 | 1998-2014 | 1998-2014 | 1999-2014 | 1998-2014 |
| 6 | Australia | 1948-2014 | 1948-2014 | 1948-2014 | 1948-2014 | 1948-2014 | 1948-2014 | 1948-1983 |
| 7 | Austria | 1946-2014 | 1949-2014 | 1946-2014 | 1946-2014 | 1963-2014 | 1946-2014 | 1946-2014 |
| 8 | Azerbaijan | 2000-2014 | 2000-2014 | 2000-2014 | 2000-2014 | 2000-2014 | — | 2000-2014 |
| 9 | Bahrain | 1998-2014 | 1998-2014 | 1998-2014 | 1998-2014 | 1998-2014 | 1998-2014 | 2000-2014 |
| 10 | Barbados | 1966-2014 | 1966-2014 | 1966-2014 | 1966-2014 | 1966-2014 | 1966-2014 | 1966-2014 |
| 11 | Belgium | 1976-2014 | 1976-2014 | 1976-2014 | 1976-2014 | 1976-2014 | 1976-2014 | 1976-2014 |
| 12 | Belize | 1970-2014 | 1970-2014 | 1970-2014 | 1970-2014 | 1976-2014 | 1970-2014 | 1970-2014 |
| 13 | Bhutan | 1983-2014 | 2005-2014 | 1983-2014 | 1983-2014 | 1983-2014 | 1983-2014 | 1983-2014 |
| 14 | Bolivia | 1964-2014 | 1964-2014 | 1964-2014 | 1964-2014 | 1964-2014 | 1964-2014 | 1999-2000 |
| 15 | Botswana | 1990-2014 | 1990-2014 | 1990-2014 | 1990-2014 | 1990-2014 | 1990-2014 | 1990-2014 |
| 16 | Bulgaria | 1995-2014 | 1995-2014 | 2000-2014 | 2000-2014 | 2000-2014 | 2000-2014 | 2000-2014 |
| 17 | Cambodia | 2000-2014 | 2004-2014 | 2000-2014 | 2000-2014 | 2000-2014 | 2000-2014 | 2008-2014 |
| 18 | Canada | 1942-2014 | 1942-2014 | 1942-2014 | 1942-2014 | 1942-2014 | 1942-2014 | — |
| 19 | Chile | 1993-2014 | 1993-2014 | 1993-2014 | 1993-2014 | 1993-2014 | 1993-2014 | 1993-2014 |
| 20 | China | 1952-2009 | 1994-2009 | 1952-2009 | — | — | — | — |
| 21 | Colombia | 1952-2014 | 1988-2014 | 1952-2014 | 1952-2014 | 1952-2014 | 1952-2014 | 1998-2014 |
| 22 | Costa Rica | 1956-2014 | 1985-2014 | 1956-2014 | 1956-2014 | 1985-2014 | 1985-2014 | 1987-2014 |
| 23 | Curaçao & St. Maarten | 1978-2014 | 1978-2014 | — | 1978-2014 | 1978-2014 | 1978-2014 | 1978-2014 |
| 24 | Cyprus | 1963-2014 | 1963-2014 | 1963-2007 | 1963-2007 | 1963-2007 | 1963-2007 | 1963-2007 |
| 25 | Czech Republic | 1992-2014 | 1992-2014 | 1992-2014 | 1992-2014 | 1992-2014 | 1992-2014 | 1992-2014 |
| 26 | Denmark | 1951-2014 | 1951-2014 | 1951-2014 | 1978-2014 | 1978-2014 | 1978-2014 | 1986-2014 |
| 27 | Dominica | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 |
| 28 | Dominican Republic | 1996-2014 | 1996-2014 | 1996-2014 | 1996-2014 | 1996-2014 | 1996-2014 | 1996-2014 |
| 29 | Egypt | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | — | 1991-2014 | — |
| 30 | Estonia | 1993-2014 | 1993-2014 | 1995-2014 | 1995-2014 | 1995-2014 | 1995-2014 | 1995-2014 |
| 31 | Ethiopia | 2000-2014 | — | 2000-2014 | 2000-2014 | 2000-2014 | 2002-2014 | 2000-2014 |
| 32 | Fiji | 1973-2014 | 1973-2014 | 1973-2014 | 1973-2014 | 1973-2014 | 1973-2014 | 1973-2014 |
| 33 | Finland | 1958-2014 | 1958-2014 | 1958-2014 | 1958-2014 | 1958-2014 | 1958-2014 | 1958-2014 |
| 34 | France | 1993-2014 | 1993-2014 | 2006-2014 | 2006-2014 | 2006-2014 | 2006-2014 | 2006-2014 |
| 35 | Georgia | 1995-2014 | 1995-2014 | 2003-2014 | 2003-2014 | 2003-2014 | 2003-2014 | 2003-2014 |
| 36 | Germany | 1949-2014 | 1949-2014 | 1949-2014 | 1949-2014 | 1951-2014 | 1949-2014 | 1968-2014 |
| 37 | Ghana | 1997-2014 | 2005-2014 | 1997-2014 | 1997-2014 | 1997-2014 | 1997-2014 | 1997-2014 |
| 38 | Greece | 1950-2014 | 1950-2014 | 1950-2014 | 1950-2014 | 2002-2014 | 1950-2014 | 1955-2014 |
| 39 | Grenada | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 |
| 40 | Guatemala | 1990-2014 | 1990-2014 | 1990-2014 | 1990-2014 | 1990-2014 | 1990-2014 | 2003-2014 |
| 41 | Guyana | 1993-2014 | 1993-2014 | 1993-2014 | 1993-2014 | — | 1993-2014 | 1993-2014 |
| 42 | Haiti | 1999-2014 | 1999-2014 | 1999-2014 | 1999-2014 | 1999-2014 | 1999-2014 | 1999-2014 |
| 43 | Honduras | 1958-2014 | 1958-2014 | 1958-2014 | 1958-2014 | 1958-2014 | 1958-2014 | 1968-2014 |
| 44 | Hong Kong | 1965-2014 | 1965-2014 | 1965-2003 | 1965-2014 | 1965-2014 | 1965-2014 | 1965-2014 |
| 45 | Hungary | 1989-2014 | 1989-2014 | 1995-2014 | 1995-2014 | 1995-2014 | 1995-2014 | 1995-2014 |
| 46 | Iceland | 1950-2014 | 1958-2014 | 1950-2014 | 1955-2014 | 1970-2014 | 1958-2014 | 1958-2014 |
| 47 | India | 1972-2013 | 1972-2013 | 1972-2013 | 1972-2013 | 1972-2013 | 1972-2013 | 1972-2013 |
| 48 | Iran | 1967-2012 | — | 1967-2012 | 1967-2012 | 1967-2012 | — | — |
| 49 | Ireland | 1948-2014 | 1948-2014 | 1948-2014 | 1948-2014 | 1948-2014 | 1948-2014 | 1985-2014 |
| 50 | Israel | 1974-2014 | 1974-2014 | 1974-2014 | 1974-2014 | 1974-2014 | 1974-2014 | 1974-2014 |
| 51 | Italy | 1948-2014 | 1948-2014 | 1948-2014 | 1948-2014 | 1948-2014 | 1948-2014 | 1948-2014 |
| 52 | Jamaica | 1967-2014 | 1970-2014 | 1967-2014 | 1967-2014 | 1967-2014 | 1967-2014 | 1977-2014 |
| 53 | Japan | 1947-2014 | 1947-2014 | 1947-2014 | 1947-2014 | 1947-2014 | 1948-2014 | 1947-2014 |
| 54 | Jordan | 1964-2014 | 1964-2014 | 1964-2014 | 1964-2014 | 1964-2014 | 1964-2014 | 1964-2014 |
| 55 | Kazakhstan | 1997-2014 | 1997-2014 | 1997-2014 | 1997-2014 | 1997-2014 | 1997-2014 | 1997-2014 |
| 56 | Kenya | 1947-2014 | 1965-2014 | 1947-2014 | 1947-2014 | 1965-2014 | 1965-2014 | 1965-2014 |

**Table C.1:** Credit Data Coverage by Country (continued)

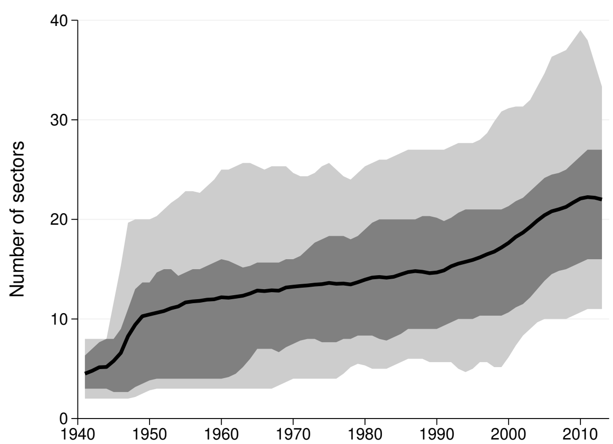
| No. | Country | Total credit | Household/ firm credit | Major corporate sectors: Agriculture | Manuf., Mining | Constr., RE | Trade etc. | Transp., Comm. |
|---|---|---|---|---|---|---|---|---|
| 57 | Kuwait | 1972-2014 | 1972-2014 | 1972-2014 | 1972-2014 | 1972-2014 | 1972-2014 | — |
| 58 | Kyrgyz Republic | 1996-2014 | 1996-2014 | 1996-2014 | 1996-2014 | 1996-2014 | 1996-2014 | 1996-2014 |
| 59 | Latvia | 2000-2014 | 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 | 2007-2014 |
| 61 | Lithuania | 1993-2014 | 1993-2014 | 1995-2014 | 1995-2014 | 1995-2014 | 1995-2014 | 1995-2014 |
| 62 | Luxembourg | 1999-2014 | 1999-2014 | — | — | — | — | — |
| 63 | Macedonia | 2004-2014 | 2004-2014 | 2004-2014 | 2004-2014 | 2004-2014 | 2004-2014 | 2004-2014 |
| 64 | Malawi | 1990-2014 | 1990-2014 | 1990-2014 | 1990-2014 | 1990-2014 | 1990-2014 | 1990-2014 |
| 65 | Malaysia | 1968-2014 | 1971-2014 | 1968-2014 | 1968-2014 | 1968-2014 | 1968-2014 | 1968-2014 |
| 66 | Maldives | 1985-2014 | 1985-2014 | 1985-2014 | 1985-2014 | 1985-2014 | 1985-2014 | 1985-2014 |
| 67 | Malta | 1969-2014 | 1969-2014 | 1969-1992 | 1969-2014 | 1969-2014 | 1969-2014 | 1993-2014 |
| 68 | Mauritius | 1967-2014 | 1967-2014 | 1967-2014 | 1967-2014 | 1992-2014 | 1967-2014 | 1979-2014 |
| 69 | Mexico | 1942-2014 | 1984-2014 | 1942-2014 | 1969-2014 | 1969-2014 | 1969-2014 | 1969-2014 |
| 70 | Mongolia | 2000-2014 | 2000-2014 | 2000-2014 | 2000-2014 | 2000-2014 | 2002-2014 | 2000-2014 |
| 71 | Montserrat | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 |
| 72 | Morocco | 1977-2014 | 1993-2014 | 1977-2014 | 1977-2014 | 1977-2014 | 1977-2014 | 1977-2014 |
| 73 | Nepal | 1975-2014 | 2002-2014 | 1975-2014 | 1975-2014 | 2002-2014 | 1975-2014 | 2002-2014 |
| 74 | Netherlands | 1990-2014 | 1990-2014 | 2010-2014 | 2010-2014 | 2010-2014 | 2010-2014 | 2010-2014 |
| 75 | New Zealand | 1940-2014 | 1940-2014 | 1940-2014 | 1940-2014 | 1956-2014 | 1940-2014 | 1940-2014 |
| 76 | Nicaragua | 1960-2014 | 1995-2014 | 1960-2014 | — | — | 1960-2014 | — |
| 77 | Nigeria | 1960-2014 | 1966-1992 | 1960-2014 | 1960-2014 | 1960-2014 | 1960-2014 | 1966-2014 |
| 78 | Norway | 1946-2014 | 1946-2014 | 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 |
| 80 | Pakistan | 1953-2014 | 1982-2014 | 1953-2014 | 1953-2014 | 1953-2014 | 1953-2014 | 1953-2014 |
| 81 | Panama | 1963-2014 | 1963-2014 | 1963-2014 | 1963-2014 | 1963-2014 | 2002-2014 | 2002-2014 |
| 82 | Peru | 1947-2014 | 1947-2014 | 1947-2014 | 1947-2014 | 1947-2014 | 1947-2014 | 1990-2014 |
| 83 | Philippines | 1980-2014 | 1981-2014 | 1980-2014 | 1980-2014 | 1980-2014 | 1980-2014 | 1980-2014 |
| 84 | Poland | 1996-2014 | 1996-2014 | 2002-2012 | 2002-2012 | 2002-2012 | 2002-2012 | 2002-2012 |
| 85 | Portugal | 1947-2014 | 1947-2014 | 1966-2014 | 1966-2014 | 1973-2014 | 1973-2014 | 1973-2014 |
| 86 | Qatar | 1977-2014 | 1977-2014 | 1977-2002 | 1977-2014 | 1977-2014 | 1977-2014 | 1977-1994 |
| 87 | Romania | 2000-2014 | 2000-2014 | 2000-2014 | 2000-2014 | 2000-2014 | — | — |
| 88 | Russia | 1998-2014 | 1998-2014 | 2002-2014 | 2002-2014 | 2002-2014 | 2002-2014 | 2002-2014 |
| 89 | Saudi Arabia | 1970-2014 | 1998-2014 | 1970-2014 | 1970-2014 | 1970-2014 | 1970-2014 | 1970-2014 |
| 90 | Seychelles | 1997-2014 | 1997-2014 | 1997-2014 | 1997-2014 | 1997-2014 | 1997-2014 | 1997-2014 |
| 91 | Sierra Leone | 1997-2014 | 2001-2014 | 1997-2014 | 1997-2014 | 1997-2014 | 1997-2014 | 1997-2014 |
| 92 | Singapore | 1962-2014 | 1980-2014 | 1962-2014 | 1962-2014 | 1962-2014 | 1962-2014 | 1963-2014 |
| 93 | Slovak Republic | 1992-2014 | 1992-2014 | 1992-2014 | 1992-2014 | 1992-2014 | 1992-2014 | 1992-2014 |
| 94 | Slovenia | 1991-2014 | 1991-2014 | 1994-2014 | 1994-2014 | 1994-2014 | 1994-2014 | 1994-2014 |
| 95 | South Africa | 1994-2013 | 1994-2013 | 1994-2013 | 1994-2013 | 1994-2013 | 1994-2013 | 1994-2013 |
| 96 | South Korea | 1952-2014 | 1952-2014 | 1952-2014 | 1952-2014 | 1952-2014 | 1952-2014 | 1952-2014 |
| 97 | Spain | 1992-2014 | 1992-2014 | 1992-2014 | 1992-2014 | 1992-2014 | 1992-2014 | 1992-2014 |
| 98 | Sri Lanka | 1996-2014 | 1996-2014 | 1996-2014 | 1996-2014 | 1996-2014 | 1996-2014 | 2009-2014 |
| 99 | St. Kitts & Nevis | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 |
| 100 | St. Lucia | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 |
| 101 | St. Vincent & Grenadines | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 |
| 102 | Suriname | 1969-2014 | 1969-2014 | 1969-2014 | 1969-2014 | 1969-2014 | 1969-2014 | 1969-2014 |
| 103 | Sweden | 1975-2014 | 1975-2014 | — | — | — | — | — |
| 104 | Switzerland | 1977-2014 | 1977-2014 | 1997-2014 | 1985-2014 | 1985-2014 | 1997-2014 | 1997-2014 |
| 105 | Taiwan | 1956-2014 | 1956-2014 | 1956-2014 | 1956-2014 | 1997-2014 | 1956-2014 | 1956-2014 |
| 106 | Tanzania | 1967-2014 | 2003-2014 | 1967-2014 | 1967-2014 | 1967-2014 | 1985-2014 | 1967-2014 |
| 107 | Thailand | 1965-2014 | 1965-2014 | 1965-2014 | 1965-2014 | 1965-2014 | 1965-2014 | 1970-2014 |
| 108 | Trinidad & Tobago | 1946-2014 | 1954-2014 | 1946-2014 | 1946-2014 | 1963-2014 | 1954-2014 | 1963-2014 |
| 109 | Tunisia | 1962-2014 | 1962-2014 | 1962-2014 | 1962-2014 | 1962-2014 | 1962-2014 | 1962-2014 |
| 110 | Turkey | 1967-2014 | 1986-2014 | 1967-2014 | 1967-2014 | 1967-2014 | 1967-2014 | 2002-2014 |
| 111 | Uganda | 1991-2014 | 2004-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 | 1991-2014 |
| 112 | Ukraine | 1995-2014 | 1995-2014 | 2000-2014 | 2000-2014 | 2000-2014 | 2000-2014 | 2000-2014 |
| 113 | United Arab Emirates | 1998-2014 | 1998-2014 | 1998-2014 | 1998-2014 | 1998-2014 | 1998-2014 | 1998-2014 |
| 114 | United Kingdom | 1946-2014 | 1946-2014 | 1946-2014 | 1946-2014 | 1946-2014 | 1946-2014 | 1946-2014 |
| 115 | United States | 1936-2014 | 1936-2014 | 1936-2014 | — | — | — | — |
| 116 | Venezuela | 2004-2014 | 2004-2014 | 2004-2014 | 2004-2014 | 2004-2014 | 2004-2014 | 2004-2014 |
| 117 | Zimbabwe | 2009-2014 | 2009-2014 | 2009-2014 | 2009-2014 | 2009-2014 | 2009-2014 | 2009-2014 |

**Figure C.3:** Comparing the Country Coverage of Different Sources on Private Credit Data




Notes: These graphs compare the coverage of different datasets on total credit (panel a) and household/firm credit (panel b) 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. (2016a), Monnet and Puy (2019), and World Bank GFDD. See text for more details.

**Figure C.4:** 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.

## C.4 Data Construction

### C.4.1 Credit Data Sources and Classification

The principal data sources for this project are 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. We used the native language versions in most cases because these sometimes contain more data. Typically, the online databases of the national authorities contain time series for at least the most recent years, usually in the range of 10 to 25 years.

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

**Step 3: Contacting the national authorities** As a third step, we contacted the statistics and banking supervision departments of all national authorities who collected or published sectoral credit data at any point in time via email. The vast majority of agencies responded and provided helpful pointers to historical sources. In many cases, they also shared unpublished data with us. At 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** For countries without an online depository for historical publications, or where we suspected additional data, we searched the libraries of several universities and central banks for easily retrievable volumes. The Bank of Japan generously 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 C.5 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.

**Figure C.5:** Source Example – Canada, Data on Sectoral Credit, 1950-1952

*CHEQUE PAYMENTS* 1139

**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.4.2 Definition and Coverage of Financial 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 financial institutions, and (2) what constitutes "credit".

**Which Financial Institutions Are Covered?** The coverage of financial 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 inaccurate 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, have different business models. In most cases, 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 financial institutions: "Commercial Banks (Banks)", "Credit Institutions (CIs)", "Monetary Financial Institutions (MFIs)", "All lenders", and "All lenders (incl. government)". We broadly follow the European Central Bank's definitions of MFIs and CIs. CIs include commercial banks and all other deposit-taking institutions, such as savings banks or credit cooperatives. MFIs additionally include money market funds (MMFs) and similar entities. "All lenders" further expands the definition to include all non-bank institutions, such as non-deposit taking specialised housing or shipping lenders, as well as investment trusts. Direct loans by the central bank are generally not included in these statistics, and we exclude them wherever they are separately reported. The institutional coverage of the raw data is noted for each individual data source in the series documentation file. Note that the reported lender coverage in the documentation refers to the raw data: where there are differences between different raw data sources that had to be adjusted to make them comparable, this is described in detail on a case-by-case basis.

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

In many countries, the share of covered institutions increases over time. When adjusting the data, we sometimes make the assumption that the more recent data is more accurate and scale up the older data using overlapping values. Costa Rica is a good example, where the statistics only include the "banking system" from 1956 to 1985 and the "total financial system" starting in 1985. To correct for a small level-shift in the data—which is most pronounced for mortgage lending—we scale up the pre-1985 data using the overlapping values to avoid exaggerated movements arising from the reclassification. Implicitly, we thus assume that the growth rates of the "banking system" are representative of the "total financial system" before 1985. The underlying assumptions are rarely strong: in most cases, differences in coverage come from commercial banks versus all monetary financial institutions, where the latter often include credit unions or savings banks with large market shares in residential mortgages but little other activities. In cases where the deviations in coverage are large or we have other background information (communicated via personal contact from or obtained from documents published by the national authorities), we stay on the conservative side and stick with a smaller coverage that is comparable over time. For more details on data adjustments and robustness tests, also see section C.4.4.

**Coverage of Credit Instruments** Debt contracts come in different forms, with a major distinction between "debt securities" (mostly bonds) and "bank credit" (mostly loans). 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. 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.4.4 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 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).[27] 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.4.3 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.

[27] 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.

**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.[28] 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.

**Classification of Non-Financial 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.[29] 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.4.4.

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).

In many countries, the most detailed available data is on the 1-digit (section) 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.

[28]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.

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

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).

For our analysis in this paper, we construct sector credit aggregates that distinguish between agriculture (A), manufacturing and mining (B and C), construction and real estate (F and L), wholesale and retail trade, accommodation, and food services (G and I), transport and communication (H and J), and other sectors.

**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.4.3) 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 tables are comparable.[30] 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.4.4 Adjustments and Harmonization

This section outlines the adjustments we made to make the data as comparable as possible across time and countries. Where necessary, adjustments were made for individual countries or even specific time series in consultation with the national authorities. All of these adjustments are described in country-specific documentation files (available upon request).

While these 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 C.5, 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.

**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

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

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.

**Adjusting for Breaks** A major issue when compiling long-run time series from multiple sources are level-shifts or breaks 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 simple chain-linking formula

$$New\ value_{it} = \frac{New\ series_{i,t+1}}{Old\ series_{i,t+1}} \times Old\ series_{i,t}. \tag{6}$$

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 6 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. 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 underlying raw 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. 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). Consider, for example, a country where manufacturing exhibits a level-shift that is adjusted using overlapping data. After this adjustment, the sum of manufacturing and other industries no longer adds up to total firm credit. To remedy this, we first calculate the sum of the individual break-adjusted industry-level time series, and then multiply the share of each sector with total break-adjusted firm 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.

**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.[31] 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 C.6 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, 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 makes sure 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. We aim to improve our estimates in the future.

**Adjusting Sector Classifications 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 categories. We used the

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

conversion tables available from the United Nations' statistics division to adjust tables using older revisions.[32] Two 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 at the 2-digit level, and documents of the national authorities were consulted to resolve any remaining issues.

**Figure C.6:** 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, 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

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

original statistical publications and with the 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).

**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 would be a time series with descriptions like “Services”, where they do not clearly specify details, documentations are not available or unclear, and national authorities did not respond to email inquiries. 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).[33]

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 **??**. Other issues include series descriptions whose meaning is fairly straightforward but not directly specified in the ISIC scheme. For example, in the case of Germany, 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 of “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.

**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.

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

## C.5 Comparability With Other Sources

We cross-checked the data with six major sources of credit data: (1) the World Bank Global Financial Development Database (Cihák et al., 2013), (2) the IMF's Global Debt Database (GDD), (3) the IMF's International Financial Statistics (IFS) data on total private credit, (4) historical IMF IFS volumes by Monnet and Puy (2019), (5) the BIS long series on credit to the private sector (Dembiermont et al., 2013), and (6) the Macrohistory Database assembled by Jordà et al. (2016a). 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.

### C.5.1 Discussion of Existing Data Sources

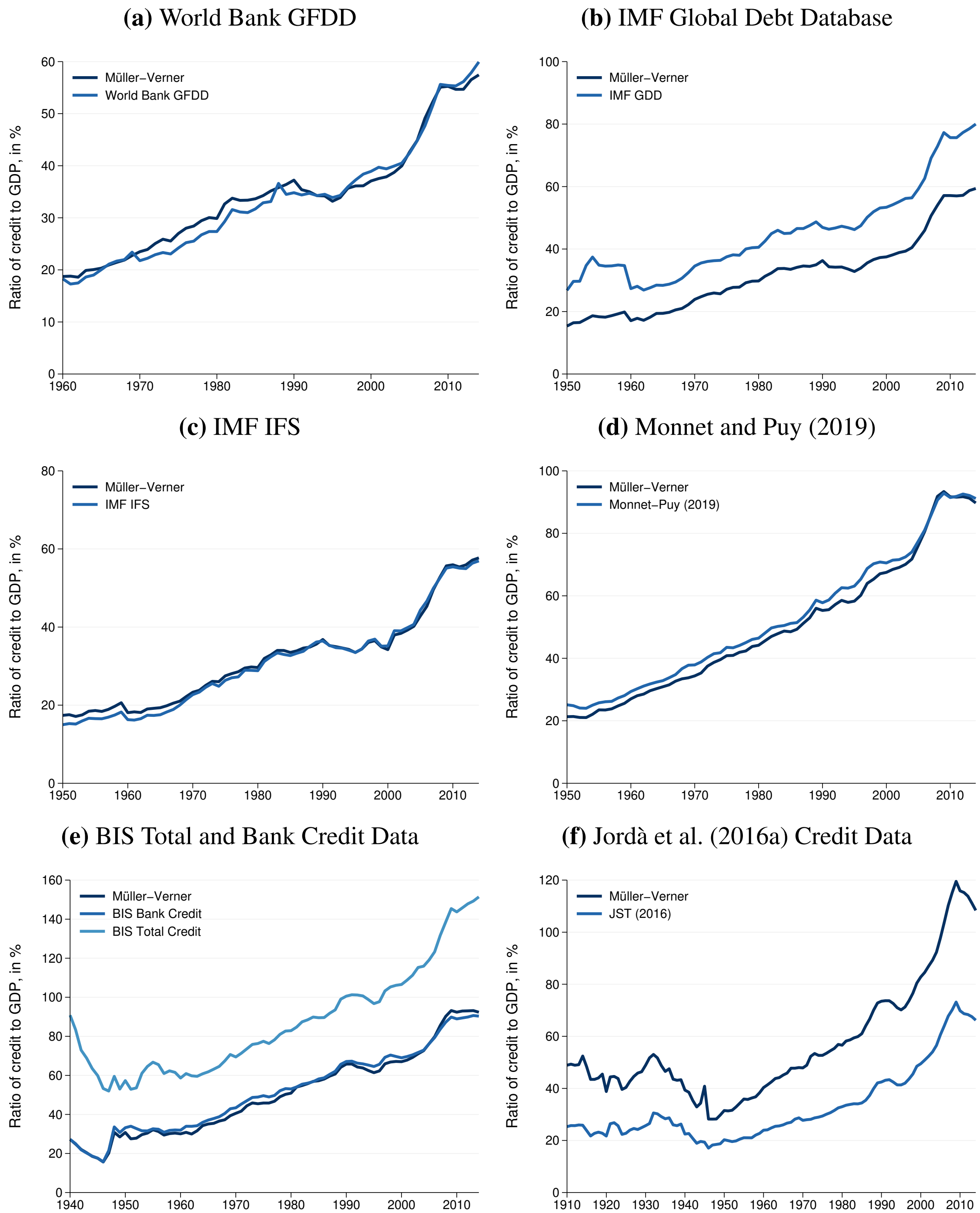
In Table 1 of the paper, we already plotted the coverage of existing sources on credit market data as well as our database. Before comparing the six alternative resources with the newly compiled data, it is important to highlight important classification differences. Apart from differences in the available countries, sectors, and time periods, they also differ in their coverage of lending institutions. Jordà et al. (2016a) 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.

### C.5.2 Comparing Total Credit Values

Due to the different sample composition highlighted above, we compare the total credit values in our database separately against each of the six sources mentioned above

Figure C.7a 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 of credit as a percentage of GDP.

**Figure C.7:** Comparison of Total Credit with Six Other Sources




**(a)** World Bank GFDD

**(b)** IMF Global Debt Database

**(c)** IMF IFS

**(d)** Monnet and Puy (2019)

**(e)** BIS Total and Bank Credit Data

**(f)** Jordà et al. (2016a) Credit Data

Panel (a) sample: 180 countries in our dataset and the World Bank's Global Financial Development Database, 1960-2014. Panel (b) sample: 158 countries in our dataset and the International Monetary Fund's Global Debt Database, 1950-2014. Panel (c) sample: 184 countries in our dataset and the IMF's International Financial Statistics, 1948-2014. Panel (d) sample: 45 countries in our dataset and the IMF data digitized and harmonized by Monnet and Puy (2019), 1950-2014. Panel (e) sample: 43 countries in our dataset and the BIS private credit data, 1940-2014. Panel (f) sample: 18 countries in our dataset and the Jordà et al. (2016a) data on private credit, 1940-2014.
Notes: Average ratio of total private credit to GDP (unweighted). IFS variables in panel (a) are *FOSAOP* and *22D* (Claims on Private Sector).

The recently introduced IMF Global Debt Database features perhaps the broadest cross-country credit dataset that singles out lending to firms and households. Figure C.7b 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 is similar to that in our data.

An early attempt at constructing data on private credit are the IMF's International Financial Statistics (IFS). Figure C.7c 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 C.7d 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 C.7e 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., 2016a). Again, we restrict the sample to the overlapping country-years in both data sources and plot the result in Figure C.7f. For the 18 overlapping countries, the picture is reassuringly very similar to the other data sources. However, our data suggest higher credit to GDP ratios, which is likely because we capture lending by all monetary financial institutions in most countries, while Jordà et al. (2016a) largely only consider bank credit.

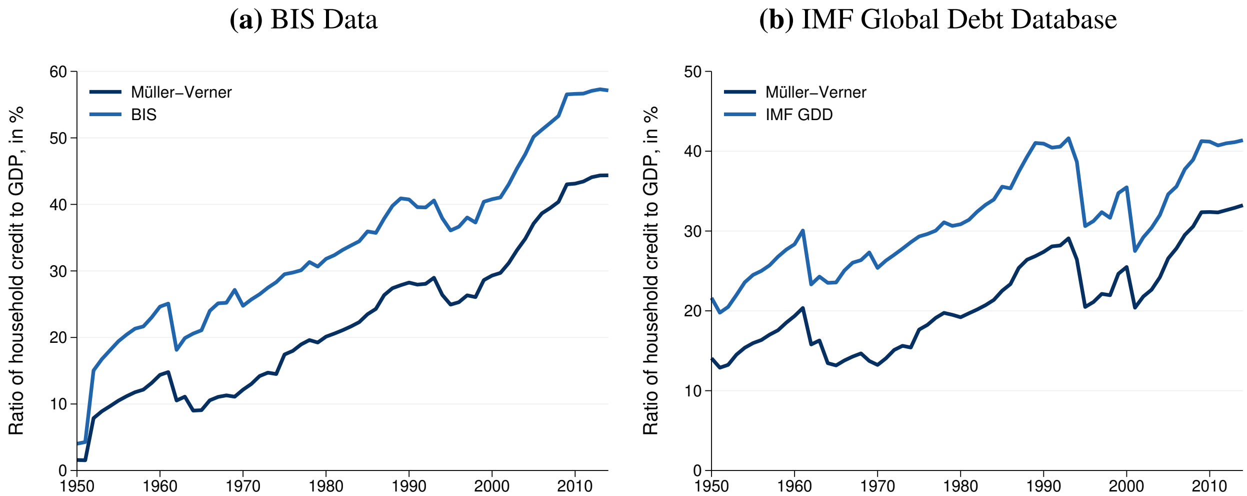
Overall, our new credit data closely track other existing sources. For the sources that use a similar coverage of lending institutions, the deviations are marginal; for those with a different lender coverage, the gap with our data is constant over time, suggesting similar trends. A natural interpretation 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.

### C.5.3 Comparing Household 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 BIS and the IMF Global Debt Database.

Figure C.8a 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 C.7e, 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. Figure C.8b compares our new data with the IMF Global Debt Database on outstanding household credit scaled over GDP. This exercise is based on an overlapping sample of 83 countries. Given the slightly broader coverage in the IMF GDD data, it is unsurprising that their values are slightly higher. Apart from this minor difference, the trends of the series track each other closely.

**Figure C.8:** Comparison with BIS and IMF GDD Household Credit Data




Sample: In panel (a), 43 countries in our dataset and the BIS data on credit to the non-financial private sector, 1950-2014. 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).

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