Corporate Debt, Boom-Bust Cycles, and Financial Crises*

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Abstract

Using a new dataset on sectoral credit exposures in 115 economies from 1940 to 2014, we provide evidence that corporate debt plays a key role in explaining boom-bust cycles, financial crises, and sluggish macroeconomic recoveries. We find that: (i) corporate debt accounts for two thirds of the aggregate credit expansion and three quarters of nonperforming loans during the bust; (ii) expansions in corporate debt predict crises; (iii) credit flowing disproportionately to some industries is associated with crises; and (iv) the recovery from financial crises is slower after a boom in corporate debt as a consequence of higher nonperforming loans.

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1 Introduction

Since the global financial crisis of 2007-08, household debt has been at the forefront of macroeconomic thinking about economic booms and busts. A wealth of evidence shows that household debt played a key role in the boom-bust cycle of the 2000s in the United States (e.g., Mian and Sufi, 2009, 2010; Keys et al., 2010). In cross-country panel data, growth in household and mortgage debt has been found to predict business cycle downturns and financial crises (e.g., Büyükkarabacak and Valev, 2010; Jordà et al., 2016b; Mian et al., 2017) as well as prolonged recessions and slow recoveries after such crises (e.g., Jordà et al., 2015; Jordà et al., 2022). These patterns are consistent with a growing theoretical literature on the interplay between credit markets, house prices, and output (e.g., Lorenzoni, 2008; Mendoza, 2010; Guerrieri and Lorenzoni, 2017; Favilukis et al., 2017; Berger et al., 2017; Justiniano et al., 2019), where fluctuations in house prices are key to the expansion and contraction of credit, as housing is the main asset backing household debt in many countries.

When it comes to the macroeconomic effects of firm debt, however, the empirical evidence is much less clear-cut.[1] Many studies emphasize the real effects of bank credit supply shocks, and works using firm-level data show that excessive leverage can hurt investment and employment (e.g., Giroud and Mueller, 2016; Kalemli-Özcan et al., 2022). In spite of this robust firm-level evidence, cross-country panel data show that corporate debt dynamics have only weak predictive power for subsequent GDP growth (e.g., Mian et al., 2017; Sufi, 2023). Similarly, Jordà et al. (2022) conclude that corporate credit booms leave a lasting imprint on the macroeconomy after financial crises only in countries with particularly inefficient corporate bankruptcy regimes.

In this paper, we show that expansions in corporate debt play a key role in business cycle fluctuations because they matter for boom-bust cycles and large crashes in GDP. Corporate debt accounts for about two-thirds of the aggregate credit growth in the three years preceding financial crises. After a crisis, the ensuing credit crunch and spike in non-performing loans is largely concentrated in credit to firms. These results contrast sharply with the patterns for household debt, which continues to grow relative to GDP even after the onset of a financial crisis and tends to account for only a small fraction of non-performing loans after crises. An expansion in corporate debt can be just as significant as household debt for predicting crises, and it also predicts the depth of the post-crisis recession, especially if it is fuelled by real estate collateral. While growth in corporate debt has relatively weak predictive ability for future GDP growth on average, unlike household debt, it is a powerful predictor for crash risk in GDP. Hence, firm credit booms can leave a lasting imprint on the macroeconomy.

The backbone of our analysis is a large historical cross-country panel dataset on credit markets from the Global Credit Project (Müller and Verner, 2023) covering 115 advanced and emerging economies from 1940 to 2014. In addition to differentiating between household and corporate sector

[1] In what follows, we use the terms corporate debt and firm debt interchangeably, and "corporate" does not only refer to large firms.

credit, these data allow us to go more granular and measure outstanding credit *by industrial sector*, namely for agriculture, manufacturing, transport/communication, construction, and retail/wholesale trade. We also construct new time series on credit to non-bank financial institutions. To the best of our knowledge, this dataset is unprecedented in its breadth and scope and overlaps with 87 episodes of systemic financial crisis.

Equipped with these data, we examine the credit booms that often precede financial crises using an event study approach and predictive regressions, as used in the previous literature. To understand the underlying mechanisms linking firm debt and crises, we make use of the sectoral variation in our data. In particular, we exploit the fact that sectors differ in the types of collateral on which they rely. Consistent with the existing literature linking real estate collateral values to firm behavior (e.g., Chaney et al., 2012; Bahaj et al., 2020), we find that sectors relying on real estate as collateral, such as the construction sector, have a relatively stronger association with crises. A one standard deviation increase in sectoral credit backed by real estate collateral relative to GDP over the past three years is associated with a 3.7 percentage point increase in the probability of a financial crisis within the next three years. We find a similar result for credit to the non-bank financial sector, which, as we show, typically tends to lend to non-financial firms.[2] These findings suggest that corporate debt expansions contain important information about macroeconomic dynamics.

We also find that credit expansion to sectors such as wholesale and retail trade is a particularly strong predictor of crises. While our cross-country data only allow us to measure a sector's reliance on real estate collateral—as we do not have data on other types of collateral— the fact that lending to the wholesale and retail trade sector is a strong predictor of crises is suggestive of other types of collateral with procyclical valuations, such as inventories or corporate earnings, also playing a role. As such, our results could also be interpreted through the lens of the growing literature that uses firm-level data from the U.S. to document the macro consequences of excessive firm debt backed by firms' cash flows (e.g., Caglio et al., 2021; Drechsel, 2023). Our results suggest an important role for firm debt in *macroeconomic* outcomes, consistent with credit dynamics being amplified by rising collateral values during booms and falling collateral values during busts (e.g., Kiyotaki and Moore, 1997; Lorenzoni, 2008; Mendoza, 2010; Gorton and Ordoñez, 2014; Asriyan et al., 2022).

The sectoral variation of our data allows us to examine whether bad credit booms are booms when some sectors grow "out of whack." We show that the dispersion of credit across sectors systematically increases during credit expansions, which suggests heterogeneous easing and tightening of financial constraints across *sectors*. We believe this stylized fact is new to the literature and mirrors the role of heterogeneous credit constraints documented in firm-level data (e.g., Gopinath et al., 2017; Ottonello and Winberry, 2018; Caglio et al., 2021).

[2]Non-banks include non-deposit taking lenders, such as leasing or finance companies, but also insurers, pension funds, and other types of financial services companies.

Our proposed measure of dispersion predicts crises over and above the magnitude of the credit expansion, as measured by changes in the credit-to-GDP ratio. In our benchmark specification, a one standard deviation increase in dispersion predicts a 3.6 percentage point increase in the probability of a crisis. Our interpretation is that, even in the case of two credit booms of the same magnitude, disproportionate growth in credit flowing to some sectors signals heightened risk-taking, with potential implications for the overall stability of the financial system.

To understand the role of corporate debt in macroeconomic outcomes, we examine whether firm debt matters for sluggish post-crisis recoveries using local projections (Jordà, 2005). In particular, we study how the path of real GDP per capita depends on the type of credit extended before the downturn. Again, we find that corporate debt is important for macroeconomic dynamics. Corporate debt not only makes financial crises more likely; it also prolongs the recovery from the recessions that usually follow, and this result is particularly strong for corporate debt backed by real estate collateral.

Three additional pieces of evidence support our interpretation that firm debt can play a critical role in periods of financial instability and the ensuing economic recessions. First, using newly collected data on nonperforming loans (NPLs) by sector, we show that firms, rather than households, account for three-quarters of total NPLs on bank balance sheets after crises. The United States in 2007 is a notable outlier: out of the 23 crises in our sample, the subprime mortgage crisis is the episode with the single highest share of household defaults in total NPLs. Second, we find that firm defaults in sectors using real estate collateral are particularly likely to spike during banking crises. In the United States, the delinquency rate for commercial real estate loans was three times that of residential real estate loans during the 1990-91 recession, and delinquency rates for commercial and residential mortgages rose similarly during the Great Recession. Using AMRO Asia data for 97 countries, we show that firm defaults were also largely concentrated in the construction/real estate sector, suggesting that commercial real estate defaults may also be associated with crises outside of the United States. Third, using local projections, we show that corporate debt booms are particularly predictive of post-crisis increases in aggregate NPLs, especially when backed by real estate collateral, while we find a more muted role for household debt expansions.

Why do our results differ from existing work that finds a limited role for firm debt relative to household debt for macroeconomic fluctuations? First, we focus on financial crises rather than average output growth. As we show, household debt robustly predicts negative average output growth much more strongly than firm debt, consistent with existing evidence (Mian et al., 2017; Sufi, 2023). Using a quantile regression approach, however, we find that growth in corporate debt matters much more for left-tail realizations than household debt, i.e. for GDP crash risk, suggesting that different types of credit are linked to the macroeconomy through different channels. Second, using data disaggregated by industry allows us to document a more robust link between firm credit and macroeconomic outcomes. Credit growth in industries that tend to rely on real estate collateral is strongly associated with a higher future probability of a financial crisis. Once the crisis occurs, credit growth in these sectors is also predictive of the extent to which loans become non-performing and the depth of the ensuing recession. Moreover, a higher dispersion of firm credit across industries–some sectors growing "out of whack"–signals a higher future crisis risk, suggesting a role for heterogeneous firm financing constraints in macroeconomic dynamics. Third, our data covers 115 advanced and emerging economies from 1940 to 2014, giving us around three times the country-year observations compared to previous work. Existing evidence documenting a limited role for corporate debt is either based on 17 advanced countries (Jordà et al., 2022), or uses more recent data, in many cases starting only in the 1990s (Mian et al., 2017). We believe that the broader coverage of our data allows us to draw more general conclusions.

Taken together, our findings suggest an important role for corporate debt in understanding credit cycles, with implications for models of macro-financial linkages. Our evidence suggests that expansions in corporate and household debt are linked to the macroeconomy through different channels. Corporate debt predicts higher future crash risk in GDP through its link to future corporate defaults, financial crises, and slow recoveries characterized by low levels of investment. Household debt is uniformly correlated with lower future growth, whether or not a country experiences a financial crisis, suggesting it works as a general drag on growth.

These results complement the empirical literature on booms and busts in credit markets and their macroeconomic implications (e.g., Borio and Lowe, 2002; Schularick and Taylor, 2012; Gourinchas and Obstfeld, 2012; Greenwood et al., 2022). Similar to our paper, Giroud and Mueller (2021) also examine the role of corporate leverage build-up in economic downturns. They find that an increase in the leverage of publicly listed US firms predicts a contemporaneous expansion of employment in their subsidiaries, followed by a sharp contraction (also see Sever, 2023). This micro result is broadly consistent with our macro result that increases in firm debt are associated with slower recoveries in GDP. Unlike their work, we compare the predictive ability of firm debt with household debt, provide evidence for an important role for corporate debt in banking crises, explore heterogeneity across sectors and collateral types, and analyze firms' default behavior.

Our work also adds to the findings in Müller and Verner (2023), who show that bad credit booms are driven by credit to the non-tradable sector, whereas credit to tradable sectors is linked to stable growth, consistent with multi-sector open economy models. Our work differs along several dimensions. Most importantly, our work shows that both corporate and household debt are strongly linked to the macroeconomy, albeit through different channels. In contrast to their work, we examine the aftermath of financial crises and show that growth in firm debt–particularly when backed by real estate collateral–is associated with slower recoveries. The measure of imbalances in credit growth we propose is also new to the literature. Together with our results on GDP crashes, these findings suggest that the distribution of credit market outcomes (rather than just their mean) might be particularly informative about macro-financial linkages. We also make important additions to the dataset introduced in Müller and Verner (2023). Specifically, we add new time series on credit to non-bank financial institutions, new data on nonperforming loans and delinquencies, as well as new data on the use of real estate collateral. Lastly, we also quantitatively benchmark the importance of growth in corporate and household debt for the macroeconomy through an exact decomposition of the credit booms preceding crises.

Finally, we also contribute to the literature showing that measures of credit spreads are highly predictive of recessions (Gilchrist and Zakrajšek, 2012; López-Salido et al., 2017; Saunders et al., 2022), and that they appear to be "abnormally" low before financial crises (Krishnamurthy and Muir, 2017). This finding is often interpreted through the lens of "financial accelerator" models, where the price of risk fluctuates with asset values, such as Bernanke et al. (1999), He and Krishnamurthy (2013), and Brunnermeier and Sannikov (2014). Our findings are complementary, as an expansion in corporate debt is a measure of the (relatively slow) build-up of the quantity of risk, and hence vulnerabilities, since many smaller and less creditworthy firms are able to borrow during periods of low spreads.

The paper proceeds as follows. Section 2 introduces the data. Section 3 examines the link between growth in corporate debt and financial crises. Section 4 analyzes the dispersion of credit growth across sectors. Section 5 shows how the defaults and macroeconomic dynamics after crises are shaped by corporate debt. Section 6 concludes.

2 Data

We construct an annual cross-country panel dataset covering 115 countries combining information on (i) changes in outstanding credit by sector, (ii) systemic financial crises, (iii) macroeconomic data, and (iv) sectoral data on nonperforming loans and firm defaults. These data sources are described below.

2.1 Sectoral Credit Data

The backbone of our analysis is an extended version of the Global Credit Project, a cross-country dataset on the sectoral composition of credit to the domestic private sector introduced by Müller and Verner (2023). The key difference from existing sources is that these data distinguish domestic credit by *borrower type*: they measure household and firm credit for all countries in the sample, and further disaggregate firm credit by industry. This level of detail is made possible by an extensive effort to digitize, combine, and harmonize hundreds of country-specific sources. In spirit, this dataset is similar to the Bank for International Settlements' data distinguishing international capital flows by borrowing sector into banks, corporates, and governments as originally constructed by Avdjiev et al. (2022).

Müller and Verner (2023) focus their analysis on an estimation sample of 75 countries and the difference between credit to tradable and non-tradable sectors together with household debt. In contrast, we focus on credit to six non-financial industries: agriculture, manufacturing and mining, construction and real estate, retail and wholesale trade, transportation and communication, and other sectors (defined as the sum of all other sectors, which includes utilities and various types of non-financial services). We also introduce a newly constructed series on loans to the non-bank financial sector for an extended sample of 115 countries.

The extended version of the Müller and Verner (2023) data we use is a departure from existing work in three dimensions. First, these data help us to distinguish between household and corporate debt for many more countries and years than previous work. For example, the data on household and non-financial corporate credit from the BIS cover 44 economies and a total of 1,224 country-year observations between 1940 and 2014. In contrast, our data covers 115 countries and 3620 country-year observations. This allows us to examine the relationship between credit expansions and crises covering the majority of major crisis episodes after World War II. Second, the data provide us with considerable detail on the composition of corporate credit. For their main analysis, Müller and Verner (2023) distinguish between firm credit to two sectors (the non-tradable and tradable sector). We use measures of changes in corporate debt for six sectors of the economy. Third, our dataset includes "intrafinancial" credit, not covered by Müller and Verner (2023). In particular, we construct time series that capture domestic credit to the non-bank financial sector, which previous data efforts have either ignored or included with firm credit to non-financial firms. (Interbank lending is not included in the statistics from which we collect our data and its reporting differs widely across countries.) We document the sources and construction of these time series in a forthcoming collection of spreadsheets.

The time series on sectoral credit measure the amount of outstanding domestic credit in millions of local currency. In practice, most of the outstanding credit refers to bank loans, but bond exposures are included when they are reported on the balance sheet of supervised financial institutions. To classify industries, the raw data are mapped to the International Standard Industrial Classification (ISIC Revision 4) whenever it is not already reported as such.[3] To measure credit growth, we follow the common practice in the literature and focus on the three-year change in the ratio of credit to GDP, which we denote Δ_3Credit/GDP.

In practice, countries differ in the way they collect and publish sectoral credit data, which sometimes requires adjustments to make them comparable. As is often the case when working with long time series from different sources, the raw data may contain "breaks" or sudden jumps that do not reflect economic events but changes in statistical methodology. In order to avoid classifying such changes as periods of very high or very low credit growth, methodological changes were manually identified using meta data in cooperation with the national central banks and financial regulators. These breaks were then adjusted, mostly by using overlapping data from different sources. Interested readers can consult the data appendix of Müller and Verner (2023) for technical details.

[3]We are grateful for the generous assistance of many dozens of staff from national central banks, statistical offices, and financial regulators in this harmonization process.

To test for a potential role of procyclical collateral values, we also construct two proxies for loans to non-financial corporations depending on the underlying collateral types. Our data mainly capture the use of real estate as collateral. We use information from five countries that publish statistics on outstanding credit by industry and collateral type: the United States, Denmark, Latvia, Switzerland, and Taiwan.[4] Table A.7 provides details on the sources, coverage, and definition of these data. For the United States, we use information from the Federal Reserve's Y-14Q data, the only administrative regulatory data among our five countries, taken from Tables 22 and 23 of Caglio et al. (2021).[5] The data for Latvia and Switzerland directly measure the share of loans secured by real estate collateral. For Denmark, we use the share of mortgage banks in total outstanding credit as a proxy. The data on Taiwan refer to the share of loans used for the purchase or construction of real estate, which is more likely to be secured by real estate collateral.

To aggregate the collateral shares from the underlying more detailed 1-digit ISIC or NAICS classifications to these combined sectors, we weight the share of real estate collateral in each 1-digit industry by the amount of outstanding credit. Overall, there is considerable variation in the reliance on real estate collateral across countries and sectors. When we take the median real estate collateral share across the five countries, we find that 84.1% of outstanding loans in the construction and real estate sectors are secured by real estate. In contrast, the figure for transport and communication is only 28.8%. The clear outlier is the United States, where the respective figures are 6.2% and 3.8%, and construction ranks only 3rd in its reliance on real estate collateral. This is likely due to the higher share of earnings-based collateral used in the U.S., particularly by small firms that dominate the U.S. economy (Caglio et al., 2021). When we rank the six combined industries in Table 6 by their reliance on real estate collateral, then lending to construction and real estate, agriculture, and retail/wholesale trade overall rank as the top three industries. As our baseline definition, we therefore use the sum of credit to these three industries as a proxy for *real estate-backed firm credit*. For robustness, we also use the ranking based on the Federal Reserve's Y-14Q data, in which the sectors most reliant on real estate collateral are construction and real estate, retail and wholesale trade, and other sectors. (As explained above, "other sectors" include the sum of utilities and miscellaneous non-financial services, which we cannot distinguish for a sufficiently large panel of countries.)

We also construct a dataset to understand the composition of lending by the *non-bank* sector. Our starting point for these data are the European Central Bank's "who-to-whom" accounts, which allow us to identify lenders and borrowers by broad sector for 27 countries. We add data from the Federal Reserve's enhanced financial accounts for the United States.

[4] With the exception of the US data, these sources were originally compiled by Müller and Verner (2023).

[5] In the Y-14Q data, we can distinguish between six types of collateral: real estate, securities, accounts receivable, fixed assets, and unsecured loans.

2.2 Financial Crisis Dates

We take data on the onset of systemic financial crises from Laeven and Valencia (2020) and Baron et al. (2020). Baron et al. (2020) date crises for 46 countries based on large declines in bank stock indices, supplemented by narrative evidence. For countries where they do not report data, we use the dates on banking crises from the widely-used work by Laeven and Valencia (2020).

To avoid double counting across sources, we use a simple filter and drop crises if we observe another crisis event in the same country in the previous five years. In total, this leaves us with a sample of 87 crises that overlap with data on growth in firm and household debt. This includes prominent episodes in major emerging economies such as the Mexican Tequila crisis of 1994, the Argentinian crisis of 2001, and the Asian financial crises of 1996-97, as well as advanced economy crises such as the Eurozone crisis of 2009-10 and the Scandinavian crises of the early 1990s.

2.3 Macroeconomic Data

We use other macroeconomic data from a variety of sources as originally compiled by Müller and Verner (2023). Data on gross domestic product (GDP), population, inflation, and nominal US dollar exchange rates are taken from the World Bank's World Development Indicators, Penn World Tables version 9.1 (Feenstra et al., 2015), the IMF's International Financial Statistics, and Jordà et al. (2016a). We fill in some values for nominal GDP from Mitchell (1998) and the UC Davis Nominal GDP Historical Series. In a few cases (USA, Taiwan, Saudi Arabia, Eastern Caribbean Currency Union, and Iceland), we add data from the national statistical offices or central banks.

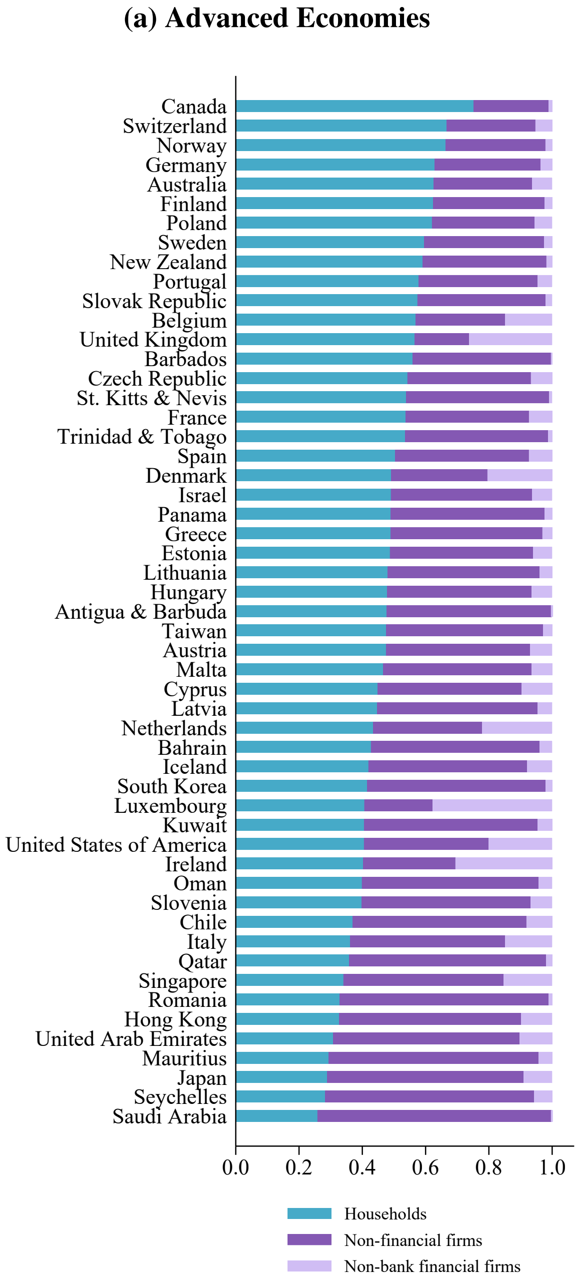
2.4 Nonperforming Loans and Defaults

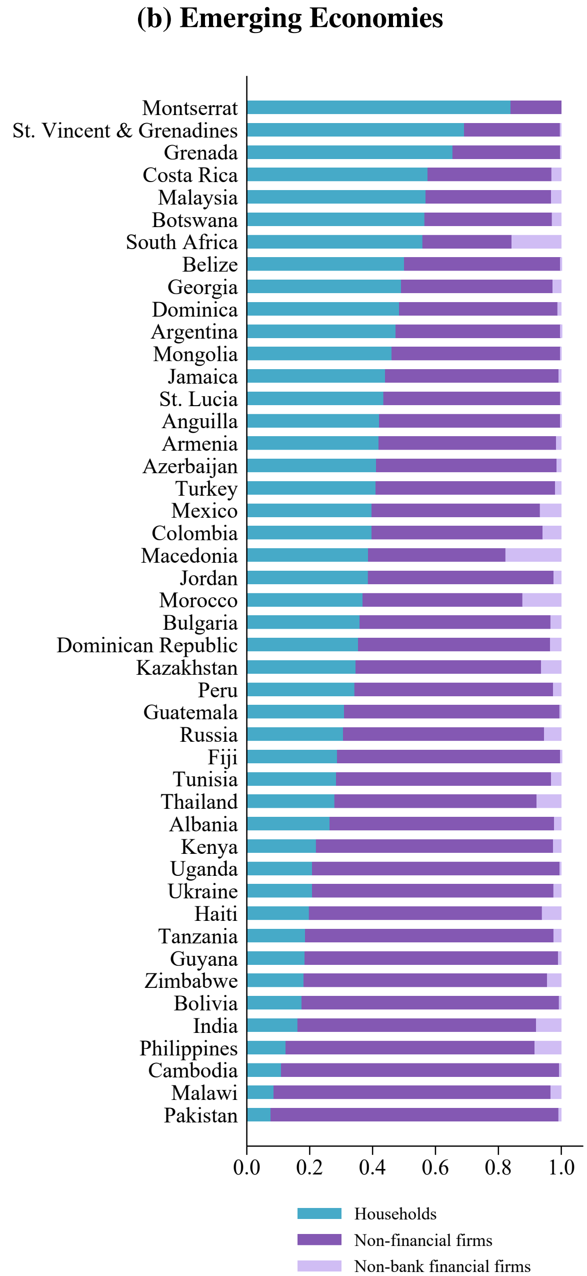
To understand who defaults during and after financial crises, we draw on several data sources. For aggregate nonperforming loans (NPLs), we obtain data from the World Bank Global Financial Development dataset, which are based on the IMF's Financial Soundness Indicators. These data cover 127 countries but only start in 1998, and thus mainly overlap with the Global Financial Crisis of 2007-08.

More important for our analysis is a new dataset on nonperforming loans by sector, which we construct based on data from the national central banks. We were able to collect these data for 19 countries.[6] The information we have overlaps with several prominent episodes of financial crises, such as the Mexican Tequila Crisis in 1994, the Spanish crisis of 2008, and the Argentine crisis of 2001. Table A.8 provides details on the sources and definitions of nonperforming loans in different countries. NPLs are defined as loans that are 90 days or more past due in almost all countries where we can disaggregate them by sector.

[6] We would like to thank Jin Cao (Norges Bank) for sharing the historical data on Norway with us.

Figure 1: Share of Firm Credit in Total Outstanding Credit





Notes: These figures plot data on the composition of total credit to the private sector as of 2014 (the last year in the sample). Panel (a) plots data for advanced economies, Panel (b) data for emerging economies. Data source: Global Credit Project (Müller and Verner, 2023).

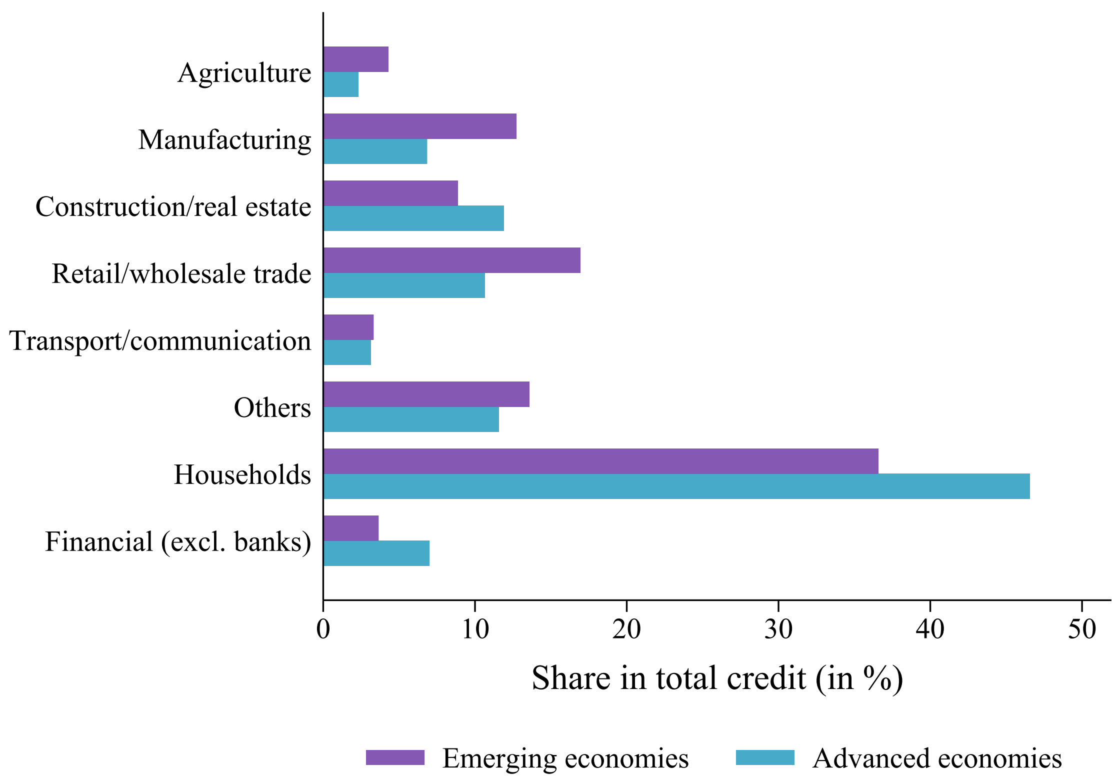
To measure defaults by sector for a broader set of countries, we also look at loan loss data published by AMRO Asia (Ong et al., 2023). They provide estimates of credit losses by sector based on a forward-looking Merton model for 97 countries since 2000, 28 of which experienced a banking crisis between 2007 and 2011.

2.5 Descriptive Statistics

Figure 1 plots the share of credit to households, non-financial corporations, and non-bank financial institutions as of 2014 for the countries with data on all three of these sectors. The share of household debt varies widely across countries and is higher in advanced than emerging economies. Figure 2 plots the industrial composition of total credit separately for advanced and emerging economies. Lending to agriculture, manufacturing, and retail and wholesale trade is more important in developing countries, while construction, finance, and household credit are more prominent in rich countries.

Table 1 presents some descriptive statistics on the characteristics of credit growth in different sectors. For this exercise, we define credit growth as the year-on-year change in (sectoral) credit-to-GDP. Changes in firm credit are more volatile than those in household credit, especially firm credit to the construction, real estate, and retail/wholesale trade industries. Household debt and loans to construction and real estate, as well as loans to non-financial firms secured by real estate, tend to be more persistent, as measured by the coefficient of an AR(1) model.

Figure 2: Credit Composition in Advanced and Emerging Economies



Notes: This figure plots data on the composition of total credit to the private sector as of 2014 (the last year in the sample), by country group. The underlying data covers 89 countries. Data source: Global Credit Project (Müller and Verner, 2023).

Table 1: Properties of Changes in Sectoral Credit-to-GDP

Sector	Mean	Std. Dev.	25%	50%	75%	AR(1)	N
Total credit	0.73	3.97	-0.82	0.55	2.27	0.26	8,875
Broad sectoral aggregates							
Firms	0.42	3.27	-0.98	0.42	1.82	0.27	4,252
Non-financial corporations	0.40	3.15	-0.99	0.38	1.79	0.29	2,677
Non-bank financial corporations	0.10	0.97	-0.13	0.02	0.28	0.16	2,677
Households	0.64	1.77	-0.14	0.36	1.29	0.35	4,252
Firm credit by industry							
Agriculture	0.00	0.37	-0.09	-0.00	0.08	0.16	1,954
Manufacturing, mining	-0.02	0.83	-0.40	-0.04	0.36	0.20	1,954
Construction, real estate	0.18	1.07	-0.20	0.07	0.48	0.44	1,954
Retail, wholesale trade	0.04	0.99	-0.34	0.05	0.42	0.17	1,954
Transport, communication	0.03	0.40	-0.12	0.01	0.18	0.13	1,954
Other firm credit	0.14	1.33	-0.32	0.10	0.62	-0.01	1,954
Firm credit by collateral							
Real estate-backed firm credit	0.22	1.87	-0.63	0.19	0.97	0.37	1,954
Firm credit backed by other collateral	0.13	1.87	-0.75	0.14	1.06	0.10	1,954

Notes: This table presents summary statistics for different measures of sectoral credit growth, defined as the annual change in credit to GDP ratio. AR(1) denotes the estimated coefficient of the first lag in an AR(1) model, a measure of persistence.

3 Corporate Debt and Financial Crises

This section examines the relation between changes in household and corporate debt around the onset of 87 systemic financial crises. We begin by decomposing the growth of total credit to the private sector into its sectoral components, then turn to predictive regressions, and finally consider the role of procyclical fluctuations in collateral values.

3.1 Decomposing Credit Growth Around Financial Crises

What accounts for the run-up in credit before systemic financial crises? What explains the credit crunch in their aftermath? Figure 3 provides event study evidence by decomposing the growth of total credit to the private sector around crises into its sectoral components. We look at the change in credit to GDP, the most widely used measure of a credit expansion. By definition, the change in total credit to GDP is the sum of the sectors.

Figure 3a begins with a sample of 87 financial crises for which we have data on corporate and household debt. The credit expansion that precedes financial crises is mainly driven by firm credit, especially in the three years before the onset of the crisis. While household debt also grows relative to GDP, this is more concentrated at longer horizons around four or five years before crises. Based on this decomposition, on average, 64% of the credit growth in the three years before financial crises is accounted for by corporate debt. Once a crisis erupts, the credit crunch is almost entirely driven by firms. In fact, household debt relative to GDP continues to rise rather than fall after crises. These results suggest that firm credit plays an important role in explaining the build-up of economy-wide leverage prior to crisis episodes and the contraction of credit in their aftermath.

Figure 3b further decomposes firm borrowers into non-financial corporations and non-bank financial institutions. We can do this decomposition for 62 crisis episodes. This exercise shows that lending to non-financial corporations accounts for most of the boom and bust in firm credit. However, loans to non-bank financial institutions also grows rapidly, especially in the three years before crises, and also contract significantly when a financial crisis breaks out.

Figures 4 replicate these event studies separately for advanced and emerging economies. We can distinguish between firm and household credit for 52 advanced economy crises and 35 emerging economy crises. Corporate debt accounts for most of the credit expansion in the run-up to crises in both groups of countries. In the three years before a crisis, corporate debt explains 62% of credit growth in advanced economies and 71% in emerging economies. As might be expected, credit booms and busts are more volatile in emerging economies. However, in terms of the importance of corporate credit in the two sets of countries, the overall patterns are the same.

Taking stock of this new granular evidence, our interpretation is that corporate debt explains most of the credit growth before financial crises. The next sections examine whether these sectoral differences also matter for the conditional probability of a crisis.

3.2 Which Credit Booms End Badly?

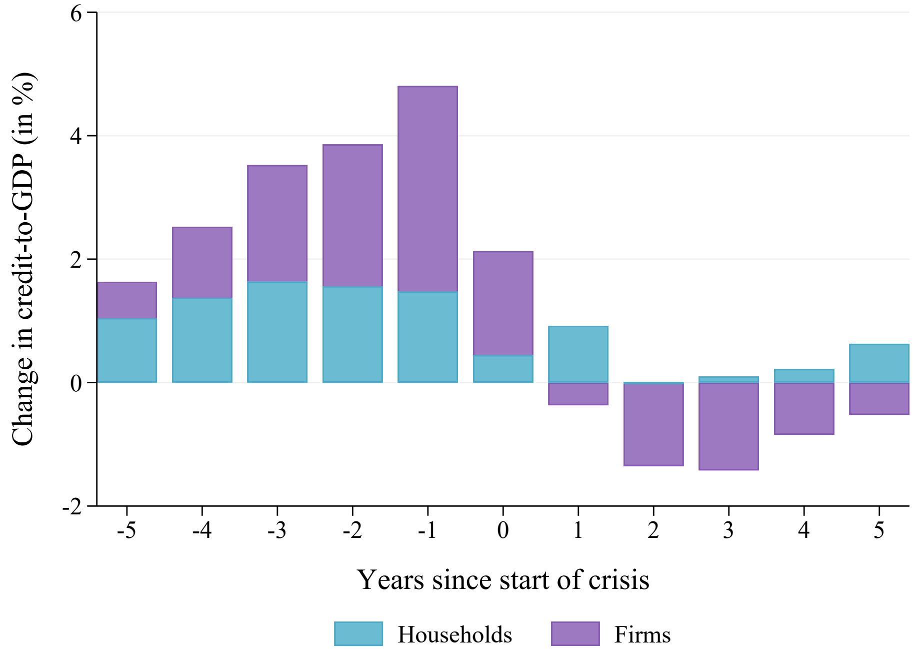
Table 2 presents statistics on the frequency and severity of systemic banking crises as a function of the type of credit boom that precedes them. We measure credit booms as periods in which the three-year change in sectoral credit to GDP is equal to or above a country's 80$^{\text{th}}$ percentile. We restrict the sample to observations for which we have data on both crises and the credit boom indicators. As a proxy for the depth of the crisis, we look at changes in real GDP per capita.

Several facts stand out. Of the 87 crises in our dataset, 39 were preceded by a boom in corporate debt. In 28 crises, we find booms in household debt. In 47 cases, we see a boom in either firm *or* household debt, and in 20 cases a boom in both. These differences between firm and household debt become more pronounced when we exclude cases where both sectors experienced a boom. We find 19 crises where corporate debt, but not household debt, was booming. The reverse is true for only 8 cases.

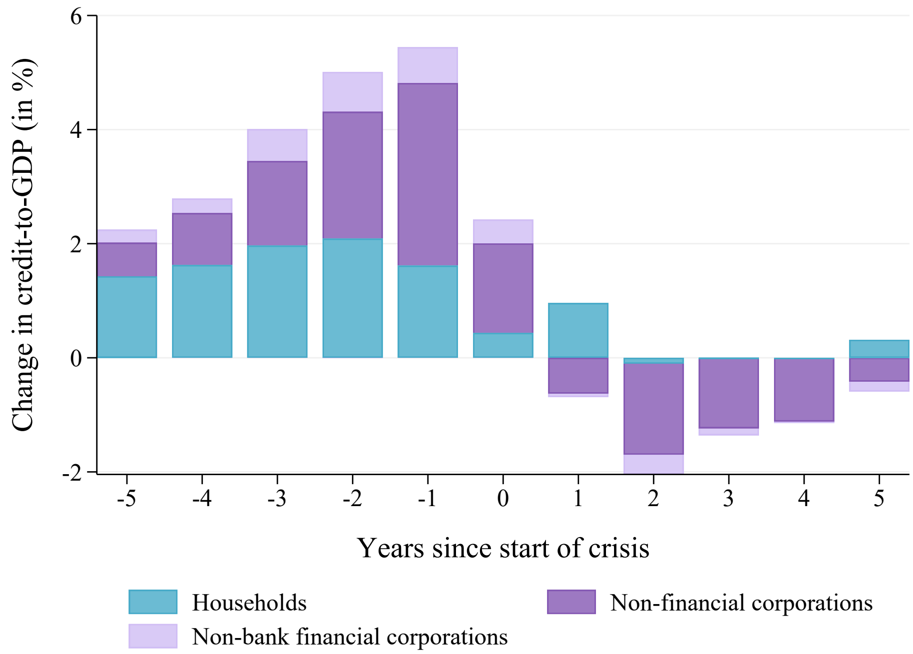
If we look at the recovery from banking crises, measured by post-crisis GDP growth after the onset of a crisis, we find a broadly similar pattern. The recessions after crises are similarly deep

Figure 3: Decomposing Credit Growth Around Financial Crises

(a) Firm vs. household debt



(b) Non-financial vs. financial firm debt

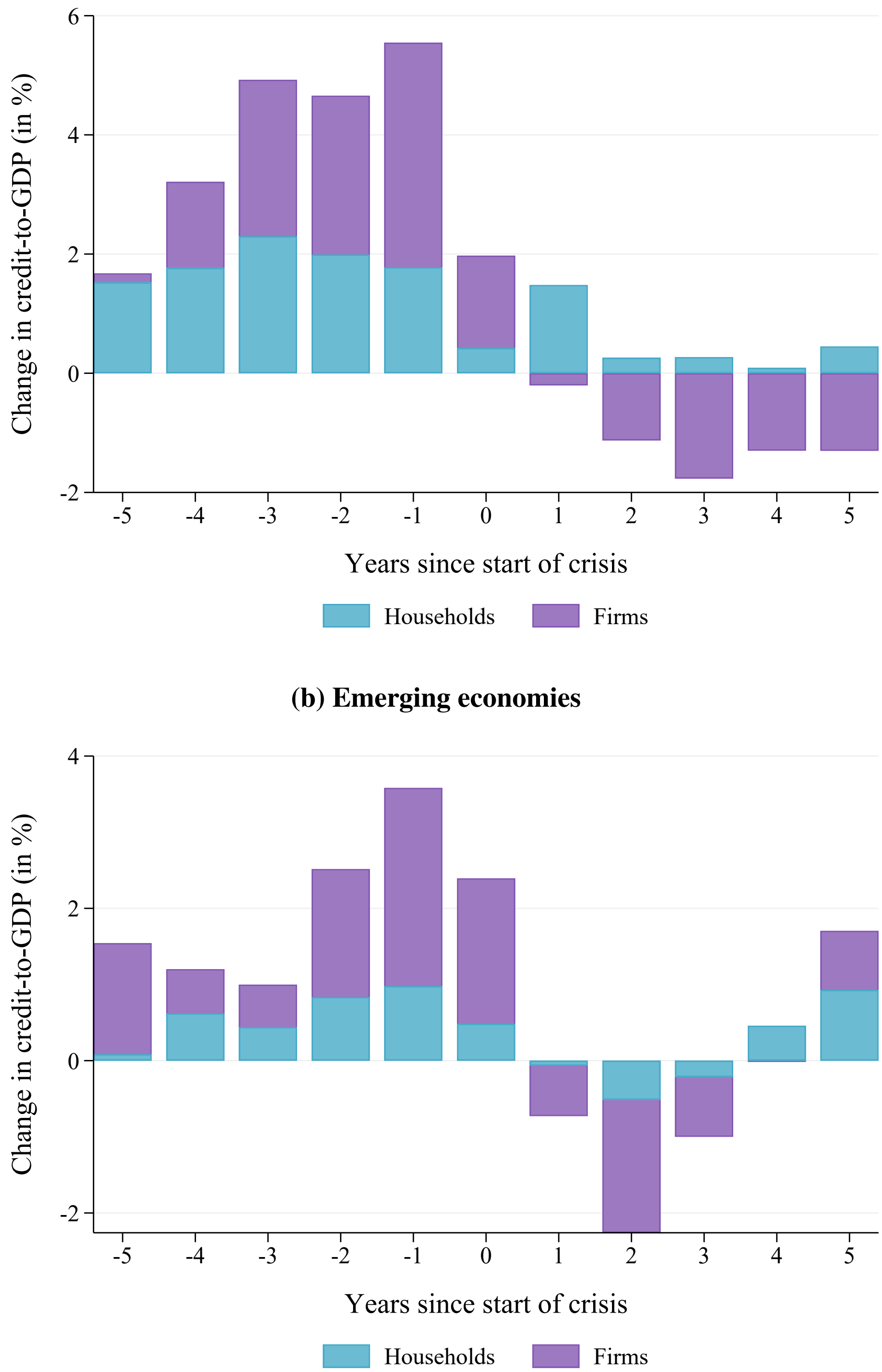


Notes: These figures decompose changes in total credit-to-GDP around the onset of systemic financial crises, where we identify the first year of a crisis based on the chronologies in Baron et al. (2020) and Laeven and Valencia (2020). Panel (a) includes 87 crises and panel (b) 62 crises. We plot the average change in credit-to-GDP for each sector in a five-year window around crises. By definition, the sum of the sectors is equal to total credit.

Figure 4: Decomposing Credit Growth Around Crises – Advanced vs. Emerging Economies

(a) Advanced economies

(b) Emerging economies



Notes: These figures decompose changes in total credit-to-GDP around the onset of systemic financial crises, where we identify the first year of a crisis based on the chronologies in Baron et al. (2020) and Laeven and Valencia (2020). We plot the average change in credit-to-GDP for each sector in a five-year window around crises. By definition, the sum of the sectors is equal to total credit. The sample is restricted to advanced and emerging economies in panels (a) and (b), respectively.

Table 2: Descriptive Statistics – Sectoral Credit Booms, Crises, and Recessions

	Crisis probability			Post-crisis GDP growth		
	Number	Prob.	% of crises	1 year	3 years	5 years
All banking crises	87	2.40	100.00	-0.46	1.80	2.35
Conditional on boom in...						
Firm debt	39	5.05	44.83	-2.96	0.35	0.97
Household debt	28	3.62	32.18	-2.50	0.65	1.37
Either	47	3.89	54.02	-2.32	0.68	1.32
Both	20	5.92	22.99	-3.84	-0.02	0.70
Firm debt only	19	4.37	21.84	-2.04	0.73	1.25
Household debt only	8	1.84	9.20	0.83	2.30	2.98

Notes: This table plots statistics on the likelihood and severity of systemic banking crises depending on the type of credit boom preceding them. All statistics except the number of crises are in percent. *Prob.* is the mean of the systemic banking crisis dummy, which measures the probability of a crisis. *% of crises* is the fraction of crises that are preceded by a particular type of credit boom. Credit booms are defined as observations where the three-year change in sectoral credit-to-GDP is equal or above the 80$^{\text{th}}$ percentile value for a given country. *Post-crisis GDP growth* is the difference in the natural logarithm of GDP per capita over a given horizon, and we report the average of annualized growth rates. Crisis dates are from Baron et al. (2020) and Laeven and Valencia (2020).

for booms in firm and household debt, and much deeper and more protracted than for the average banking crisis. Comparing episodes where only corporate debt *or* household debt booms, we find that firm credit booms are associated with worse recessions. In fact, in this sample, crises that followed a household credit boom alone experienced a faster recovery than the average financial crisis.

Of course, these patterns can only be interpreted as suggestive. For one, defining credit booms is inherently challenging and subject to measurement error. The analysis here also conditions on the occurrence of a crisis, which means that the many credit expansions that did not result in financial turmoil are ignored. To get around these limitations, the next section uses a predictive regression framework to document the link between expansions in firm and household debt with financial crises.

3.3 Predictive Regressions

Does corporate credit have benign implications for the likelihood of future crises? Existing work, including Schularick and Taylor (2012) and Gourinchas and Obstfeld (2012), shows that crises can be predicted using measures of past credit growth. We use panel regressions to examine the relative importance of firm and household debt using regressions similar to Greenwood et al. (2022) of the following form:

$$P(\text{Crisis})_{i,t+h} = \alpha_i^h + \sum_{j \in J} \beta_j^h \Delta_3 \text{Credit}^j/\text{GDP}_{i,t} + \varepsilon_{i,t}^h, \tag{1}$$

where $P(\text{Crisis})_{i,t+h}$ is a dummy variable equal to 1 if a country experiences the onset of a systemic financial crisis based on the data in Baron et al. (2020) or Laeven and Valencia (2020) over the horizon t to $t+h$. Put differently, we define $P(\text{Crisis})_{i,t+h} = max(P(\text{Crisis})_{i,t}, ..., P(\text{Crisis})_{i,t+h})$. α_i^h is a country fixed effect. To keep the number of observations constant across different forecast horizons, we end the sample in 2009. We follow Greenwood et al. (2022) and estimate these regressions using OLS with Driscoll-Kraay standard errors based on $ceil(1.5 \times h)$ lags.

We are interested in testing the predictive ability of different types of credit for crises. To implement these tests, $\sum_{j \in J} \Delta_3 \text{Credit}^j/\text{GDP}_{i,t}$ is a vector of credit growth variables referring to changes in the ratio of credit to GDP to the set of sectors in J between $t-3$ and t. To make the magnitudes for different sectoral credit variables comparable, $\Delta_3 \text{Credit}^j/\text{GDP}_{i,t}$ for each sector is standardized to have a mean of zero and a standard deviation of one. The coefficients β_j^h thus give the change in the probability of a crisis starting within h years if credit growth to sector j increases by one standard deviation.

Panel A of Table 3 reproduces the well-known finding in the literature that an expansion in the ratio of total credit to GDP predicts a higher probability of a financial crisis using a large dataset covering 6146 observations and 148 crises. A one standard deviation higher credit growth is associated with a 1.1 and 2.0 percentage point higher crisis probability within one and three years, respectively. These magnitudes are large, given that the unconditional probability of a crisis in this sample is 2.4%.

Panel B turns to our main results distinguishing between firm and household debt, where we estimate Equation (1) for $j \in \{HH, FIRM\}$ and report the coefficients β_{HH}^h and β_{FIRM}^h for $h = 1, ..., 5$. Firm credit is a highly statistically significant predictor of crises, and is an even more important predictor than household credit at horizon $h = 1$. A one standard deviation increase in corporate debt predicts a 1.6 percentage point higher crisis probability, compared to 1.2 for household debt. At longer horizons, household debt becomes more important for predicting crises. These results are consistent with the event study evidence in Section 3.1. In our view, these patterns are difficult to reconcile with the idea that a build-up of corporate debt poses lower macroeconomic risks than a build-up of household debt.

Table 4 decomposes corporate debt into loans to different industries. To maximize data availability, we focus on credit to the non-bank financial sector and broad categories of non-financial industries: agriculture; manufacturing (including mining); construction and real estate; retail and wholesale trade (including accommodation and restaurants); transport and communication; and other types of non-financial firm credit (which includes utilities and miscellaneous services). There is considerable heterogeneity in the relationship between crises and corporate debt across sectors. Credit to agriculture,

Table 3: Firm Credit, Household Credit, and Financial Crises

	Dependent variable: Crisis within...				
	1 year	2 years	3 years	4 years	5 years
Panel A: Total credit					
Δ_3TOT/GDP	0.011+	0.018*	0.020+	0.022+	0.022*
	(0.006)	(0.008)	(0.010)	(0.011)	(0.011)
Observations	6,146	6,146	6,146	6,146	6,146
# Crises	150	150	150	150	150
AUC	0.57	0.56	0.55	0.55	0.55
Panel B: Household vs. firm credit					
Δ_3HH/GDP	0.012+	0.025+	0.040*	0.052*	0.062**
	(0.007)	(0.013)	(0.018)	(0.020)	(0.019)
Δ_3FIRM/GDP	0.016**	0.027**	0.028**	0.024*	0.017
	(0.006)	(0.007)	(0.007)	(0.010)	(0.011)
Observations	3,070	3,070	3,070	3,070	3,070
# Crises	84	84	84	84	84
AUC	0.67	0.66	0.65	0.65	0.64

Notes: This table plots the coefficient estimates β_j^h for $h = 1, ..., 5$ from estimating Equation (1) using OLS. The dependent variable is a dummy for the onset of a systemic financial crisis within h years based on data from Baron et al. (2020) and Laeven and Valencia (2020). Credit growth is measured as the three-year change in credit-to-GDP. All regressions include country fixed effects. Driscoll-Kraay standard errors based on $ceil(1.5 \times h)$ lags are in parentheses. +, * and ** denote significance at the 10%, 5% and 1% level, respectively.

manufacturing, transport and communication, or other sectors has no link with the probability of a financial crisis or even attracts a *negative* sign. When credit flows to the construction and real estate or retail and wholesale trade industries, this predicts a considerably elevated crisis risk. For example, at a three-year horizon, we find that the probability of a crisis is 2.7 and 3.6 percentage points higher, respectively, when credit growth to construction/real estate and retail/wholesale trade is one standard deviation higher, respectively.

To evaluate the ability of these different models using sectoral information to correctly predict crises, we use the Area Under the Curve (AUC). The AUC is a measure used in classification problems with binary dependent variables. It is calculated as the integral under the Receiver Operating Characteristic Curve (ROC), which plots a model's true positive rate against its false positive rate of a model. This measure has been widely used in the literature to assess whether a statistical model does better than a random guess in classifying crisis and non-crisis periods. The benchmark is $AUC = 0.5$, which corresponds to a 50-50 probability that a model correctly predicts a crisis or non-crisis period.

Table 4: Industry Credit Growth and Crises

	Dependent variable: Crisis within...				
	1 year	2 years	3 years	4 years	5 years
Δ_3HH/GDP	0.023$*$	0.038$*$	0.051$**$	0.067$**$	0.071$**$
	(0.011)	(0.016)	(0.018)	(0.019)	(0.018)
Δ_3AGR/GDP	-0.001	-0.002	-0.005	-0.015	-0.025$**$
	(0.004)	(0.006)	(0.012)	(0.011)	(0.008)
Δ_3MAN/GDP	-0.011$+$	-0.020$*$	-0.018$+$	-0.013	-0.006
	(0.006)	(0.009)	(0.010)	(0.013)	(0.014)
Δ_3CRE/GDP	0.017$*$	0.026$*$	0.027$**$	0.023$+$	0.023
	(0.008)	(0.011)	(0.009)	(0.013)	(0.020)
Δ_3RET/GDP	0.015$**$	0.028$**$	0.036$**$	0.032$*$	0.028$+$
	(0.004)	(0.009)	(0.013)	(0.015)	(0.014)
Δ_3TRA/GDP	-0.002	-0.008$*$	-0.021$**$	-0.032$**$	-0.045$**$
	(0.003)	(0.004)	(0.007)	(0.012)	(0.012)
Δ_3OTH/GDP	0.001	0.003	-0.002	-0.001	-0.005
	(0.004)	(0.006)	(0.008)	(0.011)	(0.012)
Δ_3FIN/GDP	0.020$*$	0.030$**$	0.027$*$	0.020	0.014
	(0.010)	(0.011)	(0.011)	(0.015)	(0.019)
Observations	1,246	1,246	1,246	1,246	1,246
# Crises	38	38	38	38	38
AUC	0.78	0.76	0.73	0.72	0.70

Notes: This table plots the coefficient estimates β_j^h for $h = 1, ..., 5$ from estimating Equation (1) using OLS. The dependent variable is a dummy for the onset of a systemic financial crisis within h years based on data from Baron et al. (2020) and Laeven and Valencia (2020). Credit growth is measured as the three-year change in credit-to-GDP. All regressions include country fixed effects. Driscoll-Kraay standard errors based on $ceil(1.5 \times h)$ lags are in parentheses. +, * and ** denote significance at the 10%, 5% and 1% level, respectively.

We find AUC values around 0.7 or higher once we add industry-level data to our models.

Table 5 provides evidence that differentiates between advanced and emerging economies. We rerun our baseline estimation of Panel B in Table 3, which distinguishes between firm and household debt. The pattern for advanced economies in Panel A is similar to that for the full sample: corporate debt has a more statistically significant predictability for crises starting within one or two years than household debt. In emerging economies, we find relatively limited evidence that household debt is important for predicting crises, and corporate debt seems to matter at somewhat longer horizons.

We provide an extensive set of robustness exercises for our finding that corporate debt is helpful in predicting financial crises in Table A.1 in the appendix. We consider specifications that add year fixed effects, use a logit estimator, use a "credit boom" dummy for periods of high credit growth, use alternative crisis chronologies, restrict the sample to years before the 2000s housing boom, or

Table 5: Corporate Debt, Household Debt, and Crises – By Country Group

	Dependent variable: Crisis within...				
	1 year	2 years	3 years	4 years	5 years
Panel A: Advanced economies					
Δ_3HH/GDP	0.013+	0.029+	0.049$*$	0.067$*$	0.082$**$
	(0.008)	(0.016)	(0.023)	(0.028)	(0.028)
Δ_3FIRM/GDP	0.019$*$	0.030$**$	0.031$**$	0.021+	0.005
	(0.008)	(0.009)	(0.009)	(0.012)	(0.013)
Observations	1,915	1,915	1,915	1,915	1,915
# Crises	50	50	50	50	50
AUC	0.69	0.68	0.68	0.69	0.68
Panel B: Emerging economies					
Δ_3HH/GDP	0.010	0.015	0.015	0.012	0.005
	(0.009)	(0.014)	(0.018)	(0.022)	(0.024)
Δ_3FIRM/GDP	0.011	0.021	0.026$*$	0.035$**$	0.047$**$
	(0.009)	(0.013)	(0.011)	(0.012)	(0.011)
Observations	1,155	1,155	1,155	1,155	1,155
# Crises	34	34	34	34	34
AUC	0.64	0.63	0.61	0.62	0.63

Notes: This table plots the coefficient estimates β_j^h for $h = 1, ..., 5$ from estimating Equation (1) using OLS. The dependent variable is a dummy for the onset of a systemic financial crisis within h years based on data from Baron et al. (2020) and Laeven and Valencia (2020). Credit growth is measured as the three-year change in credit-to-GDP. All regressions include country fixed effects. Driscoll-Kraay standard errors based on $ceil(1.5 \times h)$ lags are in parentheses. Panel A and B restrict the sample to advanced and emerging economies, respectively. +, * and ** denote significance at the 10%, 5% and 1% level, respectively.

advanced/emerging economies, or use alternative ways of constructing credit growth. We also consider a specification that excludes the United States. In all these specifications, growth in corporate debt has a similar predictive ability for financial crises when compared with household debt, and sometimes it performs even better. An important finding is that corporate debt still predicts crises after 1990, suggesting that the predictability we document is not just about long-ago periods.

To take stock, the results in this section paint a clear picture: in the post-war period, corporate debt is not a mere sideshow to household debt. Credit growth in the non-bank financial sector, construction and real estate, and retail and wholesale trade sectors is a strong predictor of financial crises. Household debt matters more at longer horizons and has a weaker link to crises in emerging markets.

Table 6: Percent of Credit Backed by Real Estate Collateral, By Industry

ISIC codes	Industry name	Denmark	Latvia	Switzerland	Taiwan	USA
A	Agriculture	78.5	73.4	85	11.9	4.4
B+C	Manufacturing, Mining	36.9	60.7	47.9	11.6	4
F+L	Construction, Real estate	84.9	87.4	84.1	39.1	6.2
G+I	Retail, wholesale trade	49.3	65.9	57.2	17.4	7.3
H+J	Transport, communication	50.6	41.1	N/A	16.4	3.8
D+E+M+N+P+Q+R+S	Other sectors	61.5	36.1	58.3	13.1	8.7

Notes: This table plots estimates for the share of outstanding non-financial firm credit in different industries that is backed by real estate collateral. Values are in percent. Data for transport and communication is not separately reported in Switzerland. Data for the United States is taken from aggregated Y-14Q data as reported in Caglio et al. (2021). See Table A.7 for details on sources and variable construction.

3.4 Who Borrows From Non-Bank Financial Institutions?

The previous section shows that credit to non-bank financial institutions has strong predictive power in explaining systemic banking crises. This raises an important question: What do non-bank financial institutions do with the money they borrow? Understanding the portfolio of non-bank financial institutions is important because, if they lend predominantly to households, it could challenge the narrative that corporate debt itself can be a source of financial stability risks.

Figure A.8 shows data on the loan portfolio of non-bank financial institutions in 28 countries. Non-banks include all types of non-deposit taking lenders, such as leasing or finance companies, but also insurers, pension funds, and other types of financial service companies. There is considerable variation in the activities of non-bank financial institutions across countries, but some general patterns emerge. Most importantly, in most countries, the portfolio of non-banks consists mainly of loans to firms rather than to households.[7] However, Figure A.9 in the appendix shows that, on average, lending by non-banks is only a small fraction of total outstanding credit for each borrower sector except other non-banks. As such, an expansion of credit to non-bank financial institutions is perhaps best understood as having a potential amplifying effect on corporate debt rather than on household debt.

3.5 The Role of Collateral Values

To test the relevance of procyclical collateral values for the link between firm borrowing and financial crises, we exploit data on firm credit backed by different types of collateral from five countries. As the link between real estate collateral values and firm behavior has been widely studied ([e.g., Chaney et al., 2012; Bahaj et al., 2020), we focus on the share of debt backed by real estate collateral using the data on sectors' reliance on real estate collateral reported in Table 6.

[7] To keep the analysis consistent with the sectoral credit data we use in the rest of the paper, we exclude loans to governments and banks.

As Table 6 shows, there are significant differences in the use of real estate as collateral between sectors and countries. However, if we rank the sectors by their reliance on real estate as collateral, the top three sectors tend to be (1) construction and real estate, (2) retail and wholesale trade, and (3) either agriculture or other sectors (which mostly refers to various service sectors).

Table 7 shows the results of a series of predictive regressions in which we apply this distinction between real estate-backed and other firm credit. The top three sectors that use real estate collateral are grouped as "real estate-backed firm credit", and the remaining sectors are grouped together in another bucket. We find that the growth of corporate debt in sectors with a high reliance on real estate collateral is strongly associated with future crises. A one standard deviation increase in real estate-backed credit is associated with a 3.7 percentage point higher probability of a crisis within three years. As before, the coefficients on loans to non-banks are consistently positive and highly statistically significant.

Table 7: Firm Credit, Real Estate Collateral, and Crises

	Dependent variable: Crisis within...				
	1 year	2 years	3 years	4 years	5 years
Δ_3HH/GDP	0.025+	0.041$*$	0.052$*$	0.067$**$	0.073$**$
	(0.013)	(0.018)	(0.021)	(0.022)	(0.020)
Δ_3NFC, real estate-backed/GDP	0.020$**$	0.031$**$	0.037$**$	0.026	0.015
	(0.006)	(0.010)	(0.012)	(0.017)	(0.022)
Δ_3NFC, other/GDP	-0.003	-0.006	-0.013	-0.014	-0.017
	(0.004)	(0.007)	(0.010)	(0.013)	(0.012)
Δ_3FIN/GDP	0.019$*$	0.029$**$	0.026$*$	0.018	0.013
	(0.009)	(0.010)	(0.011)	(0.015)	(0.020)
Observations	1,246	1,246	1,246	1,246	1,246
# Crises	38	38	38	38	38
AUC	0.77	0.74	0.72	0.70	0.68

Notes: This table plots the coefficient estimates β_j^h for $h = 1, ..., 5$ from estimating Equation (1) using OLS. The dependent variable is a dummy for the onset of a systemic financial crisis within h years based on data from Baron et al. (2020) and Laeven and Valencia (2020). Credit growth is measured as the three-year change in credit-to-GDP. We split lending to non-financial corporations into two buckets depending on their reliance on real estate collateral; for the classification, see Table 6. Δ_3NFC, real estate-backed/GDP refers to firm lending to construction and real estate services, agriculture, retail and wholesale trade, as well as food and accommodation services. Δ_3NFC, other/GDP is defined as firm lending to manufacturing and mining, transport and communication, as well as all other sectors. All regressions include country fixed effects. Driscoll-Kraay standard errors based on $ceil(1.5 \times h)$ lags are in parentheses. +, * and ** denote significance at the 10%, 5% and 1% level, respectively.

Since we find an overall lower reliance on real estate collateral for the U.S., we perform the same exercise using a sector ranking based only on the Federal Reserve's Y-14Q data. The results are shown in Table A.4; they are similar. This is not entirely surprising as the top three sectors most reliant on real estate collateral are similar, even in the United States where earnings-based constraints may play a more dominant role in the aggregate corporate debt (as argued by Lian and Ma, 2020; Caglio et al., 2021; Drechsel, 2023).

Figure A.1 in the appendix shows an event study of credit growth around crises where we disaggregate loans to non-financial corporations according on an industry's reliance on real estate collateral. Firm credit backed by real estate collateral grows particularly rapidly before crises, but other sectors are also quantitatively important. These results are also consistent with Jordà et al. (2016b) who find that an expansion in total outstanding mortgage credit, which includes both lending to households and firms, predicts financial crises, but only in the post-World War II period. In the full sample, they find that *non-mortgage* credit is significantly more important for predicting crises (with an AUC of 0.72) than mortgage debt (with an AUC of 0.66). After World War II, however, they find that mortgages become similarly important to non-mortgages. Importantly, our results suggest that this link between real estate-backed credit and financial crises operates at least partly through *corporate debt* rather than household debt.

3.6 Corporate Debt, Household Debt, and GDP Crash Risk

While we show that growth in corporate debt has a strong relation with financial crises, Mian et al. (2017) show that it only has limited predictive ability for future average GDP growth. In this section, we show that this apparent contradiction is explained by the fact that corporate debt matters for *crash risk* in GDP, i.e. left-tail realizations, while household debt is more predictive of mean future growth.

Our starting point is an empirical model relating future GDP growth to an expansion in corporate and household debt, exactly mirroring the specification used in Table 2 of Mian et al. (2017):

$$\Delta_3 y_{i,t+k} = \alpha_i + \beta_{FIRM}\Delta_3\text{Credit}^{FIRM}/\text{GDP}_{i,t-1} + \beta_{HH}\Delta_3\text{Credit}^{HH}/\text{GDP}_{i,t-1} + \varepsilon_{i,t}, \tag{2}$$

where $\Delta_3\text{Credit}^{FIRM}/\text{GDP}_{i,t-1}$ and $\Delta_3\text{Credit}^{HH}/\text{GDP}_{i,t-1}$ are the change in firm and household debt relative to GDP from $t-4$ to $t-1$. The dependent variable is the three-year change in real GDP per capita, and we consider the values $k = -1, 0, ..., 5$, so that the estimates of β_{FIRM} and β_{HH} capture the medium-term relation between an expansion of firm or household debt with future growth. We double-cluster standard errors by country and year to account for within-country correlation in the error term induced by overlapping observations and cross-country correlation induced by contemporaneous common shocks.

Table 8 replicates the patterns reported in Mian et al. (2017) in Panel A. Although our dataset is substantially larger, the point estimates and statistical significance are remarkably similar to what they report. An expansion in household debt from $t-4$ to $t-1$ is systematically associated with a growth slowdown over the next few years, and there is only limited evidence for such a relation when looking at corporate debt.

To reconcile this finding with our results on financial crises, we turn to a quantile regression approach. In the existing literature, quantile regressions have been used to estimate the conditional distribution of GDP growth as a function of financial conditions by, among others, Adrian et al. (2019) and Adrian et al. (2022). Because we have a panel with unit fixed effects, we rely on the approach of Machado and Santos Silva (2019) and estimate regression quantiles via conditional means for different quantiles τ. The model is otherwise specified equivalently to equation 2.

Panel B of table 8 presents a first quantile regression result for $\tau = 0.5$ that relates median GDP growth to an expansion in corporate and household debt. The coefficient estimates are similar to the OLS results in Panel A, although all results are slightly more statistically significant. Panels C to E then proceed with an estimation using $\tau = 0.2$, $\tau = 0.1$, and $\tau = 0.05$, i.e. a prediction of GDP growth in the bottom 20%, 10%, or 5% of the distribution. Corporate debt becomes successively more important than household debt in the left tail of GDP growth. When we look at 5$^{\text{th}}$ percentile realizations of GDP growth, it is almost exclusively corporate debt that matters within horizons up until three years into the future, with a considerably more muted role for household debt.

These findings have important implications for theories of macro-financial linkages. An expansion in household debt robustly predicts a slowdown in *average* GDP growth, consistent with an "indebted demand" channel where debt overhang holds back household spending (see, e.g., Mian et al., 2021). At the same time, we find that household debt matters much less for putting growth at risk, and only with a considerable lag. Instead, it is corporate debt that is not only robustly related to financial crises but also major macroeconomic disasters more generally. Our analysis in the following sections suggests that these predictable GDP crashes are the result of lopsided growth in corporate debt leading to a wave of defaults that ultimately erodes banks capitalization. As such, the channels linking corporate and household debt to economic fluctuations may be quite different.

4 Lopsided Credit Expansions and Crisis Risk

One interpretation of why the allocation of credit is related to the incidence of systemic financial crises is that credit booms go bad when some sectors grow "out of whack." In this section, we propose a simple test of this hypothesis.

4.1 Measuring Imbalances in Credit Growth

We propose a simple measure to capture the lopsidedness of credit growth: the standard deviation of sectoral firm credit growth rates. If credit grows relatively uniformly in response to sector-specific

Table 8: Credit Expansion and GDP Crash Risk

	Dependent variable: $\Delta_3 y_{i+k}, k=-1,...,5$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta_3 y_{it-1}$	$\Delta_3 y_{it}$	$\Delta_3 y_{it+1}$	$\Delta_3 y_{it+2}$	$\Delta_3 y_{it+3}$	$\Delta_3 y_{it+4}$	$\Delta_3 y_{it+5}$
Panel A: OLS regression with FE							
Δ_3HH/GDP	-0.003	-0.088	-0.207*	-0.336**	-0.416**	-0.421**	-0.381**
	(0.079)	(0.076)	(0.081)	(0.083)	(0.090)	(0.099)	(0.102)
Δ_3FIRM/GDP	0.113*	-0.001	-0.080	-0.077+	-0.048	0.002	0.033
	(0.055)	(0.058)	(0.055)	(0.044)	(0.040)	(0.046)	(0.051)
Panel B: Quantile regression (50th percentile)							
Δ_3HH/GDP	-0.008	-0.093*	-0.213**	-0.341**	-0.421**	-0.425**	-0.384**
	(0.039)	(0.041)	(0.041)	(0.040)	(0.045)	(0.047)	(0.047)
Δ_3FIRM/GDP	0.115**	0.004	-0.076**	-0.074**	-0.046+	0.003	0.034
	(0.025)	(0.025)	(0.023)	(0.024)	(0.024)	(0.024)	(0.026)
Panel C: Quantile regression (20th percentile)							
Δ_3HH/GDP	0.079	-0.004	-0.096*	-0.199**	-0.286**	-0.326**	-0.311**
	(0.053)	(0.050)	(0.047)	(0.050)	(0.049)	(0.053)	(0.055)
Δ_3FIRM/GDP	0.085**	-0.074*	-0.155**	-0.139**	-0.094**	-0.022	0.007
	(0.030)	(0.030)	(0.027)	(0.028)	(0.029)	(0.026)	(0.028)
Panel D: Panel quantile regression (10th percentile)							
Δ_3HH/GDP	0.120+	0.040	-0.042	-0.128*	-0.222**	-0.274**	-0.273**
	(0.066)	(0.058)	(0.057)	(0.059)	(0.060)	(0.065)	(0.068)
Δ_3FIRM/GDP	0.071+	-0.113**	-0.191**	-0.171**	-0.117**	-0.034	-0.007
	(0.037)	(0.034)	(0.032)	(0.030)	(0.033)	(0.031)	(0.033)
Panel E: Panel quantile regression (5th percentile)							
Δ_3HH/GDP	0.159*	0.079	0.009	-0.063	-0.156*	-0.232**	-0.243**
	(0.071)	(0.072)	(0.064)	(0.067)	(0.072)	(0.073)	(0.074)
Δ_3FIRM/GDP	0.058	-0.146**	-0.226**	-0.200**	-0.140**	-0.045	-0.018
	(0.042)	(0.040)	(0.041)	(0.035)	(0.037)	(0.037)	(0.038)
Observations	3,821	3,827	3,703	3,581	3,455	3,329	3,203

Notes: This table plots the coefficient estimates β_{FIRM} and β_{HH} from estimating equation 2 for $k = -1, ..., 5$. Column (1) is a contemporaneous regression and columns (2)-(7) continuously shift forward the dependent variable by one year. Panel A estimates a fixed effects panel regression using OLS and reports standard errors double-clustered by country and year. Panel B to E estimate panel quantile regressions with country fixed effects for varying quantiles τ using the methods-of-moments estimator of Machado and Santos Silva (2019) with bootstrapped (double-clustered) standard errors based on 500 repetitions. +, * and ** denote significance at the 10%, 5% and 1% level, respectively.

shocks to expected future cash flows, there should be little dispersion, with credit flowing to the most productive firms regardless of the industry in which they operate. But during "frothy" times of easy credit, credit may flow particularly to certain sectors that are driving the boom, leading to highly lopsided credit growth. The results in Section 3.5 suggest that the distribution of real estate collateral across industries may play a role in determining which sectors tend to grow "out of whack".

We implement this measure of imbalances in credit growth in the following way. First, we require that a country-year pair has data on credit for a set of sectors J over the last three years. As a starting point, we use credit to the five non-financial sectors (excluding the residual category) and credit to non-bank financial institutions. Second, we compute the three-year change in sectoral credit to GDP in line with the measures used in Section 3. Finally, we take the standard deviation of the three-year changes in the sectoral credit-to-GDP ratios. The resulting measure captures the dispersion of medium-term fluctuations in corporate credit.[8]

Figure 5a plots the resulting measure of firm credit imbalances for Spain and Germany in the run-up to the 2007-08 Great Financial Crisis. The early 2000s in Spain are widely regarded as a period when credit to some sectors grew "out of whack;" see Gopinath et al. (2017) on the role of misallocation within the manufacturing sector. The figure shows a marked increase in the dispersion of firm credit growth during the early 2000s, consistent with an increasingly lopsided economy focused on lending to construction and real estate services. Although starting from a similar level of dispersion in 1999, there is essentially no trend in lopsidedness of firm credit growth in Germany over this period; credit went to different industries uniformly.

Figure 5b plots the distribution of sectoral firm credit growth rates in advanced and emerging economies. Interestingly, we see a *higher* dispersion of firm credit in advanced relative to emerging economies. One interpretation is that credit growth in emerging economies is much more uniform while they develop. Advanced economies, on the other hand, are more likely to experience lopsided credit growth, which may reflect unsustainable booms.

4.2 Credit Expansion and Sectoral Imbalances

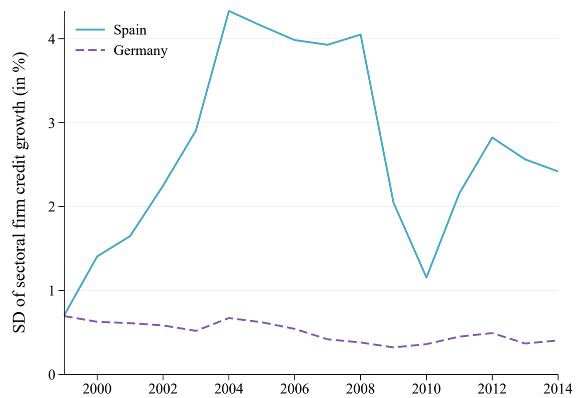
The results in Section 3 suggest that differences in credit growth across sectors, especially in the corporate sector, are important for understanding financial crises. A natural question is whether such a dispersion across sectors increases during credit expansions, which are known to be a leading indicator of such crises.

We examine this question by relating our measure of imbalances in credit growth, the standard deviation of sectoral credit growth, to the three-year change in credit to GDP. Figure 5c shows a binscatter plot visualizing the relationship. The dispersion increases during credit booms and credit

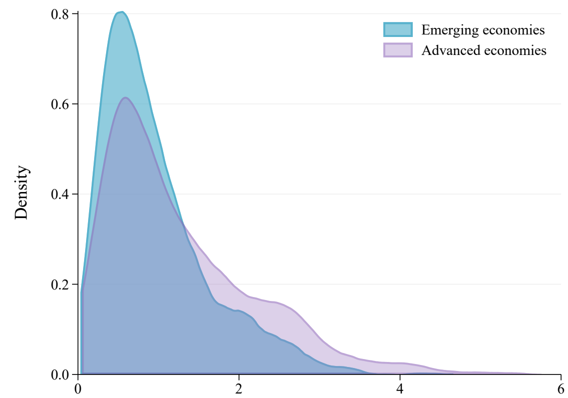
[8]This measure is also related to Gomes et al. (2018) who show that dispersion in "credit quality" across US firms predicts future recessions.

Figure 5: Sectoral Dispersion in Firm Credit Growth

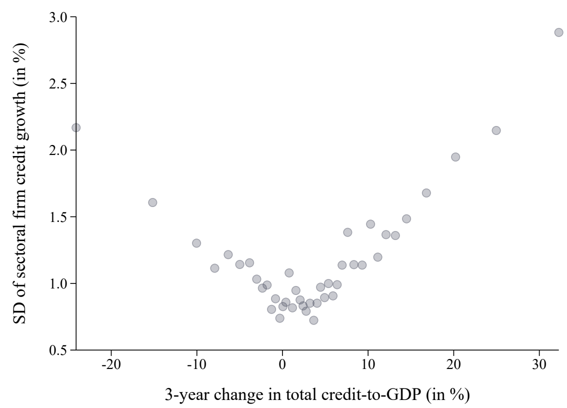
(a) Spain vs. Germany case study



(b) Advanced vs. emerging economies



(c) High Dispersion During Credit Booms and Busts



Notes: This figure plots the standard deviation of growth in credit-to-GDP to five non-financial industries and non-bank financial institutions. Panel (a) shows the trajectory in Spain and Germany during the 2000s. Panel (b) shows the distribution of the measure in advance and emerging economies. Panel (c) shows a binscatter plot of the standard deviation of the three-year change in sectoral credit-to-GDP to five non-financial industries and non-bank financial institutions conditional on the three-year change in total credit-to-GDP. The number of bins is chosen using the methods outlined in Cattaneo et al. (2019).

crunches, resulting in a V-shaped pattern. For example, the dispersion of sectoral credit growth was 4.0% of GDP in Spain at the height of the credit boom in 2006, a result of the lopsided growth of the real estate-related sectors. During the ensuing credit crunch the same sectors in turn experienced large-scale defaults and deleveraging, resulting in a dispersion value of 2.8% of GDP as of 2012. Booms and busts in credit go hand in hand with imbalances in credit flows to different sectors.

Table A.2 reports the results of a panel regression, similar to Equation (3), relating the standard deviation of sectoral credit growth to the three-year change in credit to GDP. Panel A shows that credit expansions are associated with a higher dispersion of credit across non-financial firm sectors. A one standard deviation increase in the three-year change of total credit to GDP is associated with a 11.9% increase in dispersion relative to the mean. This suggests that, because contractions in credit are rare, the right-hand side of the V-pattern in Figure 5 is more important, resulting in a positive correlation of the dispersion in sectoral credit with overall credit growth. Panel B confirms this finding by adding loans to non-bank financial institutions to the measure of dispersion. In Panel C, we add household debt and find a similar pattern.

Our interpretation of these findings is as follows. The imbalance in sectoral credit growth rates increases during a credit expansions, and it remains high during credit crunches. This evidence is consistent with the case study of Spain in the previous section, suggesting that we are capturing the extent to which credit is growing lopsidedly in certain sectors.

4.3 Credit Growth Dispersion and Crisis Risk

Credit growth in the run-up to crises varies considerably across sectors. This suggests that it is not only the magnitude of the credit expansion that matters, but also the *imbalance* of credit across different types of borrowers. Here, we ask whether our measure of imbalances in credit growth is also associated with a higher likelihood of systemic financial crises.

We test this hypothesis in Table 9. Instead of predicting crises with changes in sectoral credit to GDP, we look at the *standard deviation* of credit growth across sectors. Panel A starts again by calculating the standard deviation of credit growth in five non-financial sectors. We find that imbalanced credit growth is a highly statistically significant predictor of financial crises. When looking at the likelihood of a crisis within the next three years in column 3, a one standard deviation increase in dispersion is associated with a 3.6 percentage point higher probability of a crisis within the next three years. Column 4 adds the three-year change in total credit to GDP as a control variable. As we show in Table A.2, credit expansions are associated with a large increase in dispersion. Including total credit growth may therefore be "over-controlling", because we are interested in precisely the kind of imbalance in credit growth that accompanies credit expansions. However, even after controlling for changes in total credit to GDP, we still find that the imbalance in sectoral credit growth rates is associated with higher crisis risk. The magnitude is smaller than in the regressions that do not control for the size of the credit expansion: at $h = 3$, a one standard deviation higher dispersion is associated with a 2.2 percentage point higher probability of a crisis. The findings are similar in panels B and C where we add credit to non-bank financial institutions and households to the dispersion measure.[9]

Taken together, our evidence suggests that the most dangerous booms are the those where there is a significant imbalance in credit growth rates across sectors, i.e. where a few sectors grow "out of whack". During these kinds of booms, there is a substitution of one form of credit for another, which could indicate a misallocation of credit. Importantly, this finding holds even if we only look at the

[9] Table A.3 in the appendix also replicates our baseline result based on the range ($max - min$) rather than the standard deviation of sectoral growth rates. We find similar results.

Table 9: Sectoral Imbalances in Credit Growth and Crises

	Dependent variable: Crisis within...					
	1 year		3 years		5 years	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Dispersion in non-financial firm credit growth						
SD of sectoral credit growth	0.019*	0.012*	0.036**	0.022*	0.034**	0.020+
	(0.009)	(0.005)	(0.013)	(0.009)	(0.010)	(0.010)
Control for credit expansion	No	Yes	No	Yes	No	Yes
Observations	1,931	1,931	1,931	1,931	1,931	1,931
# Crises	53	53	53	53	53	53
AUC	0.63	0.72	0.60	0.68	0.59	0.65
Panel B: Add lending to non-bank financial institutions						
SD of sectoral credit growth	0.025+	0.015	0.040**	0.022*	0.039**	0.024+
	(0.014)	(0.009)	(0.014)	(0.010)	(0.013)	(0.013)
Control for credit expansion	No	Yes	No	Yes	No	Yes
Observations	1,468	1,468	1,468	1,468	1,468	1,468
# Crises	43	43	43	43	43	43
AUC	0.66	0.73	0.62	0.69	0.61	0.65
Panel C: Add household debt						
SD of sectoral credit growth	0.034+	0.020	0.068**	0.045*	0.072**	0.056**
	(0.018)	(0.013)	(0.021)	(0.020)	(0.015)	(0.019)
Control for credit expansion	No	Yes	No	Yes	No	Yes
Observations	1,394	1,394	1,394	1,394	1,394	1,394
# Crises	43	43	43	43	43	43
AUC	0.70	0.73	0.68	0.70	0.64	0.66

Notes: This table plots the coefficient estimates β_j^h for $h = 1, ..., 5$ from estimating Equation (1) using OLS. The dependent variable is a dummy for the onset of a systemic financial crisis within h years based on data from Baron et al. (2020) and Laeven and Valencia (2020). The independent variable of interest is the standard deviation of the three-year change in credit-to-GDP across different sectors. Total credit growth is the three-year change in total credit to GDP. All regressions include country fixed effects. Driscoll-Kraay standard errors based on $ceil(1.5 * h)$ lags are in parentheses. +, * and ** denote significance at the 10%, 5% and 1% level, respectively.

variation *within* firm credit and do not include household credit. This pattern highlights once again that expansions in corporate debt contain useful information about future macroeconomic dynamics.

5 Corporate Debt and the Recovery From Crises

Corporate debt is an important predictor of the future likelihood of systemic financial crises. In this section, we investigate whether it is also important for the recovery from such crises. In particular, we run local projections relating real GDP per capita, nonperforming loans, investment, and consumption to the growth of different types of credit during the preceding boom.

5.1 A Local Projection Approach

We are interested in the conditional path of an outcome y, principally real GDP, following systemic financial crises. The conditioning variables are measures of sectoral credit growth prior to such crises. As such, we follow a similar specification to that in Jordà et al. (2022):

$$\Delta_h y_{i,t+h} = \alpha_i^h + \delta^h \text{Crisis}_{i,t} + \sum_{j \in J} \beta_j^h \Delta_3 \text{Credit}^j/\text{GDP}_{i,t} + \sum_{j \in J} \gamma_j^h \Delta_3 \text{Credit}^j/\text{GDP}_{i,t} \times \text{Crisis}_{i,t} + \mathbf{X}'_{i,t} + \varepsilon_{i,t}^h, \tag{3}$$

where the dependent variable is the change in real GDP per capita or another outcome from t to $t+h$, α_i^h are country fixed effects, and $\text{Crisis}_{i,t}$ is a dummy equal to one for the onset of a financial crisis, defined using the dates in Baron and Xiong (2017) and Laeven and Valencia (2020), as above. $\sum_{j \in J} \Delta_3 \text{Credit}^j/\text{GDP}_{i,t}$ is a vector of credit growth variables, measured as the three-year change in the ratio of credit-to-GDP for a set of sectors J. We consider the forecast horizons $h = 1, ..., 5$. The main coefficients of interest are γ_j^h, which estimate the future path of the outcome variable as a function of the type of credit expansion prior to the crisis.

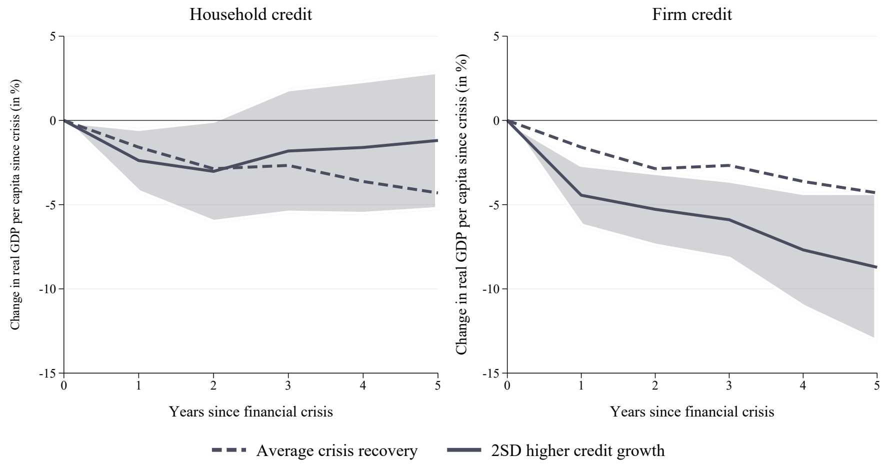
In our baseline specification, we estimate Equation (3) with controls for contemporaneous and lagged real GDP growth, as well as lags of the crisis and credit growth variables. We include five lags for all of these variables, but the results are not sensitive to this choice; they also look similar when we include no lags. For robustness, we also run specifications with contemporaneous and lagged values of additional control variables.[10] We double-cluster standard errors at the country and year level to correct for serial correlation due to overlapping observations and residual correlation across countries.

To be clear, we do not interpret the coefficients from Equation (3) as the causal effect of credit allocation on the recovery from crisis-related recessions. As we show in Section 3, the probability of crises itself depends on the type of credit expansion. Rather, we see the estimation of Equation (3) as a useful descriptive tool for understanding the conditional recovery path following such crisis events.

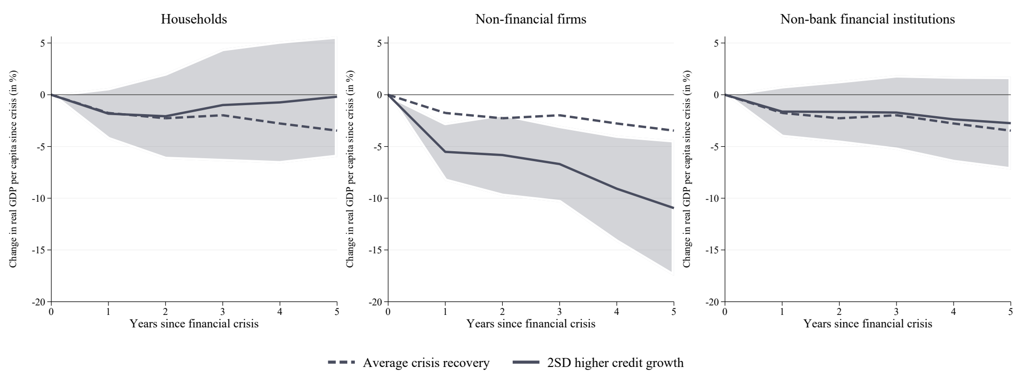
[10] When we look at nonperforming loans as an outcome in Section 5.3, we use a more parsimonious specification with no lags of the dependent or independent variables because the sample has a relatively short time series.

Figure 6: Credit Allocation and Financial Crisis Recovery

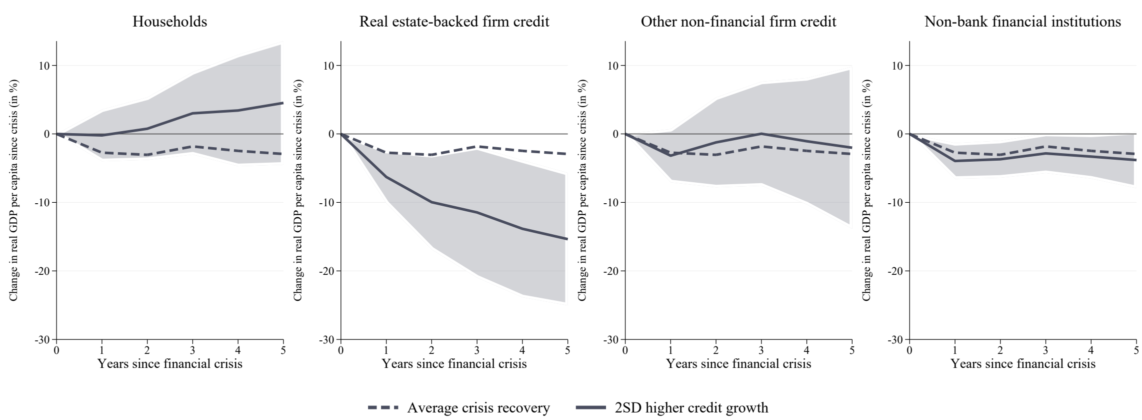
(a) Firm vs. household debt



(b) Non-financial vs. financial firm debt



(c) The role of collateral values



Notes: This figure plots the estimates of δ^h and $\delta^h + \gamma_j^h$ from Equation (3), showing how the path of log real GDP per capita five years after a financial crisis depends on the type of credit boom preceding it. We show the average recovery path estimated by δ^h and the predicted recovery for the case where the three-year change in credit-to-GDP is two standard deviations above its mean before the crisis based on $\delta^h + \gamma_j^h$. Panel (a) focuses on household vs. corporate debt. Panel (b) decomposes corporate debt into non-financial and financial firms. Shaded areas are 95% confidence intervals based on standard errors double-clustered by country and year.

Table 10: Corporate Debt, Household Debt, and Recession Recovery After Financial Crises

	Dep. var.: ΔLog(Real GDP p.c.) over...				
	1 year	2 years	3 years	4 years	5 years
Crisis	-1.59+	-2.87**	-2.67*	-3.63*	-4.30*
	(0.87)	(1.06)	(1.32)	(1.60)	(1.85)
Δ_3HH/GDP	0.11+	0.04	-0.10	-0.34**	-0.56**
	(0.06)	(0.09)	(0.11)	(0.10)	(0.12)
Δ_3FIRM/GDP	0.01	-0.05	-0.07	-0.09+	-0.08
	(0.03)	(0.04)	(0.04)	(0.05)	(0.07)
Crisis $\times$ Δ_3HH/GDP	-0.10	-0.02	0.11	0.26	0.40*
	(0.09)	(0.14)	(0.16)	(0.18)	(0.19)
Crisis $\times$ Δ_3FIRM/GDP	-0.22**	-0.18*	-0.25*	-0.31*	-0.34*
	(0.05)	(0.08)	(0.10)	(0.12)	(0.15)
R^2	0.27	0.31	0.36	0.40	0.43
Observations	2467	2467	2467	2467	2467

Notes: This table reports the coefficients of local projections as in Equation (3) that analyze how the path of log real GDP per capita after systemic financial crises depends on pre-crisis credit growth in different sectors, defined as the three-year change in credit-to-GDP (standardized to have a mean of zero and standard deviation of one). All regressions include country fixed effects, contemporaneous and three lagged values of GDP growth, as well as three lags of the crisis dummies, credit growth variables, and their interactions. Standard errors are clustered by country and year. +, * and ** denote significance at the 10%, 5% and 1% level, respectively.

5.2 Credit Allocation and Recession Recovery

We start by investigating whether the path of real GDP per capita following a financial crisis depends on the type of credit boom that preceded it. Among others, Cerra and Saxena (2008) and Reinhart and Rogoff (2009a) show that crises are followed by particularly protracted recessions, but they do not distinguish between different kinds of credit booms.

Figure 6 plots the estimates of Equation (3). Table 10 shows the corresponding regression results. In the figures, we always show the average path of crisis-related recessions as a benchmark by plotting the estimates of δ^h. To understand how recoveries from crises depend on different types of credit growth, we plot the estimated path of log real GDP per capita for a two standard deviation higher growth in either firm or household debt.

Figure 6a exploits our sectoral credit data and distinguishes between firm and household debt, as in Jordà et al. (2022). In our baseline specification, corporate debt expansions are associated with significantly slower recoveries than household debt booms. This finding is consistent with our finding in the raw data in Section 2.5 that the recovery from financial crises is slower for corporate debt booms that do not coincide with booms in household debt. A two standard deviation increase in firm credit growth is associated with 8.7% lower GDP five years after a financial crisis. We discuss in Section 5.4

what accounts for the apparent difference between these results and the existing literature.

Figure 6b next decomposes corporate debt into its non-financial and financial components. Here, we find that it is lending to non-financial corporations in particular that predicts a slow recovery from crisis-related recessions. After five years, real GDP per capita is 11.0% lower for a two standard deviation higher growth of non-financial corporate debt. We find more muted patterns for loans to non-bank financial institutions and households once credit to non-financial corporations is taken into account. Figure A.2 in the appendix shows the patterns for credit expansions to individual industries. This agnostic exercise shows that it is lending to construction and real estate and to retail and wholesale trade that is particularly associated with deep recessions following financial crises.

Figure 6c breaks down the debt of non-financial corporations according to an industry's reliance on real estate collateral. We find that firm debt backed by real estate is particularly associated with slow recoveries. Five years out, real GDP is 15.4% lower for a two standard deviation pre-crisis increase in credit flowing to sectors relying on real estate as collateral. Table A.5 shows that the interaction term for a financial crisis with real estate-backed firm credit growth is particularly predictive of deep recessions.

Figure A.3 in the appendix provides several robustness exercises. We consider specifications in which we add contemporaneous and lagged values of controls (USD exchange rate, exports/GDP, investment/GDP, and inflation), use the five-year instead of the three-year change in credit-to-GDP (as in Jordà et al., 2022), or restrict the sample to the period before 2007.[11] Figure A.4 in the appendix shows that the result for corporate debt backed by real estate collateral looks similar when we split industries based on real estate collateral shares in the Federal Reserve's Y-14Q data.

Figure A.5 in the appendix splits these estimations into emerging and advanced economies. In Table 5, we had already shown that corporate debt seems to matter at somewhat longer horizons than household debt in emerging economies. Perhaps as a result, we find that household debt expansions is associated with a brief post-crisis recession in emerging economies in the short-run. For the recovery path after five years, corporate debt is more important in both advanced and emerging economies.

In Figure A.6 and Figure A.7 in the appendix, we replace the dependent variable GDP with investment and consumption, respectively. These figures show an important heterogeneity between credit booms in firm and household debt. When a crisis hits, it is credit to firms that predicts a prolonged slump in investment. For consumption, on the other hand, we do not find an average contraction after crises (relative to GDP), but consumption is significantly lower after crises preceded by a boom in household debt. One interpretation of this finding is that expansions in certain types of corporate debt

[11] Table A.6 presents additional exercises that reproduce the finding in the literature that recessions after financial crises are worse if total credit-to-GDP increased more before the crisis starts. The estimates imply that real GDP is about 6.0 % lower five years after a financial crisis if the three-year change in total credit-to-GDP was two standard deviations higher before the crisis. This drop in GDP is larger than that for the average crisis, which is 3.1%.

are particularly damaging to GDP because they are associated with an "investment-less" recovery (similar to a "jobless" recovery).

5.3 Defaults and Nonperforming Loans During Banking Crises

Why should corporate debt be particularly important for understanding the recovery from financial crises? A straightforward interpretation is that the bankruptcy regimes in most countries allow firms, but not households, to write off debt through default (for a discussion, see, e.g., Jordà et al., 2022). If the claims on firms' debt are typically held by banks, these defaults may put pressure on the balance sheet of the banking system and ultimately erode its capitalization. Large-scale corporate defaults can thus lead to lower investment and employment and also systemic banking problems, which together ultimately stifle growth.

Understanding the role of firms relative to households in explaining the defaults during banking crises requires information on the composition of nonperforming loans. Because such data are not readily available, we collect data on nonperforming loans (NPLs) by sector for 23 crisis episodes in 19 countries. These data allow us to calculate two variables for understanding the relative importance of defaults among firms and households: (1) a sector's NPL ratio, defined as the ratio of nonperforming loans to total outstanding loans, and (2) a sector's share in total nonperforming loans. The NPL ratio can be interpreted as a proxy for the "default rate" of each sector, while a sector's share in total NPLs gives a sense of its importance in the erosion of banks' capital buffers at the heart of banking crises.

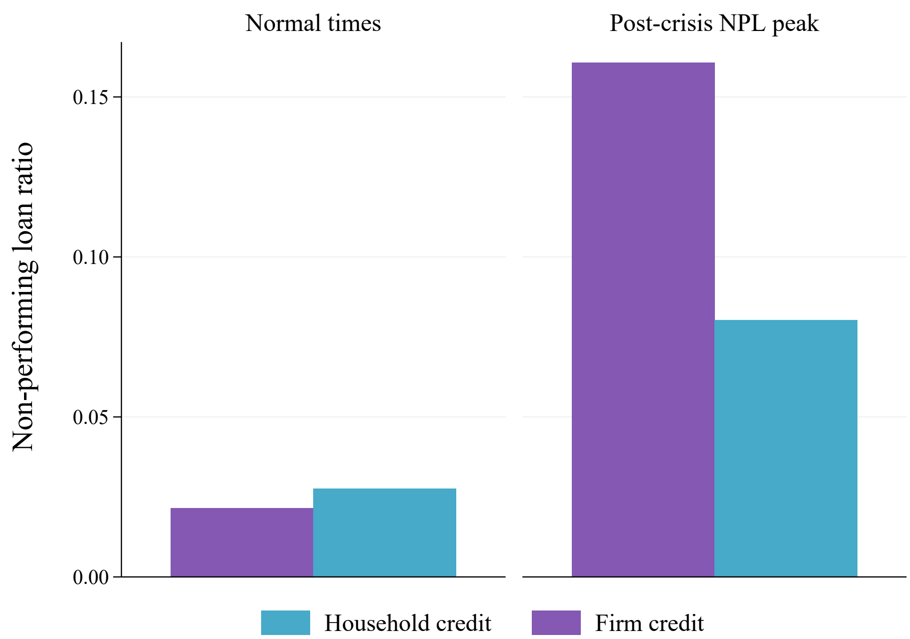
Figure 7 provides evidence consistent with the narrative that corporate defaults are important for understanding crisis episodes. Figure 7a plots NPL ratios separately for firms and households, depending on whether a country experiences a financial crisis or not. To account for the lagging nature of NPL ratios, post-crisis episodes are defined as the year in which NPLs peak within ten years of a crisis. The data suggest that, in "normal times", NPLs among firms are if anything somewhat less frequent. During crises, however, they increase significantly more than NPLs among households. On average, 16% of corporate debt and 9% of household debt becomes nonperforming after crises.

Figure 7b plots the share of firms in total nonperforming loans. We define this share for the year in which the aggregate NPL ratio peaks within ten years of a financial crisis. The resulting picture shows that the 2007 crisis in the United States is a major outlier: in almost all other episodes, firms accounted for the vast majority of NPLs. For the median crisis, 74% of NPLs are attributable to corporate debt. This finding is the result of a combination of two facts that we document in this paper: (1) corporate debt accounts for most of the credit growth before crises, and (2) firms are more likely to default than households during crises.

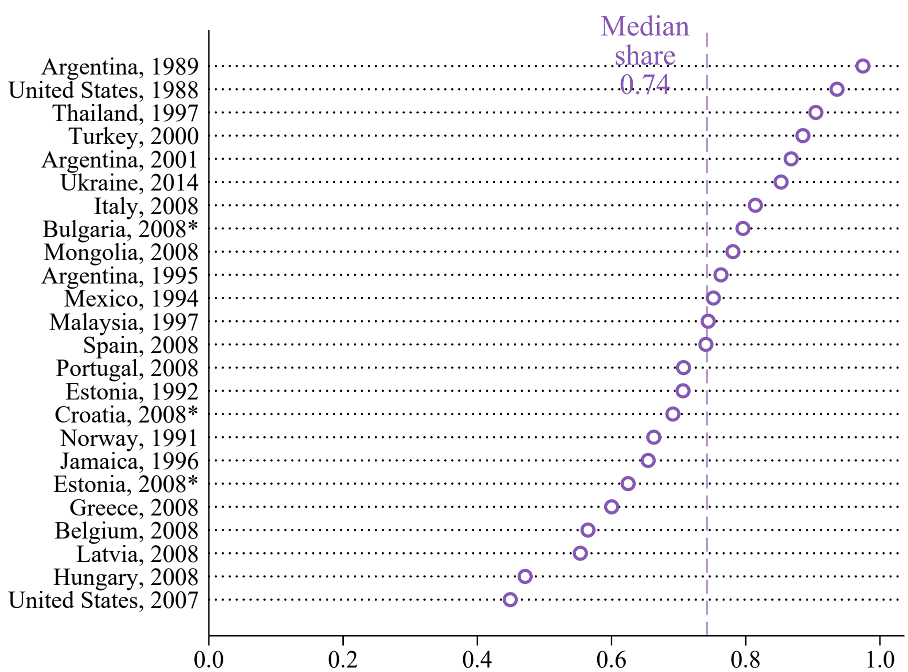
Figure 8a shows data on delinquency rates for commercial and residential real estate loans in the United States. During the 1990-91 recession, about 12% of commercial real estate (CRE) loans became delinquent, a much larger share than that for residential mortgages. Even during the Great

Figure 7: Firm Defaults and Financial Crises

(a) NPL ratios by sector



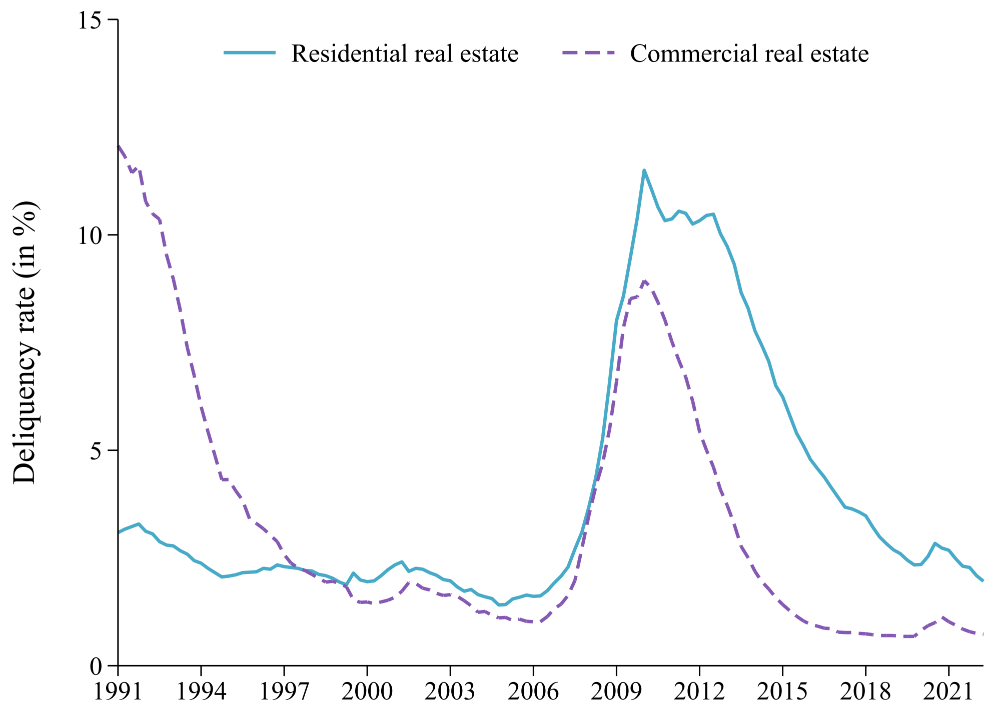
(b) Share of firms in total nonperforming loans



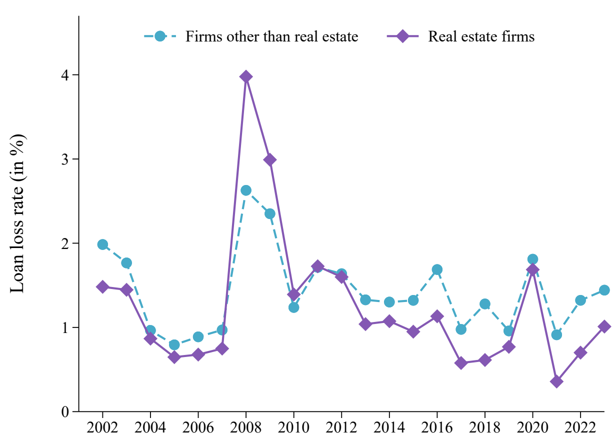
Notes: These figures plot data on nonperforming loans by sector for selected financial crises. Panel (a) plots NPL ratios by sector, defined as nonperforming loans divided by outstanding loans. Panel (b) plots the share of firms in total nonperforming loans. We plot values during the year with the peak total nonperforming loan ratio within ten years following a crisis. Normal times are defined as periods outside of the ten years after a crisis. * indicates countries that experienced deep recessions during 2008 following large credit expansions but had no financial crisis according to Laeven and Valencia (2020). See text and appendix Table A.8 for sources and details on data definitions.

Figure 8: Real Estate Sector Defaults During Banking Crises

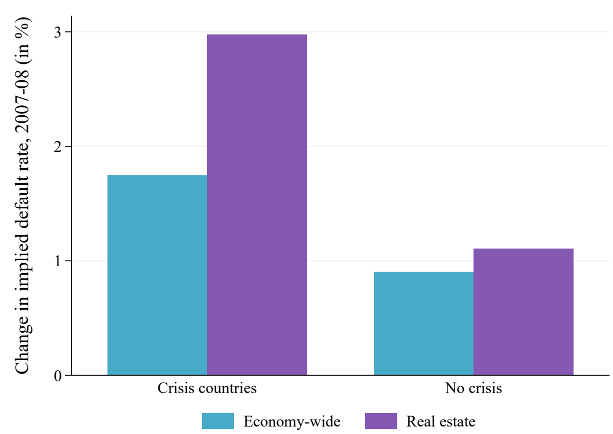
(a) Delinquency rates in the United States



(b) Bank loan losses during 2007-08



(c) Real estate losses in crisis countries



Notes: These figures plot data on default rates by sector during periods of systemic banking crises. Panel (a) plots delinquency rates on commercial and residential real estate loans in the United States based on data from the Federal Reserve H.8 release. Panels (b) and (c) plot changes in implied bank loan losses estimated from firm-level expected default rates by AMRO Asia, based on data for 97 countries around the Global Financial Crisis 2007-08. Crisis countries in Panel (c) are defined as those that experienced a systemic banking crisis between 2007 and 2011; the sample in Panel (b) is restricted to these crisis countries.

Recession, 9% of CRE loans were delinquent, not far from the 11% residential delinquency rate at the height of the recession. Thus, even during the 2007-08 episode that constitutes a major outlier in our cross-country comparison of defaults, corporate defaults were widespread.

For the Global Financial Crisis of 2007-08, we can also look at which industries accounted for loan losses for a broader set of 97 countries. AMRO Asia calculates this information based on firms' estimated probability of default; see Ong et al. (2023) for more details. Figure 8b shows that, while defaults in the real estate sector are typically more muted than in other sectors, they experienced a much larger spike in 2008. Figure 8c also shows that this spike in real estate defaults was much more pronounced in countries experiencing a banking crisis. These patterns suggest that defaults on corporate loans backed by real estate are particularly dangerous for the health of bank balance sheets because they later translate into higher NPLs.

To test more formally the link between firm credit secured by real estate collateral and NPLs, we run local projections as in Equation (3) where the dependent variable is the aggregate NPL ratio of the banking sector (in logs). There is relatively limited data available on NPLs, which largely restricts this analysis to the financial crises of the 2000s, so the results can only be suggestive. With this limitation in mind, Figure 9 shows a clear pattern: higher credit growth to non-financial corporations predicts a large post-crisis increase in NPLs. Using our baseline definition, a two standard deviation higher pre-crisis growth in corporate debt secured by real estate is associated with a 81.4% increase in NPLs. Similar to the findings on the recovery from recessions, the magnitude of the expansion of household debt plays a relatively muted role in explaining the dynamics of post-crisis defaults.

Taken together, these facts challenge the view that household debt is the predominant threat to financial stability. Empirically, firms account for the vast majority of nonperforming loans in the aftermath of crises. To the best of our knowledge, the stylized facts on the composition of defaults during crises that we provide here are new to the literature.

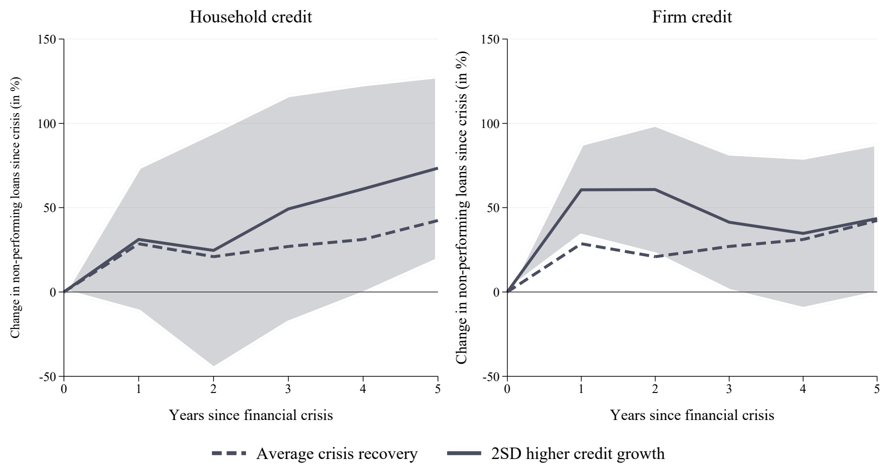
5.4 Relationship to the Literature

Our paper contributes to a growing literature on the macroeconomic implications of expansions in firm and household debt. The main contribution of our paper is to show the unambiguous role of corporate debt in macroeconomic crashes, especially in the run-up to and recovery from financial crises. Corporate debt matters particularly for the waves of defaults and nonperforming loans that ultimately lie at the heart of major banking crises and the deep recessions with investment-less recoveries that follow them, while household debt is more uniformly correlated with lower future growth.

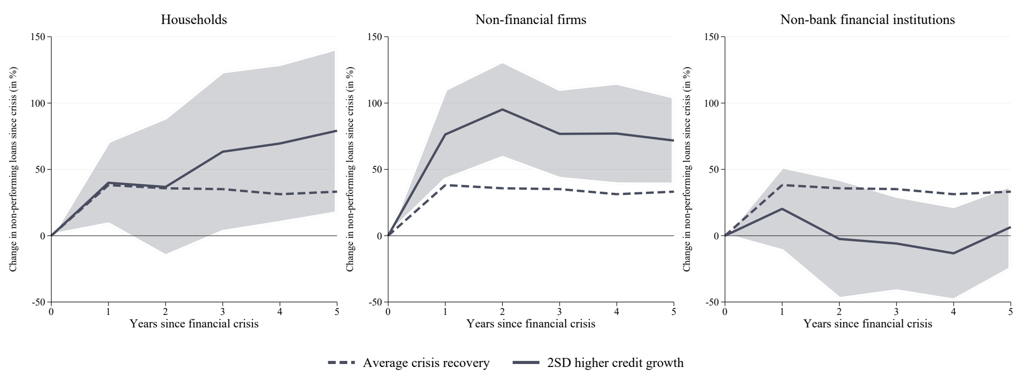
Similar to Jordà et al. (2022), we find that corporate debt predicts a slower recovery, but their analysis suggests that this channel only matters for countries with high bankruptcy frictions where defaults cannot be resolved quickly. For the average country, they find that household debt is more important than corporate debt in explaining the path of real GDP per capita after financial crises. In our

Figure 9: Credit Allocation and Nonperforming Loans

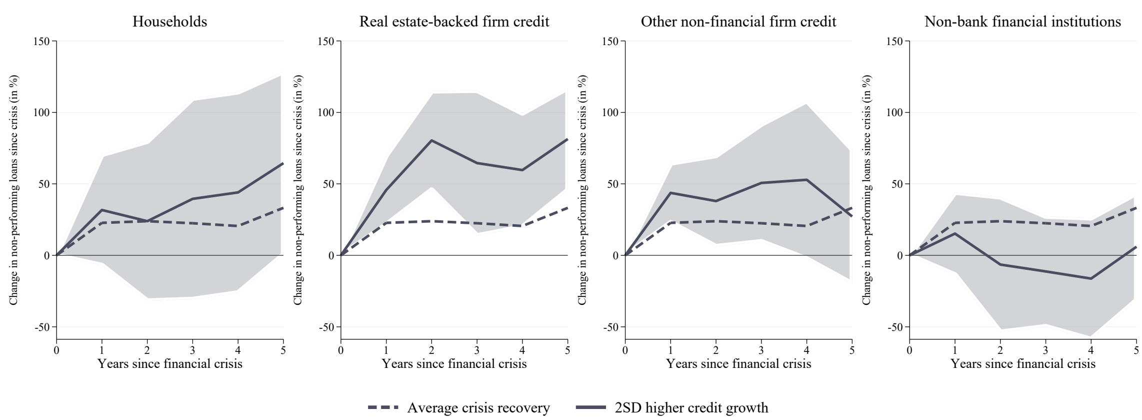
(a) Firm vs. household debt



(b) Non-financial vs. financial firm debt



(c) The role of real estate collateral



Notes: This figure plots the estimates of δ^h and $\delta^h + \gamma_j^h$ from Equation (3), showing how the path of the log nonperforming loan ratio five years after a financial crisis depends on the type of credit boom preceding it. We show the average recovery path estimated by δ^h and the predicted recovery for the case where the three-year change in credit-to-GDP is two standard deviations above its mean before the crisis based on $\delta^h + \gamma_j^h$. Panel (a) focuses on household vs. corporate debt. Panel (b) decomposes corporate debt into non-financial and financial firms. Panel (c) decomposes non-financial firms into industries relying on real estate collateral and other sectors, where the ISIC sector combinations F+L, G+I, and A are classified as real estate-backed firm credit. Shaded areas are 95% confidence intervals based on standard errors double-clustered by country and year.

baseline specification, we find that, for the average country, it is an expansion in (real estate-backed) corporate debt rather than household debt during the boom that predicts worse post-crisis recessions.

To reconcile the results in Jordà et al. (2022) with ours, Figure A.10 replicates our findings using data from the Jordà-Schularick-Taylor (JST) Macrohistory Database (Jordà et al., 2016a), which covers 18 advanced economies over the period 1870-2020.[12] Figure A.10a first replicates in the JST data the basic finding of Jordà et al. (2022) that the five-year change in household debt-to-GDP, but not corporate debt, predicts a deeper recession following a crisis. Using exactly the same empirical specification applied to our sample of 115 countries, including many emerging economies, we find that both household and corporate debt growth are associated with a deeper recession, but corporate debt is still more important in the long run. Figure A.10b then replicates our baseline finding using the three-year change in credit to GDP in the JST data. Consistent with our results in Figure 6, we now find a deeper post-crisis recession following expansions in firm but not household debt.

This analysis shows that several factors are at play when it comes to the role of corporate debt in the recovery from crises. First, the length and amplitude of the pre-crisis credit expansion could be quite different for households and firms, which may explain why matters how exactly one measures the pre-crisis credit boom. In Section 3, we find clear evidence that the predictability of future crises based on corporate and household debt differs across forecast horizons. Another difference may be the definition of corporate debt. Jordà et al. (2022) include bonds and other liabilities, while our data mainly cover bank loans. This difference may be important because (a) bond markets are biased towards large firms, and (b) bond market defaults have been found to be largely uncorrelated with recessions (Giesecke et al., 2014). Another possible explanation is that the relative importance of firm and household debt growth in explaining macroeconomic dynamics has changed significantly over time, as Jordà et al. (2022) use data going back to 1870, while our dataset starts after World War II.

Investigating these issues could be a potentially fruitful avenue for future research. Importantly, however, none of these issues affect our main finding that firm credit (especially when backed by real estate collateral) is unambiguously associated with particularly deep recessions following financial crises (see Section 5.2).

6 Conclusion

Does corporate debt matter for macroeconomic dynamics? The emphasis on household debt since the Global Financial Crisis of 2007-08 has led some to question whether it does. While our study confirms the importance of household credit in business cycle fluctuations, we show that corporate

[12] To remain consistent with the rest of our analysis, we make two changes to the regression specification relative to Jordà et al. (2022). First, we directly examine the path of real GDP per capita after crises, rather than using the recession peak associated with a crisis, as they do. Second, we estimate Equation (3) in the full panel dataset rather than restricting the data to a sample of post-crisis periods, which is the method used in Jordà et al. (2022).

credit matters similarly because of its link to systemic financial crises, lower investment, defaults, and GDP crash risk.

Our results can be summarized as follows. An expansion in corporate credit is associated with a higher probability of a future financial crisis. After a crisis, the recovery from the recession is crucially shaped by the allocation of corporate credit in the run-up to the crisis. The majority of loans that become nonperforming during crises are in the corporate sector, and the extent of overall NPLs is predictable with the expansion of corporate credit. This evidence suggests that booms and busts in corporate debt may be particularly likely to trigger periods of financial sector distress by eroding the health of banks' balance sheets, which are then followed by slower recoveries characterized by lower investment. In this respect, the experience of the United States in 2007 stands out as an outlier in the historical record: in the vast majority of financial crises for which we have data, corporate defaults are the dominant source of loan losses at the heart of banking sector disruptions.

Our interpretation of this new evidence is that the channels linking corporate and household debt to the real economy differ in important dimensions. Higher levels of household debt may lead to debt overhang and the associated lower growth even in the absence of a financial crisis, consistent with an "indebted demand" channel (Mian et al., 2021). Corporate debt, in turn, matters particularly for systemic financial crises through its link with large-scale corporate defaults and lower investment. Our evidence linking household debt robustly to lower average GDP growth and corporate debt to higher crash risk in GDP is supportive of this interpretation.

Our takeaways are threefold. First, economists should much more explicitly "rule in" corporate debt as a key factor in understanding financial crises, given the focus in the literature and among policy makers on household debt. Second, from a policy perspective, our findings underscore the importance of monitoring firm credit for financial stability purposes. Our work raises the question of whether macroprudential regulation should not also limit the leverage of firms, as is done for households, through debt-to-income or loan-to-value limits. Third, we show that firm credit backed by real estate collateral is particularly prone to boom-bust cycles. Indeed, at the time of writing, there are growing concerns about defaults in the commercial real estate sector (IMF, 2017; Jiang et al., 2023; Beck et al., 2023). Our findings suggest that regulators may want to pay particular attention to risks arising from sectors where real estate collateral dominates, including industries other than real estate.

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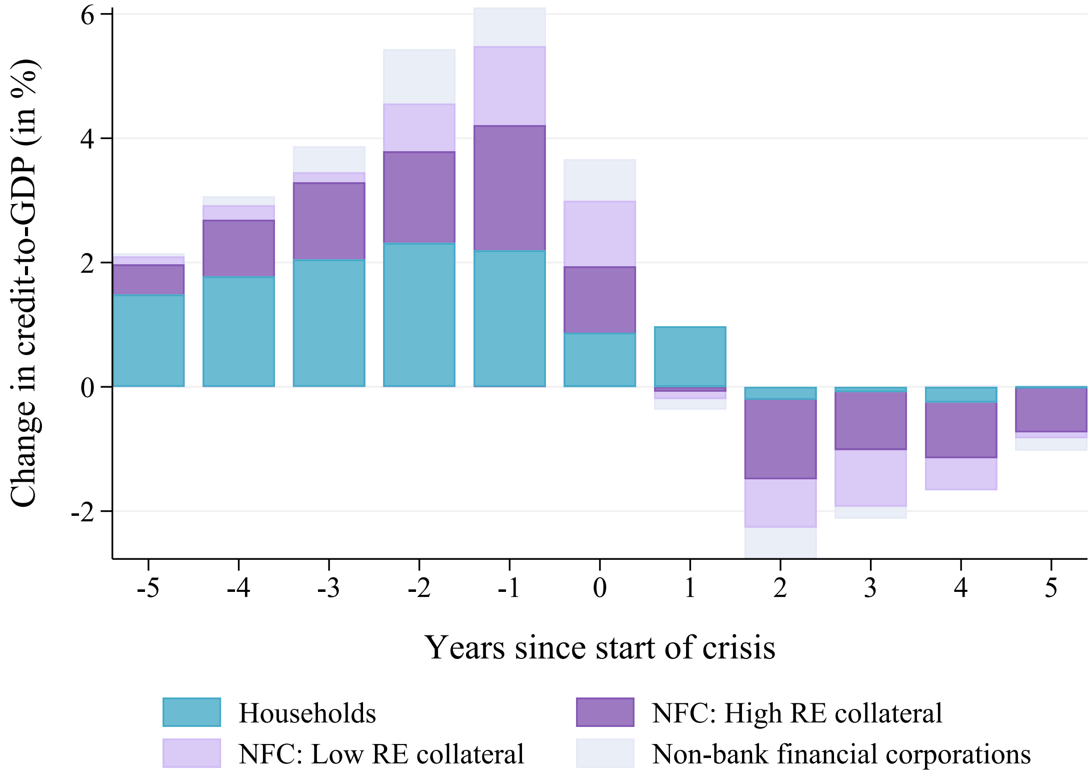
Corporate Debt, Boom-Bust Cycles, and Financial Crises
Appendix

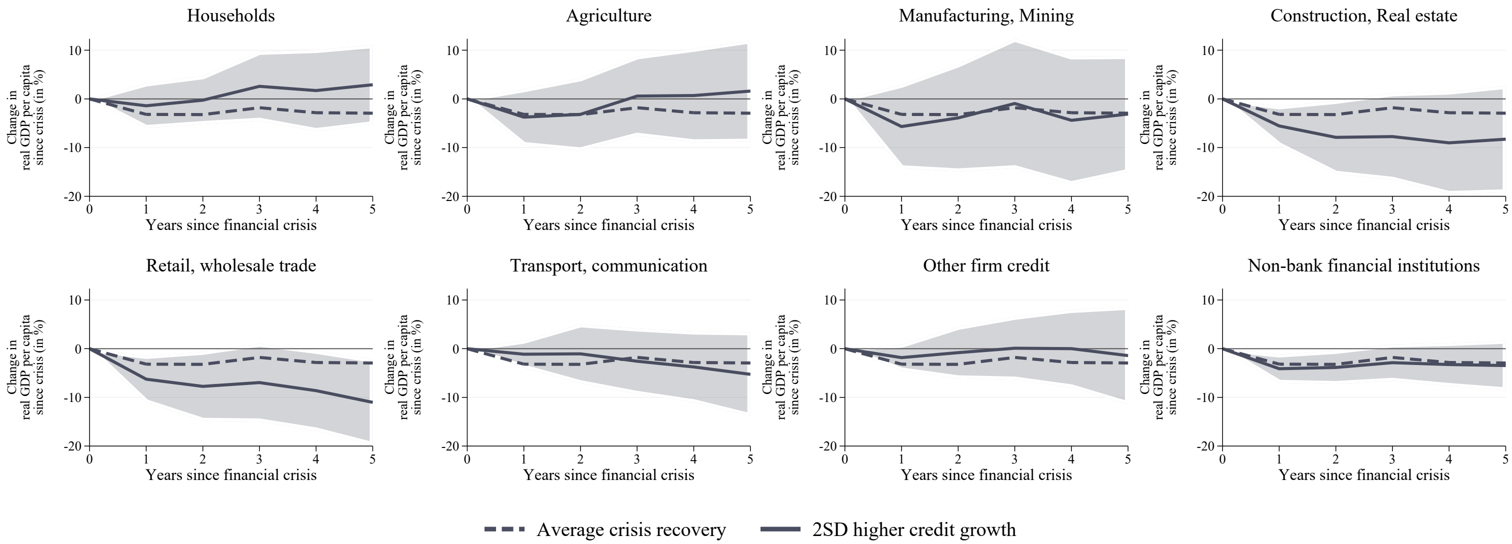
This appendix contains additional figures and tables that support the analysis in the paper *Corporate Debt, Boom-Bust Cycles, and Financial Crises* by Victoria Ivashina, Şebnem Kalemli-Özcan, Luc Laeven, and Karsten Müller.

Figure A.1: Corporate Debt, Real Estate Collateral, and Financial Crises



Notes: This figure decomposes changes in total credit-to-GDP around the onset of financial crises, where we identify the first year of a crisis based on the chronologies in Baron et al. (2020) and Laeven and Valencia (2020). We plot the average change in credit-to-GDP for each sector in a five-year window around crises, where sectors by definition add up to total credit. We classify "High RE collateral" and "Low RE collateral" non-financial firm credit based on Table 6. "High RE collateral" refers to firm lending to construction and real estate services, agriculture, retail and wholesale trade, as well as food and accommodation services. "Low RE collateral" is defined as firm lending to manufacturing and mining, transport and communication, as well as all other sectors.

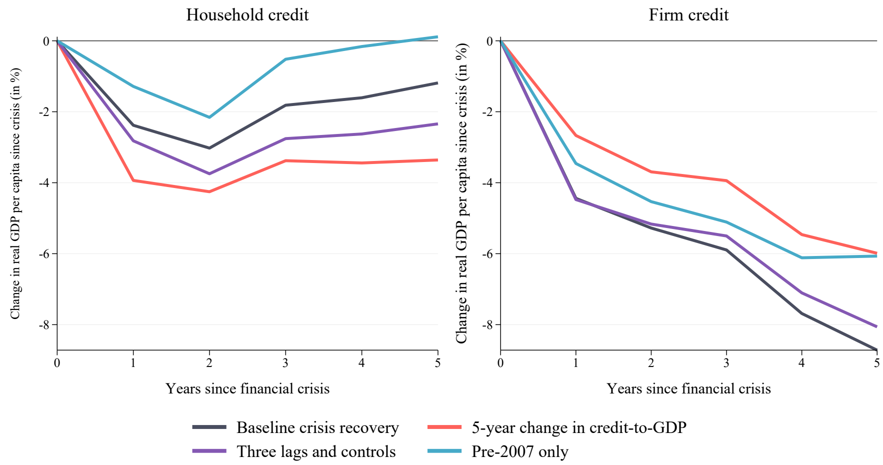
Figure A.2: Industry Credit Expansions and Crisis Recovery



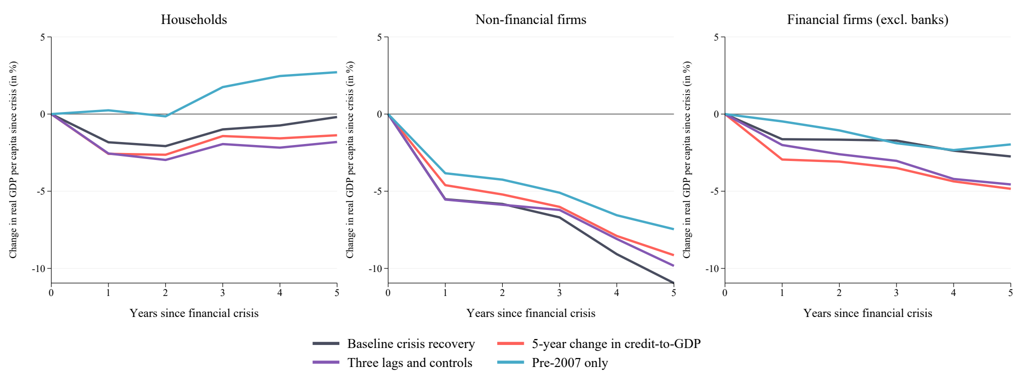
Notes: This figure plots the estimates of δ^h and $\delta^h + \gamma_j^h$ from Equation (3), showing how the path of log real GDP per capita five years after a financial crisis depends on the type of credit boom preceding it. We show the average recovery path estimated by δ^h and the predicted recovery for the case where the three-year change in credit-to-GDP is two standard deviations above its mean before the crisis based on $\delta^h + \gamma_j^h$. We split lending to non-financial corporations into the underlying industry-level data. Shaded areas are 95% confidence intervals based on standard errors double-clustered by country and year.

Figure A.3: Credit Allocation and Financial Crisis Recovery – Robustness

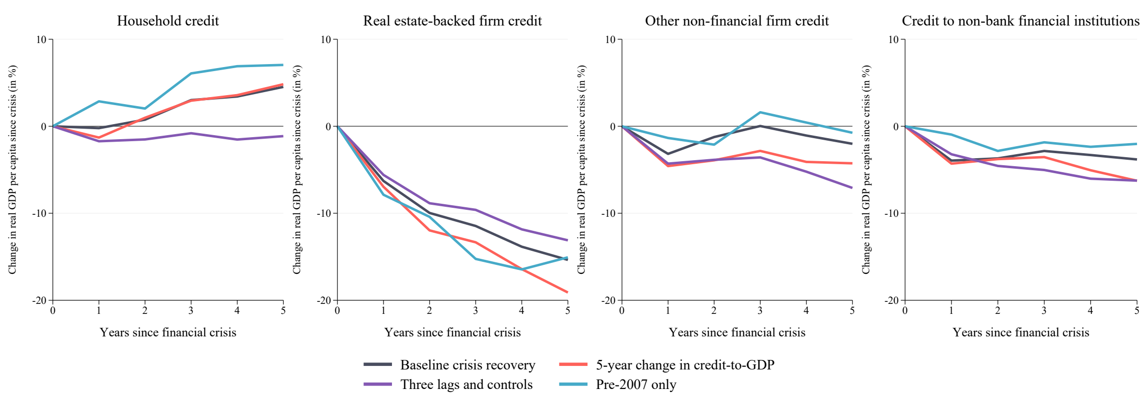
(a) Firm vs. household debt



(b) Non-financial vs. financial firm debt

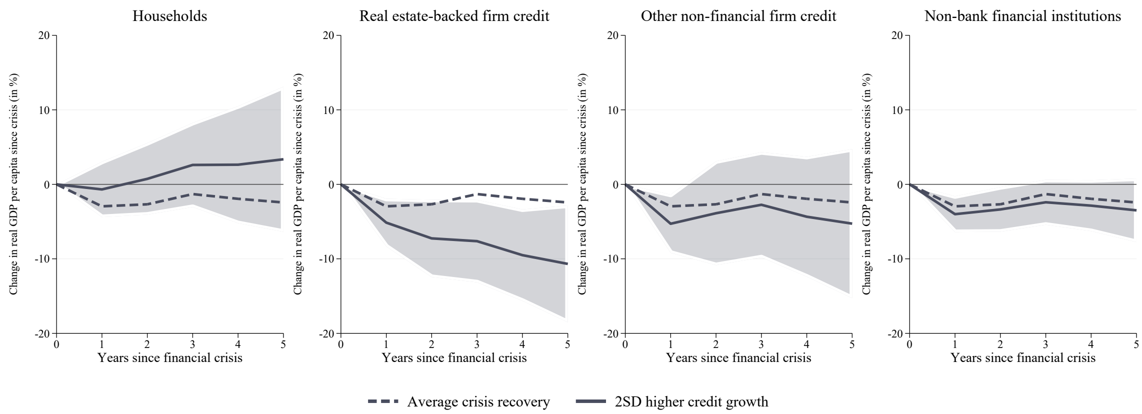


(c) The role of real estate collateral



Notes: This figure plots the estimates of δ^h and $\delta^h + \gamma_j^h$ from Equation (3), showing how the path of log real GDP per capita five years after a financial crisis depends on the type of credit boom preceding it. We show the average recovery path estimated by δ^h and the predicted recovery for the case where the three-year change in credit-to-GDP is two standard deviations above its mean before the crisis based on $\delta^h + \gamma_j^h$. We consider four specifications: (1) the baseline specification shown in Figure 6 as reference, (2) a specification using the five-year instead of three-year change in credit-to-GDP before the crisis, (3) a specification including three lags of the dependent and independent variables as well as contemporaneous and three lagged values of the three-year change in the USD exchange rate, exports/GDP, investment/GDP, and inflation as covariates, and (4) the baseline specification but dropping observations after 2007.

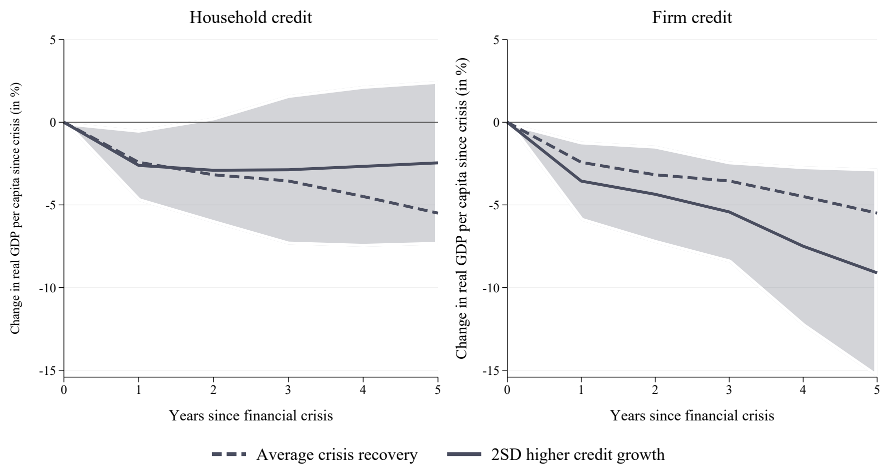
Figure A.4: Real Estate-Backed Firm Credit and Crisis Recovery (US Y-14Q Classification)



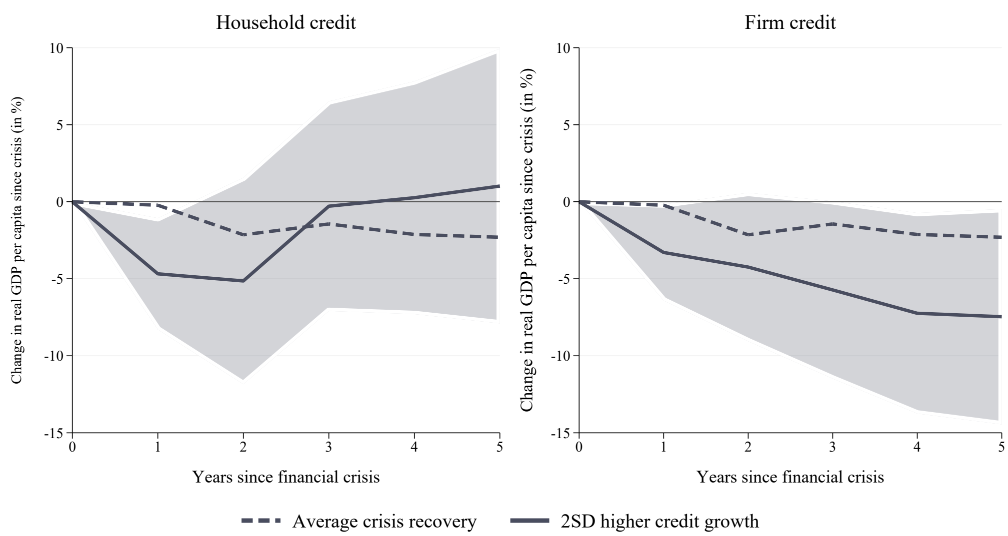
Notes: This figure plots the estimates of δ^h and $\delta^h + \gamma_j^h$ from Equation (3), showing how the path of log real GDP per capita five years after a financial crisis depends on the type of credit boom preceding it. We show the average recovery path estimated by δ^h and the predicted recovery for the case where the three-year change in credit-to-GDP is two standard deviations above its mean before the crisis based on $\delta^h + \gamma_j^h$. We split lending to non-financial corporations into two buckets based on industries' reliance on real estate collateral. To calculate these collateral shares, we use information on the composition of outstanding credit from the United States based on the Federal Reserve's Y-14Q data, taken from Caglio et al. (2021). *Real estate-backed firm credit* refers to the sum of firm lending to ISIC sectors F+L, G+I, and D+E+M+N+P+Q+R+S. As shown in Table 6, these sectors are the ones with the highest reliance on real estate collateral. *Other non-financial firm credit* is defined as the sum of firm lending to ISIC sectors B+C, H+J, and A. Shaded areas are 95% confidence intervals based on standard errors double-clustered by country and year.

Figure A.5: Credit Allocation and Financial Crisis Recovery – By Country Group

(a) Advanced Economies



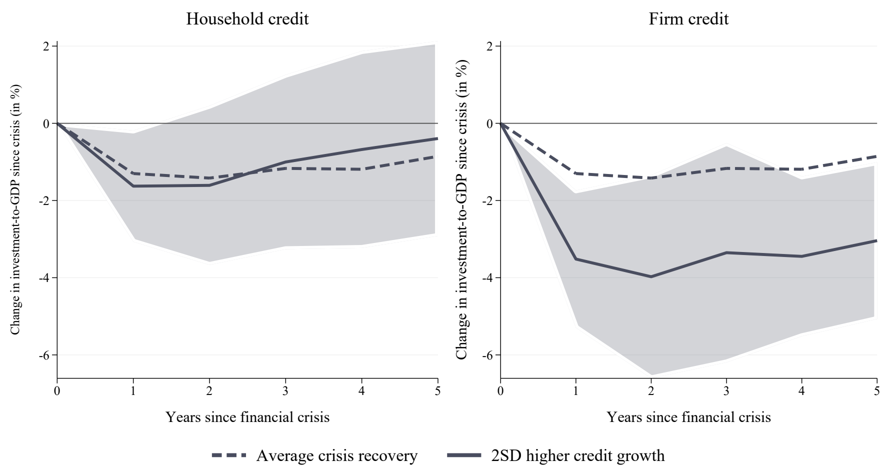
(b) Emerging Economies



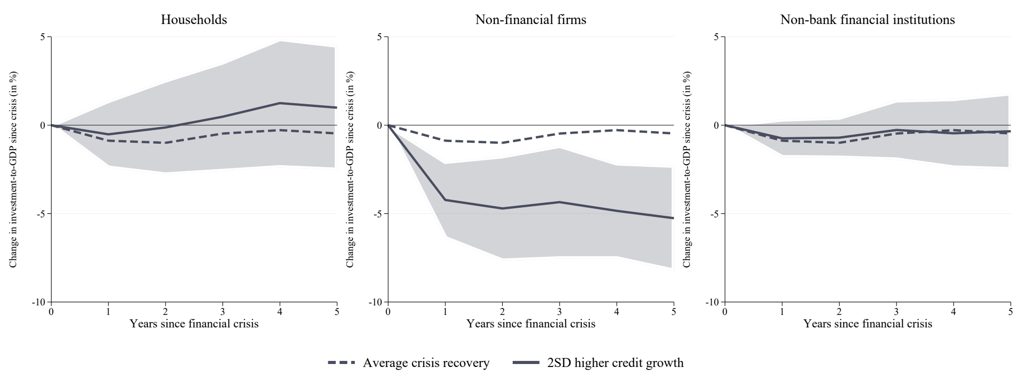
Notes: This figure plots the estimates of δ^h and $\delta^h + \gamma_j^h$ from Equation (3), showing how the path of log real GDP per capita five years after a financial crisis depends on the type of credit boom preceding it. We show the average recovery path estimated by δ^h and the predicted recovery for the case where the three-year change in credit-to-GDP is two standard deviations above its mean before the crisis based on $\delta^h + \gamma_j^h$. The sample is restricted to advanced economies in panel (a) and emerging economies in panel (b). Shaded areas are 95% confidence intervals based on standard errors double-clustered by country and year.

Figure A.6: Credit Allocation and Investment After Crises

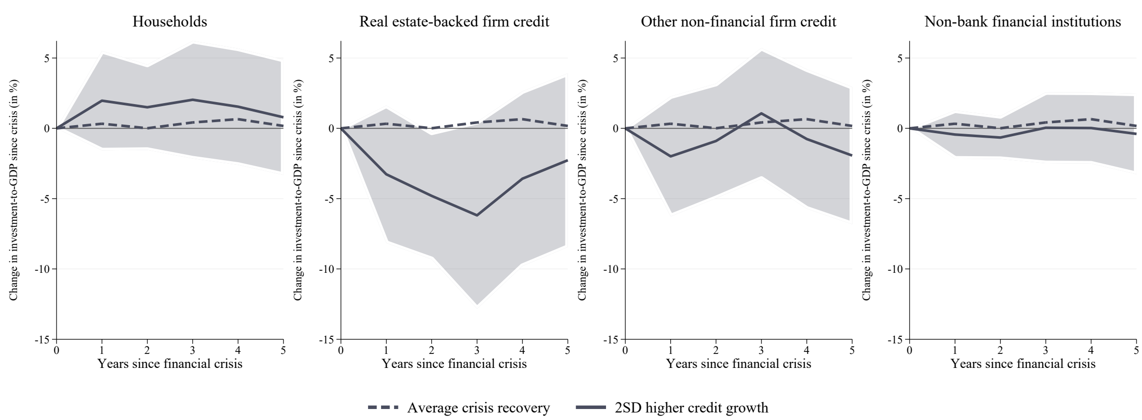
(a) Firm vs. household debt



(b) Non-financial vs. financial firm debt



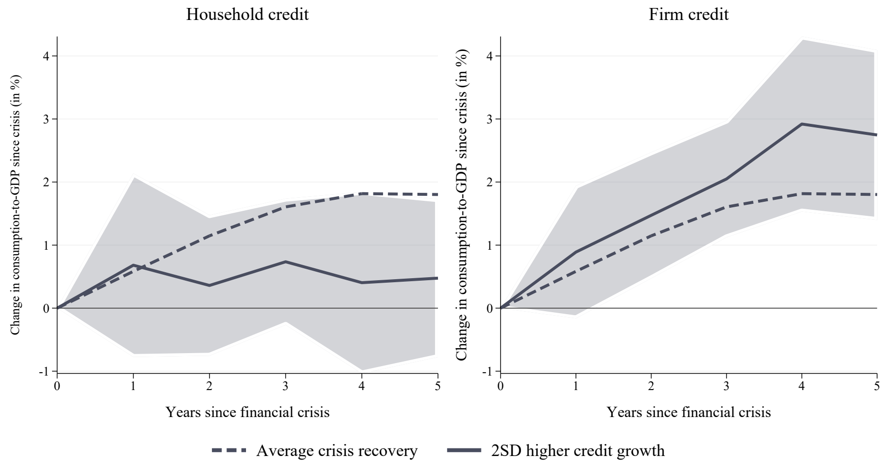
(c) The role of real estate collateral



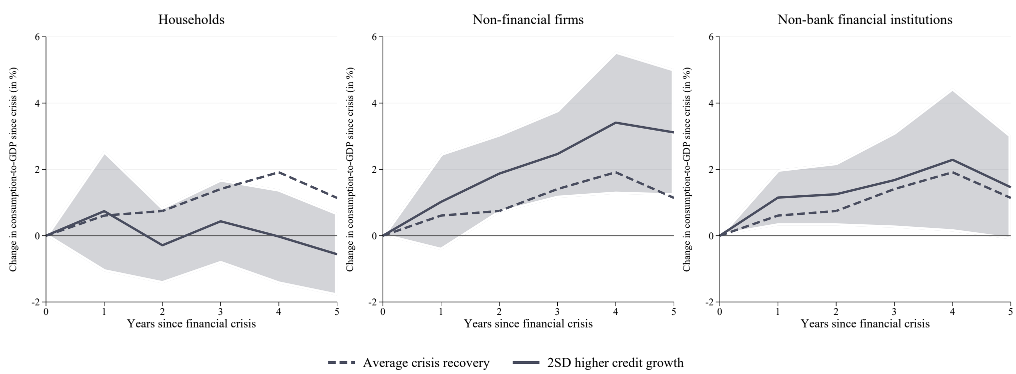
Notes: This figure plots the estimates of δ^h and $\delta^h + \gamma_j^h$ from Equation (3), showing how the path of investment-to-GDP five years after a financial crisis depends on the type of credit boom preceding it. We show the average recovery path estimated by δ^h and the predicted recovery for the case where the three-year change in credit-to-GDP is two standard deviations above its mean before the crisis based on $\delta^h + \gamma_j^h$. Panel (a) focuses on household vs. corporate debt. Panel (b) decomposes corporate debt into non-financial and financial firms. Panel (c) decomposes non-financial firms into industries relying on real estate collateral and other sectors, where the ISIC sector combinations F+L, G+I, and A are classified as real estate-backed firm credit. Shaded areas are 95% confidence intervals based on standard errors double-clustered by country and year.

Figure A.7: Credit Allocation and Consumption After Crises

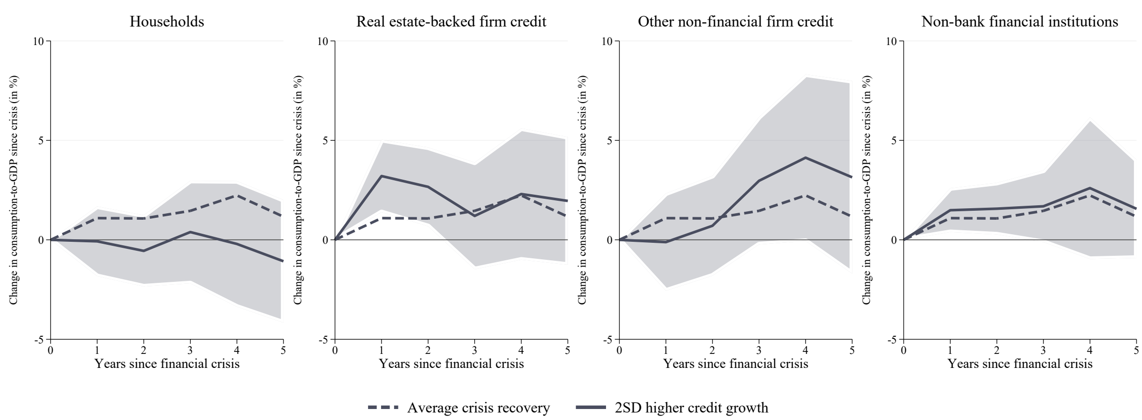
(a) Firm vs. household debt



(b) Non-financial vs. financial firm debt

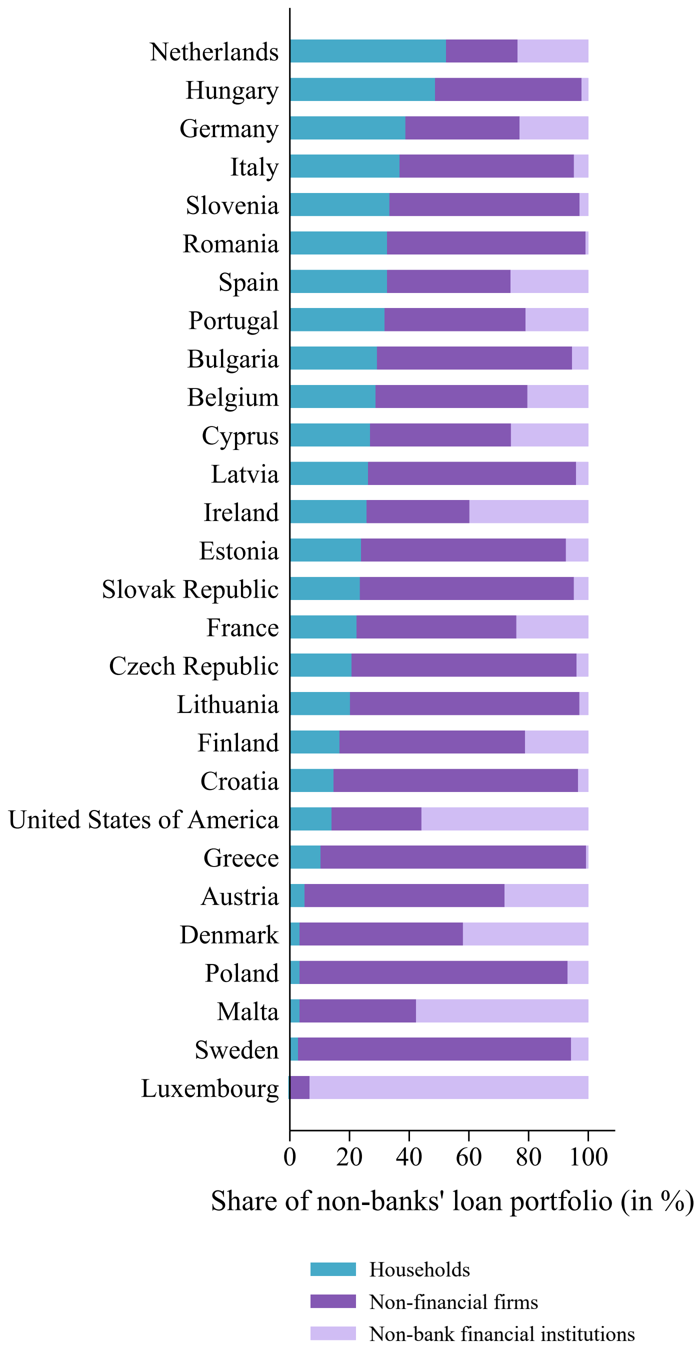


(c) The role of real estate collateral



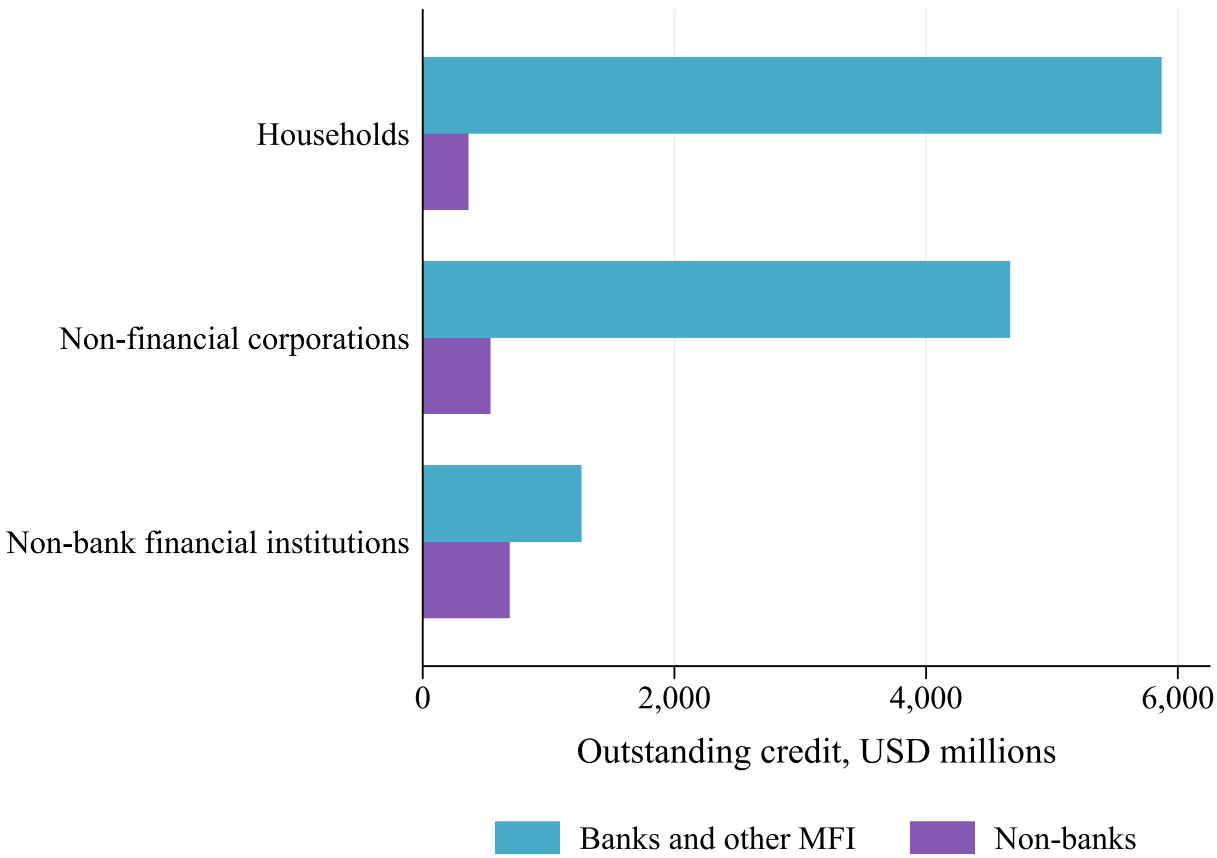
Notes: This figure plots the estimates of δ^h and $\delta^h + \gamma_j^h$ from Equation (3), showing how the path of consumption-to-GDP five years after a financial crisis depends on the type of credit boom preceding it. We show the average recovery path estimated by δ^h and the predicted recovery for the case where the three-year change in credit-to-GDP is two standard deviations above its mean before the crisis based on $\delta^h + \gamma_j^h$. Panel (a) focuses on household vs. corporate debt. Panel (b) decomposes corporate debt into non-financial and financial firms. Panel (c) decomposes non-financial firms into industries relying on real estate collateral and other sectors, where the ISIC sector combinations F+L, G+I, and A are classified as real estate-backed firm credit. Shaded areas are 95% confidence intervals based on standard errors double-clustered by country and year.

Figure A.8: Who Borrows From Non-Bank Financial Institutions?



Notes: This figure plot data on the loan portfolio of non-banks for 28 countries based on the European Central Bank's "who-to-whom" accounts and the Federal Reserve's enhanced financial accounts. We plot the share of different borrowing sectors in total outstanding lending by non-banks. Note that we exclude lending to governments and interbank credit to be consistent with the Global Credit Project data we use.

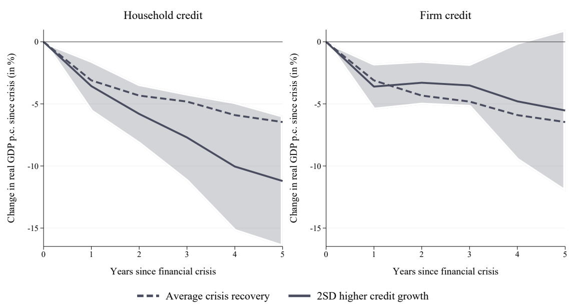
Figure A.9: Non-Bank Market Shares, by Borrower Sector



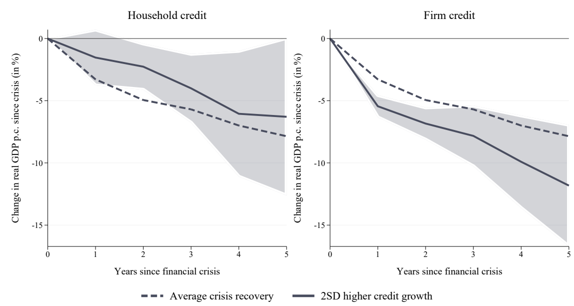
Notes: This figure plots data on the outstanding amount of credit to different borrower sectors for bank and non-bank lenders. We report averages for 28 countries based on the European Central Bank's "who-to-whom" accounts and the Federal Reserve's enhanced financial accountss. Note that we exclude lending to governments and interbank credit to be consistent with the Global Credit Project data we use.

Figure A.10: Comparison with Jordà et al. (2022)

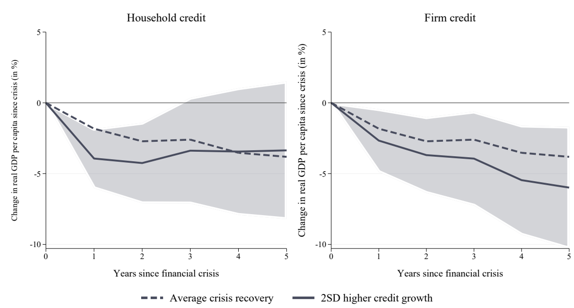
(a) JST data, Δ_5Credit/GDP



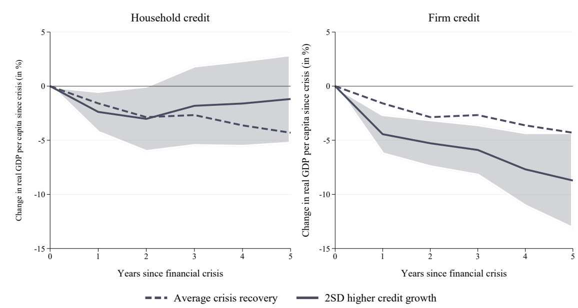
(b) JST data, Δ_3Credit/GDP



(c) Our data, Δ_5Credit/GDP



(d) Our data, Δ_3Credit/GDP



Notes: This figure plots the estimates of δ^h and $\delta^h + \gamma_j^h$ from Equation (3), showing how the path of log real GDP per capita five years after a financial crisis depends on the type of credit boom preceding it. We show the average recovery path estimated by δ^h and the predicted recovery for the case where the three-year change in credit-to-GDP is two standard deviations above its mean before the crisis based on $\delta^h + \gamma_j^h$. In panels (a) and (b), the data are taken from the Jordà-Schularick-Taylor Macrohistory Database (Jordà et al., 2016a), which covers 18 advanced economies over 1870-2020. In panels (c) and (d), we reproduce the results using our own data with the full sample of 115 countries, replicating the patterns also shown in Figure 6a and Figure A.3, respectively. In all figures, we plot the average recovery path after a financial crisis and the predicted recovery for the case where the five-year or three-year change in credit-to-GDP is two standard deviations higher before the crisis. Δ_3 and Δ_5 refer to the three and five-year change ($t-3$ or $t-5$ to t), respectively. Shaded areas are 95% confidence intervals based on standard errors double-clustered by country and year.

Table A.1: Corporate Debt and Financial Crises – Robustness

		Obs.	Countries	Crises	AUC	Households β	Households $[t]$	Firms β	Firms $[t]$
(1)	Baseline (LPM, country FE)	3,070	114	84	0.66	2.54	1.92+	2.68	3.83**
(2)	LPM, country + year FE	3,069	113	84	0.66	1.49	1.99+	2.83	3.70**
(3)	Logit	3,070	114	84	0.66	1.39	3.16**	2.33	4.80**
(4)	Logit, country FE	2,216	58	83	0.65	9.56	3.27**	9.77	2.99**
(5)	Boom (>= Mean + 2 × SD)	3,070	114	84	0.59	8.06	1.71+	18.69	3.68**
(6)	Boom (>= 80th percentile)	3,070	114	84	0.66	6.87	2.16*	5.75	3.63**
(7)	Boom (>= 80th percentile, OOS)	3,070	114	84	0.66	4.25	2.09*	5.47	3.60**
(8)	RR crisis dates	2,181	62	68	0.64	2.67	2.23*	2.68	3.30**
(9)	LV crisis dates only	2,584	113	82	0.64	2.67	1.96+	1.53	1.94+
(10)	Pre-2000 only	2,068	86	54	0.59	1.21	1.48	2.84	3.14**
(11)	Post-1990 only	1,656	114	64	0.68	2.71	1.68	3.23	2.58*
(12)	Advanced economies	1,915	47	50	0.68	2.66	1.81+	2.99	3.40**
(13)	Emerging economies	1,155	67	34	0.63	1.93	1.11	2.20	1.66+
(14)	Exclude USA	3,005	113	81	0.66	2.60	2.05*	2.70	3.72**
(15)	3 lags of annual Δ credit/GDP	2,717	108	79	0.65	2.60	2.05*	0.02	2.29*
(16)	5-year change in credit/GDP	2,859	111	81	0.66	3.55	2.12*	1.51	2.06*
(17)	3-year MA of Δ credit/GDP	2,833	111	81	0.66	2.93	2.13*	2.85	4.13**
(18)	Hamilton-filtered Δ credit/GDP	2,051	56	64	0.69	2.52	2.28*	3.46	3.53**

Notes: This table presents different regression specifications of our baseline crisis prediction model at a 2-year horizon:

$$P(\text{Crisis}_{it+1 \text{ to } t+2}) = \alpha_i + \beta_1 \Delta_3 \text{Credit/GDP}_{it}^{HH} + \beta_2 \Delta_3 \text{Credit/GDP}_{it}^{Firm} + \epsilon_{it}$$

.

$\text{Crisis}_{it+1 \text{ to } t+2}$ is a dummy variable equal to 1 if a financial crisis happens within the next two years. α_i are country fixed effects. $\Delta_3\text{Credit/GDP}_{it}^{HH}$ and $\Delta_3\text{Credit/GDP}_{it}^{Firm}$ refer to the three-year change in household and corporate debt relative to GDP, respectively. Model (1) is the baseline linear probability model with country fixed effects (FE). Model (2) adds year FE. Model (3) is a logit model with standard errors clustered by country. Model (4) is a conditional logit model with bootstrapped standard errors. Model (5) uses "boom" indicators for country-year observations where the three-year change in credit-to-GDP is two standard deviations above the mean. Model (6) uses boom indicators for credit growth being in the top 20% in the full sample, and model (7) the top 20% in a backward-looking manner. Models (8) and (9) use the banking crisis dates from Reinhart and Rogoff (2009b) and Laeven and Valencia (2020), respectively. Model (10) is restricted to data before 2000, and model (11) to data after 1970. Models (12) and (13) restrict the sample to advanced and emerging economies, respectively, and model (14) drops the United States. Model (15) replaces the three-year change in credit-to-GDP with three lags of the annual change in credit-to-GDP; we report the linear combination of coefficients. Model (16) uses the five-year change in credit-to-GDP. Model (17) uses the three-year backward-looking moving average of annual changes in credit-to-GDP. Model (18) uses the Hamilton (2018) filter to detrend annual changes in credit-to-GDP. Except for the logit models, we report t-statistics based on Driscoll and Kraay (1998) standard errors with two lags. +, * and ** denote significance at the 10%, 5% and 1% level, respectively. Coefficients are multiplied by 100 for readability.

Table A.2: Credit Expansion and Dispersion in Credit Growth

	Dep. var.: Dispersion of credit growth in...				
	1 year	2 years	3 years	4 years	5 years
Panel A: Dispersion in non-financial firm credit growth					
Δ_3TOT/GDP	0.163$**$	0.151$**$	0.149$**$	0.136$**$	0.116$**$
	(0.041)	(0.026)	(0.017)	(0.026)	(0.030)
Observations	2,137	2,137	2,137	2,137	2,137
Within-R^2	0.06	0.05	0.05	0.04	0.03
Panel B: Add lending to non-bank financial institutions					
Δ_3TOT/GDP	0.201$**$	0.188$**$	0.179$**$	0.139$**$	0.095$**$
	(0.060)	(0.039)	(0.022)	(0.029)	(0.029)
Observations	1,649	1,649	1,649	1,649	1,649
Within-R^2	0.09	0.07	0.07	0.04	0.02
Panel C: Add household debt					
Δ_3TOT/GDP	0.415$**$	0.304$**$	0.215$**$	0.137$*$	0.076
	(0.062)	(0.056)	(0.052)	(0.057)	(0.050)
Observations	1,536	1,536	1,536	1,536	1,536
Within-R^2	0.17	0.09	0.05	0.02	0.01

Notes: This table shows the results of regressing the standard deviation of three-year changes in sectoral credit to GDP on the three-year change in total credit to GDP. In Panel A, the dependent variable is the standard deviation of sectoral firm credit growth in five non-financial sectors. In Panel B, we add lending to the non-bank financial sector. In Panel C, we add household credit to the list of sectors. All regressions include country fixed effects. Driscoll-Kraay standard errors based on $ceil(1.5 * h)$ lags are in parentheses. +, * and ** denote significance at the 10%, 5% and 1% level, respectively.

Table A.3: The Range of Credit Growth and Crises

	Dependent variable: Crisis within...					
	1 year		3 years		5 years	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Range of non-financial firm credit growth						
Max-min of sectoral credit growth	0.008*	0.005+	0.016**	0.009+	0.016**	0.009+
	(0.004)	(0.002)	(0.006)	(0.005)	(0.005)	(0.005)
Control for total credit	No	Yes	No	Yes	No	Yes
Observations	1,931	1,931	1,931	1,931	1,931	1,931
# Crises	53	53	53	53	53	53
AUC	0.63	0.71	0.60	0.68	0.58	0.65
Panel B: Add lending to non-bank financial institutions						
Max-min of sectoral credit growth	0.009+	0.005	0.014**	0.007*	0.015**	0.010+
	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)	(0.005)
Control for total credit	No	Yes	No	Yes	No	Yes
Observations	1,468	1,468	1,468	1,468	1,468	1,468
# Crises	43	43	43	43	43	43
AUC	0.65	0.73	0.61	0.69	0.60	0.65
Panel C: Add household debt						
Max-min of sectoral credit growth	0.008+	0.005	0.016**	0.010*	0.018**	0.013**
	(0.004)	(0.003)	(0.005)	(0.005)	(0.004)	(0.005)
Control for total credit	No	Yes	No	Yes	No	Yes
Observations	1,394	1,394	1,394	1,394	1,394	1,394
# Crises	43	43	43	43	43	43
AUC	0.69	0.73	0.67	0.70	0.64	0.66

Notes: This table plots the coefficient estimates β_j^h for $h = 1, ..., 5$ from estimating Equation (1) using OLS. The dependent variable is a dummy for the onset of a systemic financial crisis within h years based on data from Baron et al. (2020) and Laeven and Valencia (2020). The independent variable of interest is the range ($max - min$) of the three-year change in credit-to-GDP across different sectors. All regressions include country fixed effects. Driscoll-Kraay standard errors based on $ceil(1.5 * h)$ lags are in parentheses. +, * and ** denote significance at the 10%, 5% and 1% level, respectively.

Table A.4: Firm Credit, Real Estate Collateral, and Crises (US Y-14Q Classification)

	Dependent variable: Crisis within...				
	1 year	2 years	3 years	4 years	5 years
Δ_3HH/GDP	0.026$*$	0.041$*$	0.053$*$	0.066$**$	0.070$**$
	(0.013)	(0.019)	(0.022)	(0.022)	(0.018)
Δ_3NFC, real estate-backed/GDP	0.017$**$	0.035$**$	0.036$*$	0.034$*$	0.031$+$
	(0.006)	(0.012)	(0.014)	(0.016)	(0.017)
Δ_3NFC, other/GDP	-0.002	-0.009	-0.013$+$	-0.024$*$	-0.036$**$
	(0.004)	(0.007)	(0.007)	(0.009)	(0.009)
Δ_3FIN/GDP	0.020$*$	0.031$**$	0.027$*$	0.020	0.014
	(0.010)	(0.011)	(0.011)	(0.015)	(0.019)
Observations	1,246	1,246	1,246	1,246	1,246
# Crises	38	38	38	38	38
AUC	0.77	0.75	0.72	0.70	0.68

Notes: This table plots the coefficient estimates β_j^h for $h = 1, ..., 5$ from estimating Equation (1) using OLS. The dependent variable is a dummy for the onset of a systemic financial crisis within h years based on data from Baron et al. (2020) and Laeven and Valencia (2020). Credit growth is measured as the three-year change in credit-to-GDP. We split lending to non-financial corporations into two buckets based on industries' reliance on real estate collateral. To calculate these collateral shares, we use information on the composition of outstanding credit from the United States based on the Federal Reserve's Y-14Q data, taken from Caglio et al. (2021). Δ_3NFC, real estate-backed/GDP refers to the sum of firm lending to ISIC sectors F+L, G+I, and D+E+M+N+P+Q+R+S. As shown in Table 6, these sectors are the ones with the highest reliance on real estate collateral. Δ_3NFC, other/GDP is defined as the sum of firm lending to ISIC sectors B+C, H+J, and A. All regressions include country fixed effects. Driscoll-Kraay standard errors based on $ceil(1.5 \times h)$ lags are in parentheses. +, * and ** denote significance at the 10%, 5% and 1% level, respectively.

Table A.5: Firm Debt, Real Estate Collateral, and Recession Recovery After Crises

	Dep. var.: ΔLog(Real GDP p.c.) over...				
	1 year	2 years	3 years	4 years	5 years
Crisis	-2.74+	-3.05	-1.82	-2.47	-2.93
	(1.42)	(1.84)	(1.85)	(2.00)	(2.41)
Δ_3HH/GDP	0.14+	0.06	-0.14	-0.34$*$	-0.55$**$
	(0.08)	(0.11)	(0.13)	(0.17)	(0.19)
Δ_3NFC, real estate-backed/GDP	0.01	-0.11	-0.07	-0.13	-0.16
	(0.14)	(0.20)	(0.26)	(0.37)	(0.41)
Δ_3NFC, other/GDP	-0.12	-0.21$*$	-0.31$*$	-0.36$*$	-0.31+
	(0.09)	(0.10)	(0.12)	(0.14)	(0.18)
Δ_3FIN/GDP	0.04	-0.08	-0.12	0.01	0.03
	(0.09)	(0.18)	(0.15)	(0.21)	(0.27)
Crisis × Δ_3HH/GDP	0.29$*$	0.44$*$	0.56$*$	0.68+	0.86$*$
	(0.13)	(0.18)	(0.27)	(0.37)	(0.39)
Crisis × Δ_3NFC, real estate-backed/GDP	-0.46	-0.89+	-1.25+	-1.47$*$	-1.61$*$
	(0.28)	(0.46)	(0.62)	(0.70)	(0.75)
Crisis × Δ_3NFC, other/GDP	-0.06	0.25	0.26	0.19	0.13
	(0.26)	(0.42)	(0.53)	(0.61)	(0.71)
Crisis × Δ_3FIN/GDP	-0.32$*$	-0.17	-0.27	-0.22	-0.23
	(0.14)	(0.24)	(0.28)	(0.36)	(0.45)
R^2	0.36	0.41	0.49	0.53	0.56
Observations	875	875	875	875	875

Notes: This table shows the results of local projections as in Equation (3) that analyze how the path of log real GDP per capita after crises depends on different types of credit growth, defined as the three-year change in credit-to-GDP (standardized to have a mean of zero and standard deviation of one). All regressions include country fixed effects. Standard errors are clustered by country and year. ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

Table A.6: Corporate Debt and Recession Recovery After Financial Crises – Additional Results

	Dep. var.: ΔLog(Real GDP p.c.) over...				
	1 year	2 years	3 years	4 years	5 years
Panel A: Total credit					
Crisis	-1.56+	-2.03*	-2.73*	-2.89+	-3.06+
	(0.78)	(1.01)	(1.22)	(1.56)	(1.66)
Δ_3TOT/GDP	0.02	-0.02	-0.03	-0.07	-0.13*
	(0.02)	(0.03)	(0.04)	(0.05)	(0.05)
Crisis $\times$ Δ_3TOT/GDP	-0.17**	-0.19**	-0.16*	-0.18+	-0.18
	(0.05)	(0.06)	(0.08)	(0.10)	(0.11)
R^2	0.21	0.25	0.29	0.32	0.34
Observations	5265	5265	5265	5265	5265
Panel B: Non-financial vs. financial firm debt					
Crisis	-1.76	-2.27	-1.98	-2.78	-3.47
	(1.19)	(1.70)	(1.84)	(2.10)	(2.31)
Δ_3HH/GDP	0.10	0.02	-0.12	-0.34**	-0.51**
	(0.07)	(0.10)	(0.12)	(0.11)	(0.14)
Δ_3NFC/GDP	0.00	-0.07	-0.12	-0.19+	-0.16
	(0.04)	(0.07)	(0.08)	(0.11)	(0.13)
Δ_3FIN/GDP	0.02	0.03	0.08	0.14	0.02
	(0.08)	(0.16)	(0.23)	(0.30)	(0.31)
Crisis $\times$ Δ_3HH/GDP	-0.01	0.02	0.12	0.24	0.38
	(0.11)	(0.16)	(0.21)	(0.24)	(0.25)
Crisis $\times$ Δ_3NFC/GDP	-0.29**	-0.28*	-0.37*	-0.49**	-0.58**
	(0.08)	(0.12)	(0.15)	(0.18)	(0.21)
Crisis $\times$ Δ_3FIN/GDP	0.03	0.16	0.07	0.11	0.19
	(0.16)	(0.25)	(0.35)	(0.41)	(0.48)
R^2	0.27	0.28	0.32	0.36	0.39
Observations	1384	1384	1384	1384	1384

Notes: This table plots the coefficients of local projections as in Equation (3) that analyze how the path of log real GDP per capita after systemic financial crises depends on pre-crisis credit growth in different sectors, defined as the three-year change in credit-to-GDP (standardized to have a mean of zero and standard deviation of one). All regressions include country fixed effects, contemporaneous and three lagged values of GDP growth, as well as three lags of the crisis dummies, credit growth variables, and their interactions. Standard errors are clustered by country and year. +, * and ** denote significance at the 10%, 5% and 1% level, respectively.

Table A.7: Sources of Collateral Data

Country	Methodology	Coverage	Definition of collateral	Source
United States	Administrative	Firms who borrow greater than or equal to $1 million from U.S. BHCs, U.S. IHCs of foreign banking organizations (FBOs), and covered SLHCs with $50 billion or more in total consolidated assets. Participation is mandatory.	Type of collateral backing a loan (principal and any drawals and rollovers). Raw data comes with six types of collateral posted.	Federal Reserve: Y-14Q
Latvia	Supervisory	All credit institutions registered in the Latvia and branches of Euro member state credit institutions.	Type of collateral backing the principal amount of outstanding loans.	Latvijas Banka: Quarterly Credit Institution Reports
Switzerland	Survey	Banks in Switzerland whose domestic lending amounts to at least CHF 280 million are required to report data.	Mortgage loans to non-banks that are stated under the balance sheet items mortgage loans' and 'other financial instruments at fair value'.	Swiss National Bank: Credit Volume Statistics (KRED)
Taiwan	Survey	All banks registered in Taiwan.	Loans used for the purpose of purchasing real estate or construction, including revolving loans for construction.	Central Bank of the Republic of China (Taiwan): Financial Statistics Monthly
Denmark	Administrative	Mortgage banks	Share of outstanding credit provided by mortgage banks as a fraction of all bank lending. Credit to different industries by mortgage banks is taken from table DNRUDDKB, and credit by all banks is defined as the sum of these values and those for other banks in table DNPUDDKB.	Danmarks Nationalbank: Banking and Mortgage Lending

Notes: This table outlines details about the data underlying our estimates for how much different industries rely on collateral. U.S. and Latvia provides all types of collateral whereas other countries info is only on real estate collateral. The data for the U.S. is from Caglio et al. (2021). The data for Switzerland, Taiwan, Latvia, and Denmark were originally collected by Müller and Verner (2023).

Table A.8: Sources and Definition of Nonperforming Loan Data

Country	Table	NPL definition	Source
Argentina	Table XVI Financing Based on Economic Activity	Loans that are not in ”normal condition”, meaning those who owe loan balances but did not repay for 31 days or more.	Central Bank of Argentina
Belgium	Nonperforming Loans and Asset Quality	Loans classified as overdue for more than 90 days following EBA classification.	National Bank of Belgium
Croatia	Loan Quality of Credit Institutions	Loans classified as overdue for more than 90 days.	Croatian National Bank
Cyprus	Information on Nonperforming Loans	Loans classified as overdue for more than 90 days.	Central Bank of Cyprus
Estonia	11. Stock of Overdue Loans	Loans classified as overdue for more than 90 days (before December 2000, overdue more than 60 days).	Eesti Pank
Greece	Evolution Of Total Loans & Non Performing Loans	Loans classified as overdue for more than 90 days following EBA classification.	Bank of Greece
Hungary	Supervisory Banking Statistics	Loans classified as overdue for more than 90 days.	Magyar Nemzeti Bank
Italy	Tables ATECO200 and BSIB0600	Bad loans net of provisions, obtained by subtracting from bad loans both the provisions (entered in reporting banks’ accounts) and the cumulative amount of the write-downs made directly in the accounts.	Bank of Italy
Jamaica	Tables FS.DTI.00 and FS.CB.03	Loans classified as overdue for more than 90 days.	Bank of Jamaica
Latvia	Quality of Loans to Non-banks	Loans classified as overdue for more than 90 days.	Latvijas Banka
Malaysia	Nonperforming Loans by Sector	Loans classified as overdue for more than 90 days.	Bank Negara Malaysia
Mexico	Credit by Main Activity of Debtor	Not precisely defined.	Banco de Mexico
Mongolia	Banking Sector Loan Indicators	Loans classified as overdue for more than 90 days.	Mongolbank
Norway	Public Accounting Reporting from Banks and Finance Companies (ORBOF)	Loans on which a borrower has not made repayments of principal or interest for more than 90 days.	Statistics Norway
Portugal	Tables B.4.2.1 and B.4.1.4	Loans classified as overdue for more than 90 days.	Banco de Portugal
Spain	Statistical Bulletin Table 4.18	Loans classified as overdue for more than 90 days.	Banco d’Espana
Thailand	Gross NPLs Outstanding Classified by Business Sector	Loans classified as overdue for more than 90 days.	Bank of Thailand
Turkey	Sectoral Loan Distribution	Loans classified as overdue for more than 90 days.	BDDK
Ukraine	The Amount of Credit Operations and the Rate of Nonperforming Exposures	Loans classified as overdue for more than 90 days.	National Bank of Ukraine
USA	Quarterly Loan Portfolio Performance Indicators	Loans classified as overdue for more than 90 days.	FDIC