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

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May 2026

Abstract

Using a new dataset on sectoral credit exposures in 114 economies from 1940 to 2014, we provide evidence that corporate debt plays a key role in explaining macroeconomic boom-bust cycles, financial crises, and sluggish recoveries. We find that: (i) corporate debt accounts for two-thirds of aggregate credit expansion and three-quarters of nonperforming loans during downturns; (ii) firm credit growth is linked to future crises more so when it is backed by pro-cyclical collateral; (iii) expansions in corporate debt predict crises, conditional on expansions in household credit; (iv) increasing dispersion in corporate credit also predicts financial crises, consistent with heterogeneous firm financial frictions; (v) financial crises following booms in corporate debt are associated with slower macro recoveries.

JEL codes: E2, F3, G01, G2

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Conflict-of-interest disclosure statement

Victoria Ivashina

In addition to Harvard University, in the past three years, I received significant financial compensation from the Carlyle AlpInvest, Cornerstone, Federal Reserve Bank of Boston, and Superintendency of Banking and Insurance of Peru.

Şebnem Kalemli-Özcan

I have nothing to disclose.

Luc Laeven

I have nothing to disclose.

Karsten Müller

I have nothing to disclose.

1 Introduction

What is the macroeconomic role of corporate debt? Despite an extensive theoretical literature on the negative impact of corporate debt on investment, productivity, and firm growth (e.g., Khan and Thomas, 2013; Gopinath et al., 2017), as well as its well-studied role in the transmission of financial shocks to the real economy (e.g., Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997; Bernanke et al., 1999; Ottonello and Winberry, 2020), the empirical literature does not deliver a clear answer to this question.[1] Many studies that use firm-level data emphasize the real effects of bank credit supply shocks, and that excessive leverage can hurt investment and employment (e.g., Rosengren and Peek, 2000; Khwaja and Mian, 2008; Giroud and Mueller, 2016; Huber, 2018; Kalemli-Özcan et al., 2022). However, evidence on the macroeconomic role of corporate debt remains inconclusive. Influential work by Mian et al. (2017) and Jordà et al. (2022), for example, concludes that corporate debt has no predictive power for future growth, and that recessions preceded by corporate credit booms do not leave a lasting imprint on the macroeconomy. Greenwood et al. (2022), on the other hand, find that growth in corporate credit, taken as a stand-alone explanatory variable, predicts financial crises.

In this paper, we study the role of corporate debt in shaping credit dynamics and economic outcomes and contrast it with the role of the household debt. As we elaborate in the next section, models with firm financing frictions generate several key predictions for identifying when expansions in corporate debt may have macroeconomic consequences. These predictions highlight the importance of firms' collateral constraints, fluctuations in corporate net worth, heterogeneity in financing constraints across firms, and the accumulation of corporate defaults on bank balance sheets. We provide new empirical evidence along each of these dimensions.

The backbone of our analysis is a historical cross-country panel dataset on credit markets covering 114 advanced and emerging economies from 1940 to 2014 that allows us to differentiate between household and firm credit. Specifically, we extend the Global Credit Project introduced by Müller and Verner (2024) by constructing novel granular series of outstanding firm credit *by industrial*

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

sector for up to 18 sectors, including lending to non-bank financial institutions.[2] This is a significant expansion of Müller and Verner (2024) who has data on 5 broad industry groups and predominantly focus on the distinction between the tradable and non-tradable sector. To the best of our knowledge, our dataset is unprecedented in its breadth and scope and overlaps with 84 episodes of systemic financial crises. This sector-level information is central to our analysis because it allows us to test models with financing frictions that rely on heterogeneity in firm credit.

Equipped with these data, we first show that, historically, corporate debt accounted for about two-thirds of the aggregate credit growth in the three years preceding financial crises and the entirety of the credit crunch once a crisis materialized. These results contrast with those for household debt, which continues to grow relative to GDP even after the onset of a financial crisis. These patterns mirror the fact that three-quarters of the loans that become nonperforming after crises are accounted for by firms, as opposed to households. The United States in 2007 is a notable outlier: out of the 24 crises in our sample, the subprime mortgage crisis is the episode with the single highest share of household defaults in total NPLs.

To understand the amplifying mechanisms linking firm debt and crises, we exploit the fact that sectors differ in the types of collateral they rely on. First, consistent with the earlier literature linking real estate collateral values to firm behavior (e.g., Gan, 2007; Chaney et al., 2012; Bahaj et al., 2020), we show that the relation between corporate debt, financial crises, and slow recoveries is strongest for sectors that rely on real estate collateral, such as the construction sector. Second, we also find that credit flowing to the wholesale and retail trade sectors is a strong predictor of crises. This result suggests a role for other types of collateral with procyclical valuations in addition to real estate, such as inventories or corporate earnings, which play a central role in cash-flow-based borrowing (Lian and Ma, 2020; Caglio et al., 2021). Using issuance-level data on unsecured corporate bonds and syndicated loans not secured on real estate, we show that an expansion in firm debt backed by cash flows or firm net worth also predicts crises, consistent with models in the tradition of Townsend (1979), Bernanke and Gertler (1989), Hart and Moore (1994) or Holmstrom and Tirole (1997).

[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.

While the above patterns are in-line with models with firm financing frictions, they could at least in part also be rationalized by *household* borrowing constraints based on collateral values (as in Iacoviello, 2005) or (expected) income (as in Aiyagari, 1994; Eggertsson and Krugman, 2012). To further investigate a distinct role for corporate debt, we provide evidence based on the predictions of heterogeneous firm models with financing constraints and default risk. In models with firm heterogeneity, firms differ in their response to interest rate and credit shocks, leading to an increase in the dispersion of credit growth across firms. We thus propose a simple measure for changes in heterogeneous firm borrowing constraints: the standard deviation of firm debt growth across sectors or firms. Our granular data on credit to up to 18 industrial sectors in particular enables us to construct long-run estimates of the dispersion in credit growth. As we show, this measure of dispersion increases systematically during credit expansions and contractions, suggesting heterogeneous easing and tightening of financing constraints. A higher degree of dispersion of credit growth, in turn, predicts financial crises over and above the magnitude of credit expansion.

To examine the role of corporate debt in macroeconomic outcomes, we look at whether firm debt matters for sluggish post-crisis recoveries using local projections. In particular, we study how the path of post-crisis real GDP per capita and nonperforming loans depend on the type of credit extended before the downturn. We find that corporate debt is important for macroeconomic dynamics. Corporate debt is thus not only linked to a higher likelihood of financial crises; it also predicts a prolonged recovery from the recessions that usually follow. Importantly, we obtain these results while controlling for the pre-crisis fluctuations in household debt, which has a more limited ability to predict the recovery from crises.[3]

We also investigate the unconditional predictive relation between corporate and household debt with future GDP growth. Consistent with existing evidence, household debt is more predictive of *average* future growth (e.g., Mian et al., 2017; Sufi, 2023). But conditional on growth in household debt, we find that growth in corporate debt is highly predictive of GDP crashes, i.e. left-tail realizations

[3] Jordà et al. (2022) find that the corporate debt is only consequential in economies with weak restructuring regimes. In contrast to their paper, our dataset includes many emerging markets where bankruptcy frictions may be more severe, and also allows us to differentiate firm credit by industry.

of GDP growth rather than its mean. This evidence suggests that the lack of a link between corporate debt and future economic outcomes documented in the existing literature is partly due to a focus on average future growth.

Why is corporate debt particularly strongly linked to major economic crashes, while it has only moderate predictability for average future GDP growth? We argue that the answer likely lies in the structure of insolvency regimes. Until recently, "most countries did not have a consumer bankruptcy system" (Niemi-Kiesiläinen et al., 2003, p. 1), leaving delinquent household borrowers with little or no way to discharge their debts. By contrast, bankruptcy frameworks for firms typically allow corporate debt to be written off more readily (Robe and Steiger, 2015; World Bank, 2017). At least in part, this distinction arises from the fact that firms can be "completely dismembered and allowed to die" (World Bank, 2014, p.17), while such a fate should ideally be avoided for natural persons.[4]

The flip side of this greater leniency toward firm borrowers is that corporate defaults during downturns spill over to the banking system. If such defaults become sufficiently widespread, they can erode banks' capital buffers and precipitate a crisis. This mechanism helps explain why corporate debt is associated with non-linear crash risk, whereas household debt is more uniformly correlated with weaker future growth. While excessive household debt may weigh on consumption, which Mian et al. (2021) call "indebted demand," it is somewhat less likely than firm debt to trigger a wave of defaults.

Our 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; Giroud and Mueller, 2021; Sever, 2023; Müller and Verner, 2024). Unlike the previous literature, we focus on the distinction between corporate and household debt in shaping macroeconomic outcomes. Our core contribution is to "rule in" a distinct role of firm debt in macroeconomic fluctuations over and above household debt. In particular, we show that corporate debt plays a role in the economic crashes often associated with financial crises, and that the preceding firm credit expansions are characterized by a heterogeneous loosening of financing

[4] A 2011 survey by the World Bank of 59 major economies found that more than half of the surveyed emerging economies — but also advanced economies such as Italy, Croatia, and Hungary — "still do not have a system for collectively dealing with consumer insolvency" (World Bank, 2014, p.1.). Even where insolvency frameworks for private persons exist, they were often only introduced in the 1990s.

constraints across firms, indicated by a rising dispersion in firm credit growth and higher firm credit growth backed by both real estate collateral and cash flows. We also show that the credit crunch and the increase in nonperforming loans following crises are largely concentrated among firm borrowers. Corporate defaults thus play a key role in the erosion of bank capital at the heart of banking sector meltdowns.

Our analysis also complements the "price of risk" literature which shows that firm credit spreads are highly predictive of recessions (e.g., Gilchrist and Zakrajšek, 2012; López-Salido et al., 2017; Saunders et al., 2025), a finding that is often interpreted through the lens of financial accelerator models, where the price of risk fluctuates with asset values (e.g., Bernanke et al., 1999; He and Krishnamurthy, 2013). Our findings on the potential economic fallout from corporate credit expansions point to vulnerabilities associated with the "quantity of risk" to the extent that less creditworthy firms are able to borrow more during booms (Greenwood and Hanson, 2013) given the compression in credit spreads (e.g. Gertler and Gilchrist (1993)).

The paper proceeds as follows. Section 2 reviews models of firm and household financing frictions and derives testable predictions. Section 3 introduces the data. Section 4 examines the link between growth in corporate debt and financial crises. Section 5 provides evidence on the role of various firm borrowing constraints. Section 6 documents a key role for corporate debt in predicting the defaults and macroeconomic dynamics after crises. Section 7 concludes.

2 Conceptual Framework

In this section, we review theoretical frameworks linking corporate debt to financial crises and business cycle downturns, and discuss the empirical predictions these frameworks generate.

2.1 Models with Firm Financing Frictions

Firm borrowing constraints play a central role in macroeconomic models that incorporate financing frictions. The foundational work of Kiyotaki and Moore (1997) emphasizes the role of borrowing constraints for a firm's borrowing capacity. To illustrate a common formulation of firm financing frictions in this literature, it is useful to write down a firm's borrowing constraint as follows:

$$b_t \leq \theta q_{t+1} k_t, \tag{1}$$

where b_t is borrowing, q_{t+1} is the expected price of land (or capital), and k_t is the stock of a firm's production inputs. θ is the fraction of the market value of the production inputs (such as land) that can be pledged as collateral. k serves a dual function in these models: it is used both as collateral and as an asset in firms' production.

In this framework, firms' net worth is effectively determined by the value of their hard assets. A negative productivity shock reduces the demand for land and leads to a drop in asset prices. The decline in asset prices tightens borrowing constraints, forcing firms to cut back on investment, ultimately reducing future output. This feedback loop between asset prices and borrowing capacity amplifies the initial shock, which can lead to significant and persistent fluctuations in output or firm investment (see Liu et al., 2013).

Other work on firm borrowing constraints has emphasized the role of cash flows or firm net worth beyond hard assets, starting with early contributions such as Townsend (1979), Bernanke and Gertler (1989), Hart and Moore (1994), Holmstrom and Tirole (1997), and Bernanke et al. (1999). A growing literature studies various debt contract features that directly link a firm's borrowing capacity to its cash flows (see, e.g., Lian and Ma, 2020; Caglio et al., 2021; Drechsel, 2023; Hartman-Glaser et al., 2022). Although the borrowing constraint in these frameworks is not tied to the value of land or other forms of capital, it still generates an amplification mechanism: lower net worth leads to reduced or more costly access to external financing, which in turn depresses investment and output.

More recent theoretical work has emphasized heterogeneity across firms. Khan and Thomas (2013) develop a model where heterogeneous firms face collateral constraints. In their model, firms react differently to credit shocks depending on their reliance on investment loans, and tightening credit conditions predict a slowdown in aggregate TFP because it leads to a misallocation of capital across firms. Ottonello and Winberry (2020) build a model for firms where relationship between firm default risk and impact of monetary policy shocks is ambiguous. They show that listed firms with low default risk react more to these shocks, whereas Caglio et al. (2021) show private firms with high default risk react more to the same shocks. These results indicate extensive heterogeneity in firm financing constraints where default risk may not be the only measure for financial constraints as such risk is endogenous to macro-cycles and policy shocks. For example, in Gopinath et al. (2017), a decrease in the interest rate leads to credit flowing to firms with high net worth but low productivity, which depresses aggregate TFP. In these heterogeneous firm models, a shock to the interest rate results in different borrowing responses across firms, leading some firms to issue more debt than others. As a result, heterogeneous firm financing frictions lead to a higher *dispersion* in debt growth across firms, which in turn is associated with a business cycle downturn.[5]

Finally, the literature has considered the role of default risk in models of firm borrowing (e.g., Schneider and Tornell, 2004; Jermann and Quadrini, 2012; Gilchrist et al., 2014; Arellano et al., 2019). In these models, default risk arises endogenously depending on the firm's financial condition and economic shocks. Higher default risk increases the cost of debt because lenders demand higher interest rates or restrict credit, reducing corporate borrowing, and constraining investment. During downturns, rising default risk can trigger sharp declines in investment and production, amplifying the recession. In practice, this default mechanism is most relevant for firms, because most countries do not allow households to meaningfully reduce their debt as part of a bankruptcy filing.

2.2 Empirical Predictions

In models of firm borrowing that incorporate collateral constraints, the key empirical prediction is that credit to corporate sectors more reliant on real estate as collateral is more likely to exhibit boom-bust patterns than credit to other industries. Testing this prediction is useful because it can reject the null hypothesis that there is no empirical relation between corporate debt and macroeconomic outcomes. However, such a test does not fully distinguish between firm financing constraints and household

[5]Similarly, Crouzet (2018) develops a general equilibrium model in which heterogeneous firms differ in the amount and type of debt they use. Firms face a trade-off between choosing bank debt, which is more flexible during periods of financial distress, and cheaper but less flexible market-based debt. The resulting substitution of debt types in response to aggregate shocks indicates that cross-sectional dispersion in firm debt growth may contain information about future crisis risks.

borrowing constraints, because loose credit conditions and rising house prices may also affect the economy through household borrowing constraints (Iacoviello, 2005; Mian and Sufi, 2014; Mian et al., 2020).

In models of firm debt relying on cash flow or net worth, the main prediction is that borrowing capacity fluctuates with revenues and net worth. Given that household income and corporate revenues both tend to be procyclical, it is not straightforward to employ these models to differentiate between the role of firm and household borrowing constraints. However, this challenge can be partly addressed by focusing on firms in sectors that are less sensitive to household demand. If firm borrowing constraints play an independent role, an expansion in firm debt backed by cash flows *excluding* sectors that are highly sensitive to household demand (e.g., construction and real estate) should predict an economic downturn.

According to models with firm heterogeneity, firms differ in their response to interest rate and credit shocks, leading to an increase in the dispersion of credit growth across firms. These models predict that credit expansions should be accompanied by a higher dispersion of credit growth *within* the corporate sector, and that this higher dispersion should be indicative of future financial distress.

Finally, according to models with borrowing constraints that incorporate default risk, we expect to observe elevated corporate defaults and rising nonperforming loans in the aftermath of a credit expansion. These nonperforming loans weaken banks' balance sheets, reduce firms' borrowing capacity, and thereby contribute to the economic downturn during financial crises. This mechanism should be less relevant for households because most countries do not allow household debt forgiveness on a scale comparable to firm bankruptcies.

In sum, models with firm financing frictions generate four predictions to identify when an expansion in corporate debt may have macroeconomic consequences. These predictions suggest a role for (i) collateral constraints, (ii) firm borrowing constraints based on cash flows or net worth, (iii) heterogeneous firm financing constraints, and (iv) firm defaults. Taken together, these predictions are not easily generated by frameworks that only consider household borrowing constraints, and thus allow us to test for a distinct role for firm debt.

3 Data

We construct an annual cross-country panel dataset covering 114 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.

3.1 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 (2024). 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).

We extend the Müller and Verner (2024) data by constructing new time series on credit to 18 industries, including loans to the non-bank financial sector, for an extended sample of 114 countries.[6] To work with the largest possible sample, our baseline exercises focus on a parsimonious set of 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).[7]

Our dataset 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

[6] The full set of 18 industries comprises of the sectors with the (partly combined) ISIC codes A, B, $C10-12$, $C13-15$, $C16-18$, $C19-22$, $C23$, $C24-28$, $C29-30$, F, G, H, J, I, K, L, $M+N$, and $P+Q+R+S$.

[7] Müller and Verner (2024) 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.

covers 114 countries and 3053 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 (2024) distinguish between firm credit to two sectors (the non-tradable and tradable sector). We use measures of changes in corporate debt for up to 18 sectors of the economy. Third, our dataset includes "intrafinancial" credit, not covered by Müller and Verner (2024). 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.[8] 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 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 (2024) for technical details.

[8]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 collateral constraints, 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.[9] Table A.6 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).[10] 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 VII 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

[9] With the exception of the US data, these sources were originally compiled by Müller and Verner (2024).

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

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.

3.2 Additional Firm and Issuance-Level Data

In some empirical tests, we rely on data capturing debt issuance from the following standard sources: Compustat Global, Orbis, SDC Platinum, LPC Dealscan, and the BIS Debt Securities dataset.

From Compustat Global and Orbis, we construct measures of the standard deviation of debt issuance. To do so, we first create a measure of debt issuance on the firm-level, calculated as the change in outstanding long-term and short-term debt over the past three years relative to assets three years ago. We then calculate the standard deviation of this measure on the country-year level whenever we observe at least three individual firms in a given country and year. For Orbis, we restrict the sample to 1999 onwards, where the data become more reliable. Because we are interested in financing frictions other than collateral constraints, we exclude the construction and real estate sectors (*SIC* sectors 1500-1799 and 6500-6599) from these calculations.

We also construct measures capturing the amount of newly issued debt backed by cash flows or net worth from SDC Platinum (bonds) and LPC Dealscan (syndicated loans). In SDC Platinum, we only keep unsecured bond issues. In the LPC Dealscan data, we drop all loans that are either explicitly secured by real estate, property, or plants, or alternatively mention the term "real estate" in the loan's description. For both bonds and syndicated loans, we exclude borrowers in the construction and real estate sectors, as above. After these exclusions, we collapse the total amount of newly-issued debt on the country-year level. Lastly, we obtain estimates on the stock of outstanding debt securities issued by non-government borrowers from the BIS Debt Securities database.

3.3 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. We use their joint crisis list, which includes episodes of banking crises with and without panics. 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 84 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.

3.4 Macroeconomic Data

We use other macroeconomic data from a variety of sources as originally compiled by Müller and Verner (2024). 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.

3.5 Nonperforming Loans and Defaults

To understand who defaults during and after financial crises, we draw on several data sources. Most importantly, we construct a new dataset on nonperforming loans by sector based on data from the national central banks. We were able to collect these data for 20 countries.[11] The information we have

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

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.7 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.

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. 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.

Table I: 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
Other non-financial firm credit	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.

3.6 Descriptive Statistics

Figure I 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 II 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 I 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, with the most volatile components of firm credit being the construction, real estate, and retail/wholesale trade industries, as well as credit to other sectors. We also report the persistence of credit growth, which prior literature has shown to be a strong predictor of crises, measured by the coefficient of an AR(1) model. 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.

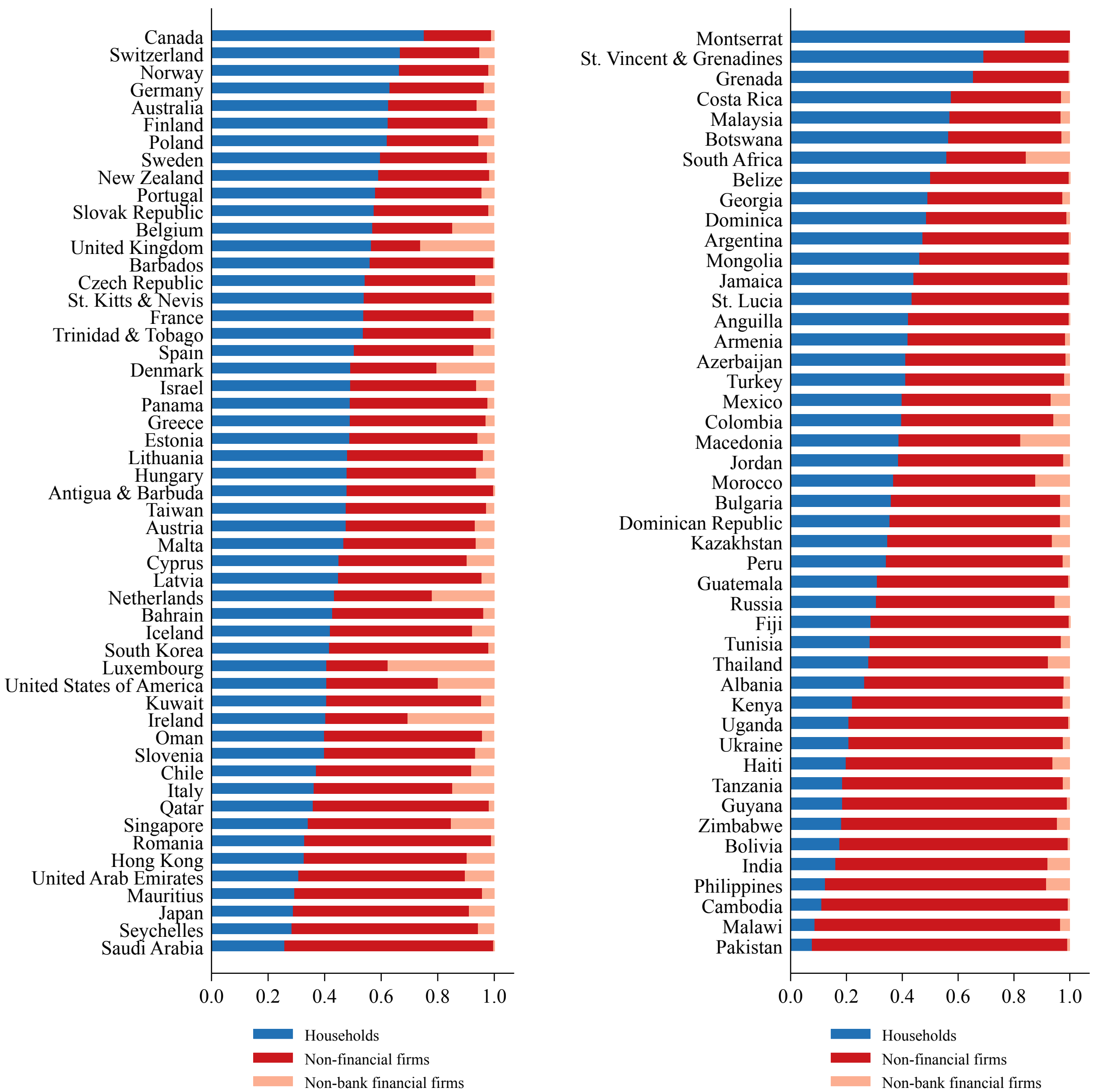
4 Corporate Debt and Financial Crises

This section examines the relation between changes in household and corporate debt around the onset of 84 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.

4.1 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? To answer these questions, we first discuss individual cases of crises and then turn to a more systematic investigation.

Figure I: Share of Firm Credit in Total Outstanding Credit

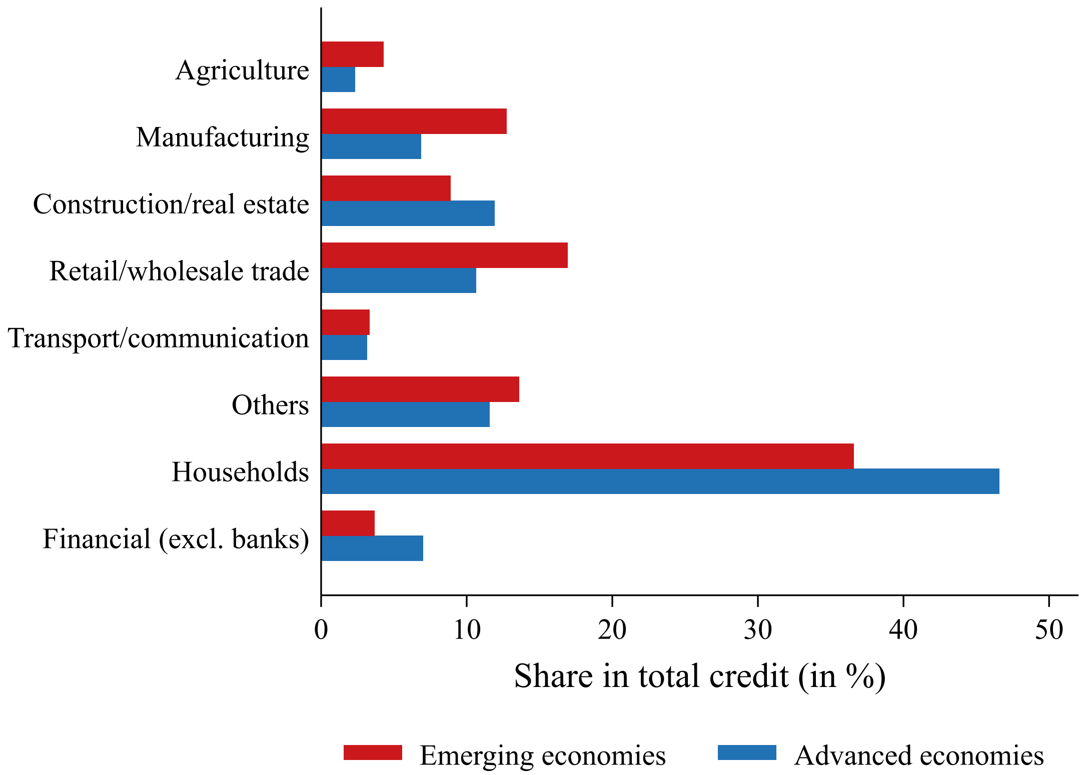


(a) Advanced Economies **(b) Emerging Economies**

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, 2024).

Figure III plots the three-year change in credit/GDP in the run-up to prominent crisis episodes. Different from previous work, our data allows us to decompose the credit expansion into its sectoral components. By definition, the change in credit is the sum of firm and household credit. These

Figure II: Credit Composition in Advanced and Emerging Economies

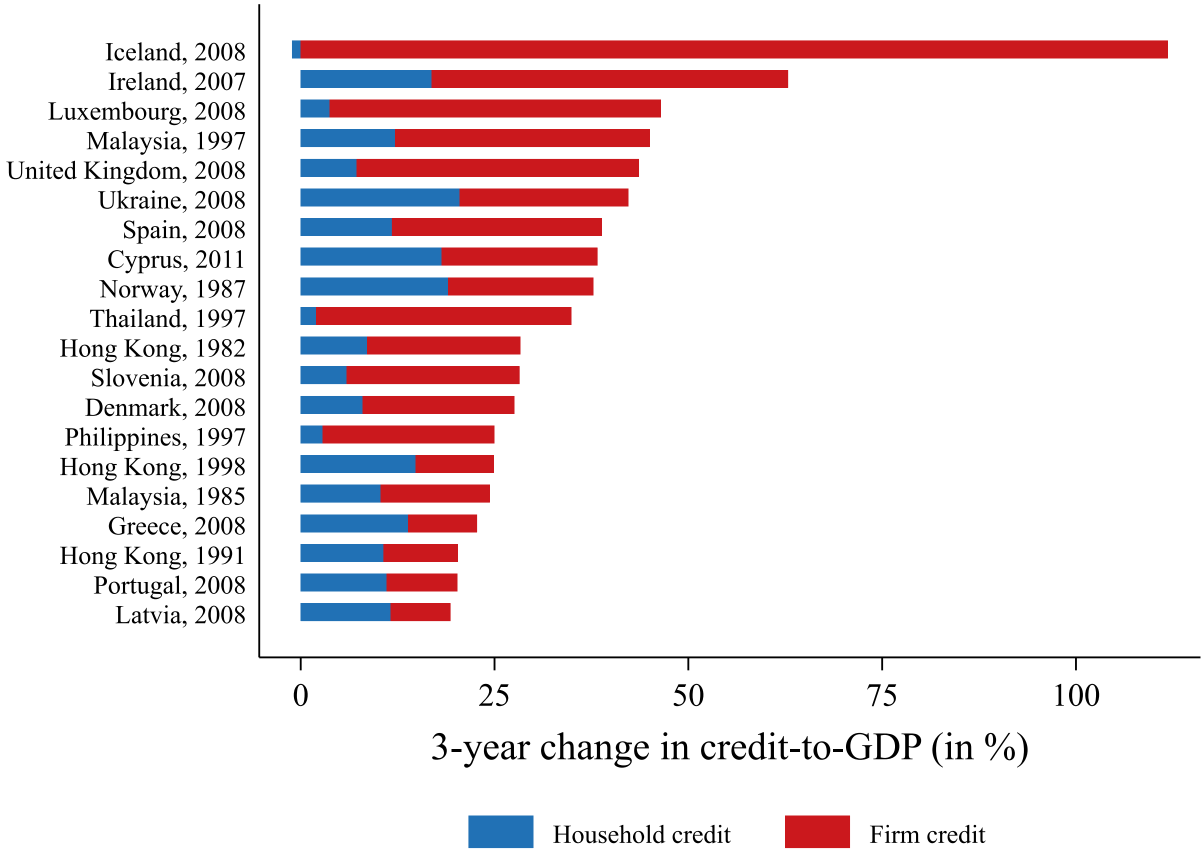


Notes: This figure plots data on the composition of total credit to the private sector as of 2014 (the last year in the sample), by country group. The underlying data covers 89 countries. Data source: Global Credit Project (Müller and Verner, 2024).

case studies reveal that corporate debt played a critical and perhaps underappreciated role in the credit expansion preceding major financial crises. The largest pre-crisis credit booms in the post-war historical record are overwhelmingly corporate, not household, events. In seventeen of the twenty largest episodes, firm credit accounts for more than half of the three-year run-up in credit-to-GDP. And in several cases — Iceland 2008, Luxembourg 2008, Malaysia 1997, Thailand 1997, Hong Kong 1982, and the Philippines 1997 — it accounts for essentially all of it. Iceland 2008 is the most extreme case in the sample, with a three-year expansion in firm credit exceeding 100 percent of GDP and almost no contribution from households, reflecting the well-documented wholesale-funded expansion of Icelandic banks' lending to domestic and cross-border corporates and non-bank financial entities.

The importance of corporate debt in the run-up to financial crises is visible across both advanced-economy and emerging-market episodes, and it spans four decades from the early 1980s through the

Figure III: The Role of Firm Debt in The Twenty Largest Pre-Crisis Credit Expansions



Notes: This figure decomposes the contribution of corporate and household debt to the twenty largest credit expansions preceding financial crises. We measure credit expansions as the three-year change in the ratio of credit to GDP, where by definition the sum of the sectors is equal to total credit. We identify the first year of a crisis based on the chronologies in Baron et al. (2020) and Laeven and Valencia (2020).

Eurozone crises of 2008–2011. While household debt expands markedly before crises, Figure III suggests that the modal pre-crisis credit boom is predominantly a corporate credit boom. Even episodes where household credit saw a large expansion — such as Ireland 2007, the UK 2008, Ukraine 2008, Norway 1987, Greece 2008, or Latvia 2008 — are typically booms in *both* household and corporate credit, rather than concentrated household-centered events.

Figure IV provides event study evidence that investigates the dynamics of average changes in sectoral credit relative to GDP around crises. Figure IVa begins with a sample of 84 financial crises for which we have data on corporate and household debt. The credit expansion that precedes financial crises is mainly explained by firm credit growth, 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 accounted for by firm credit. 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 IVb 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.

Figure V replicates these event studies separately for advanced and emerging economies. We can distinguish between firm and household credit for 50 advanced economy crises and 34 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.

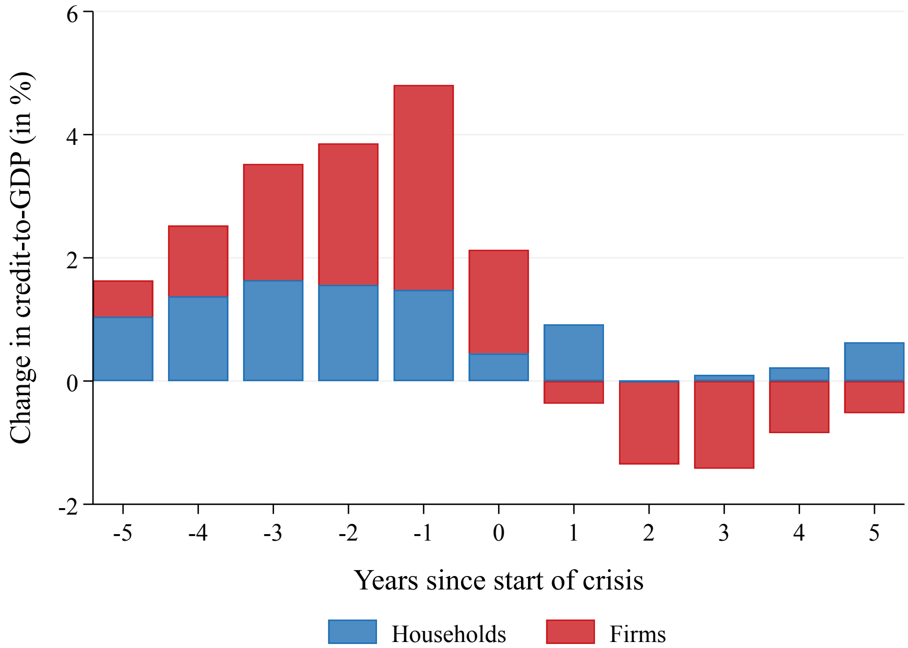
Taking stock of this new granular evidence, our interpretation is that corporate debt explains most of the credit growth before financial crises. The next sections examine whether these sectoral differences also matter for the conditional probability of a crisis.

4.2 Which Credit Booms End Badly?

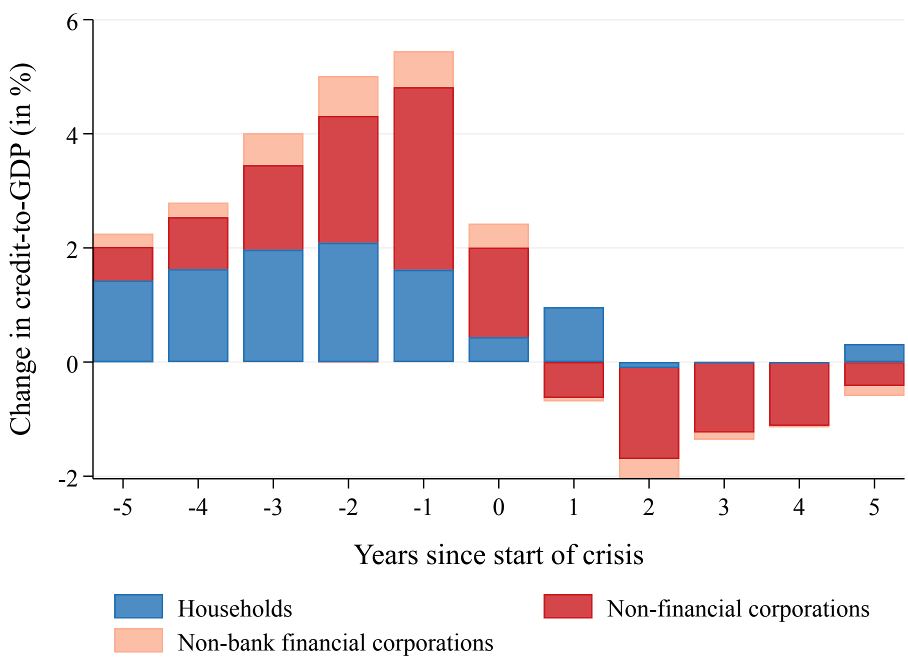
Table II presents statistics on the frequency and severity of systemic banking crises as a function of the type of credit boom that precedes them. We measure credit booms as periods in which the three-year change in sectoral credit to GDP is equal to or above a country's 80$^{\text{th}}$ percentile. We restrict the sample

Figure IV: Decomposing Credit Growth Around Financial Crises

(a) Firm vs. household debt

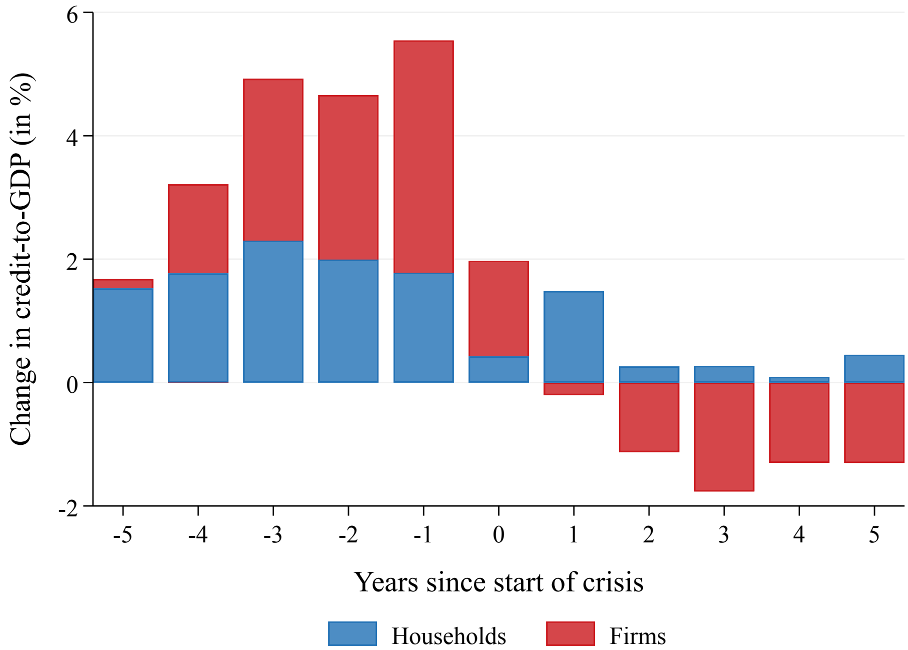


(b) Non-financial vs. financial firm debt

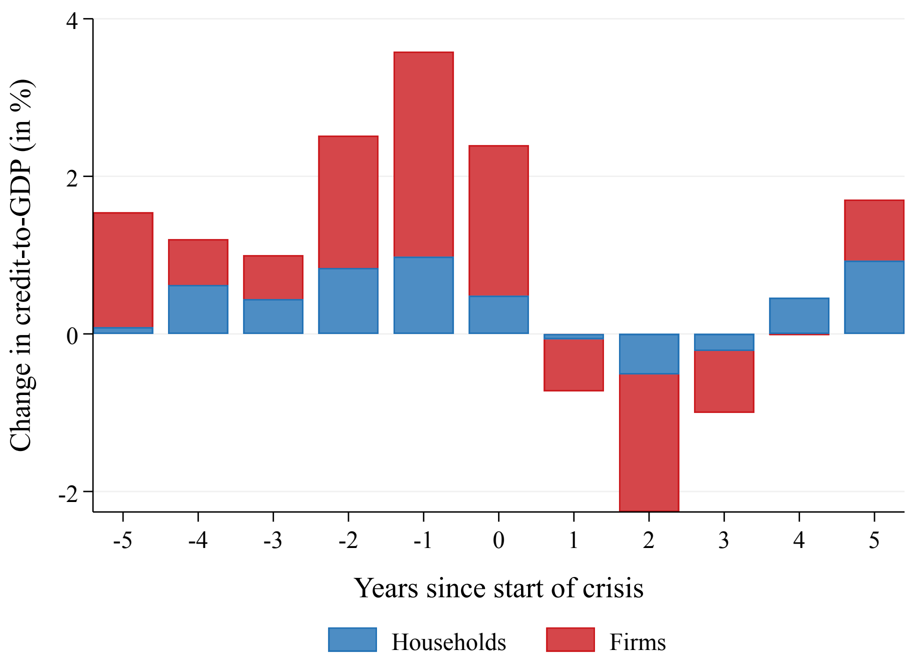


Notes: These figures decompose changes in total credit-to-GDP around the onset of systemic financial crises, where we identify the first year of a crisis based on the chronologies in Baron et al. (2020) and Laeven and Valencia (2020). Panel (a) includes 84 crises and panel (b) 62 crises. We plot the 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 V: 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 II: 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	84	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. Credit booms are defined as observations where the three-year change in sectoral credit-to-GDP is equal or above the 80th percentile value for a given country. 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. *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).

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 84 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 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.

4.3 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:

$$\text{Crisis}_{i,t\to t+h} = \alpha_i^h + \sum_{j\in J} \beta_j^h \Delta_3 \left(\frac{\text{Credit}^j}{\text{GDP}}\right)_{i,t} + \varepsilon_{i,t+h}, \tag{2}$$

where $\text{Crisis}_{i,t\to t+h}$ equals 1 if country i experiences the onset of a systemic financial crisis at any point during the horizon from t to $t+h$, and 0 otherwise. Crises are defined based on the data in Baron et al. (2020) or Laeven and Valencia (2020), but we consider other definitions for robustness. The coefficient α_i^h captures country fixed effects, and $\varepsilon_{i,t+h}$ is the error term. 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 a linear probability model using OLS with Driscoll-Kraay standard errors based on $ceil(1.5\times h)$ lags; we consider logit models for robustness later on.

We are interested in testing the predictive ability of different types of credit for crises. To implement these tests, $\sum_{j\in J}\Delta_3\left(\frac{\text{Credit}^j}{\text{GDP}}\right)_{i,t}$ 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, defined as $\frac{Credit^j_{i,t}}{GDP_{i,t}} - \frac{Credit^j_{i,t-3}}{GDP_{i,t-3}}$. To make the magnitudes for different sectoral credit variables comparable, we standardize each credit growth measure to have zero mean and unit standard deviation. The coefficients β_j^h thus give the

Table III: 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
# Countries	156	156	156	156	156
First year	1945	1945	1945	1945	1945
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
# Countries	114	114	114	114	114
First year	1945	1945	1945	1945	1945
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 (2) 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.

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 III 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 an expanded dataset that covers all observations for which data on total credit is available, including instances without a breakdown between household and corporate credit. 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 (2) for $j \in \{HH, FIRM\}$ and report the coefficients β^h_{HH} and β^h_{FIRM} 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 4.1. 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 IV 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, 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 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

Table IV: 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
# Countries	70	70	70	70	70
First year	1949	1949	1949	1949	1949
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 (2) 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.

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

Table V provides evidence that differentiates between advanced and emerging economies. We rerun our baseline estimation of Panel B in Table III, 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

Table V: 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
# Countries	47	47	47	47	47
First year	1945	1945	1945	1945	1945
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
# Countries	67	67	67	67	67
First year	1950	1950	1950	1950	1950
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 (2) 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.

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 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.

The fact that credit to non-bank financial institutions has strong predictive power in explaining systemic banking crises raises an important question: What do non-bank financial institutions do with the money they borrow? If non-bank financial institutions 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.[12] 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.

[12] 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.

4.4 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):

$$\Delta_3 y_{i,t+k} = \alpha_i + \beta_{FIRM}\Delta_3\text{Credit}^{FIRM}/\text{GDP}_{i,t-1} + \beta_{HH}\Delta_3\text{Credit}^{HH}/\text{GDP}_{i,t-1} + \varepsilon_{i,t}, \tag{3}$$

where the dependent variable $\Delta_3 y_{i,t+k} = y_{i,t+k} - y_{i,t+k-4}$ is the three-year change in real GDP per capita. The predictors $\Delta_3\text{Credit}^{FIRM}/\text{GDP}_{i,t-1}$ 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 $t-1$. 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 VI 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 3.

Panel B of Table VI 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 for predicting 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, and the estimated coefficients are statistically significant at the 1% level.

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 corporate debt matters much more for putting growth at risk. As such, corporate debt 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.

5 The Role of Heterogeneous Firm Borrowing Constraints

The results in the previous section suggest that growth in corporate debt is closely linked to future financial crises and GDP crash risk. In this section, we build on our conceptual framework to test whether these results can partly be explained by collateral constraints or other types of heterogeneous financing constraints, and we also investigate the role of firm defaults.

Table VI: Credit Expansion and GDP Crash Risk

	Dependent variable: $\Delta_3 y_{i+k}, k = -1, \ldots, 5$						
	(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	-0.015	-0.111	-0.230**	-0.307**	-0.377**	-0.361**	-0.298**
	(0.078)	(0.078)	(0.085)	(0.076)	(0.084)	(0.089)	(0.098)
Δ_3FIRM/GDP	0.160**	0.043	-0.013	-0.012	0.016	0.065	0.088
	(0.050)	(0.061)	(0.054)	(0.049)	(0.047)	(0.049)	(0.056)
Panel B: Quantile regression (50th percentile)							
Δ_3HH/GDP	-0.018	-0.117	-0.263**	-0.390**	-0.468**	-0.457**	-0.398**
	(0.081)	(0.078)	(0.067)	(0.044)	(0.081)	(0.084)	(0.077)
Δ_3FIRM/GDP	0.160**	0.045	-0.053	-0.074+	-0.037	0.008	0.035
	(0.056)	(0.048)	(0.042)	(0.040)	(0.044)	(0.044)	(0.043)
Panel C: Quantile regression (20th percentile)							
Δ_3HH/GDP	0.136+	0.003	-0.148+	-0.272*	-0.372**	-0.407**	-0.366**
	(0.080)	(0.073)	(0.086)	(0.115)	(0.092)	(0.095)	(0.087)
Δ_3FIRM/GDP	0.164**	0.004	-0.121**	-0.138**	-0.080*	-0.018	0.008
	(0.049)	(0.047)	(0.033)	(0.031)	(0.036)	(0.054)	(0.034)
Panel D: Panel quantile regression (10th percentile)							
Δ_3HH/GDP	0.207*	0.060	-0.094	-0.214*	-0.326**	-0.381**	-0.350**
	(0.101)	(0.079)	(0.093)	(0.100)	(0.112)	(0.082)	(0.091)
Δ_3FIRM/GDP	0.167*	-0.016	-0.153**	-0.170**	-0.101*	-0.032	-0.006
	(0.069)	(0.060)	(0.057)	(0.043)	(0.049)	(0.057)	(0.045)
Panel E: Panel quantile regression (5th percentile)							
Δ_3HH/GDP	0.280*	0.114	-0.049	-0.159	-0.284*	-0.361**	-0.337**
	(0.142)	(0.105)	(0.103)	(0.104)	(0.127)	(0.128)	(0.085)
Δ_3FIRM/GDP	0.169**	-0.034	-0.180**	-0.200**	-0.119*	-0.043	-0.017
	(0.057)	(0.059)	(0.060)	(0.048)	(0.059)	(0.052)	(0.045)
Observations	3,137	3,137	3,137	3,137	3,137	3,137	3,137

Notes: This table plots the coefficient estimates β_{FIRM} and β_{HH} from estimating equation 3 for $k = -1, \ldots, 5$. 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.

Table VII: 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.6 for details on sources and variable construction.

5.1 Collateral Constraints

Models with firm collateral constraints, going back to Kiyotaki and Moore (1997), propose a key role for the valuation of physical collateral such as land in business cycle fluctuations. While the link between real estate collateral values and firm behavior has been widely studied using micro data ([e.g., Gan, 2007; Chaney et al., 2012; Bahaj et al., 2020), we are interested in the relation of an expansion in real estate-backed firm debt with *macroeconomic* outcomes.

To develop an empirical test, we exploit heterogeneity in how much different industries tend to rely on real estate as collateral. Table VII plots the share of debt backed by real estate collateral across sectors for several countries, which suggests significant variation. If we rank sectors by their reliance on real estate as collateral, however, 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 VIII shows the results of a predictive regression 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 as "other" sectors. We find that growth of corporate debt in sectors with a high reliance on real estate collateral is particularly 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.

Since we find an overall lower reliance on real estate collateral in the Federal Reserve's Y-14Q data, we perform the same exercise using a sector ranking based U.S. data. The results are shown in Table A.3; they are similar. This is not entirely surprising as the top three sectors most reliant on real estate collateral are similar.

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.

Our findings are 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. 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. Given that real estate sectors tend to have low levels and growth rates of productivity (e.g., Goolsbee and Syverson, 2023), it is also related to the finding in Gorton and Ordoñez (2014) that "bad" credit booms are those that coincide with a slowdown in productivity growth.

In sum, our findings suggest that collateral constraints link firm credit to boom-bust cycles. As such, they provide reduced-form evidence for models such as Liu et al. (2013), in which fluctuations in collateral values drive business cycles by loosening or tightening firm borrowing constraints. While this evidence provides prima facie evidence for a role of firm debt, collateral constraints are also a feature of many models with household borrowing constraints, such as Iacoviello (2005). The next sections thus describe several additional pieces of evidence on heterogeneous firm borrowing constraints that are, in sum, not easily explained by models that feature household borrowing constraints alone.

5.2 Constraints Based on Cash Flows or Net Worth

While collateral constraints have been a popular way of modeling firm borrowing frictions, the literature following Townsend (1979), Bernanke and Gertler (1989), Hart and Moore (1994), and Holmstrom and

Table VIII: **Firm Borrowing Constraints and Crises**

	Dependent variable: Crisis within three years						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ_3NFC, real estate-backed/GDP	0.037**						
	(0.012)						
Δ_3NFC, other/GDP	-0.013						
	(0.010)						
Δ_3FIN/GDP	0.026*						
	(0.011)						
Δ_3HH/GDP	0.052*		0.013**		0.014**		0.015*
	(0.021)		(0.004)		(0.005)		(0.006)
Δ_3Bond issuance/GDP (BIS)		0.052*	0.036*				
		(0.022)	(0.016)				
Δ_3Bond issuance/GDP (SDC)				0.042**	0.028**		
				(0.012)	(0.009)		
Δ_3Loan issuance/GDP (Dealscan)						0.045**	0.048**
						(0.012)	(0.013)
Observations	1,246	1,814	1,504	1,409	1,269	1,689	1,325
# Crises	38	68	55	63	56	43	41
# Countries	70	88	77	72	66	123	96
First year	1949	1965	1965	1966	1966	1993	1993
AUC	0.72	0.66	0.68	0.61	0.67	0.75	0.76

Notes: This table plots the coefficient estimates β_j^h for $h = 3$ from estimating Equation (2) using OLS. The dependent variable is a dummy for the onset of a systemic financial crisis within three years based on data from Baron et al. (2020) and Laeven and Valencia (2020). In column 1, 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 VII. Δ_3NFC, real estate-backed/GDP refers to firm lending to construction and real estate services, agriculture, retail and wholesale trade (incl. 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. Columns 2-3 consider the three-year change in outstanding international corporate bond debt-to-GDP, based on data from the Bank for International Settlements's Debt Securities statistics. Columns 4-5 consider the three-year change in bond issuance-to-GDP, constructed from primary issuance data on unsecured corporate bonds from SDC Platinum that exclude the construction and real estate sector. In columns 6-7, the predictor of interest is the three-year change in newly issued syndicated loans/GDP, based on Dealscan data, where we exclude loans secured on real estate of any type as well as borrowers in the construction and real estate 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.

Tirole (1997) has instead tied firms' borrowing capacity to their cash flows or net worth, rather than the value of their physical assets. A growing empirical literature lends support to the view that such firm borrowing constraints are important (see, e.g., Lian and Ma, 2020; Caglio et al., 2021; Drechsel, 2023; Hartman-Glaser et al., 2022).

Similar to collateral constraints, firm borrowing backed by firms' cash flows or net worth could also give rise to a boom-bust cycle. To test this hypothesis, we turn to issuance-level data on bonds and syndicated loans. Since almost all bonds are unsecured, they are by definition not backed by physical assets, but rather by firms' ability to service their debt. Syndicated loans are almost always either unsecured or secured on all of the firm's assets, as emphasized in Lian and Ma (2020); because we exclude loans that are (partly) backed by real estate collateral, the remaining syndicated loans should also serve as a good proxy for firm debt backed by cash flows or firm net worth. We also explicitly exclude borrowers in the construction and real estate sectors to further abstract from collateral constraints.

Table VIII reports several predictive regressions relating the onset of a financial crisis to our measures of debt issuance backed by cash flows or net worth in columns 2-7. Since the flow of new debt is highly persistent, we always calculate the three-year change in issuance relative to GDP, mirroring our measures of credit expansions used above. Columns 2-3 begin by looking at changes in outstanding corporate bonds issued in international markets from the BIS. Columns 4-5 are based on issuance-level data from SDC Platinum, which allows us to drop secured bonds and the construction and real estate sector. Similarly, columns 6-7 are based on syndicated loans. We always consider a specification with and without a control for an expansion in household debt, measured by the three-year change in household credit to GDP.

Throughout these exercises, a consistent pattern emerges. Higher growth in firm debt backed by net worth or cash flows is associated with a higher crisis likelihood, whether or not one controls for the magnitude of the household credit expansion. The implied increase in crisis probabilities is also sizable. The results in column 6, for example, suggest that a one standard deviation higher growth in syndicated loan issuance (backed by net worth rather than real estate) is associated with a 4.5 higher likelihood of a financial crisis within three years. Taken together, these findings emphasize that firm debt plays a role in crisis dynamics outside of collateral constraints, as emphasized by models where firm financing constraints are based on cash flows or net worth.

5.3 Dispersion in Firm Debt Growth

Heterogeneous firm models with borrowing constraints suggest that firms react differently to shocks in credit conditions. If firms differ in their distance to borrowing constraints (e.g., Khan and Thomas, 2013; Ottonello and Winberry, 2020), an aggregate loosening of credit conditions relaxes constraints unequally, so that episodes of easy credit are mechanically accompanied by rising dispersion in firm-level debt growth. Empirically, Gopinath et al. (2017) document that the Spanish credit boom in the 2000s coincided with a sharp rise in the dispersion of the marginal revenue product of capital, suggesting a misallocation of capital. In models of heterogeneous debt-type choice, such as Crouzet (2018), aggregate shocks induce cross-sectional substitution across debt instruments, which mechanically raises dispersion in measured debt growth. In both classes of models, elevated dispersion signals that the boom is reallocating credit unevenly across firms in ways associated with deteriorating average borrower quality (Greenwood and Hanson, 2013). Such lopsided booms, in turn, are the ones most likely to end in a wave of defaults, consistent with the "bad booms" view of Gorton and Ordoñez (2019), in which credit expansions accompanied by weak productivity growth are precisely the episodes that precipitate crises.

To test for the empirical relevance of heterogeneous financing constraints, we propose a simple measure picking up dispersion in credit conditions: the standard deviation of debt growth across sectors or firms. If credit grows relatively uniformly, there should be little dispersion. But during "frothy" times of easy credit, credit may flow particularly to certain firms or sectors that are driving the boom, leading to highly lopsided credit growth.

We implement this measure of imbalances in credit growth in three steps. First, we require that a country-year pair has data either on credit from for a set of sectors J or on firm debt for a number of firms I over the last three years. As our baseline measure, we use credit to five non-financial sectors (excluding the residual category) and credit to non-bank financial institutions, so $J = 6$. For robustness, we extend the data from Müller and Verner (2024) and consider a broader set of 18 sectors, so $J = 18$.[13] As an additional exercise, we also consider firm-level data from Compustat and Orbis, where we also

[13] For the measure using 18 sectors, we allow for some of the sectoral credit growth rates to be missing so as not to lose too many observations.

require firms to have at least three years of data, and further require there to be at least 10 firms within a country-year cell. The advantage of using firm-level data is the broader cross-section of firms; the disadvantage is the considerably shorter time series.

In the second step, we compute three-year changes in sectoral credit or firm debt. As in Section 4, we compute the three-year change in sectoral credit-to-GDP; for firms we compute debt issuance over the last three years, defined as the change in debt relative to lagged assets. Third, and finally, we take the standard deviation of these measures of a debt expansion within a given country-year cell. The resulting measures thus capture the dispersion of medium-term fluctuations in corporate debt.[14]

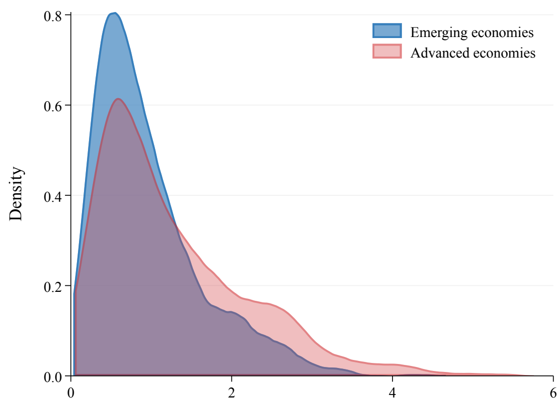
Figure VIa plots the distribution of the dispersion in firm debt growth based on our baseline measure with six sectors, for which we have the broadest coverage, separately for advanced and emerging economies. Interestingly, we see a *higher* dispersion of firm credit in advanced relative to emerging economies. One interpretation is that credit growth in emerging economies is much more uniform while they develop, perhaps because it is inefficiently low due to more binding financing constraints. Advanced economies, on the other hand, are more likely to experience lopsided credit growth, which may reflect unsustainable booms but also more of a reallocation of resources due to lower financing constraints.

Figure VIb plots the same measure of firm credit dispersion based on sectoral data 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 a heterogeneous loosening of borrowing constraints. Although starting from a similar level of dispersion in 1999, there is essentially no trend in the dispersion of firm credit growth in Germany over this period; credit went to different industries uniformly.

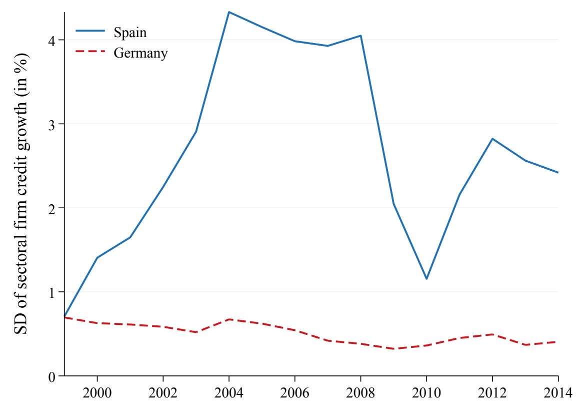
Figure VIc plots the relationship between credit expansions and the dispersion of firm credit growth for the full sample using a binscatter plot. The dispersion increases during credit booms and

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

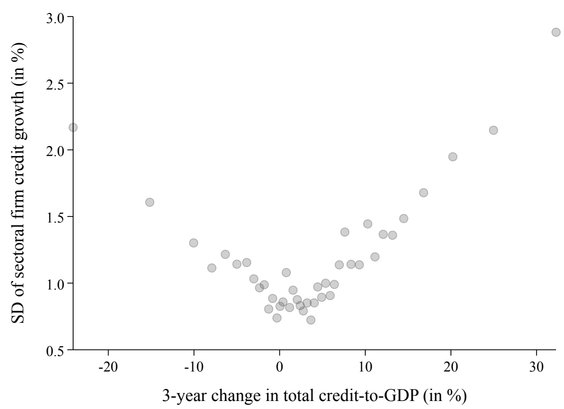
Figure VI: Sectoral Dispersion in Firm Credit Growth



(a) Advanced vs. emerging economies



(b) Spain vs. Germany case study



(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).

credit crunches, resulting in a V-shaped pattern, consistent with heterogeneous loosening and tightening of borrowing constraints. For example, the dispersion of sectoral credit growth was 4.0 in Spain at the height of the credit boom in 2006, dropped during the unwinding in 2007-08, and spiked again during the ensuing credit crunch, standing at 2.8 as of 2012. Booms and busts in credit go hand in hand with imbalances in credit flows to different sectors. Table A.2 in the Online Appendix shows that, on average, the dispersion of credit is strongly procyclical, increasing by 15.1% for every standard deviation increase in the three-year change in credit-to-GDP.

We test whether heterogeneous firm borrowing constraints can also signal periods of impending financial fragility by regressing a dummy for the start of a financial crisis within five years on our measures of dispersion in firm debt growth. Table IX plots the results. We find that imbalances in firm credit growth are a highly statistically significant predictor of financial crises. A one standard deviation increase in the dispersion of firm credit growth based on the six baseline sectors is associated with a 3.0 percentage point higher probability of a crisis within the next three years.

Column 2 adds the three-year change in total credit to GDP as a control variable. As we show in Table A.2 in the Online Appendix, credit expansions are associated with an increase in dispersion. Including total credit growth may therefore be "over-controlling", because we are interested in precisely the kind of imbalances in credit growth that accompany credit expansions. Nevertheless, 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. Importantly, in column 3, we find a similar pattern when we control separately for an expansion in household credit, credit to non-financial firms depending on whether it is backed by real estate collateral, and credit to non-bank financial intermediaries. These findings suggest that a higher dispersion not merely reflects collateral constraints, but a more general lopsidedness in debt growth.

Columns 4-6 confirm this finding by expanding the number of industries to 18, based on newly-collected data that expands the dataset introduced in Müller and Verner (2024). The larger number of industries results in more meaningful dispersion but, importantly, yields qualitatively and quantitatively comparable results. Columns 7-10 use firm-level data from Compustat Global and Orbis to construct measures of the dispersion of debt issuance, where we explicitly exclude the construction and real estate sectors from the calculations to abstract from collateral constraints. These exercises suggest that dispersion in firm debt growth is a statistically significant predictor of financial crises, over and above what would be explained by a credit expansion or household borrowing working through collateral constraints.

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, a straightforward prediction of heterogeneous firm models with borrowing constraints that could also indicate a misallocation of capital, as in Gopinath et al. (2017) or Gilchrist et al. (2013). Since these findings hold even after dropping firms in construction and real estate that are most likely to be affected by shocks to household demand, or explicitly controlling for credit growth in these industries, these patterns suggest an independent role for corporate debt in macroeconomic dynamics.

Table IX: Dispersion in Firm Debt Growth and Future Financial Crises

	Dependent variable: Crisis within the next 5 years									
	6 sectors			18 sectors			Compustat		Orbis	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dispersion of firm debt growth	0.038∗∗	0.023+	0.036∗	0.041∗∗	0.026∗	0.029+	0.033∗	0.028∗	0.008	0.009∗
	(0.012)	(0.013)	(0.014)	(0.012)	(0.012)	(0.015)	(0.015)	(0.014)	(0.005)	(0.004)
Δ_3TOT/GDP		0.005∗∗			0.005∗∗			0.006∗		0.002
		(0.001)			(0.001)			(0.002)		(0.001)
Δ_3HH/GDP			0.016∗∗			0.016∗∗				
			(0.005)			(0.005)				
Δ_3NFC, real estate-backed/GDP			0.003			0.003				
			(0.006)			(0.006)				
Δ_3NFC, other/GDP			-0.004			-0.005				
			(0.004)			(0.003)				
Δ_3FIN/GDP			0.003			0.003				
			(0.010)			(0.011)				
Observations	1,468	1,468	1,246	1,468	1,468	1,246	879	879	1,071	1,071
# Crises	43	43	38	43	43	38	38	38	30	30
# Countries	74	74	70	74	74	70	67	67	110	110
First year	1949	1949	1949	1949	1949	1949	1954	1954	1999	1999
AUC	0.61	0.65	0.68	0.60	0.65	0.68	0.55	0.65	0.56	0.68

Notes: This table plots the coefficient estimates β_j^h for $h = 5$ from estimating Equation (2) 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 dispersion in firm debt growth, calculated as the standard deviation of the three-year change in sectoral credit-to-GDP or firm-level debt issuance, where debt issuance is defined as the change in outstanding debt to lagged assets. Columns 1-3 compute this standard deviation based on sectoral credit data covering 6 sectors, and columns 4-6 for 18 sectors; when using 18 sectors, we allow for some sectoral credit growth rates to be missing. Columns 7-8 use changes in debt issuance based on Compustat data, and columns 9-10 use the equivalent measure based on Orbis data. The measures based on firm-level data exclude firms in the construction and real estate 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.

5.4 Firm Defaults

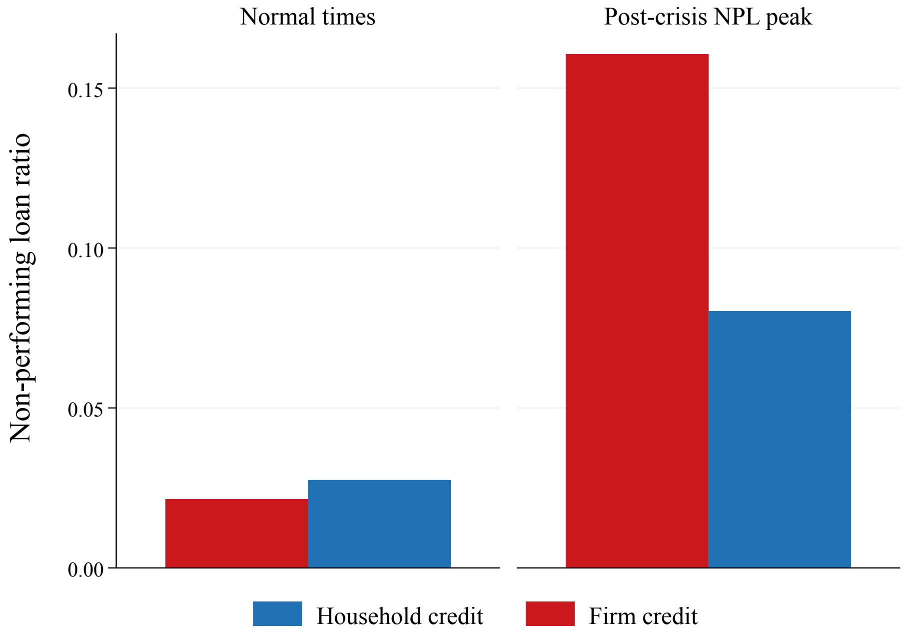
An important factor in the transmission of defaults to the macroeconomy may be that the bankruptcy regimes in most countries allow firms, but not households, to write off debt during default (for a discussion, see, e.g., Jordà et al., 2022). Large-scale firm defaults may thus put pressure on the balance sheet of the banking system and ultimately erode its capitalization, leading 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 (NPLs). Because such data are not readily available, we collect data on NPLs by sector for 24 crisis episodes in 20 countries. These data allow us to calculate two variables to assess 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.

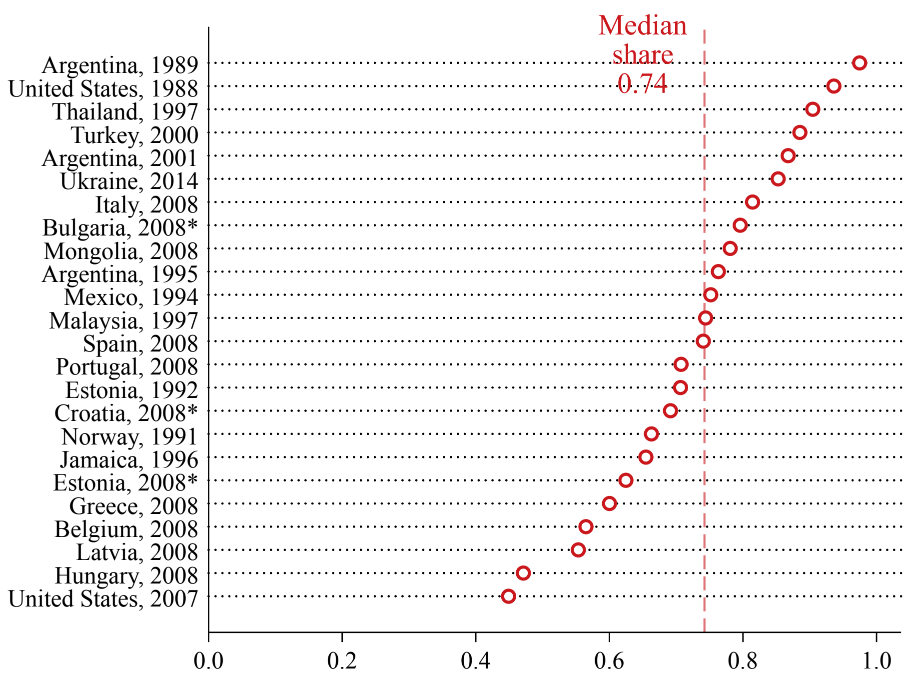
Figure VII provides evidence consistent with the notion that corporate defaults are important for understanding crisis episodes. Figure VIIa plots NPL ratios separately for firms and households, depending on whether a country experiences a financial crisis or not. To account for the lagging nature of 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 8% of household debt becomes nonperforming after crises.

Figure VIIb 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 new facts that we document in this paper: (1) corporate debt accounts for most of the credit growth before crises, and (2) firms are more

Figure VII: 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.7 for sources and details on data definitions.

likely to default than households during crises.

Figure VIIIa 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 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 VIIIb 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 VIIIc 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, where collateral constraints may play a critical role, are particularly dangerous for the health of bank balance sheets because they later translate into higher NPLs.

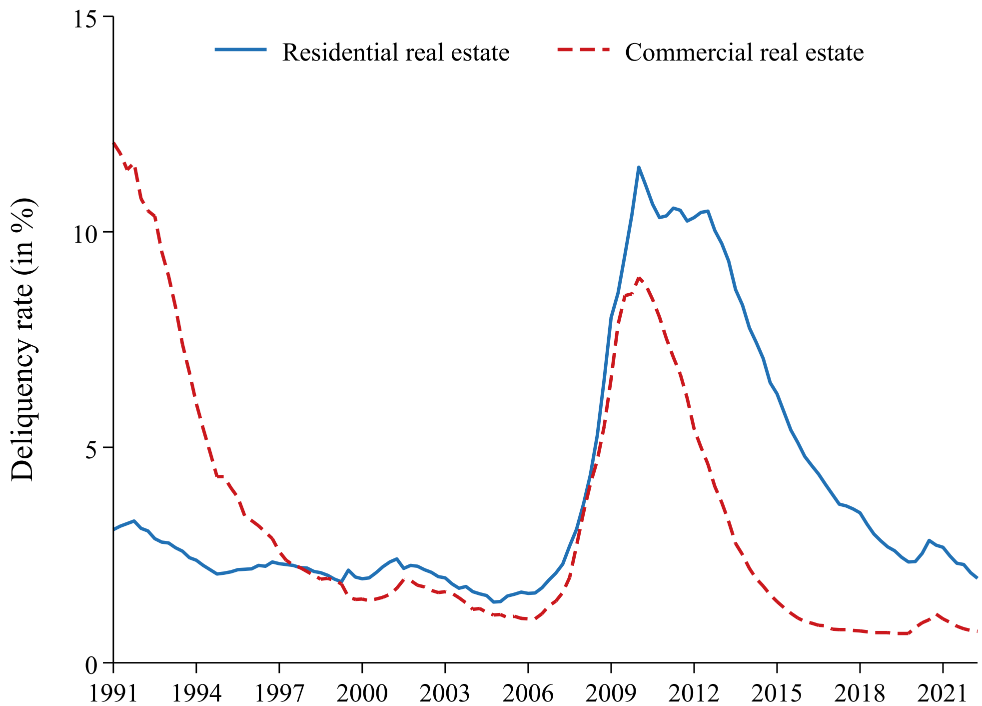
6 Corporate Debt and the Recovery From Crises

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.

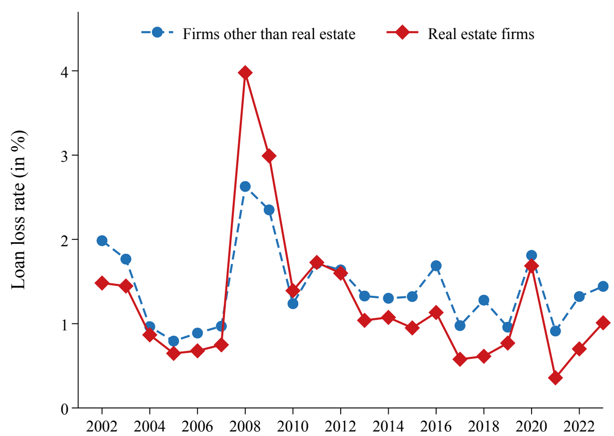
6.1 A Local Projection Approach

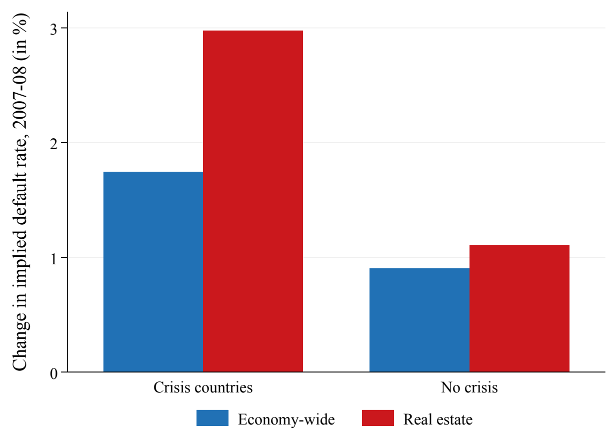
We are interested in the conditional path of an outcome y, principally real GDP, following systemic financial crises. The conditioning variables are measures of sectoral credit growth prior to such crises.

Figure VIII: 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.

As such, we follow a similar specification to that in Jordà et al. (2022):

$$\Delta_h y_{i,t+h} = \alpha_i^h + \delta^h \text{Crisis}_{i,t} + \sum_{j \in J} \beta_j^h \Delta_3 \text{Credit}^j/\text{GDP}_{i,t} + \sum_{j \in J} \gamma_j^h \Delta_3 \text{Credit}^j/\text{GDP}_{i,t} \times \text{Crisis}_{i,t} + \mathbf{X}'_{i,t} + \varepsilon_{i,t}^h, \tag{4}$$

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 $h = 1, \ldots, 5$. 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 (4) 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.[15] 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 (4) as the causal effect of credit allocation on the recovery from crisis-related recessions. As we show in Section 4, the probability of crises itself depends on the type of credit expansion. Rather, we see the estimation of Equation (4) as a useful descriptive tool for understanding the conditional recovery path following such crisis events.

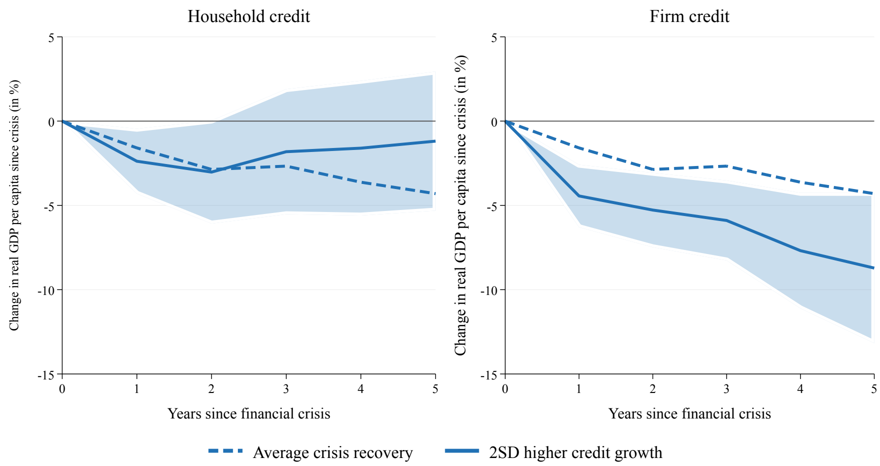
6.2 Credit Allocation and Nonperforming Loans Through the Cycle

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

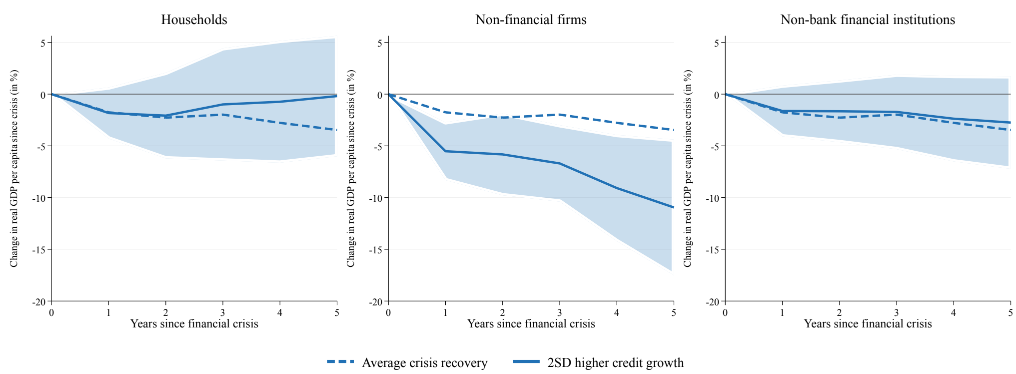
[15] When we look at nonperforming loans as an outcome in Figure X, we use a more parsimonious specification with no lags of the dependent or independent variables because the sample has a relatively short time series.

Figure IX: Credit Allocation and Financial Crisis Recovery

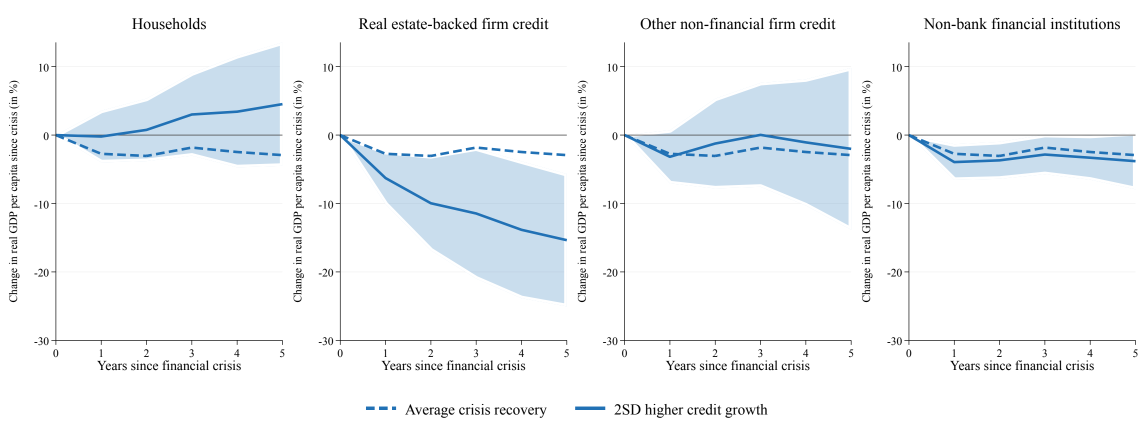
(a) Firm vs. household debt



(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 (4), 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 X: 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 × Δ_3HH/GDP	-0.10	-0.02	0.11	0.26	0.40*
	(0.09)	(0.14)	(0.16)	(0.18)	(0.19)
Crisis × 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 (4) 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.

Rogoff (2009a) show that crises are followed by particularly protracted recessions, but they do not distinguish between different kinds of credit booms.

Figure IX plots the estimates of Equation (4). Table X 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 IXa 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 3.6 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 6.3 what accounts for the apparent difference between these results and the existing literature.

Figure IXb 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 IXc 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.4 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.[16] 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 V, 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

[16]Table A.5 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 5.3 % 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 3.8%.

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

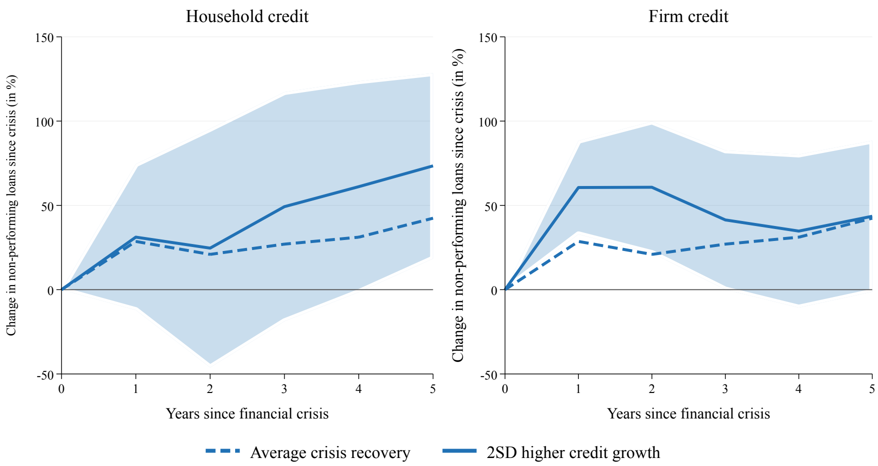
To test more formally the link between firm credit secured by real estate collateral and NPLs, we run local projections as in Equation (4) where the dependent variable is the aggregate NPL ratio of the banking sector (in logs). There is relatively limited data available on NPLs, which largely restricts this analysis to the financial crises of the 2000s, so the results can only be suggestive. With this limitation in mind, Figure X 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.

6.3 Relationship to the Literature

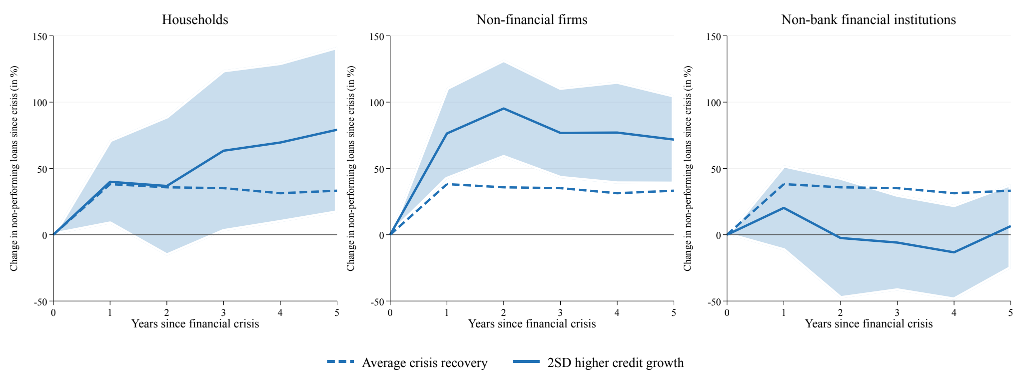
Similar to Jordà et al. (2022), we find that corporate debt predicts a slower recovery, but their analysis suggests that this channel only matters for countries with high bankruptcy frictions where defaults cannot be resolved quickly. In our baseline specification, we find that, for the average country, it is an expansion in (real estate-backed) corporate debt rather than household debt during the boom that predicts worse post-crisis recessions.

Figure X: Credit Allocation and Nonperforming Loans

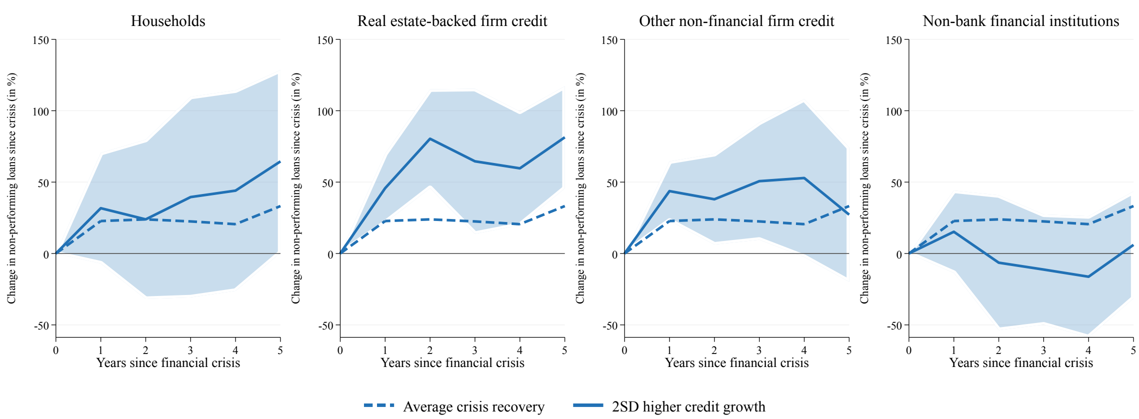
(a) Firm vs. household debt



(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 (4), 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.

To reconcile the results in Jordà et al. (2022) with ours, Figure A.10 replicates our analysis using data from the Jordà-Schularick-Taylor (JST) Macrohistory Database (Jordà et al., 2016a), which covers 18 advanced economies over the period 1870-2020.[17] 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. However, using exactly the same empirical specification applied to our sample of 114 countries, including many emerging economies, we find that both household and corporate debt growth are associated with a deeper recession, and that corporate debt is more important in the long run (Figure A.10b). Figure A.10c then replicates the analysis using the three-year change in credit to GDP in the JST data. Consistent with our results in Figure IX, we now find a deeper post-crisis recession following expansions in firm but not household debt. The same is true in our data (Figure A.10d).

These results show that we can replicate the findings in JST on the importance of household credit using their sample of countries and their definition of credit booms. However, the role of corporate credit gains in importance when using our dataset with a larger number of countries. Moreover, the results on household credit are sensitive to the definition of credit booms, and in particular to the length of the pre-crisis credit expansion employed.

7 Conclusion

Is corporate debt central to macroeconomic dynamics? Despite a large body of theoretical work emphasizing its importance, the focus on household debt since the Global Financial Crisis has led some to question the role of corporate credit in shaping economic cycles. Using a large cross-country panel dataset, we show that while household credit is indeed important for understanding business cycles, corporate credit is strongly associated with systemic financial crises, elevated default risk, reduced investment, greater GDP crash risk, and sluggish macroeconomic recoveries.

[17] 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 (4) 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).

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 U.S. in 2007 stands out as an outlier in the historical record: in the vast majority of financial crises, corporate defaults are the dominant source of loan losses linked to 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 associated lower economic growth even in the absence of a financial crisis, consistent with an "indebted demand" channel. Corporate debt, in turn, matters particularly for systemic financial crises through its link with large-scale corporate defaults and lower investment, being then the key culprit behind sluggish recoveries via the investment channel. Our evidence linking household debt robustly to lower average GDP growth and corporate debt to higher crash risk in GDP with lower investment is supportive of this interpretation.

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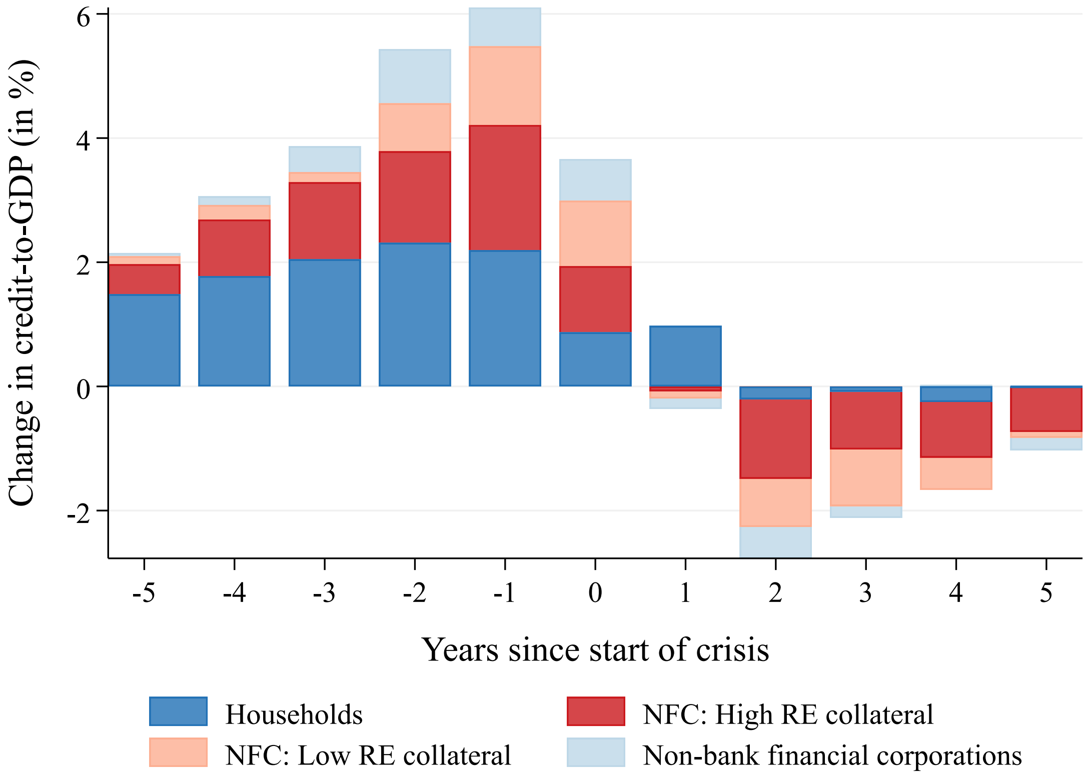
Online Appendix

Corporate Debt, Boom-Bust Cycles, and Financial Crises

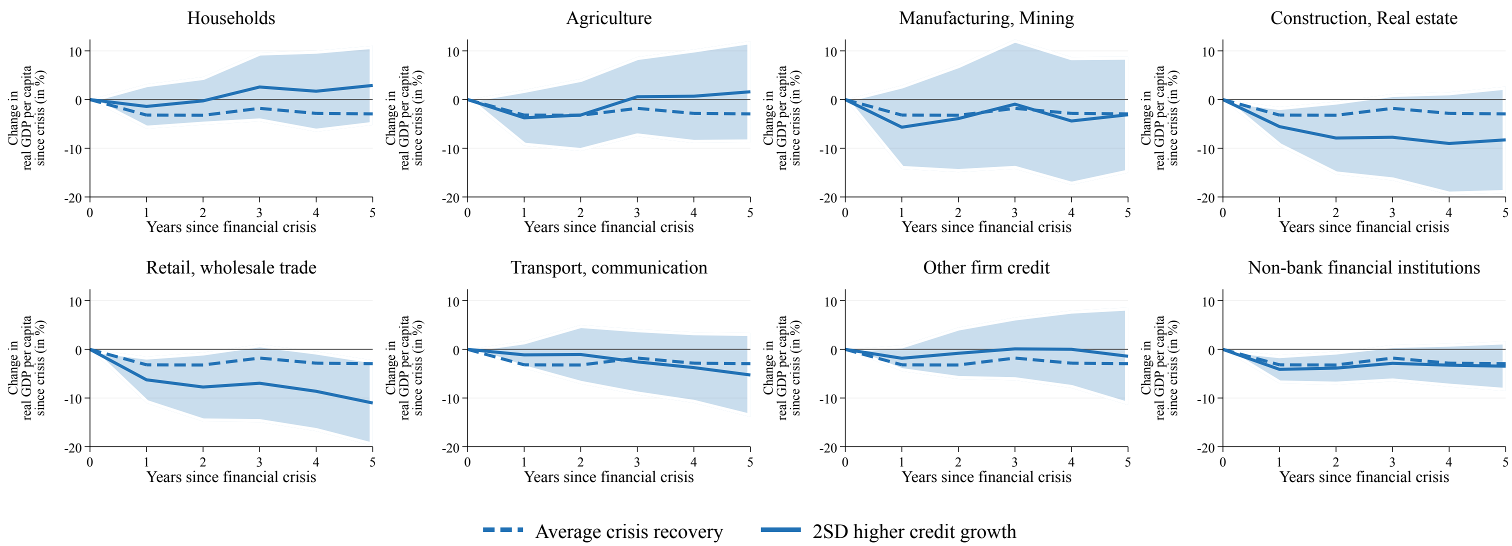
This appendix contains additional figures and tables that support the analysis in the paper *Corporate Debt, Boom-Bust Cycles, and Financial Crises* by Victoria Ivashina, Şebnem Kalemli-Özcan, Luc Laeven, and Karsten Müller.

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 VII. "High RE collateral" refers to firm lending to construction and real estate services, agriculture, retail and wholesale trade (incl. 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.

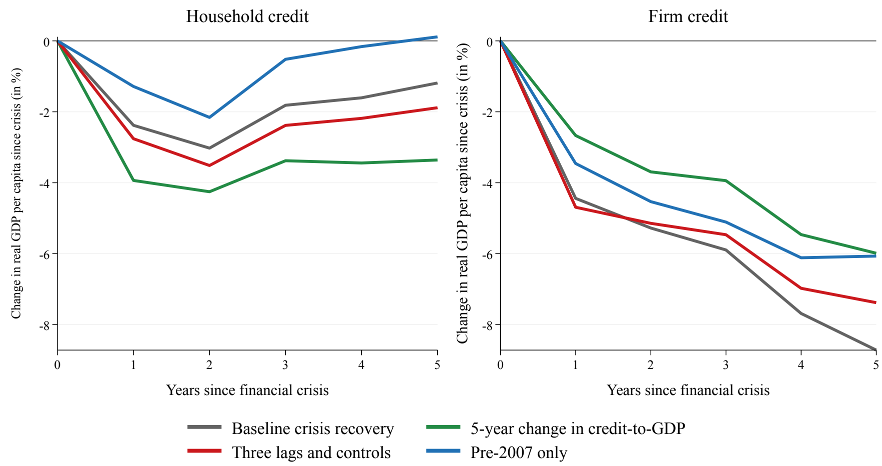
Figure A.2: Industry Credit Expansions and Crisis Recovery



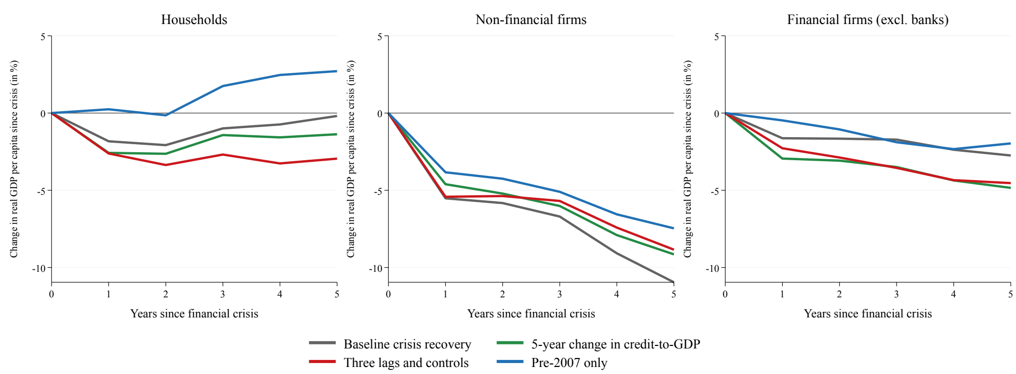
Notes: This figure plots the estimates of δ^h and $\delta^h + \gamma_j^h$ from Equation (4), showing how the path of log real GDP per capita five years after a financial crisis depends on the type of credit boom preceding it. We show the average recovery path estimated by δ^h and the predicted recovery 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

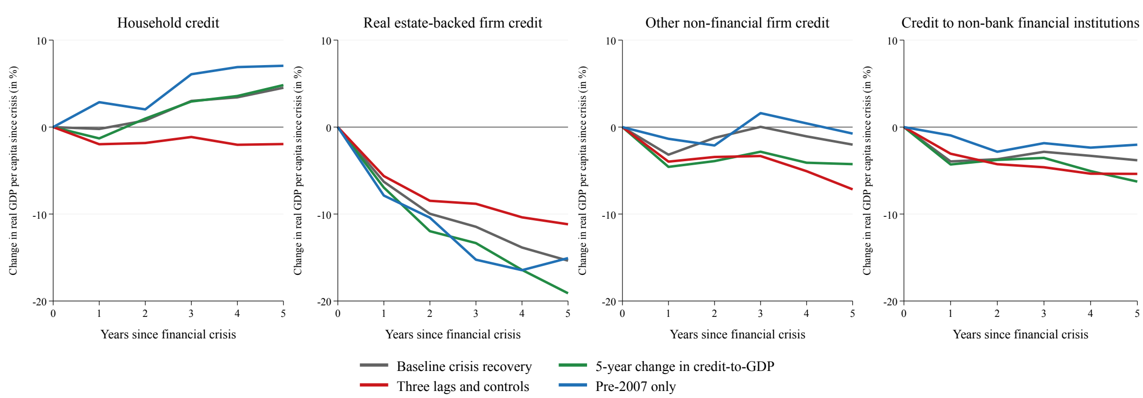
(a) Firm vs. household debt



(b) Non-financial vs. financial firm debt

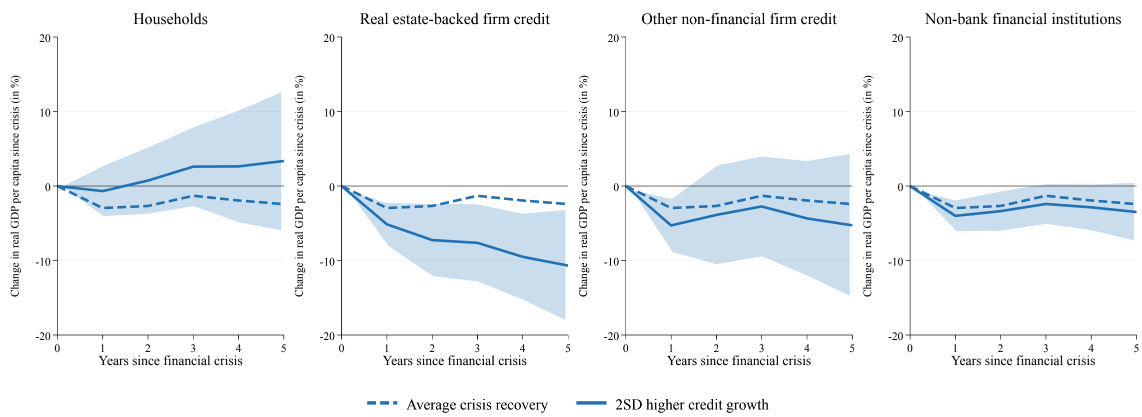


(c) The role of real estate collateral



Notes: This figure plots the estimates of δ^h and $\delta^h + \gamma_j^h$ from Equation (4), 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 IX 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.

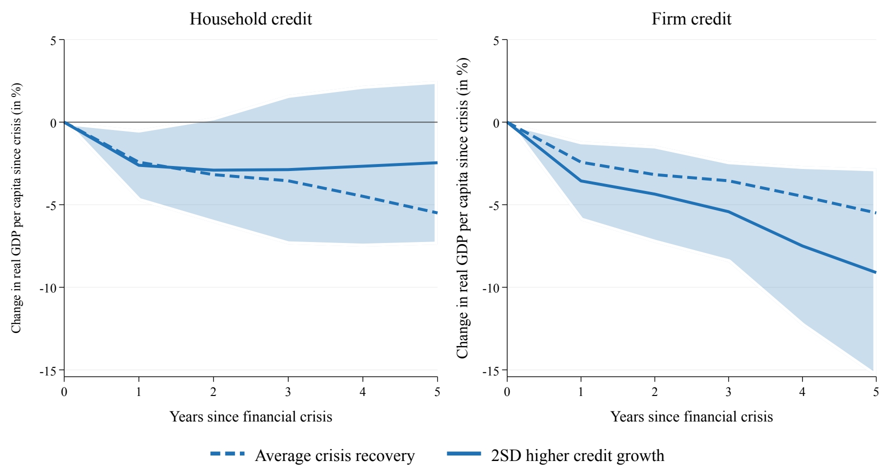
Figure A.4: Real Estate-Backed Firm Credit and Crisis Recovery (US Y-14Q Classification)



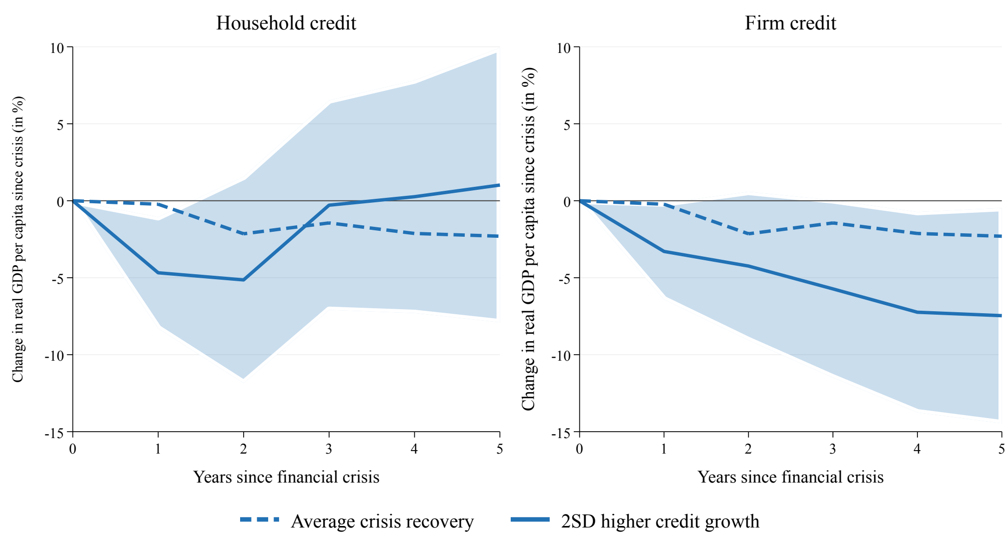
Notes: This figure plots the estimates of δ^h and $\delta^h + \gamma_j^h$ from Equation (4), showing how the path of log real GDP per capita five years after a financial crisis depends on the type of credit boom preceding it. We show the average recovery path estimated by δ^h and the predicted recovery 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 VII, 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



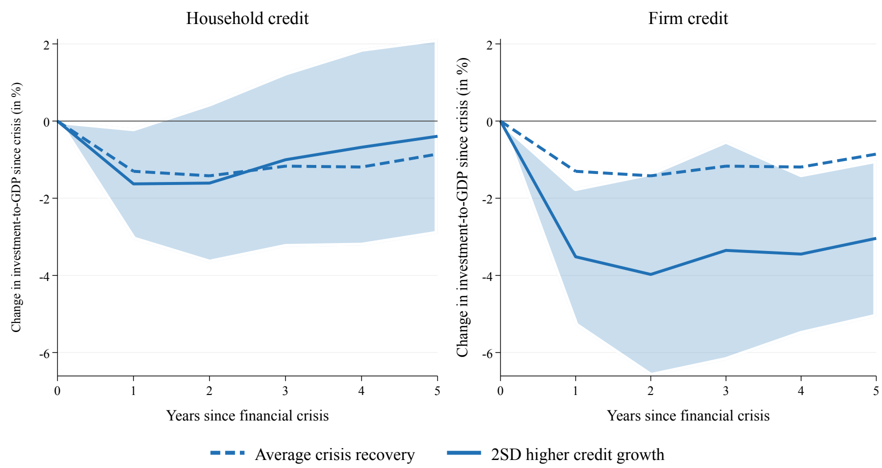
(b) Emerging Economies



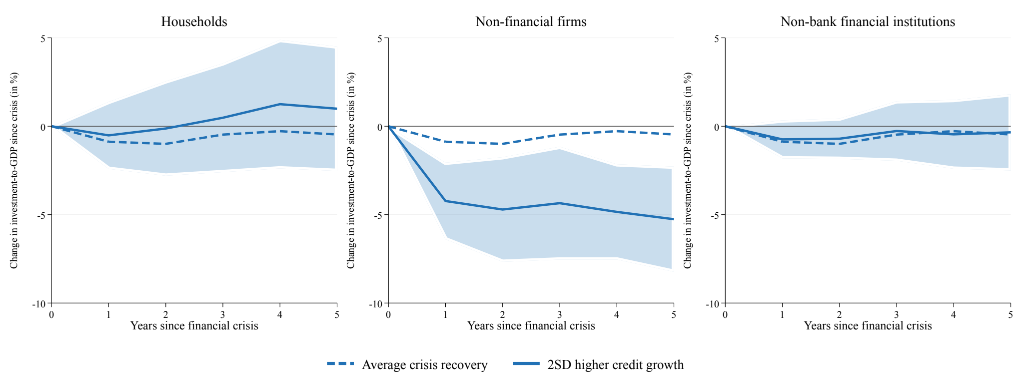
Notes: This figure plots the estimates of δ^h and $\delta^h + \gamma_j^h$ from Equation (4), showing how the path of log real GDP per capita five years after a financial crisis depends on the type of credit boom preceding it. We show the average recovery path estimated by δ^h and the predicted recovery 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

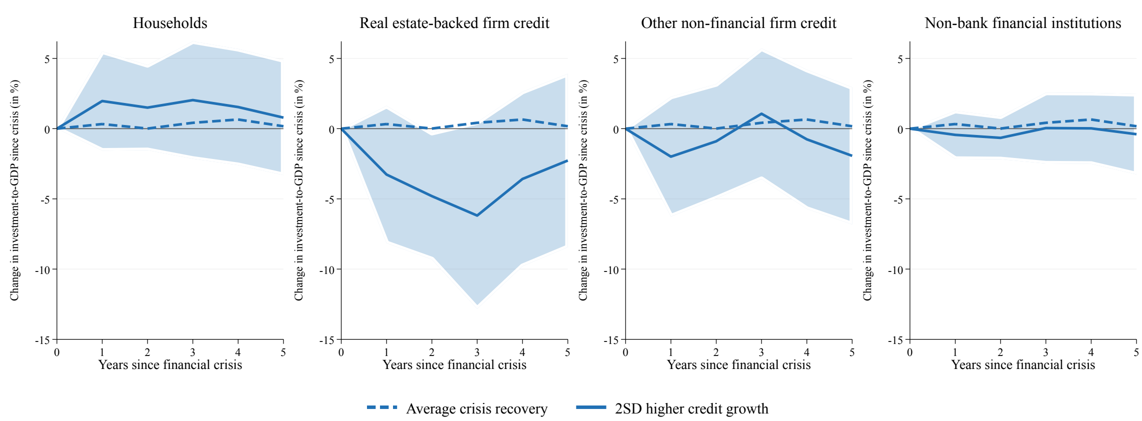
(a) Firm vs. household debt



(b) Non-financial vs. financial firm debt



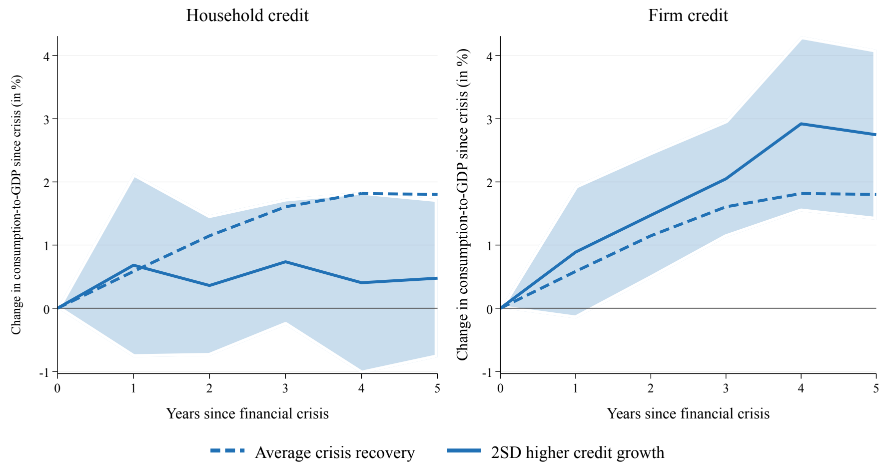
(c) The role of real estate collateral



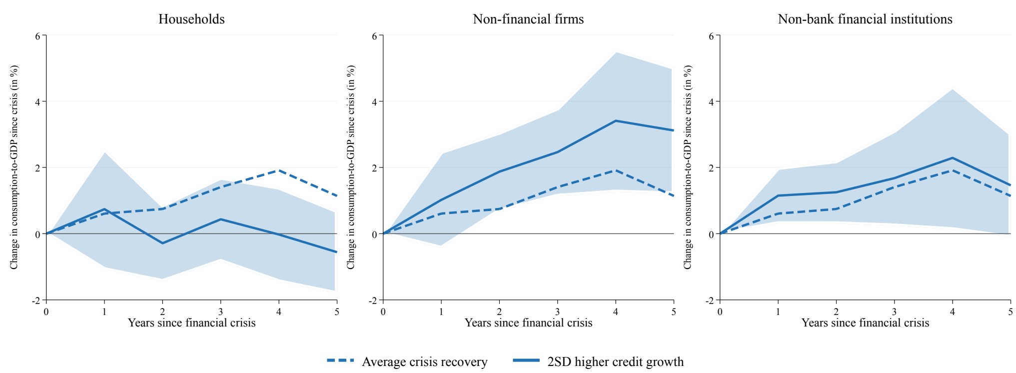
Notes: This figure plots the estimates of δ^h and $\delta^h + \gamma_j^h$ from Equation (4), showing how the path of investment-to-GDP five years after a financial crisis depends on the type of credit boom preceding it. We show the average recovery path estimated by δ^h and the predicted recovery for 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

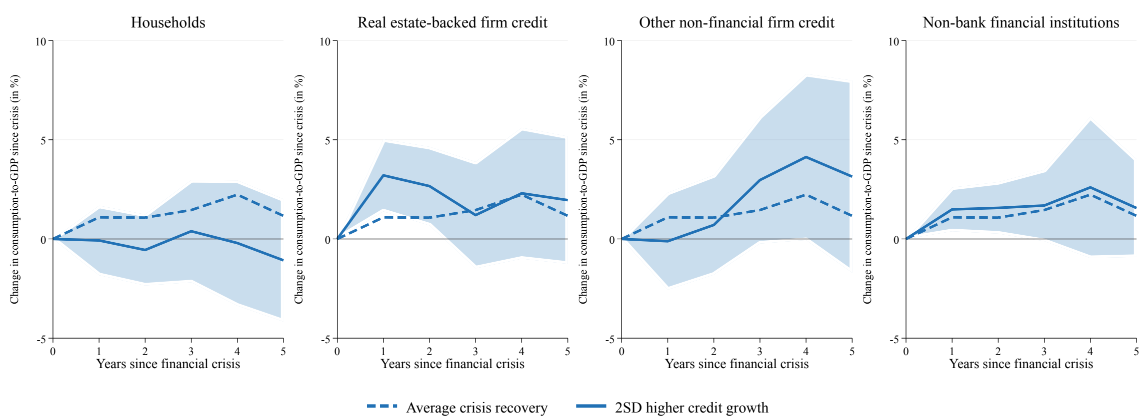
(a) Firm vs. household debt



(b) Non-financial vs. financial firm debt

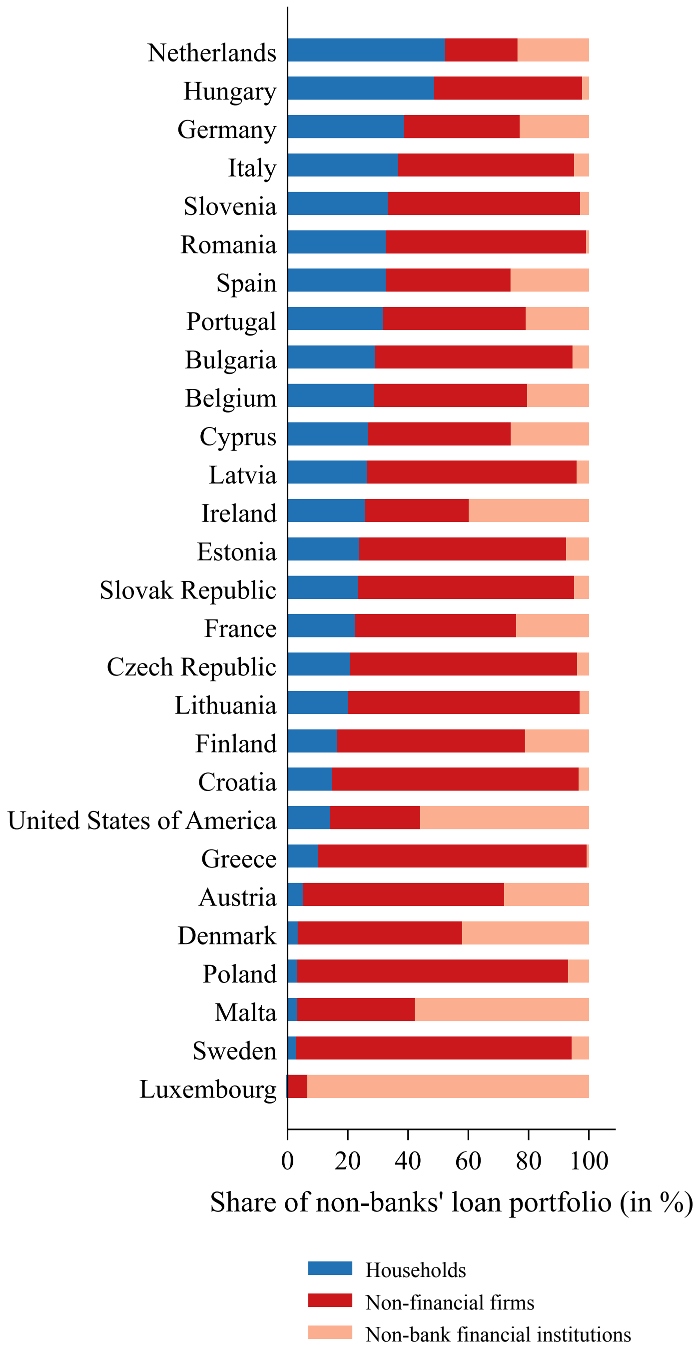


(c) The role of real estate collateral



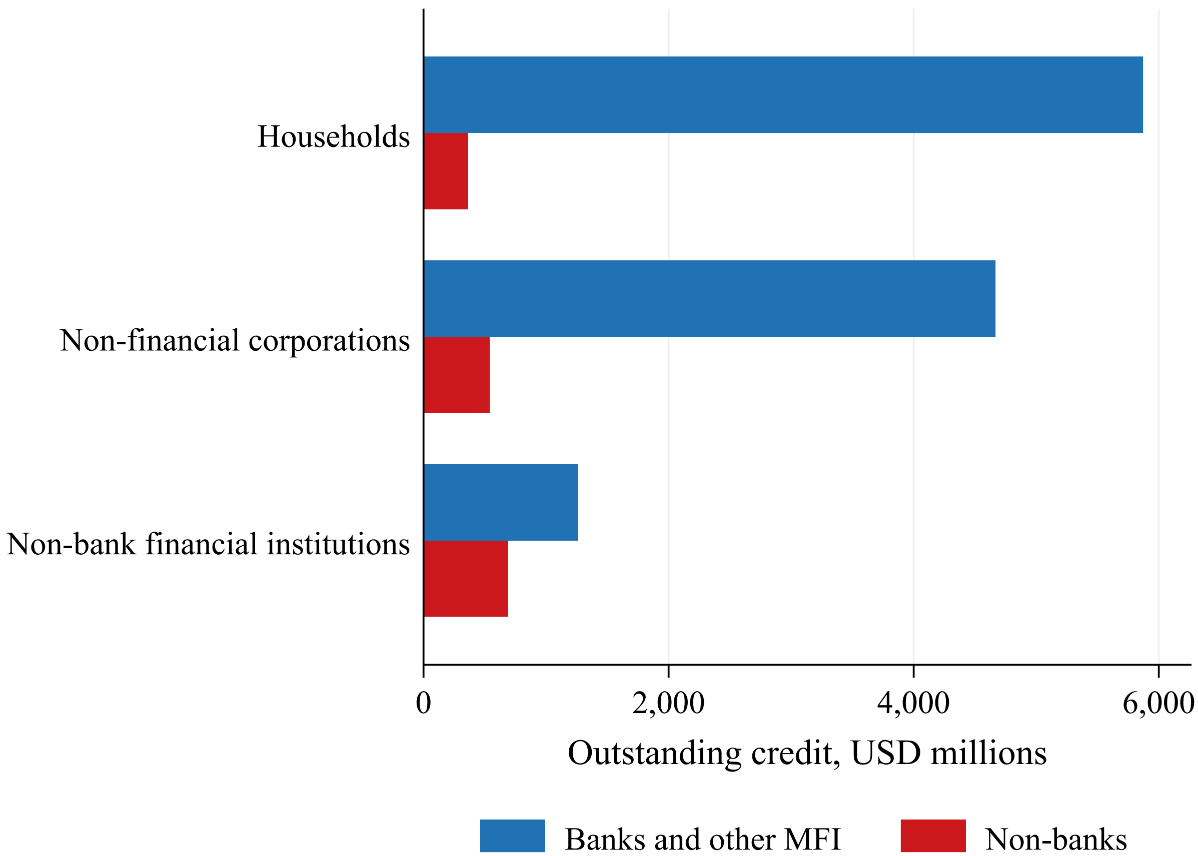
Notes: This figure plots the estimates of δ^h and $\delta^h + \gamma_j^h$ from Equation (4), showing how the path of consumption-to-GDP after a financial crisis depends on the type of credit boom preceding it. We show the average recovery path estimated by δ^h and the predicted recovery for the case 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.

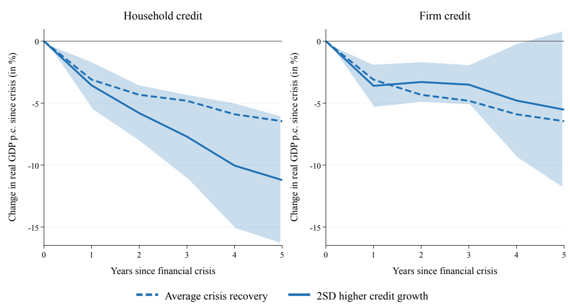
Figure A.9: Non-Bank Market Shares, by Borrower Sector



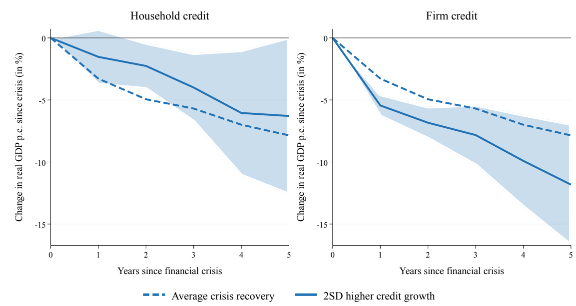
Notes: This figure plots data on the outstanding amount of credit to different borrower sectors for bank and non-bank lenders. We report averages for 28 countries based on the European Central Bank's "who-to-whom" accounts and the Federal Reserve's enhanced financial accountss. Note that we exclude lending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

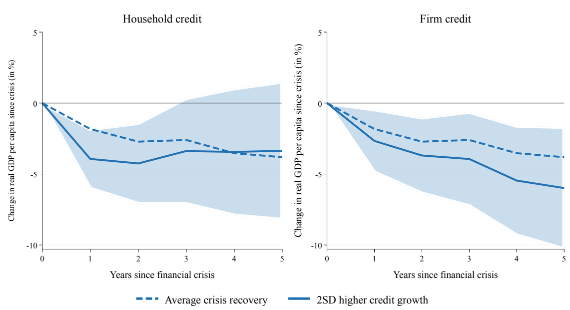
(a) JST data, Δ_5Credit/GDP



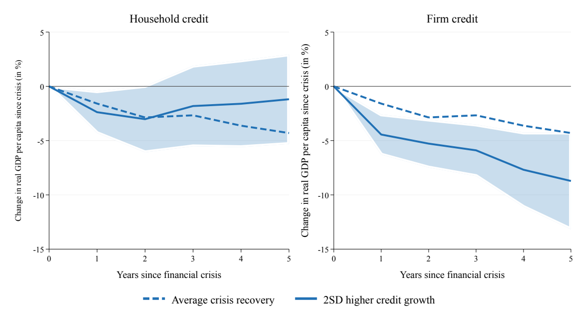
(b) JST data, Δ_3Credit/GDP



(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 (4), 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 114 countries, replicating the patterns also shown in Figure IXa 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	4.38**	9.77	7.00**
(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:

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

.

$\text{Crisis}_{it+1\text{ to }t+2}$ 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			
	6 sectors	18 sectors	Compustat	Orbis
	(1)	(2)	(3)	(4)
Δ_3TOT/GDP	0.222**	0.196**	0.077*	0.049*
	(0.066)	(0.052)	(0.030)	(0.019)
Observations	1,649	2,953	949	1,238
# Countries	83	106	72	117
First year	1948	1942	1953	1998
Within-R^2	0.09	0.06	0.01	0.00

Notes: This table shows the results of regressing the standard deviation of three-year changes in sectoral credit to GDP or firm debt growth on the three-year change in total credit to GDP. Columns (1) and (2) calculate dispersion across 6 and 18 sectors, respectively, where debt growth is defined as the three-year change in credit-to-GDP. Columns (3) and (4) use firm-level data from Compustat Global and Orbis, respectively, where debt growth is defined as the three-year change in outstanding debt relative to initial period assets. 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: 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
# Countries	70	70	70	70	70
First year	1949	1949	1949	1949	1949
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 (2) 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 VII, 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.4: **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 (4) 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.5: 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	-1.60	-2.95	-2.34	-3.23	-3.80
	(1.27)	(1.81)	(2.27)	(2.80)	(3.16)
Δ_3TOT/GDP	-0.14	-0.36	-0.58	-0.57	-0.76+
	(0.18)	(0.28)	(0.40)	(0.46)	(0.45)
Crisis × Δ_3TOT/GDP	-1.13+	-0.97	-1.38	-1.23	-0.82
	(0.61)	(1.02)	(1.04)	(1.21)	(1.41)
R^2	0.24	0.27	0.31	0.35	0.38
Observations	2243	2243	2243	2243	2243
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 × Δ_3HH/GDP	-0.01	0.02	0.12	0.24	0.38
	(0.11)	(0.16)	(0.21)	(0.24)	(0.25)
Crisis × Δ_3NFC/GDP	-0.29**	-0.28*	-0.37*	-0.49**	-0.58**
	(0.08)	(0.12)	(0.15)	(0.18)	(0.21)
Crisis × 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 (4) 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.6: 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 (2024).

Table A.7: Sources and Definition of Nonperforming Loan Data

Country	Table	NPL definition	Source
Argentina	Table XVI Financing Based on Economic Activity	Loans classified as overdue for more than 30 days.	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.	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 and the cumulative amount of write-downs.	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