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Credit Allocation and Macroeconomic Fluctuations

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

1. INTRODUCTION

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

In this paper, we argue that the allocation of credit across sectors is important for answering these questions. Our analysis is motivated by models of credit cycles with sectoral heterogeneity and credit frictions (e.g., Schneider and Tornell, 2004; Reis, 2013; Benigno and Fornaro, 2014; Kalantzis, 2015; Ozhan, 2020; Benigno et al., 2020). These models distinguish between firms in the tradable and non-tradable sectors. Firms in the non-tradable sector are assumed to be more financing constrained and more exposed

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to feedbacks through collateral values and domestic demand linkages. This model set-up yields two predictions about the link between the sectoral allocation of credit and macroeconomic fluctuations. First, times of "easy credit" will lead to disproportionate lending growth to firms in the non-tradable sector. Second, credit booms concentrated in the non-tradable sector may lead to slower economic growth through increased financial fragility. In contrast, lending to the tradable sector is more likely to coincide with strong growth without increased financial fragility.

To examine the link between sectoral credit allocation and macroeconomic outcomes empirically, we construct a novel database on private credit for 117 countries, starting in 1940, by drawing on more than 600 sources. Existing datasets on credit distinguish, at best, between firm and household lending. In contrast, our database covers up to 60 different industries. This allows us to differentiate between credit to the tradable and non-tradable sectors, and key industries such as manufacturing, construction, and non-tradable services. These new time series on credit by economic sector are consistent with existing aggregate data on private credit. The data also cover a considerably longer time span than other sources. We believe these data have many applications in macroeconomics, finance, and international economics.[1]

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

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

The allocation of credit during the boom predicts whether the boom ends in a bust. While all credit booms coincide with strong output growth, only credit booms concentrated toward non-tradable sector firms and households result in sharp growth reversals. The magnitude of these growth reversals is sizeable. Five years after a credit boom biased toward the non-tradable sector or households starts, real GDP is 5 percent lower relative to a credit boom biased toward the tradable sector. As a result, there is significant heterogeneity in the unconditional predictability of credit expansions for future GDP growth. Expansion in credit to the non-tradable sector predicts subsequent GDP growth slowdowns, defined as a significant decline in growth relative to the previous trend. In contrast, a tradable sector credit expansion is associated with stable or, in

1. We discuss details of the data construction at length below and in the data appendix. Our approach builds on best practices in the construction of national accounts used by the United Nations (e.g., United Nations, 2009, 2018) and other data sources on private credit (e.g., Dembiermont et al., 2013). We view our efforts as a reasonable starting point for constructing sectoral credit data in a transparent and consistent way, which we plan to build on in the future.

some specifications, higher growth in the medium run. Our analysis thus highlights that heterogeneity within the corporate sector is important for understanding the aftermath of credit expansions.

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

Why does credit expansion to the non-tradable sector, but not to the tradable sector, foreshadow lower future economic growth?[2] Guided by theory, we present several pieces of evidence that increased financial fragility and the risk of financial crises explain the poor growth performance after non-tradable credit booms. At the outset, we emphasize that causal identification of the exact mechanisms is challenging in such a broad and long macro panel. Instead, our goal is to understand which theories are most consistent with the empirical patterns.

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

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

Third, non-tradable credit expansions are more strongly associated with real estate price growth and subsequent busts. This pattern is consistent with greater financial fragility from exposure to collateral feedbacks (Kiyotaki and Moore, 1997). Finally, non-tradable credit expansions coincide with an appreciation of the real exchange rate and a reallocation of labor and value added toward the non-tradable sector, suggesting rising sectoral imbalances. At the same time, these booms predict lower future productivity growth, consistent with the lower productivity in the non-tradable sector (Reis, 2013; Benigno and Fornaro, 2014; Borio et al., 2016; Benigno et al., 2020). Lending to the

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

tradable sector, on the other hand, is associated with higher productivity growth and a stable real exchange rate.

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

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

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

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

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

2. SECTORAL CREDIT DATABASE: DATA AND METHODS

In this section, we outline the construction of our new sectoral credit database. We address additional technical details and comparisons with other data sources in much greater detail in a dedicated data appendix.[3]

2.1. *Data Coverage*

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

TABLE 1
Comparison with Existing Data Sources on Private Credit

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

Notes: Panel A compares data that differentiate between different sectors of the economy (e.g., household vs. firm credit). Panel B compares different sources of data on total credit to the private sector. WB GFDD stands for the World Bank's Global Financial Development Database (Cihák et al., 2013). BIS refers to the credit to the non-financial sector statistics described in Dembiermont et al. (2013). IMF IFS and GDD refer to the International Monetary Fund's International Financial Statistics and Global Debt Database (Mbaye et al., 2018), respectively. The data in Monnet and Puy (2019) is from historical paper editions of the IMF IFS. *Country-year obs.* refers to the number of country-year observations covered by the datasets. *Sectors* refers to the number of covered sectors; the mean refers to the average number of sectors in a country-year panel. *Country-sector-year obs.* refers to country-sector-year observations. We count observations until 2014.

3. The sectoral credit database and the data appendix are available at http://www.globalcreditproject.com.

Table 1 compares our database to existing datasets on private credit. Panel A highlights the difference in our approach. The most disaggregated available data in Jordà et al. (2016a) differentiates between household, firm, and mortgage credit for 18 advanced economies. Our database contains a more detailed sectoral breakdown for many more countries. It covers more than three times the country-year observations in Jordà et al. (2016a) and more than four times the data on household and firm credit published by the Bank for International Settlements (BIS). Because of the sectoral structure of our data, it contains a total of 89,019 observations, orders of magnitude more than previous work. Panel B shows how our database extends series on total credit to the private sector. Here, we add long-run data starting in 1910 for a significant number of countries.

2.2. *Data Sources*

Most countries have collected sectoral credit data for several decades. However, historical data are often not available in digitized form and are not reported on a harmonized basis. We draw on hundreds of scattered sources to construct these time series. The main sources are statistical publications and data appendices published by central banks and statistical offices. A large share of the data was digitized for the first time from PDF or paper documents. Many national authorities also shared previously unpublished data with us. In the process, we discovered many untapped sources of total credit to the private sector that allow us to extend existing time series.

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

2.3. *Concepts and Methods*

We are interested in the sectoral distribution of outstanding credit to the private sector. Ideally, the data should follow a harmonized definition of corporations and households, economic sectors and industries, and coverage of debt instruments. In practice, there are systematic differences in classifications across countries and time that require adjustments. To harmonize data from a wide range of sources, we draw on the metadata in historical publications and consulted with the national authorities publishing information on sectoral credit.

The resulting dataset measures end-of-period outstanding claims of financial institutions on the domestic private sector. In most countries, this definition mainly covers loans, including foreign currency loans. We also include the bond exposures recorded on financial institutions' balance sheets wherever they are reported. In practice, however, domestic credit is almost entirely accounted for by loans, while bonds are often held by foreign financial institutions.

We try to cover the entire financial system wherever possible. In most countries, the data predominantly measures credit extended by deposit-taking institutions such as commercial banks, savings banks, credit unions, and other types of housing finance companies. Comparisons with existing sources suggest that, on average, our numbers are in line with the IMF IFS or BIS data on bank credit to the non-financial private sector.

At times, we find somewhat larger values than the data in Jordà et al. (2016a), which largely covers lending by different types of banks.

To classify different sectors of the economy, we follow the System of National Accounts (SNA 2008) in differentiating between households and corporations (United Nations, 2009).

We classify industries based on the International Standard Industrial Classification of All Economic Activities (ISIC), Revision 4 (United Nations, 2008). Most countries have adopted this standard for reporting sectoral data, including on credit. In most countries, we can differentiate between credit to the major "sections" in ISIC parlance (Agriculture, Mining, Manufacturing, and so forth). The data generally capture credit to the (non-bank) private sector. However, most data sources do not systematically differentiate between lending to private and state-owned corporations; in principle, the data thus also include lending to state-owned firms. We do not include direct lending to general or local governments.

A key issue when dealing with time series data covering long time periods is how to deal with level shifts (or "breaks"). The most important challenge is to understand if such breaks arise because of actual economic changes (e.g., large-scale debt write-offs) or because of changes in classification (e.g., in the types of financial institutions covered). To address this issue, we coded country-specific classification changes based on a reading of the metadata and additional methodological publications, as well as exchanges with the national authorities. We adjusted breaks due to methodological changes using chain-linking, following methods used in previous datasets on private credit (Dembiermont et al., 2013; Monnet and Puy, 2019). To guarantee internal consistency of the data, we rescale chain-linked time series to match an aggregate such as "total credit to non-financial corporations" when needed, in line with the United Nations' recommendation on backcasting national accounts (United Nations, 2018).

2.4. *Variable and Sample Construction*

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

We construct a country-year panel dataset by merging the new credit data with macroeconomic outcomes, house prices, and value added by sector. For our main analysis, we restrict the sample to 75 countries with a population greater than one million in 2000 to avoid the results being influenced by large fluctuations in very small countries. Appendix Table A.1 reports the countries and years used in our main analysis. The sample includes broad coverage of both advanced and emerging market economies. We winsorize variables at the 1% and 99% level to mitigate the influence of outliers, although our results are similar without winsorizing. Table 2 reports summary statistics for key variables.

To investigate the characteristics of different sectors, we use data on firm size from the OECD's Structural Business Statistics (SBS) and compute the share of firms with

TABLE 2
Descriptive Statistics

Panel A: Summary statistics

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

Panel B: Correlation matrix

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

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

less than 10 employees for each industry. We also collect data on the type of collateral posted in different sectors, which we could identify for five countries (Denmark, Latvia, Switzerland, Taiwan, and the United States). These data come from the national central banks, banking regulators, or Compustat (for the United States).

We use data on gross domestic product (GDP) in current national currency, investment, consumption, population, inflation, and nominal US dollar exchange rates from the World Bank's World Development Indicators, Penn World Tables Version 9.1 (Feenstra et al., 2015), IMF IFS, GGDC (Inklaar et al., 2018), Jordà et al. (2016a), Mitchell (1998), and the UC Davis Nominal GDP Historical Series. For a few countries, we use data from national sources: Taiwan (National Statistics), the United States (FRED), and Saudi Arabia (Saudi Arabian Monetary Authority). For labor and total factor productivity, we use data from the Total Economy Database (TED). Data on effective real exchange rates comes from the World Bank, BIS, and Bruegel (Darvas, 2012).

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

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

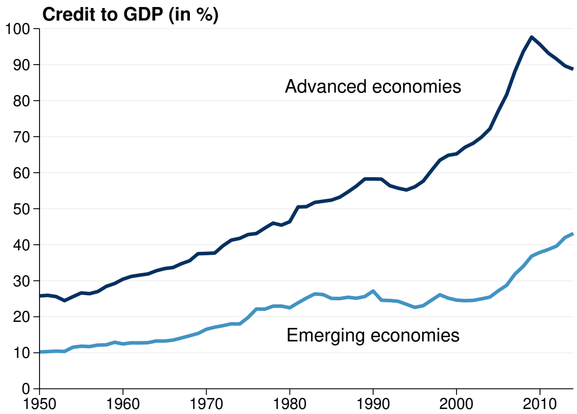
2.5. *Stylized Facts About Private Credit Around the World*

In this section, we present three stylized facts about long-term trends in credit markets based on our new database. We start by revisiting facts about the amount of outstanding private credit relative to GDP and then turn to the main novelty of the data: the sectoral distribution of credit.

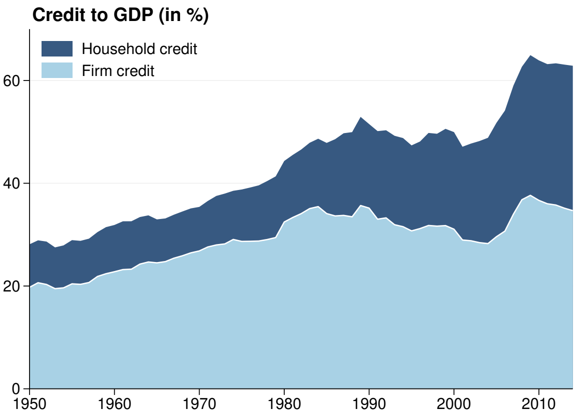
Fact #1: Credit/GDP has risen sharply over the past five decades. We begin with a look at the long-run development of total private credit-to-GDP around the world. The novelty of our data here is mainly the extension of long-run credit series to the period before 1960. Figure 1a plots the average credit-to-GDP ratio for advanced and emerging economies. This figure confirms the “hockey stick” pattern of rising private debt in advanced economies documented by Schularick and Taylor (2012), but it also reveals that the rise in credit is less pronounced in emerging economies.

Fact #2: Household debt has boomed globally, while firm credit has stalled. The newly constructed data allows us to provide a first glimpse at sectoral credit allocation over time using a large number of countries. Figure 1b plots averages of household and firm credit-to-GDP over time. This shows that most of the growth in credit-to-GDP since the early 1980s is accounted for by a rise in household debt. Relative to GDP, the rise in lending to firms has been modest. This reinforces previous evidence in Jordà et al. (2016b), who showed a similar pattern for a smaller sample of 17 advanced economies.

Fact #3: Firm credit has shifted from tradable sectors to construction, real estate, and other non-tradable sectors. It is a well-known phenomenon that countries undergo structural change as they develop, away from primary sectors toward manufacturing and then service sectors. One may expect to find similar trends



(a) By country group



(b) By sector

FIGURE 1
Private Credit-to-GDP (in %) by Country Group and by Sector, 1950-2014

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

in corporate credit. At the same time, the finding of rising household debt may suggest an increasing role of the housing sector, at least in advanced economies. Can we detect complementary patterns in the composition of corporate financing?

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

The second major trend is that construction and real estate lending has come to make up considerable shares of corporate loan portfolios. In advanced economies, the share of construction credit in the 1950s was negligible. Today, this share has risen to around 24 percent. While the housing boom of the 2000s has clearly played a role, the share had already grown in the 1990s. Strikingly, a similar pattern also holds true in emerging economies. In 1960, lending to industry and agriculture accounted for more than 73 percent of corporate financing. Today, the ratio is closer to 26 percent. At the same time, construction and real estate has increased from around 5 percent to 14 percent. Other services have also seen a substantial increase in their lending share. For example, in advanced economies, other services have increased from around 18 percent in 1960 to around 35 percent in recent years. Taken together, these findings suggest that the financing of manufacturing, the activity perhaps most commonly associated with commercial banking, has come to play a minor role for understanding modern credit markets.

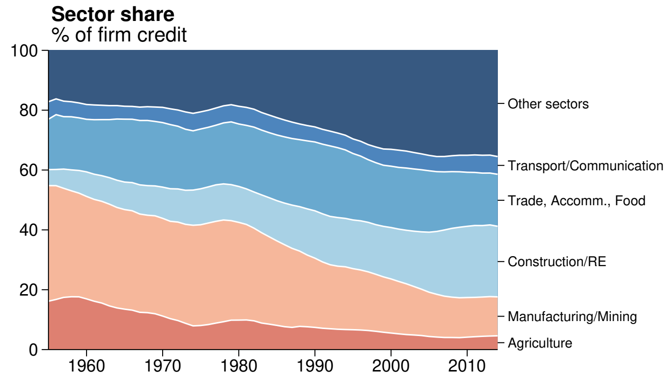
3. CONCEPTUAL FRAMEWORK

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

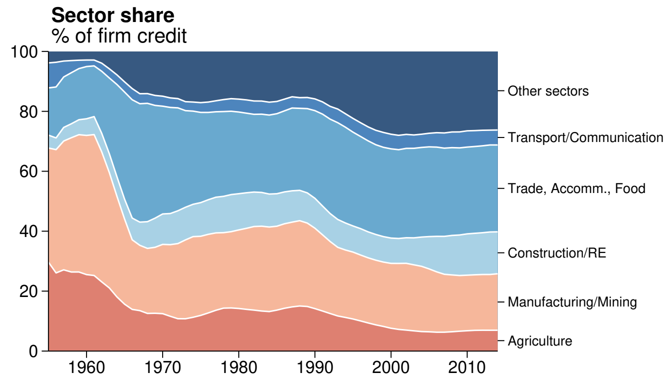
3.1. *Easy Credit Hypothesis*

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

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



(a) Advanced economies



(b) Emerging economies

FIGURE 2
Sector Shares in Corporate Credit

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

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

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

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

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

The same factors that lead non-tradable sector firms to disproportionately benefit from an expansion in credit can also explain why such credit booms increase financial fragility and are more likely to end in a bust. More severe financing frictions in the non-tradable sector imply a greater sensitivity to a reversal in credit supply following a negative real or financial shock. Reliance on lending secured by real estate allows non-tradable sector firms to lever up during the boom, but also exposes them to tightening borrowing constraints and the possibility of fire sales in the bust (Kiyotaki and Moore, 1997).[6] Furthermore, firms in the non-tradable sector are often less productive, so lending to the non-tradable sector can shift resources to less productive firms that are more likely to default, as in the models of Reis (2013), Benigno and Fornaro (2014), and Bleck and Liu (2018). The higher fragility of non-tradable sector firms can lead to large-scale defaults that cause a banking crisis, depressing credit supply and output. If borrowers and lenders do not fully anticipate the downside risks during non-tradable credit booms, this can lead to disappointed expectations following an increase in defaults, as in behavioral models of credit cycles (Bordalo et al., 2018; Maxted, 2019).

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

5. Ozhan (2020) refers to the financing constraint and demand mechanisms as the "banking" and "trade" channels of sectoral reallocation. A distinct prediction for the relevance of financial frictions, which we test below, is that non-tradable sector *leverage* (e.g., credit-to-output) rises during credit expansions and predicts subsequent output slowdowns.

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

TABLE 3
Comparing Non-Tradable and Tradable Sector Characteristics

	Tradable/Non-tradable			Key industries		
	T	NT	NT - T	Manuf.	Constr./RE	Food, Accomm.
Small firm share	0.79	0.90	0.12	0.78	0.91	0.86
Mortgage share	0.19	0.36	0.17	0.18	0.67	0.56
Labor productivity growth	5.03	2.65	-2.38	4.82	2.52	2.74
Total factor productivity growth	2.02	0.51	-1.51	2.19	-0.20	1.07

Notes: This table compares sectoral characteristics of non-tradable and tradable industries. *Small firm share* is defined as the share of businesses with less than 10 employees, based on the OECD Structural and Demographic Business Statistics. *Mortgage share* is the share of loans secured on real estate relative to all outstanding loans based on data from five countries: Denmark, Latvia, Switzerland, Taiwan, and the United States. For Denmark, we define use the ratio of lending by mortgage banks in each sector relative to total lending by mortgage and commercial banks, using data for 2014-2020 from Danmarks Nationalbank. For Latvia, we use the share of loans secured by mortgages using data for 2006-2012 from the Financial and Capital Market Commission. For Switzerland, we use the share of mortgage lending in each sector using data for 1997-2020 from the Swiss National Bank. For Taiwan, we compute the share of lending for real estate purposes in each sector using data for 1997-2015 from the Central Bank of the Republic of China (Taiwan). For the United States, we construct the weighted average ratio of mortgages and other secured debt (`dm`) to total long-term debt (`dltt`) using Compustat. *Labor productivity growth* is defined as the average yearly percentage growth in value added per engaged person in 2005 PPP USD, calculated based on data from EU KLEMS, WIOD, and OECD STAN, as well as data on sectoral relative prices from GGDC. The estimates are based on data from 39 countries. *Total factor productivity growth* is from EU KLEMS and is based on data from 18 countries.

3.2. *Productivity-enhancing Credit Hypothesis*

Productivity and credit. Credit growth could also reflect higher anticipated productivity and output growth. In basic permanent income hypothesis models, households and firms demand more credit to finance consumption and investment in response to higher expected future income or productivity, so expansions in credit should be associated with stronger future growth (e.g., Aguiar and Gopinath, 2007). In Coimbra and Rey (2017), a positive productivity shock leads to an increase in credit without endangering financial stability. In their model, "productivity driven leverage booms are not a concern for financial stability in the same way that credit supply driven ones are."

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

Does the sectoral allocation of credit matter for growth?. Productivity-enhancing credit growth could occur in all sectors, but it may be more likely when credit is financing the tradable sector, especially manufacturing. Manufacturing has a high level of productivity and has seen high productivity growth. Table 3 shows that annual labor productivity growth has been over 2 percentage points higher in the tradable compared

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

to the non-tradable sector. Growth in TFP has been 1.5 percentage points higher in the tradable relative to the non-tradable sector. Moving resources to manufacturing may have a positive effect on aggregate growth rates, making manufacturing an “engine of growth” (Rodrik, 2012, 2016). Tradable sectors are more likely to learn about foreign knowledge through trade and foreign competition, and productivity gains in the tradable sector may be associated with positive spillovers to other firms in the economy (e.g., Benigno and Fornaro, 2014). The tradable sector also accounts for a disproportionate share of investments in innovation, which can contribute to long-run growth (Benigno et al., 2020). Lending growth biased toward tradables may thus capture times of strong subsequent productivity and output growth without an elevated risk of a financial crisis.

4. THE ALLOCATION OF CREDIT DURING CREDIT BOOMS

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

4.1. *Case Studies*

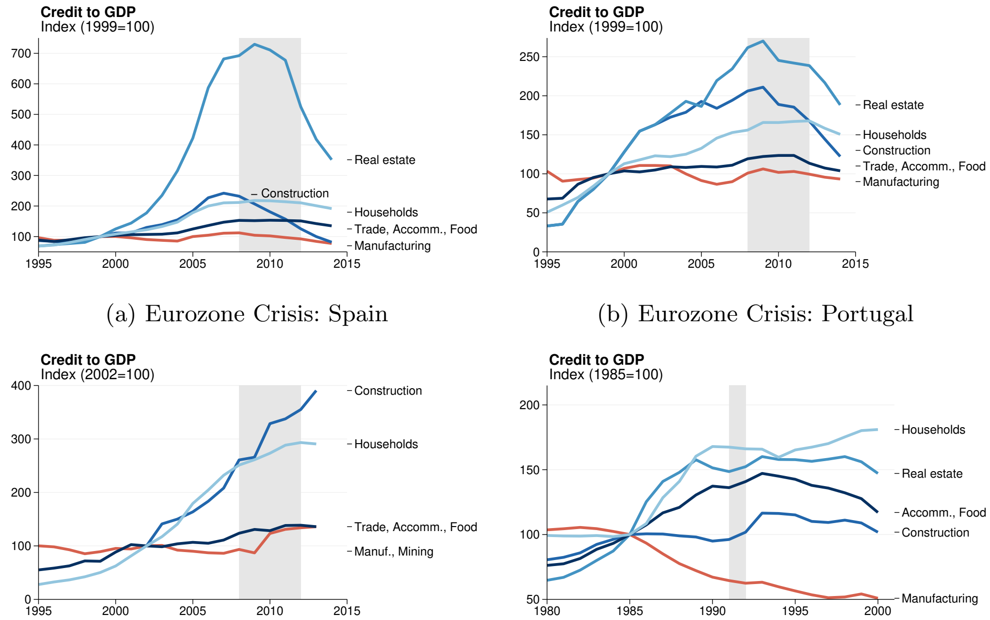
To motivate our empirical analysis, we begin by investigating two case studies of prominent credit booms.[8] The first is the case of Greece, Spain, and Portugal in the run-up to the Eurozone Crisis. The peripheral countries of the Eurozone experienced a major boom-bust cycle over the period 2000-2012. The creation of the European Monetary Union eliminated currency risk, which led to a large reduction in country spreads and large capital flows from core to peripheral economies (Baldwin and Giavazzi, 2015). These capital inflows financed rapid loan growth.

Which sectors of the economy were financed by this credit expansion? Panels (a) through (c) in Figure 3 reveal a large increase in lending to real estate firms, construction firms, and households. In relative terms, lending to the real estate sector grew the fastest in Portugal and Spain, while the absolute increase in debt was largest for the household sector in all three countries. In contrast, credit to the manufacturing sector stagnated. The lending boom was associated with house price booms and stagnant productivity growth, as relatively unproductive firms in the non-tradable sector expanded at the expense of the more productive firms in the tradable sector (Reis, 2013). The Global Financial Crisis of 2008 led to a reversal of inflows, a sharp contraction in credit, falling asset prices, severe recessions, and banking crises.

The second case is that of Japan in the 1980s. Japan experienced a rapid credit boom in the second half of the 1980s, which culminated in a prolonged period of banking sector distress and slow growth in the 1990s. The credit boom followed a period of gradual financial deregulation and loose monetary policy (Cargill, 2000). The boom was characterized by surging stock and urban real estate prices, which reinforced speculative investment in housing by real estate finance companies (Ueda, 2000).

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

8. Appendix B provides additional case study evidence for 18 episodes.



(a) Eurozone Crisis: Spain

(b) Eurozone Crisis: Portugal

(c) Eurozone Crisis: Greece

(d) Japanese Financial Crisis

FIGURE 3

Case Studies: The Eurozone and Japanese Crises

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

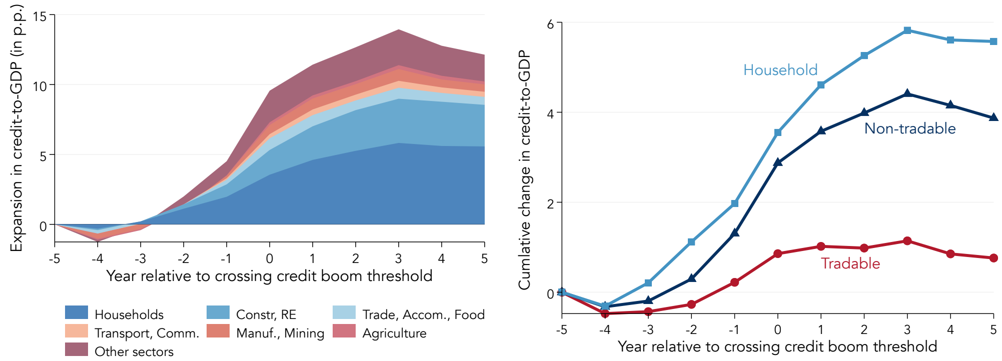
4.2. *Credit Booms and Credit Allocation: Systematic Evidence*

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

9. The results are similar when we use an HP-filter or identify credit booms as periods when the three-year expansion in credit-to-GDP is in its top quintile.

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

Table 4 shows substantial heterogeneity in the importance of different sectors for the credit expansion during credit booms. The largest increase in absolute terms is accounted for by household credit. This is followed by credit to construction and real estate and the trade, accommodation, and food services sectors. These sectors account for roughly 70% of the total increase in private credit. Thus, credit booms are largely a story of lending to the real estate sector, other non-tradable sectors, and households. The outsized role played by construction and real estate, other non-tradables, and households also stands out in case studies of many prominent credit booms and crises (see Appendix B). Among tradable sectors, manufacturing and mining represent the largest increase relative to GDP, while the expansion in lending to agriculture is small.



(a) Sectoral breakdown of aggregate credit expansion

(b) Non-tradable, tradable, and household sectors

FIGURE 4

The Allocation of Credit During Credit Booms

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

4.3. *Which Characteristics Shape Credit Allocation During Booms?*

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

$$\Delta_3 \ln(d_{i,s,t}) = \alpha_i + \beta_1 \mathbf{Boom}_{i,t} + \beta_2(\mathbf{Boom}_{i,t} \times \text{High Characteristic}_s) + \epsilon_{i,s,t}, \tag{4.1}$$

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

Table 4 presents the estimates of equation (4.1). Credit booms are associated with 23% higher three-year sectoral credit growth compared to other periods. However, there is important heterogeneity across sectors. During credit booms, the three-year growth rate in credit is 7.1% higher in the non-tradable sector, 7.1% higher in sectors with a high share of small firms, and 5.1% higher in sectors with a high mortgage share.

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

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

5. CREDIT ALLOCATION AND BUSINESS CYCLES

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

5.1. *Growth Around Major Credit Boom Episodes*

We start with the sample of credit boom events constructed in the previous section. We then divide these booms into two groups based on the sectoral allocation of credit. Specifically, we define “tradable-biased” and “non-tradable-biased” booms, depending on whether the change in the share of tradable credit, $s_{it}^T = d_{it}^T/(d_{it}^T + d_{it}^{NT} + d_{it}^{HH})$, over the previous five years is positive or negative. We denote these booms as $\mathbf{Boom}_{it}^T$ and $\mathbf{Boom}_{it}^{NT}$, respectively. We group households and non-tradables to obtain two

TABLE 4
Credit Booms and Credit Reallocation

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

Notes: This table presents estimates of equation (4.1) in a country-sector-year panel, where the dependent variable is the log change (times 100) in sectoral credit-to-GDP over the previous three years. There are five sectors: agriculture; manufacturing and mining; construction and real estate; wholesale and retail trade, accommodation, and food services; and transport and communication. Non-tradable industries are: construction and real estate; wholesale and retail trade, accommodation, and food services; and transport and communication. Non-tradable industries are classified based on the inverse of the exports to value-added ratio in the United States. Industries with a high small firm share are: agriculture; construction and real estate; and transport and communication. High mortgage share industries are: agriculture; construction and real estate; and wholesale and retail trade, accommodation, and food services. See Table 3 for details on the industry characteristics. Driscoll and Kraay (1998) standard errors with six lags in parentheses. +, * and ** denote significance at the 10%, 5% and 1% level.

disjoint sets of events.[10] In total, we identify 25 tradable-biased booms and 88 non-tradable-biased booms in our sample. The preponderance of non-tradable-biased booms is consistent with the systematic credit reallocation toward non-tradables documented in the previous section.

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

$$y_{t+h} - y_{t-1} = \alpha_i^h + \beta_T^h \mathbf{Boom}_{it}^T + \beta_{NT}^h \mathbf{Boom}_{it}^{NT} + \epsilon_{it+k}^h, \quad h = -5,...,5. \tag{5.2}$$

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

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

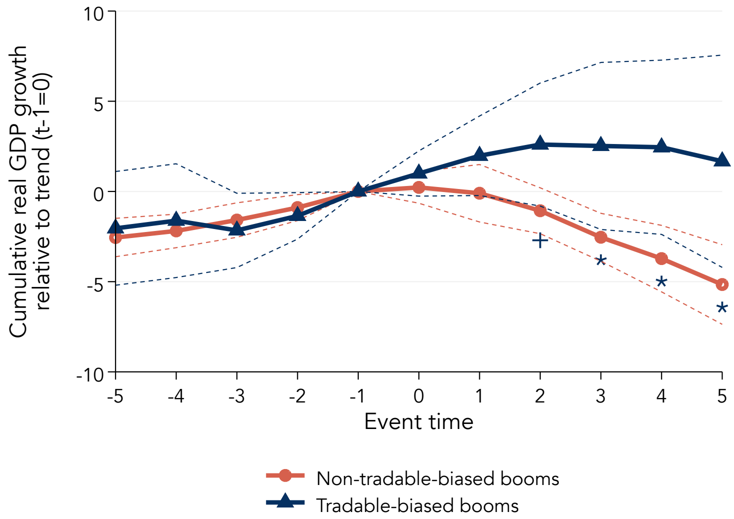


FIGURE 5

Output Dynamics around Tradable and Non-tradable Biased Credit Booms

Notes: This figure plots results from estimating equation (5.2). Time zero is defined as the first year in which the credit boom is identified. Tradable-biased (non-tradable-biased) credit booms are defined as booms in which the share of tradable-sector credit (non-tradable and household sector credit) rises from time $t=-5$ to $t=0$. The union of $\mathbf{Boom}_{it}^{T}$ and $\mathbf{Boom}_{it}^{NT}$ thus comprises all identified credit booms. Dashed lines represent 90% confidence intervals based on Driscoll and Kraay (1998) standard errors with lag length $ceiling(1.5(3+h))$. +, * and ** indicate that the difference between the estimates, $\hat{\beta}_T^h - \hat{\beta}_{NT}^h$, is statistically significant at the 10%, 5% and 1% level, respectively.

5.2. *Growth Following Sectoral Credit Expansions*

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

$$\Delta_h y_{it+h} = \alpha_i^h + \sum_{k \in K} \sum_{j=0}^{J} \beta_{h,j}^k \Delta d_{it-j}^k + \sum_{j=0}^{J} \gamma_{h,j} \Delta y_{it-j} + \epsilon_{it+h}, \quad h=1,...,H, \tag{5.3}$$

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

Figure 6 presents the impulse responses of real GDP to innovations in non-tradable sector credit, tradable sector credit, and household credit given by the estimated sequence of coefficients $\{\hat{\beta}^k_{h,0}\}$ for $k \in \{NT,T,HH\}$. Panel (a) presents results from an estimation that includes the tradable and non-tradable corporate sectors, and panel (b) presents results that add household credit to the specification. We emphasize that these impulse responses are not necessarily causal, but provide a sense of the predicted dynamics of GDP following innovations in sector k credit, holding fixed GDP growth and credit growth in other sectors.

The left panel in Figure 6a reveals that an innovation in non-tradable sector credit-to-GDP is associated with slower GDP growth after three to four years. The decline persists for several years, leaving GDP below its initial trend. In terms of magnitudes, a one percentage point innovation in non-tradable credit-to-GDP predicts 0.8% lower cumulated GDP growth over the next five years. In contrast, the right panel in Figure 6a shows that expansion in tradable sector credit is not associated with lower GDP growth. The predictive relation is positive in the medium-term after five years. A one percentage point innovation in tradable credit-to-GDP predicts 0.6% stronger cumulated growth over the next five years and 2.1% cumulated over ten years.

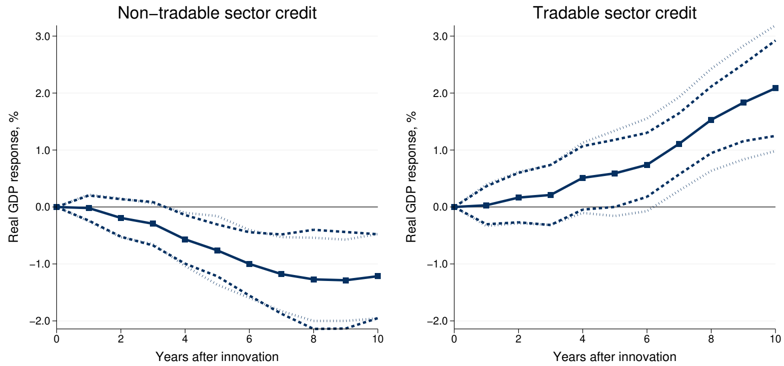
Panel (b) adds household credit to the estimation of equation (5.3). Household credit-to-GDP innovations are a strong predictor of lower GDP after three to four years. This confirms the result in Mian et al. (2017) with a sample that is more than twice as large. The patterns implied by the estimates on Δd^{NT}_{it} and Δd^{T}_{it} are similar to panel (a), but slightly more muted. As non-tradable and household credit are relatively strongly correlated (see Table 2), the estimates for non-tradable sector credit fall by about one-third with the inclusion of household credit. This is consistent with non-tradable and household credit capturing similar periods of credit expansions, which theory suggests may be explained by similar exposure to easy credit conditions and to collateral and demand feedbacks.

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

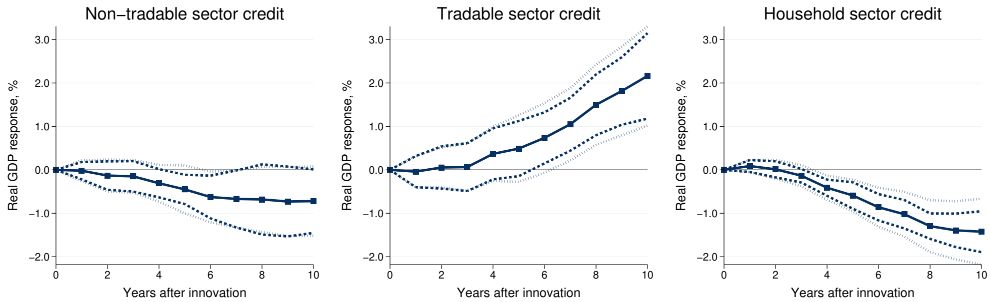
$$\Delta_3 y_{i,t+h} = \alpha^h_i + \beta^{NT}_h \Delta_3 d^{NT}_{it} + \beta^T_h \Delta_3 d^T_{it} + \beta^{HH}_h \Delta_3 d^{HH}_{it} + \epsilon_{it+h}, \tag{5.4}$$

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

Panel A in Table 5 presents the estimates of (5.4) for tradable and non-tradable credit, and Panel B adds household credit. Non-tradable credit expansions are positively correlated with GDP growth contemporaneously (column 1). In the medium run, however, the sign reverses (columns 4-6). At the strongest horizon of $h=3$, the estimate in Panel B implies that a one standard deviation increase in $\Delta_3 d^{NT}$ is associated with 0.70 percentage points lower growth from t to $t+3$. The pattern for household credit is similar, though household credit has a weaker contemporaneous correlation with growth (column 1) and stronger negative predictability further into the future (columns 4-6). The



(a) Non-tradable and Tradable Sector Credit



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

FIGURE 6

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

Notes: This figure presents local projection impulse responses of real GDP following innovations in tradable sector credit, non-tradable sector credit, and household credit (all measured relative to GDP). The impulse responses are based on estimation of (5.3). Panel (a) includes non-tradable and tradable firm credit, while panel (b) presents results from the same specification that also includes household credit. Dashed lines represent 95% confidence intervals computed using Driscoll and Kraay (1998) standard errors, and dotted lines represent 95% confidence intervals from standard errors two-way clustered on country and year.

estimate for the $h=3$ horizon implies that a one standard deviation increase in $\Delta_3 d_{it}^{HH}$ is associated with 1.60 percentage points lower growth from t to $t+3$. In contrast, an expansion in tradable sector credit is associated with positive growth in both the short and medium run, although the individual estimates are not statistically significant.

5.3. *Additional Results and Robustness*

This section presents additional results for the predictive relation between sectoral credit expansions and subsequent real GDP growth. Appendix A presents a series of additional robustness exercises. These show that the main results on sectoral credit expansion and real GDP growth are robust to accounting for bond issuance and to including a range of

TABLE 5
Sectoral Credit Expansion and GDP Growth

Panel A: Non-tradable and tradable sector credit

	Dependent var.: GDP growth over...					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 d_{it}^k$	(t-3,t)	(t-2,t+1)	(t-1,t+2)	(t,t+3)	(t+1,t+4)	(t+2,t+5)
Tradables	0.087	0.11	0.19	0.30	0.38	0.39
	(0.15)	(0.18)	(0.18)	(0.19)	(0.24)	(0.26)
Non-tradables	0.46**	0.15	-0.18+	-0.38**	-0.47**	-0.43**
	(0.088)	(0.11)	(0.10)	(0.11)	(0.14)	(0.16)
Observations	1,890	1,820	1,748	1,677	1,605	1,533
# Countries	75	75	75	75	75	75
R^2	0.05	0.01	0.01	0.02	0.03	0.03

Panel B: Including household credit

	Dependent var.: GDP growth over...					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 d_{it}^k$	(t-3,t)	(t-2,t+1)	(t-1,t+2)	(t,t+3)	(t+1,t+4)	(t+2,t+5)
Tradables	0.086	0.095	0.16	0.26	0.33	0.34
	(0.14)	(0.17)	(0.17)	(0.17)	(0.20)	(0.23)
Non-tradables	0.47**	0.21+	-0.045	-0.19*	-0.23**	-0.19*
	(0.075)	(0.11)	(0.100)	(0.079)	(0.069)	(0.091)
Households	-0.0070	-0.11	-0.25**	-0.39**	-0.53**	-0.55**
	(0.090)	(0.088)	(0.075)	(0.071)	(0.10)	(0.13)
Observations	1,890	1,820	1,748	1,677	1,605	1,533
# Countries	75	75	75	75	75	75
R^2	0.05	0.01	0.02	0.05	0.08	0.08

Notes: This table presents the results from estimating (5.4). The dependent variable in column h is the change in log real GDP (times 100) from year $t-3+h$ to $t+h$. The right-hand-side variables, $\Delta_3 d_{it}^k$, are the changes in the credit/GDP ratio (in percentage points) for sector k from $t-3$ to t. Driscoll and Kraay (1998) standard errors in parentheses with lag length $ceiling(1.5(3+h))$. +, * and ** denote significance at the 10%, 5% and 1% level.

additional controls. We also explore alternative sector classifications and show that the results hold across various subsamples.

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

We use two approaches to address this question. First, Appendix Figure A.2a presents results from estimating (5.3) with additional controls for the share of the non-tradable and tradable sectors in value added, which hold constant any reallocation of output to the non-tradable sector. Second, Appendix Figure A.2b presents estimates of impulse responses from (5.3) where we replace sectoral credit-to-GDP with credit scaled by

11. See the discussion of Table 8 below, as well as Kalantzis (2015) and Mian et al. (2020).

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

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

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

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

6. THE ROLE OF FINANCIAL FRAGILITY

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

6.1. *Financial Crises*

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

We start with a descriptive event-study analysis that examines how credit evolves across sectors around the start of financial crises. Figure 7 plots the average yearly

12. Kirti (2018) has generously posted his international panel of high-yield share estimates on his https://sites.google.com/site/divyakirti/webpage.

change in sectoral credit-to-GDP for five years before and after a systemic banking crisis, relative to non-crisis times. The sample includes 59 crises. Panel (a) shows that non-tradable firm and household credit tend to expand more rapidly than the sample average in the run-up to crises. Non-tradable sector credit expands more than twice as rapidly relative to GDP as tradable sector credit, surpassing the growth of household debt in the three years immediately before crises.

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

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

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

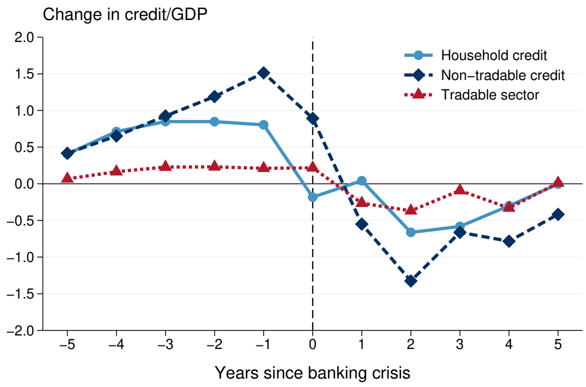
$$Crisis_{it+1\ to\ it+h} = \alpha_i^h + \sum_{k \in K} \beta_k^h \Delta_3 d_{it}^k + \epsilon_{it+h}, \tag{6.5}$$

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

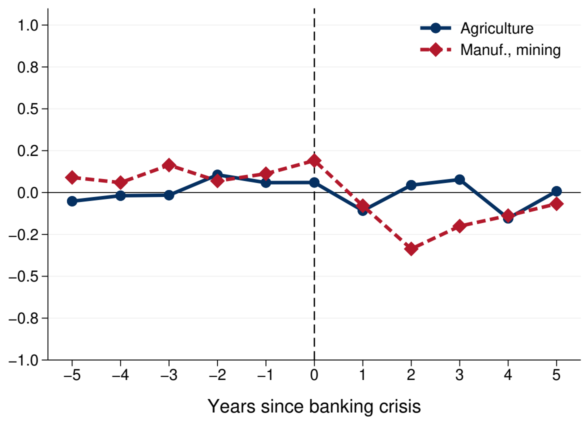
Table 6 reports the results from estimating equation (6.5). Panel A examines the predictive content of tradable, non-tradable, and household credit. Non-tradable and household credit expansions predict an elevated probability of a financial crisis at the one to four-year horizons. In terms of magnitudes, a two standard deviation higher three-year change in non-tradable sector credit-to-GDP is associated with a 5% higher crisis probability over the next year. This is sizeable relative to the unconditional probability of a crisis of around 3%. For households, the magnitude is around 4%. In contrast, tradable sector credit expansion predicts a slightly *lower* probability of a subsequent financial crisis. The estimates on tradable sector credit are negative and mostly statistically significant at the 10% level.[13]

Panel B shows the results for the individual corporate sectors. The estimates further support the notion that banking crises tend to be preceded by credit expansions in specific sectors of the economy. In particular, we find a strong role for lending to various subsectors of the non-tradable sector: both lending to firms in the construction and real

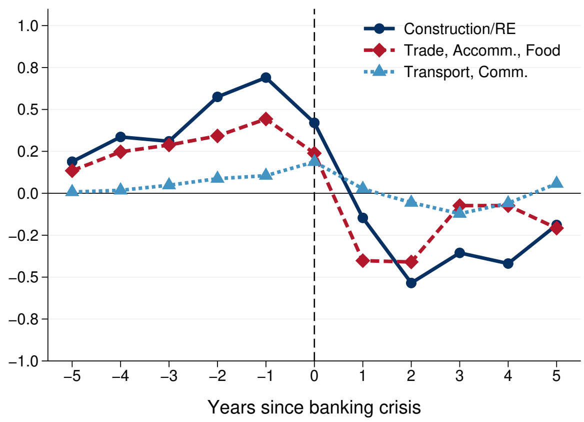
13. Appendix A presents a series of sensitivity analyses and shows that the results on crisis predictability are broadly robust to a range of additional controls, alternative specifications, alternative crisis dates, and subsamples.



(a) Tradable vs. Non-Tradable Sector



(b) Tradable Sector Industries



(c) Non-Tradable Sector Industries

FIGURE 7
Credit Dynamics around Systemic Banking Crises

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

TABLE 6
Sectoral Credit Expansions and Financial Crises

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

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

Panel B: Individual corporate sectors

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

Notes: This table presents the results from estimating equation (6.5). In Panel A, we differentiate between credit to the tradable, non-tradable, and household sectors. In Panel B, we use individual corporate sectors. Crisis dates are from Baron et al. (2021), supplemented with dates from Laeven and Valencia (2018) for countries not covered by Baron et al. (2021). Driscoll and Kraay (1998) standard errors with lag length $ceiling(1.5(3+h))$ are in parentheses. +, * and ** denote significance at the 10%, 5% and 1% level.

estate and in trade, accommodation, and food service sectors is associated with future crises. At horizons of 2-4 years, these types of firm credit expansions have predictive power that rivals or exceeds that of household credit. Credit to the primary sectors and manufacturing have no predictability for banking crises.

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

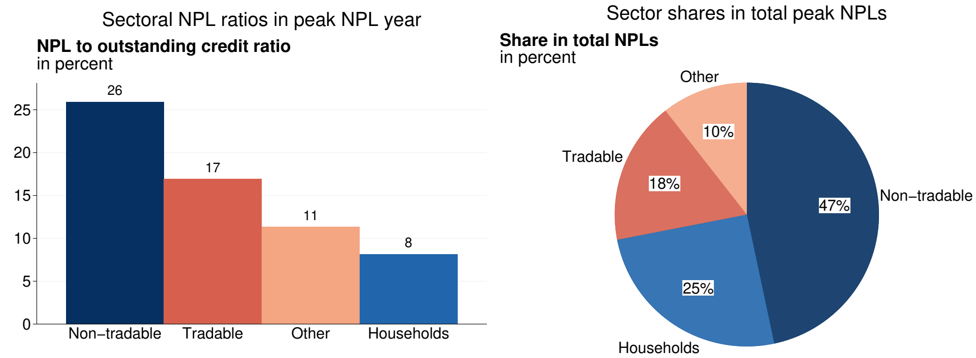


FIGURE 8

Financial Crises and Sectoral Loan Losses: Evidence from Ten Banking Crises

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

The in-sample AUC in column 1 is 0.73, consistent with the informativeness of credit expansion for predicting crises. In a rolling out-of-sample estimation, the corresponding AUC is 0.75 (unreported). These AUC values are similar or slightly higher than the AUCs from other studies using linear or logit models of crisis prediction. For example, in a longer sample with fewer countries, Schularick and Taylor (2012) report AUCs of 0.67 to 0.72. Using only total private credit rather than sectoral credit on the same sample as in Table 6 column 1, we obtain an AUC of 0.70, compared to 0.73 (panel A) or 0.75 (panel B) with sectoral credit measures.[14]

The increased likelihood of banking crises is central to understanding the slowdown in real GDP growth in the aftermath of credit expansions toward non-tradable sectors. To illustrate this, Appendix Figure A.6 presents local projection impulse responses of real GDP growth to sectoral credit expansions separately for periods with a banking crisis within the next three years and periods outside of banking crises. The real GDP response to a non-tradable credit expansion is close to zero and insignificant outside of banking crises, but large and significant for credit expansions that are followed by banking crises. As an interesting contrast, the aftermath of household credit expansions is as severe when excluding banking crises, consistent with theories emphasizing depressed household demand from household debt overhang (Mian et al., 2021).

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

6.2. *Sectoral Defaults During Financial Crises*

What ties sectoral credit expansions to a banking crisis that affects the economy as a whole? In Figure 8, we provide evidence that sectoral losses are important for understanding why the banking sector can end up in distress following credit expansion to non-tradable sectors. To measure losses, we look at non-performing loans (NPLs), which a few countries' central banks or financial regulators report disaggregated by sector, although usually only starting in the mid-2000s. We focus on ten financial crisis episodes for which we were able to identify sectoral NPL data. See Figure 8 for the list of episodes.

The left panel in Figure 8 plots the NPL rates of different sectors, and the right panel shows a sector's share in total NPLs. Banking crises tend to be followed by default rates that are concentrated among firms in the non-tradable sector. Moreover, loans to non-tradables and households account for nearly three-quarters of total bank NPLs post-crisis, as shown in the right panel. Losses on loans to the non-tradable sector account for nearly half of total NPLs in the aftermath of crises, while households account for a quarter of NPLs.

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

6.3. *House Price Booms and Busts*

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

Table 7 investigates the dynamic relation between real estate price growth and sectoral credit expansions. We estimate equation (5.4) with real house price growth as the dependent variable. Column 1 shows that house price growth over $t-3$ to t is positively correlated with credit expansions over the same three-year period. The correlation is positive for all sectors and strongest for credit to the non-tradable sector.[15]

The subsequent columns in Table 7 reveal that non-tradable and household credit predict a sizeable fall in *future* house price growth. A one standard deviation increase in non-tradable credit expansion predicts 5.1 percentage points lower house price growth from t to $t+3$. A one standard deviation increase in household credit expansion predicts

15. Appendix Figure A.7 confirms these patterns also hold in a local projection framework by estimating (5.3) with log real house prices as the outcome variable.

TABLE 7
Sectoral Credit Expansions and House Price Growth

	Dependent var.: Real house price growth over...					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 d^k_{it}$	(t-3,t)	(t-2,t+1)	(t-1,t+2)	(t,t+3)	(t+1,t+4)	(t+2,t+5)
Tradables	0.63	0.88$^+$	1.14*	1.06*	1.13**	0.85**
	(0.47)	(0.51)	(0.54)	(0.50)	(0.41)	(0.26)
Non-tradables	0.95**	0.16	-0.68$^+$	-1.16**	-1.33**	-1.04**
	(0.26)	(0.34)	(0.35)	(0.32)	(0.20)	(0.19)
Households	0.49	0.16	-0.20	-0.64**	-0.95**	-0.90**
	(0.33)	(0.34)	(0.21)	(0.15)	(0.15)	(0.20)
Observations	895	881	864	847	829	810
# Countries	42	42	42	42	42	42
R^2	0.11	0.02	0.03	0.09	0.14	0.10

Notes: This table presents the results from estimating equation (5.4) with $\Delta_3 \ln(HPI)_{it+h}$ (the three-year change in log real house prices) as the dependent variable. All columns include country fixed effects. Driscoll and Kraay (1998) standard errors in parentheses with lag length $ceiling(1.5(3+h))$. +, * and ** denote significance at the 10%, 5% and 1% level.

3.0 percentage points lower house price growth over the same period. In contrast, tradable credit expansions are associated with stronger future house price growth. This evidence is consistent with heightened financial fragility through falling real estate prices following expansions in non-tradable and household credit.

6.4. *Sectoral Reallocation, Real Appreciation, and Productivity Dynamics*

Credit expansion to the non-tradable sector can lead to sectoral imbalances and real exchange rate overvaluation. This can increase financial fragility in multi-sector models with asymmetric financing frictions (e.g., Schneider and Tornell, 2004; Kalantzis, 2015; Rojas and Saffie, 2022). In models with sectoral heterogeneity in productivity dynamics (Reis, 2013; Benigno and Fornaro, 2014; Benigno et al., 2020), sectoral imbalances further lead to lower productivity. Low productivity growth is a direct source of low GDP growth and can also increase the risk of a financial crisis (Gorton and Ordoñez, 2019). In contrast, credit expansion to the tradable sector, often seen as an engine of growth, could finance productivity improvements.

Table 8 investigates how sectoral credit expansions correlate with the sectoral allocation of real activity and the real exchange rate. Columns 1 and 2 reveal that non-tradable credit expansions coincide with a reallocation of real activity toward the non-tradable sector, both in terms of output and employment. Credit expansion to the non-tradable sector also correlates with a real exchange rate appreciation (column 3).[16] While these patterns are not necessarily causal, they are consistent with the predictions of multi-sector open economy models. Real appreciation could arise from strong domestic demand that increases the scarcity of non-tradables (Mendoza, 2002; Schneider and Tornell, 2004; Kalantzis, 2015; Mian et al., 2020). It could also be driven by misallocation that leads to a higher cost per unit of produced non-tradable output (Reis, 2013). In contrast, credit expansion to the tradable sector is not associated with significant sectoral reallocation or real exchange rate appreciation.

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

TABLE 8

Sectoral Credit Expansions, Sectoral Real Activity, and the Real Exchange Rate

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

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

TABLE 9

Sectoral Credit Expansions and Labor Productivity Growth

	Dependent variable: Labor productivity growth over...					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_3 d^k_{it}$	(t-3,t)	(t-2,t+1)	(t-1,t+2)	(t,t+3)	(t+1,t+4)	(t+2,t+5)
Tradables	0.186+	0.173*	0.208*	0.219+	0.199	0.169
	(0.093)	(0.081)	(0.086)	(0.113)	(0.150)	(0.179)
Non-tradables	0.066	-0.072	-0.168*	-0.147*	-0.080	-0.009
	(0.142)	(0.125)	(0.082)	(0.067)	(0.054)	(0.059)
Households	-0.147*	-0.183**	-0.226**	-0.261**	-0.312**	-0.308**
	(0.061)	(0.061)	(0.057)	(0.067)	(0.076)	(0.068)
Observations	1,451	1,451	1,451	1,451	1,451	1,451
# Countries	69	69	69	69	69	69
R^2	0.01	0.01	0.03	0.03	0.03	0.03

Notes: This table presents the results from estimating equation (5.4) with the three-year change in the log of labor productivity as the dependent variable. Driscoll and Kraay (1998) standard errors in parentheses with lag length $ceiling(1.5(3+h))$. +, * and ** denote significance at the 10%, 5% and 1% level.

Table 9 examines whether credit expansions to different sectors predict differences in future productivity. To do so, we replace the dependent variable in equation (5.4) with the change in labor productivity, measured as the natural logarithm of output per worker. The results in Table 9 show that credit expansions to the non-tradable sector are systematically associated with lower productivity growth. The opposite is true for lending to the tradable sector, which correlates with higher growth in labor productivity in both the short and medium run.[17]

17. Appendix Table A.8 shows that the patterns are similar using total factor productivity growth as the dependent variable.

7. CONCLUSION

There is increasing awareness that credit markets play a key role in macroeconomic fluctuations. However, a lack of detailed, comparable cross-country data on credit markets has left many questions about the relation between credit cycles and the macroeconomy unanswered. By introducing a new worldwide database on sectoral credit, this paper shows that heterogeneity in the allocation of credit across sectors—what credit is used for—plays an important role for understanding linkages between the financial sector and the real economy.

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

While we are cautious about making welfare claims based on our reduced-form evidence, these findings have interesting policy implications if taken at face value. An ongoing policy debate has weighed whether financial regulation, including macroprudential policy, should have a stronger focus on sectoral risks (Basel Commitee on Banking Supervision, 2019b,a; European Banking Authority, 2020). Our results suggest that such regulations could make sense, although there may be other concerns, e.g., about political economy constraints (Müller, 2019). However, the debate about risks in particular sectors has focused mainly on household debt and housing. We find that lending to certain corporate sectors also matters.

Some caveats are in order. First, the importance of non-tradable and household credit that we document here may be a more recent phenomenon. While we cover a large proportion of economic downturns and crises since the 1950s, things may have been different in the pre-World War II period. Second, while we point to a number of potentially relevant sources of heterogeneity across industries, we cannot precisely identify the exact underlying mechanisms. Third, the predictive patterns we document in this paper are not necessarily causal. We hope that future work will find creative ways to identify shocks to credit in different sectors, which could then be linked to economic outcomes.

The data and code underlying this research is available on Zenodo at https://doi.org/10.5281/zenodo.8347045.

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