Credit Booms, Labor Reallocation, and Productivity Growth*

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We investigate how credit expansion affects labor reallocation and labor productivity growth in a sample of over 20 advanced economies between 1979 and 2009. Using industry-level data, we decompose aggregate labor productivity growth for each country into a common and an allocation component. We then run country fixed-effects panel regressions to examine how credit expansion influences each of these components. Next, we run industry-level regressions to examine how the sensitivity of employment growth to labor productivity growth varies with the intensity of credit expansion. Both analyses lead to the conclusion that credit growth tends to reduce aggregate labor productivity growth. The evidence also suggests that during credit booms this reduction occurs through labor reallocations toward lower productivity growth sectors.

JEL Codes: E24, E51, O47.

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1. Introduction

The productivity performance of the U.S. economy in the dot-com boom of the 1990s differed significantly from that in the housing boom of the 2000s. At the height of the dot-com boom, over the period 1996–99, aggregate labor productivity grew on average by 2.4 percent a year. At the same time, private credit remained broadly stable as a share of GDP. By contrast, at the height of the housing boom, over the period 2004–07, aggregate labor productivity grew only by 1.2 percent a year, despite a substantial credit expansion. Is it just a coincidence that aggregate productivity was increasing at a lower rate when credit was expanding fast and vice versa?[1]

In this paper, we document a systematic negative relationship between the strength of credit expansion and aggregate labor productivity growth for a sample of advanced economies over the period 1979–2009. Furthermore, we show that when aggregate credit to GDP grows quickly, this negative relationship arises from the reallocation of labor into low productivity growth sectors; that is, sectors with weaker productivity gains tend to outpace the others in terms of employment growth, thereby dragging aggregate productivity growth down.

Our evidence is based on a simple decomposition of aggregate labor productivity growth into two components (similar to Olley and Pakes 1996), which we name common and allocation components, respectively. The common component corresponds to the simple average of the growth rates of labor productivity across all sectors of the economy. The allocation component, by contrast, reflects the relationship between productivity growth and employment growth across sectors. The allocation component is positive if employment growth is stronger in sectors that experience high productivity growth and negative if employment growth is weaker in sectors that experience high productivity growth.[2]

[1]Similarly, according to Fernald (2014), aggregate total factor productivity in the United States grew by 1.6 percent over 1995–2000 but only by 0.6 percent between 2004 and 2007.

[2]As will be clear in Section 2, the allocation component is the covariance across sectors between the growth rate of the sectoral employment share and the growth rate of sectoral productivity. Hence, in theory, it measures both the impact of labor reallocation across sectors and that of changes in productivity growth

Building on this decomposition, we perform two empirical exercises. In the first, we compute for each pair of country-time period in the sample the common and the allocation components. We then run country fixed-effects panel regressions to investigate how each component moves with measures of credit growth. We find a strong negative relationship between measures of credit growth and productivity growth.[3] Moreover, during credit boom episodes, i.e., periods of particularly fast-growing credit, this negative association is driven by the allocation component. In a subsequent step, we are able to determine that what drives this negative relationship are changes in the distribution of *employment growth rates* across sectors rather than changes in the distribution of *productivity growth rates* across sectors. Shifts in the allocation of labor into low productivity growth sectors therefore account for weaker aggregate labor productivity growth during credit booms. Our results are robust to a number of checks, including for reverse causation, and are economically significant: an increase of 10 percentage points in the credit-to-GDP ratio over a period of five years is found to dampen labor productivity growth by between 0.8 and 1.4 percentage points, or approximately between 0.15 and 0.30 percentage point per year.

In the second exercise, we exploit the fact that the allocation component reflects the sensitivity of sector-level employment growth to labor productivity growth. If credit booms reduce the allocation component, then they should also weaken the link between employment growth and productivity growth at the sector level. We therefore regress sector-level growth in employment on sector-level growth in productivity, and interact the latter with measures of credit growth. We find that an increase in the growth rate of the credit to GDP ratio reduces employment creation in sectors with higher productivity growth. Furthermore, consistent with the country-level

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across sectors. In practice, however, the data show that changes in the allocation component are essentially driven by changes in the distribution of labor across sectors. That is why we use this shortcut, stating that the allocation component measures the impact of labor reallocations across industries.

[3]One reason for the absence of a statistically significant relationship between credit booms and the common component of labor productivity growth could be as follows. On the one hand, credit booms allow firms to invest more, which should raise labor productivity growth given that capital and labor tend to be complements. On the other hand, credit booms usually coincide with more employment creation, which reduces labor productivity at the margin.

evidence, we find that the effect is non-linear: only above-sample median growth in credit to GDP is found to significantly affect labor reallocation, confirming that only credit booms matter.

Our empirical findings are consistent with several non-mutually exclusive economic hypotheses. One is that firms' ability to borrow may be lower in relatively higher-productivity growth sectors. For example, it could be that the collateral provided by firms characterized by high productivity growth (e.g., those in the most innovative sectors) could be particularly difficult to assess. As a result, a change in aggregate credit supply, e.g., a drop in the cost of capital, would have relatively muted effects on their ability to borrow. By contrast, firms characterized by lower productivity growth may operate in sectors in which collateral is easier to evaluate, for example, because they use more standard technologies and/or more tangible capital. If so, a drop in the cost of capital may translate into a proportionally greater ability to borrow. The possibility of borrowing more and hence increasing financial leverage may, in turn, make investing in low productivity growth sectors more profitable despite their lower return on assets. Section 5 provides a simple model that formalizes this intuition. In addition, alternative, complementary mechanisms may also operate on the demand side. For example, a credit expansion may not only induce households to consume more as a share of their income, but could also shift the composition of their consumption basket towards goods and services produced in low-productivity growth sectors, such as housing and non-tradable services.

Our work is related to two strands of the literature on (re)allocation and productivity. The first quantifies labor reallocation over the business cycle and shows that it matters for productivity growth. In particular, several studies find that labor reallocation during recessions improves productivity by causing resources to move from less to more efficient producers (e.g., Baily, Bartelsman, and Haltiwanger 2001; Caballero and Hammour 1994, 1996; Hall 2000; and Mortensen and Pissarides 1994). However, more recent work has also found that recessions can also have scarring effects, which could mitigate or even dominate its cleansing effects.[4] In

[4]Indeed, firms exiting tend to be disproportionately young, and not all firms exiting have low productivity (e.g., Baden-Fuller 1989, Dunne, Roberts, and Samuelson 1989, Eslava et al. 2015). This could be either because labor market matching tends to become less efficient (Barlevy 2002), or because credit

common with this literature, our paper too looks at the effects of labor reallocation on productivity growth. However, our focus is not on how reallocation and productivity growth vary over the business cycle, but on how they vary during credit booms. In addition, we focus on reallocation across sectors rather than misallocation within sectors. Finally, our focus on credit booms might be a reason why we find significant reallocation across sectors while the literature argues, based on U.S. firm-level data, that a large part of reallocation reflects within sector reallocation (Foster, Haltiwanger, and Krizan 2001).

A second strand of the literature quantifies resource misallocation and the extent to which it can explain cross-country differences in per capita income (Banerjee and Duflo 2005; Buera, Kaboski, and Shin 2011; Hsieh and Klenow 2009; Midrigan and Xu 2014; and Restuccia and Rogerson 2008).[5] Gopinath et al. (2017) extend this literature to show how misallocation is influenced by credit and financial factors.[6] They find that since the onset of the European Monetary Union, the within-sector dispersion of capital returns had been increasing and total factor productivity (TFP) growth falling in several Southern European countries, a development they relate to the increased availability of cheap capital.[7] Consistent with these findings, Cette, Fernald, and Mojon (2016) argue that the fall in the real interest rate favored resource reallocation that was detrimental to productivity growth in Italy and Spain. Another related paper is Mueller and Verner (2021), which shows that credit to households and the non-tradable sector contributes to deepening macroeconomic boom-bust cycles and increased financial fragility.

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frictions worsen (Barlevy 2003) or for the ability to learn about idiosyncratic productivity declines during recessions (Ouyang 2009).

[5]See also the survey of Restuccia and Rogerson (2013).

[6]These empirical findings are closely related with recent analytical contributions. Reis (2013), for instance, argues that unproductive firms expand to the expense of productive ones when financial integration exceeds financial deepening. Gorton and Ordoñez (2020), in turn, build a model in which credit booms finance a greater share of declining quality investment projects, resulting in a gradual decline in TFP growth.

[7]Similar patterns for the euro area have been documented by Dias, Marques, and Richmond (2016). For a larger sample of high- and low-income countries, Benigno, Converse, and Fornaro (2015) show that a surge in capital inflows is normally associated with a shift in resources from trade to non-tradable sectors and a decline in TFP productivity growth.

In common with this literature, our paper is also concerned with the adverse implications of credit booms.[8] However, its contribution is to provide empirical estimates of how credit booms affect reallocation *across sectors* and productivity growth. Our paper also differs in at least two other respects from past empirical contributions. First, unlike Hsieh and Klenow (2009) and other studies mentioned above, it does not compute a measure of misallocation using a theoretical benchmark. Instead, it uses an identity to disentangle changes in labor productivity that are common across industries and those that are associated with changes in sectoral employment shares. Second, our empirical analysis focuses on industry-level rather than firm-level data. The focus on industry-level data is appropriate in that credit booms are likely to affect aggregate productivity growth not only by affecting the efficiency with which individual sectors produce their output, but also by affecting the sectoral composition of aggregate output and employment.

The paper is organized as follows. Section 2 describes how we decompose aggregate labor productivity growth into a common and an allocation component. Section 3 first investigates the relationship between credit booms and labor reallocation across sectors at the country level. Section 4 complements the country-level analysis by investigating the relationship between employment and productivity growth at the sector level and how aggregate credit growth affects this relationship. Section 5 proposes a simple model of credit and reallocation across sectors that focuses on differences in credit sensitivities across sectors as a possible mechanism for how credit booms affect productivity growth. Section 6 concludes.

2. Decomposing Labor Productivity Growth

2.1 Common and Allocation Components

We begin by defining the concept of labor reallocation we will be using throughout the paper. We rely on a simple identity to

[8] A large literature has also linked credit booms to financial crises (see, for instance, Schularick and Taylor 2012 and, for evidence on emerging market economies, Gourinchas, Valdes, and Landerretche 2001 and Mendoza and Terrones 2014). In this paper, we look at the relationship between credit booms and productivity growth, irrespective of the occurrence of financial crises.

decompose aggregate labor productivity growth. Let us write aggregate output y (aggregate employment l) as the sum of individual sectors output y_s (individual sectors employment l_s):

$$y = \sum_s y_s \text{ and } l = \sum_s l_s. \tag{1}$$

Assuming the economy is made up of S different sectors and denoting $\overline{x}$ the unweighted average for variable x_s across all sectors ($\overline{y} = y/S$; $\overline{l} = l/S$), aggregate productivity y/l can be written as the sum of two terms:

$$\frac{y}{l} = \frac{1}{S}\sum_s \left(\frac{l_s}{l/S}\right) \cdot \left(\frac{y_s}{l_s}\right) = \overline{y_s/l_s} + cov\left(\frac{y_s}{l_s}; \frac{l_s}{\overline{l}}\right). \tag{2}$$

The first term represents unweighted average productivity computed across all sectors in the economy, while the second term measures whether sectors with high productivity also account for a large share in total employment. When this is the case, the covariance is positive and aggregate productivity y/l is higher than the unconditional average sector-level productivity $\overline{y_s/l_s}$.

Building on the decomposition in expression (2) and denoting sector s relative output size as $\omega_s = y_s/\overline{y}$, the growth rate of aggregate labor productivity can be written as follows:

$$1 + \frac{\Delta(y/l)}{y/l} = \frac{1}{S}\sum_s \left(1 + \frac{\Delta(l_s/l)}{l_s/l}\right) \cdot \left(1 + \frac{\Delta(y_s/l_s)}{(y_s/l_s)}\right) \cdot \omega_s.$$

Then using the property $\overline{\omega_s} = 1$, the growth rate of aggregate real labor productivity can be written as the sum of two terms:

$$\begin{aligned} 1 + \frac{\Delta(y/l)}{y/l} &= \underbrace{\left[1 + \overline{\frac{\Delta(l_s/l)}{l_s/l}}\right]\left[1 + \overline{\frac{\Delta(y_s/l_s)}{y_s/l_s}\omega_s}\right]}_{\text{common component}} \\ &\quad + \underbrace{cov\left(\frac{\Delta(l_s/l)}{l_s/l}; \left(1 + \frac{\Delta(y_s/l_s)}{y_s/l_s}\right)\omega_s\right)}_{\text{allocation component}}. \end{aligned} \tag{3}$$

The first term on the right-hand side, named common component of labor productivity growth (henceforth *com*), is the product of

Table 1. A Simple Example of Productivity Growth Decomposition

Sector	Employment Growth		Productivity Growth		Aggregate Productivity Growth	Emp./Prod. Growth Correlation
	A	B	A	B		A and B
Scenario 1	0	0	–10	+10	0	0
Scenario 2	–10	+10	–10	+10	+1	+1
Scenario 3	+10	–10	–10	+10	–1	–1

the average growth rate in sector-level employment shares and the size-weighted average growth rate of labor productivity across sectors. The second term on the right-hand side, named allocation component of labor productivity growth (henceforth *alloc*), is the covariance across sectors between the growth rate of sector-level employment shares and the sector-level size-weighted labor productivity growth. For a given distribution of sector sizes ω_s, it measures whether labor is reallocated towards high or low productivity growth sectors.

To illustrate this decomposition, consider a hypothetical economy made up of two sectors, A and B, of equal output and equal employment size facing three different scenarios. All three scenarios assume that aggregate employment is constant and productivity grows by 10 percent in sector B but drops by 10 percent in sector A. They differ only with respect to the assumed sectoral employment growth rates: in scenario 1, employment is constant in both sector A and sector B; in scenario 2, employment grows by 10 percent in sector B, where productivity growth is positive, but drops by 10 percent in sector A, where productivity growth is negative; finally, in scenario 3, the opposite is true: employment grows by 10 percent in sector A but drops by 10 percent in sector B.

The scenarios have different implications for productivity growth. In scenario 1, employment is constant in both sectors, so aggregate productivity growth is the simple average productivity growth across sectors, which is zero. By contrast, in scenario 2, employment grows in the sector enjoying a productivity gain and drops in the sector facing a productivity loss. Thus, aggregate productivity goes up.

Finally, in scenario 3, the opposite holds: employment grows in the sector suffering a productivity loss and drops in the sector enjoying a productivity gain. This results in negative aggregate productivity growth. In these three scenarios, by construction, the common component as defined in decomposition (3) is equal to zero, since both average employment growth and average productivity growth across sectors are zero. Aggregate productivity growth is therefore equal to the allocation component. This, in turn, is equal to the covariance across sectors between employment and productivity growth, consistent with decomposition (3). We now turn to quantifying each of the terms in decomposition (3) based on the available data.

2.2 The Data

We rely on three different sources of industry-level data: the OECD-STAN database, the EU-KLEMS database, and the GGDC 10-sector database. These three data sets provide information on value-added and employment at the sector level following the International Standard Industrial Classification (ISIC) 3 Rev. 1 classification. Overall, we consider nine different sectors: Agriculture (A and B), Mining (C), Manufacturing (D), Utilities (E), Construction (F), Trade Services (G and H), Transport Services (I), Finance, Insurance and Real Estate Services (J and K), and Government and Personal Services (L to Q). To build our data set, we require for each country/year pair that industry-level output and employment sum up to the economy-wide aggregates. This limits the number of countries and years that can be included in the analysis.[9] We end up with an unbalanced sample covering 21 countries starting in 1979 and ending in 2009.[10]

[9]In this paper we focus on *net* changes in sector-level employment, without separating employment destruction from employment creation. Another difference from the literature is that we focus on employment or persons employed as opposed to jobs. As a result, we are probably underestimating the extent of labor reallocation in the economy. For example, Davis and Haltiwanger (1992) estimate that each year around 20 percent of jobs are either created or destroyed in U.S. manufacturing. By contrast, our net employment change represents a few percentage points of total employment in our sample.

[10]The countries included in the sample are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States. The start and end dates (1979 and

Following previous notation, using decomposition (3), aggregate real labor productivity growth $(LP)_{c,t}^{n}$ in country c between year t and year $t+n$ can be written as

$$\frac{y_{c,t+n}/l_{c,t+n}}{y_{c,t}/l_{c,t}} = (LP)_{c,t}^{n} = (com)_{c,t}^{n} + (alloc)_{c,t}^{n}. \tag{4}$$

On the right-hand side, (com) represents the common component of productivity growth and $(alloc)$ represents the allocation component as defined in decomposition (3). To compute the various growth measures we consider non-overlapping periods of either three or five years. This is because reallocations must surely take considerable time, especially across industries as widely defined as those considered here.[11] Shorter periods, of, say, one or two years, could mask the "true" extent of the reallocations. Using five-year windows yields 120 observations and three-year windows 182 observations.

2.3 A First Glance at the Data

Table 2 provides summary statistics—pooling all the data—for aggregate real labor productivity growth, i.e., the left-hand side of expression (3), and for its common and allocation components, i.e., respectively, the first and second terms on the right-hand side of expression (3). The first three columns of Table 2 provide summary statistics using five-year windows and the last three using three-year windows.

Over a five-year interval, real labor productivity grows on average 8.6 percent, i.e., around 1.6–1.7 percent per year. On average, the common component represents around 5.4 percentage points (or

2009) were chosen mainly because of constraints on the availability of consistent industry data. Unfortunately, the industrial classification of the data changed in 2009, which precludes an extension to more recent years.

[11]Blanchard and Katz (1992) consider the effect of state-specific shocks to labor demand across U.S. states. According to their estimates, it can take up to seven years for their effects on state unemployment and participation to disappear. More recently, based on longitudinal data, Walker (2013) estimates the transitional costs associated with reallocating workers in the wake of new environmental regulations. His results suggest that these costs are significant: the average worker in a regulated sector experienced a total earnings loss equivalent to 20 percent of their pre-regulatory earnings, with almost all of the estimated earnings losses driven by workers who separate from their firm.

Table 2. Summary Statistics

	Productivity Growth	Allocation Component	Common Component	Productivity Growth	Allocation Component	Common Component
	Five-Year Growth			Three-Year Growth		
Average	8.61	3.24	5.37	5.25	1.87	3.38
Median	8.23	3.21	4.45	5.11	1.98	2.72
Standard Deviation	6.27	2.76	6.69	4.51	2.10	4.93
Standard Deviation (Within)	4.74	2.41	4.75	3.64	1.97	3.94
Observations	120	120	120	182	182	182

Source: Author's calculations.

just under two-thirds) and the allocation component the remaining 3.2 percentage points of the total. The figures based on three-year windows are similar: aggregate real labor productivity grows by 1.7 percent per year on average, with the common component representing two-thirds of the total.

The volatility (standard deviation) of the allocation component accounts for 45 to 55 percent of the volatility of aggregate productivity growth, depending on the window length. The common component is roughly as volatile as aggregate productivity growth, implying a negative covariance with the allocation component. This means that changes in the common component are systematically associated with opposite, but smaller, changes in the allocation component. For example, an economy-wide shock that raises productivity growth uniformly across all sectors tends to be partly offset by labor reallocations towards those with lower productivity growth.

Table 3 provides the correlation matrix for aggregate productivity growth and the two components, focusing on within-country correlations. Correlations in the upper left matrix are computed using five-year windows; those in the lower right matrix using three-year ones. The matrix shows that aggregate productivity and its allocation component co-move positively and the relationship is statistically significant. Labor reallocations towards high (low) productivity growth sectors therefore tend to come hand-in-hand with stronger (weaker) aggregate productivity growth.

3. Country-Level Evidence

3.1 Credit Expansions on the Components of Productivity Growth

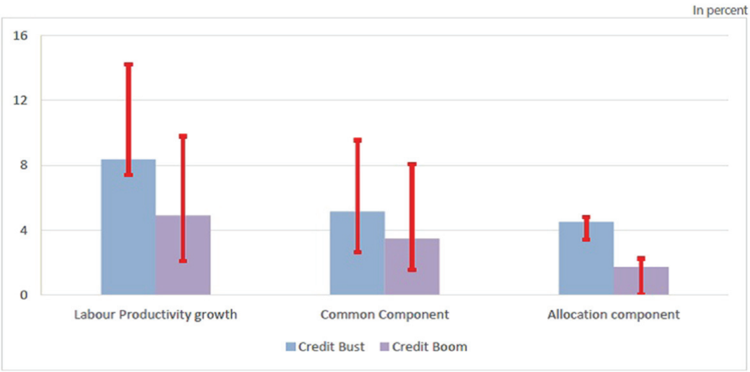
How do the two components of productivity growth behave as a credit boom develops? Put simply, we find that credit booms are associated with lower productivity growth and that this works through the allocation component. By contrast, we do not find any a statistically significant link between credit booms and the common component. This basic result emerges already quite clearly from a few simple exercises, which we detail below, and survives increasingly demanding tests.

Table 3. Correlation Matrix

		Productivity Growth	Allocation Component	Common Component	Productivity Growth	Allocation Component	Common Component
		Five-Year Growth			Three-Year Growth		
Productivity Growth	Five-Year Growth Rates	1					
Allocation Component		0.248***	1				
Common Component		0.871***	–0.260***	1			
Productivity Growth	Three-Year Growth Rates				1		
Allocation Component					0.222***	1	
Common Component					0.865***	–0.298***	1

Source: Author's calculations.

Figure 1. Productivity Growth, Credit Booms, and Credit Busts, Computed over Five-Year Windows



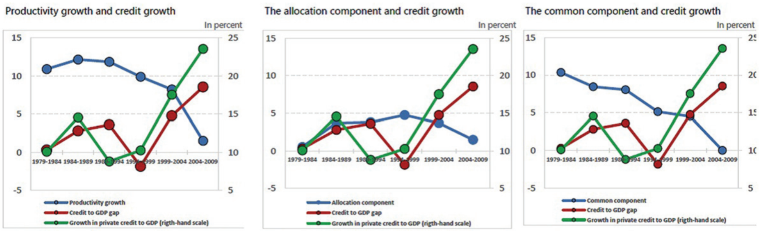
Note: Blue bars represent the cross-country median for each variable reported in the legend, considering for each country the five-year period with the lowest credit-to-GDP growth. Purple bars represent the cross-country median for each variable reported in the legend, considering for each country the five-year period with the highest credit-to-GDP growth. Vertical red lines show the first and the third quartile of the cross-country distribution. The sample includes 21 economies (Australia, Austria, Belgium, Canada, Finland, France, Germany, Greece, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States) and six periods of five years (1979–84, 1984–89, 1989–94, 1994–99, 1999–2004, 2004–09).

Let us start by comparing productivity growth and its components during periods of high credit growth and periods of low credit growth. To do so, we consider for each country the five-year periods with the highest and lowest growth rates in the private sector credit-to-GDP ratio, which we label as credit booms and credit busts, respectively, in Figure 1.[12] Figure 1 shows that median labor productivity growth is typically lower during credit booms than credit busts.

Moreover, this difference is due to the common and the allocation components, which are both lower during credit booms. Yet only the allocation component tends to be significantly lower during credit booms relative to credit busts, as differences in interquartile ranges show.

[12]All credit-related data used in this paper are drawn from the Bank for International Settlements (BIS) database on credit to the non-financial private sector.

Figure 2. Credit Booms, Productivity Growth, and Its Components over Time: Computed Average across Countries over the Five-Year Windows

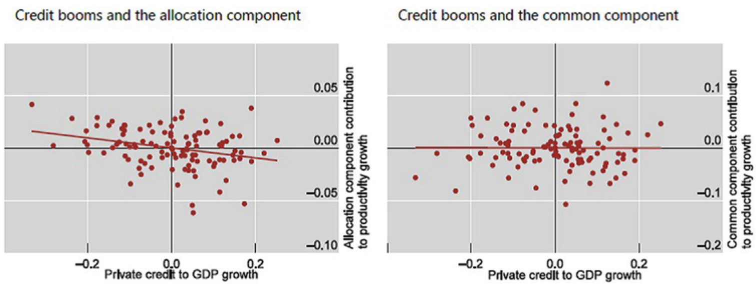


Note: The left-hand panel plots the growth rate in private credit to GDP against the allocation component of labor productivity growth, both variables being taken as deviations from country and period means. The right-hand panel plots the growth rate of private credit to GDP against the common component of labor productivity growth, both variables being taken as deviations from country and period means. The sample includes 21 economies (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States) and six periods of five years (1979–84, 1984–89, 1989–94, 1994–99, 1999–2004, 2004–09).

Next, we take look at the time pattern of labor productivity growth and its components. Considering cross-country averages, Figure 2 shows that the negative correlation between credit growth and labor productivity growth over time is accounted for by the beginning (1984–89) and the end of the sample (2004–09). In both cases, credit growth increases relative to the previous period, while labor productivity growth and its components fall (relative to the previous period). In addition, the common component is subject to a large secular decline, from 10 percent over 1979–84 (i.e., about 2 percent a year) to roughly zero over 2004–09. It therefore remains to be seen how credit growth and the common component of productivity growth correlate once the data are filtered for secular trends.

Figure 3 goes some way in answering this question. It plots the allocation components (left-hand panel) and the common component (right-hand panel), respectively, against the growth rate in the ratio of private credit to GDP (shown on the x-axes) focusing on deviations from country and time averages. The figure traces a negative and statistically significant relationship between credit growth

Figure 3. Financial Booms and Productivity Growth Components, Computed over Five-Year Windows and Taken as Deviations from Country and Period Means



Note: The left-hand panel plots the growth rate in private credit to GDP against the allocation component of labor productivity growth, both variables being taken as deviations from country and period means. The right-hand panel plots the growth rate of private credit to GDP against the common component of labor productivity growth, both variables being taken as deviations from country and period means. The sample includes 21 economies (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States) and six periods of five years (1979–84, 1984–89, 1989–94, 1994–99, 1999–2004, 2004–09).

and the allocation component. By contrast, no such relationship emerges for the common component. To give a sense of the economic magnitudes involved, a one-standard-deviation increase in the growth rate of private credit to GDP (about 3 percentage points per year) is associated with a yearly 0.13 percentage point cut in aggregate productivity growth through the reduction of the allocation component.

To test whether these correlations survive a more rigorous econometric analysis, we estimate the following three regressions:

$$\begin{aligned}(LP)^n_{c,t} &= \alpha_c + \alpha_t + \beta x_{c,t} + \beta_l L^n_{c,t} + \theta F^n_{c,t} + \varepsilon_{c,t}\\ (com)^n_{c,t} &= \alpha_{1,c} + \alpha_{1,t} + \beta_1 x_{c,t} + \beta_{1,l} L^n_{c,t} + \theta_1 F^n_{c,t} + \varepsilon_{c,t}\\ (alloc)^n_{c,t} &= \alpha_{2,c} + \alpha_{2,t} + \beta_2 x_{c,t} + \beta_{2,l} L^n_{c,t} + \theta_2 F^n_{c,t} + \varepsilon_{c,t}.\end{aligned} \tag{5}$$

Here, $(LP)^n_{c,t}$ stands for the growth rate of labor productivity in country c between year t and $t+n$, and $(alloc)^n_{c,t}$ and $(com)^n_{c,t}$ for the corresponding allocation and common components, respectively.

The independent variables include a set of country and time dummies ($\alpha_c; \alpha_t$) as well as a vector of (pre-determined) control variables $x_{c,t}$.[13] The growth rate of employment in country c between year t and $t+n$ is denoted by $L^n_{c,t}$, while $F^n_{c,t}$ is a variable measuring the intensity of the credit boom in country c between year t and $t+n$. Finally, ε's are residuals.[14] We estimate regressions (5) using the two different window lengths, three and five years, and two different measures of credit booms, the rate of growth in the ratio of private credit to GDP (our benchmark measure) and the deviation of the same ratio from its long-term trend (the "credit gap").[15]

In the baseline regressions, the vector x of controls includes the following variables: (i) the ratio of credit to GDP; (ii) government size, measured as the ratio of government consumption to GDP; (iii) CPI inflation; (iv) openness to trade, measured as the ratio of imports plus exports to GDP; (v) a dummy for the occurrence of a financial crisis; and (vi) the log of the initial level of output per worker. These data are all from the OECD Economic Outlook database, except the data on financial crises, which are from Laeven and Valencia (2013).

The choice of control variables deserves some explanation. Controlling for credit in relation to GDP helps disentangling the effect of the level of credit to GDP from the effect of growth in credit to GDP. On the one hand, easier credit access may have a positive impact on productivity growth through easier financing of innovation and R&D spending (Aghion et al. 2019). On the other hand, if, say, the credit-to-GDP ratio grows more slowly when the level of the credit to GDP is higher, then a negative correlation between our measure of credit booms and productivity growth could simply reflect the previously mentioned positive effect of a higher credit-to-GDP ratio. We include

[13]Note that including country fixed effects ensures we focus on within-country credit booms, while including time fixed effects ensures we focus on country-specific credit booms and filter out global ones.

[14]Aggregate employment growth controls for the cyclical position of the economy. When the economy expands, productivity growth may fall simply because the marginal worker is less productive. During those expansions, credit may also increase faster. Thus controlling for the cyclical position ensures that the credit variable does not spuriously capture this effect.

[15]Data on the credit gap are from Borio and Drehman (2009). Moreover, for the sake of brevity, we only report estimations using five-year windows. Estimations using three-year windows are available upon request.

government expenditures because credit booms boost tax revenues, allowing the government to increase its spending and employment. If the government sector exhibits low productivity growth, the negative correlation identified above might just be capturing changes in its size. The addition of inflation reflects the well-known view that inflation can lead to misallocation by introducing noise in the signals agents receive about relative prices (Lucas 1975). If credit booms coincide with higher inflation, then we may just be picking up this effect. Trade openness should be expected to boost productivity gains across sectors, including through reallocations towards sectors enjoying some comparative advantage. The financial crises variable may pick up output losses from crises, which tend to be preceded by credit booms.

The regression results using the growth rate in private credit to GDP as a measure of credit booms fully confirm the preliminary bivariate tests (Table 4). Based on five-year windows, growth in private credit to GDP is negatively correlated with aggregate productivity growth, with a magnitude similar to the one found in the simple bivariate test. The result appears to be entirely driven by a strong and statistically highly significant relationship with the allocation component (column 3A); there is no significant relationship between credit growth and the common component. The conclusions are very similar if we use credit-to-GDP gaps as a proxy for credit booms, albeit with some qualifications. Labor productivity growth correlates negatively with the average deviation of the credit-to-GDP ratio from its trend (column 1B) and this negative correlation is still driven by the allocation component (column 3B), even if this correlation is statistically weaker.[16]

Turning to the control variables, some interesting patterns emerge. There is little evidence of a financial deepening effect: the level of private credit to GDP does not seem to matter for aggregate productivity growth nor for its two components. Employment

[16]The results using a three-year window are very similar, except that now there is some evidence of a statistically significant link also with the common component, albeit only at the 10 percent level. Possibly, over the shorter window, credit booms boost demand across all sectors, leading to a generalized increase in employment which leads to a productivity slowdown. But as the credit boom proceeds, the incidence across sectors becomes more differentiated so that the average effect fades out while labor reallocations keep taking place.

Table 4. Credit Booms, Productivity Growth, and Its Components

	(1A)	(2A)	(3A)	(1B)	(2B)	(3B)
	Productivity Growth	**Allocation Component**	**Common Component**	**Productivity Growth**	**Allocation Component**	**Common Component**
Credit Boom Variable	**–0.077****	**–0.032**	**–0.045*****	**–0.0729*****	**–0.0318**	**–0.0412***
	(0.0370)	*(0.0399)*	*(0.0170)*	*(0.0131)*	*(0.0549)*	*(0.0228)*
Initial Private Credit to GDP	0.023	0.026	–0.003	0.0588	0.0403	0.0186
	(0.0347)	*(0.0415)*	*(0.0216)*	*(0.0488)*	*(0.0396)*	*(0.0187)*
Employment Growth	–0.372***	–0.514***	0.142**	–0.409***	–0.529***	0.120**
	(0.0796)	*(0.0931)*	*(0.0575)*	*(0.0665)*	*(0.0935)*	*(0.0579)*
Government Consumption to GDP	–0.674*	–0.705*	0.031	–0.587	–0.671	0.836
	(0.344)	*(0.412)*	*(0.224)*	*(0.338)*	*(0.412)*	*(0.223)*
CPI Inflation	–0.075	0.125	–0.199*	–0.141	0.0958	–0.237**
	(0.165)	*(0.219)*	*(0.108)*	*(0.0741)*	*(0.216)*	*(0.116)*
Openness to Trade	0.096	0.154*	–0.058	0.107	0.158**	–0.0510
	(0.0732)	*(0.0795)*	*(0.0466)*	*(0.0551)*	*(0.0777)*	*(0.0475)*
Dummy for Financial Crisis	–0.013	–0.022	0.009	–0.0164	–0.0229	0.0065
	(0.0118)	*(0.0142)*	*(0.00708)*	*(0.0209)*	*(0.0145)*	*(0.00728)*
Initial GDP per Person Employed (log of)	–0.271***	–0.222***	–0.049	–0.270***	–0.222***	–0.0480
	(0.0443)	*(0.0607)*	*(0.0407)*	*(0.0251)*	*(0.0618)*	*(0.0411)*
Observations	108	108	108	108	108	108
R-squared	0.864	0.854	0.695	0.858	0.854	0.681

Note: This table reports the estimated coefficient for independent variables reported in the first column, the dependent variable being aggregate productivity growth (columns 1A and 1B), the allocation component (columns 2A and 2B), and the common component (columns 3A and 3B). Credit boom variable in columns 1A–3A is private-credit-to-GDP growth and average private-credit-to-GDP gap in columns 1B–3B. Growth rates and averages computed using five-year windows. Estimation period: 1979–2009. All estimations include country and time fixed effects. Robust standard errors are in parentheses. Statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively, is indicated with ***, **, and *.

growth tends to coincide with lower aggregate productivity growth even as it goes hand-in-hand with productivity-enhancing reallocations, with the negative impact on the common component dominating. And we can discard the view that labor reallocations are driven by changes in government expenditures. Government consumption does appear to dampen productivity growth, although the relationship is only weakly statistically significant, but this works through the common rather than the allocation component.[17] The role of CPI inflation is consistent with priors: inflation correlates negatively and significantly with the allocation component of productivity growth, although there is no statistically significant relationship with productivity growth as a whole. Also as expected, trade openness co-varies positively with the common component of productivity growth, even if, as in the case of inflation, there is no statistically significant link with labor productivity growth as a whole. Finally, financial crises do not appear to affect productivity growth nor any of its components in a statistically significant way.[18]

The regressions also shed light on the so-called catch-up effect, i.e., the tendency for productivity growth to converge across countries. They indicate that the effect reflects almost exclusively the operation of the common component, since the correlation between the initial productivity level and the allocation component is not statistically significant. This implies that the allocation component is relatively more important in economies with higher productivity levels, because overall productivity growth will generally be lower there. If so, credit booms are likely to be more costly in advanced economies.

3.2 Some Robustness Checks

The negative correlation between credit expansions and the allocation component of productivity growth could reflect several specific features of our data. As noted above, one possibility could be that the

[17]This hypothesis can be formally tested by computing productivity growth and its components, excluding the government sector. See Table 5 in section 3.2.

[18]This last result may sound surprising, but it is important to remember that the inclusion of employment growth controls for the cyclical position of the economy and captures the depressing effect of financial crises on productivity growth.

period prior to the Global Financial Crisis (GFC) drives the negative association, as this period saw a significant increase in credit growth and decrease in labor productivity growth. Another could be that countries or periods which saw large credit booms, e.g., Spain or the United States in the run-up to the Global Financial Crisis, are driving the negative correlation. Finally, periods of high credit growth could essentially be favorable times for non-market activities—e.g., the government sector—to grow disproportionately faster, which could indeed account for the negative correlation between growth in credit and (the allocation component of) labor productivity growth.

The first three columns in Table 5 show that labor productivity growth still correlates negatively with credit-to-GDP growth when the period prior to the GFC, i.e., 2004–09, is removed from the sample estimation. In addition, the allocation component of productivity growth still drives the negative association between credit and productivity growth when the sample estimation ends in 2004, and estimated coefficients seem slightly larger, i.e., more negative, when the period 2004–09 is removed. Second, large credit boom periods do not appear to be driving the negative correlation between growth in credit and growth in productivity (see column 1B). However, they seem to account for the negative association between credit growth and the allocation component of productivity growth (see column 3B), as the correlation is statistically significant only when credit growth is above the sample median. In the alternative case, the negative correlation rather comes from the common component of productivity growth (column 2B) even if it is not statistically significant. Last, running the estimations on truncated economies, where the government sector is excluded—from the computation of the common and allocation components of productivity growth—bears little consequence for our results, except that the negative association between credit and productivity growth seems to be equally driven by a drop in the common and allocation components of productivity growth (columns 1C–3C).

3.3 Investigating Potential Mechanisms

What economic mechanisms could account for the negative correlation between credit growth and the allocation component of productivity growth? To provide answers to this (difficult) question, let us

Table 5. Credit, Productivity, and Its Components: Some Robustness Checks

	(1A)	(2A)	(3A)	(1B)	(2B)	(3B)	(1C)	(2C)	(3C)
	Total	Common	Allocation	Total	Common	Allocation	Total	Common	Allocation
	Removing GFC Period			Allowing for Non-linearities			Removing Government Sector		
Growth in Private Credit to GDP	**–0.101***	**–0.048**	**–0.053*****				**–0.107****	**–0.058****	**–0.050****
	(0.051)	*(0.054)*	*(0.016)*				*(0.043)*	*(0.045)*	*(0.020)*
Growth in Private Credit to GDP Below Sample Median				**–0.093**	**–0.072**	**–0.021**			
				(0.074)	*(0.080)*	*(0.033)*			
Growth in Private Credit to GDP Above Sample Median				**–0.074****	**–0.024**	**–0.050*****			
				(0.037)	*(0.040)*	*(0.018)*			
Employment Growth	–0.365***	–0.481***	0.116**	–0.479***	–0.550***	0.071	–0.425***	–0.670***	0.245***
	(0.079)	*(0.098)*	*(0.058)*	*(0.074)*	*(0.097)*	*(0.057)*	*(0.085)*	*(0.100)*	*(0.058)*
Dummy for Financial Crisis	–0.019	–0.028*	0.009	0.002	0.002	–0.001	–0.012	–0.022	0.010
	(0.014)	*(0.015)*	*(0.006)*	*(0.011)*	*(0.015)*	*(0.007)*	*(0.014)*	*(0.017)*	*(0.009)*
Initial Private Credit to GDP	–0.014	0.011	–0.025	0.043	0.047	–0.005	0.0179	0.0180	–0.000
	(0.049)	*(0.060)*	*(0.027)*	*(0.033)*	*(0.038)*	*(0.025)*	*(0.044)*	*(0.050)*	*(0.024)*
Government Consumption to GDP	–0.725*	–0.676	–0.049	–0.234	–0.553	0.319	–0.244	–0.263	0.019
	(0.391)	*(0.454)*	*(0.224)*	*(0.364)*	*(0.530)*	*(0.320)*	*(0.425)*	*(0.483)*	*(0.268)*
Openness to Trade	0.049	0.086	–0.037	0.142**	0.166**	–0.024	0.060	0.119	–0.059
	(0.087)	*(0.077)*	*(0.054)*	*(0.056)*	*(0.095)*	*(0.062)*	*(0.103)*	*(0.105)*	*(0.054)*
CPI Inflation	–0.045	0.139	–0.184*	–0.294*	–0.377	–0.083	–0.131	0.0356	–0.167
	(0.173)	*(0.215)*	*(0.104)*	*(0.172)*	*(0.234)*	*(0.125)*	*(0.179)*	*(0.229)*	*(0.124)*
Initial GDP per Person Employed (log of)	–0.268***	–0.299***	–0.031	–0.062	–0.002	–0.059	–0.251***	–0.201***	–0.045
	(0.075)	*(0.083)*	*(0.04)*	*(0.067)*	*(0.082)*	*(0.045)*	*(0.056)*	*(0.083)*	*(0.049)*
Observations	92	92	92	70	70	70	108	108	108
R-squared	0.840	0.848	0.707	0.889	0.847	0.692	0.838	0.848	0.747

Note: This table reports the estimated coefficient for independent variables reported in the first column, the dependent variable being aggregate productivity growth (columns 1A, 1B, and 1C), the common component (columns 2A, 2B, and 2C), and the allocation component (columns 3A, 3B, and 3C). Growth in Private Credit to GDP Above (Below) Sample Median is equal to Growth in Private Credit to GDP when above (below) the sample median and 0 otherwise. Growth rates computed using five-year windows. Estimation period: 1979–2009. All estimations include country and time fixed effects. Robust standard errors are in parentheses. Statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively, is indicated with ***, **, and *.

first note that the impact of credit growth may differ depending on credit growth volatility. For instance, in the run-up to a financial crisis, credit tends to grow very quickly but usually drops significantly after the crisis occurs (Schularick and Taylor 2012). As a result, credit growth may be associated with weak productivity growth, not because it reduces productivity growth per se, but because of the high volatility that comes with it. According to a second possibility, the negative correlation between productivity and credit growth could hold more specifically when the credit-to-GDP level is relatively low, as this would reflect the inability to allocate funds efficiently. The allocation component, in particular, could correlate negatively with credit growth but less so with higher credit-to-GDP levels. Last, to the extent allowed by the data, determining which type of credit, credit to households versus credit to firms, matters most for the negative association between credit and productivity growth could prove useful to understand whether the negative association between credit and productivity growth stems from demand factors (credit to households) or supply factors (credit to firms).

Estimation results in Table 6 show that the volatility of credit-to-GDP growth does not seem to play a significant role in the relationship between credit growth and productivity growth. Empirical estimates in columns 1A–3A are broadly unchanged relative to those obtained from the baseline specification, reported in columns 1A–3A of Table 4. Turning to the impact of the level of credit to GDP, estimation results in columns 1B–3B show that the interaction between credit-to-GDP growth and credit-to-GDP level is weakly significant. Consistent with the intuition developed above, the allocation component of productivity growth correlates negatively with credit-to-GDP growth but less so in countries with a higher credit-to-GDP level. Last, a breakdown of aggregate credit growth into credit to firms and credit to households indicates that household credit growth seems to correlate negatively with the allocation component, although this is by no means a strong negative association.

3.4 Decomposing the Allocation Component

The previous results highlight how labor reallocations during credit booms dampen productivity growth, but they are silent about the

Table 6. Credit, Productivity, and Its Components: Some Additional Checks

	(1A)	(2A)	(3A)	(1B)	(2B)	(3B)	(1C)	(2C)	(3C)
	Total	Common	Allocation	Total	Common	Allocation	Total	Common	Allocation
	Controlling for Volatility Growth in Credit			Interacting Credit Growth and Level			Separating Household from Corporate Credit		
Growth in Private Credit to GDP	**–0.075****	**–0.031**	**–0.045*****	**–0.165**	**–0.029**	**–0.136****			
	(0.037)	*(0.040)*	*(0.017)*	*(0.106)*	*(0.122)*	*(0.056)*			
Volatility of Growth in Private Credit to GDP	–0.326	0.282	0.044						
	(0.280)	*(0.339)*	*(0.163)*						
Growth in Private Credit to GDP × Initial Private-Credit-to-GDP Level				0.070	–0.002	0.073*			
				(0.088)	*(0.096)*	*(0.043)*			
Growth in Household Credit to GDP							**–0.024**	**0.011**	**–0.034***
							(0.029)	*(0.035)*	*(0.016)*
Employment Growth	–0.358***	–0.501***	0.143**	–0.370***	–0.514***	0.144**	–0.411***	–0.504***	0.092
	(0.082)	*(0.099)*	*(0.061)*	*(0.078)*	*(0.093)*	*(0.055)*	*(0.095)*	*(0.111)*	*(0.070)*
Dummy for Financial Crisis	–0.015	–0.023*	0.009	–0.012	–0.022	0.010	–0.020	–0.022	0.001
	(0.013)	*(0.015)*	*(0.007)*	*(0.011)*	*(0.014)*	*(0.007)*	*(0.014)*	*(0.016)*	*(0.007)*
Initial Private Credit to GDP	0.027	0.029	–0.002	0.009	0.026	–0.017	0.059	0.054	0.005
	(0.036)	*(0.043)*	*(0.022)*	*(0.039)*	*(0.046)*	*(0.023)*	*(0.041)*	*(0.050)*	*(0.025)*
Government Consumption to GDP	–0.706**	–0.733**	–0.027	–0.578	–0.708*	0.130	–0.832*	–0.700	–0.132
	(0.340)	*(0.413)*	*(0.225)*	*(0.348)*	*(0.409)*	*(0.219)*	*(0.461)*	*(0.542)*	*(0.280)*
Openness to Trade	0.092	0.150*	–0.058	0.092	0.154*	–0.061	0.202**	0.269**	–0.067
	(0.074)	*(0.082)*	*(0.047)*	*(0.072)*	*(0.080)*	*(0.046)*	*(0.085)*	*(0.103)*	*(0.058)*
CPI Inflation	–0.105	0.098	–0.204*	–0.026	0.123	–0.149	0.006	0.311	–0.305***
	(0.173)	*(0.215)*	*(0.104)*	*(0.172)*	*(0.234)*	*(0.125)*	*(0.198)*	*(0.224)*	*(0.105)*
Initial GDP per Person Employed (log of)	–0.272***	–0.223***	–0.049	–0.290***	–0.221	–0.069	–0.248***	–0.203***	–0.045
	(0.045)	*(0.062)*	*(0.041)*	*(0.044)*	*(0.064)*	*(0.046)*	*(0.054)*	*(0.071)*	*(0.055)*
Observations	108	108	108	108	108	108	92	92	92
R-squared	0.866	0.856	0.696	0.866	0.854	0.708	0.868	0.865	0.717

Note: This table reports the estimated coefficient for independent variables reported in the first column, the dependent variable being aggregate productivity growth (columns 1A, 1B, and 1C), the common component (columns 2A, 2B, and 2C), and the allocation component (columns 3A, 3B, and 3C). Growth in Private Credit to GDP × Initial Private-Credit-to-GDP Level is the product of the two variables. Growth rates and volatilities computed over five-year windows. All estimations include country and time fixed effects. Robust standard errors are in parentheses. Statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively, is indicated with ***, **, and *.

nature of the reallocations. Specifically, when the allocation component declines over time, is this because, for a given distribution of sectoral productivity growth, employment grows more rapidly in low productivity growth sectors ("employment driven")? Or is it because, for a given distribution of sectoral employment growth, productivity slows down in sectors with rapidly expanding employment ("productivity driven")? Put differently, do changes over time in the allocation component reflect changes in the distribution of employment across sectors (as our use of the term "labor reallocation" suggests) or changes in the distribution of productivity across sectors?

To isolate these channels, let $\overline{x_s}^t$ be the average over time of any variable x_s and $\underline{x_s} = x_s - \overline{x_s}^t$ the deviation from the average. The allocation component can then be written as the sum of four terms:

$$
\begin{aligned}
&cov\left(\frac{\Delta(l_s/l)}{l_s/l};\left(1+\frac{\Delta(y_s/l_s)}{y_s/l_s}\right)\omega_s\right)\\
&\quad = cov\left(\overline{\frac{\Delta(l_s/l)}{l_s/l}}^t;\overline{\left(1+\frac{\Delta(y_s/l_s)}{y_s/l_s}\right)\omega_s}^t\right)\\
&\quad + cov\left(\overline{\frac{\Delta(l_s/l)}{l_s/l}}^t;\underline{\left(1+\frac{\Delta(y_s/l_s)}{y_s/l_s}\right)\alpha_s}\right)\\
&\quad + cov\left(\underline{\frac{\Delta(l_s/l)}{l_s/l}};\overline{\left(1+\frac{\Delta(y_s/l_s)}{y_s/l_s}\right)\omega_s}^t\right)\\
&\quad + cov\left(\underline{\frac{\Delta(l_s/l)}{l_s/l}};\underline{\left(1+\frac{\Delta(y_s/l_s)}{y_s/l_s}\right)\alpha_s}\right). \qquad (6)
\end{aligned}
$$

The first term on the right-hand side, the covariance between average growth in sectoral employment shares and average growth in sectoral size-weighted productivity growth, varies only across countries and hence will be captured by the country fixed effects in the regressions. The second term, the covariance between average growth in sectoral employment shares and deviations of sectoral size-weighted productivity growth from averages, reflects the impact of changes in sector-level size-weighted productivity growth rates, holding changes in employment shares constant. We will call this second term the productivity-driven allocation component. The third term, the covariance between deviations of growth in sectoral employment shares from averages and sectoral size-weighted productivity growth, captures the impact of changes in employment shares, holding size-weighted sectoral productivity growth constant. We will call this third term the employment-driven allocation component. Finally, the fourth term, the covariance between deviations of sectoral growth in employment shares from their long-run averages and deviations of sectoral size-weighted productivity growth rates from their own long-run average, measures how the allocation component of productivity growth depends on both types of changes. We therefore call it the jointly driven allocation component.

We can now run the same regressions as (5) using as a dependent variable each of the right-hand side components of the variance decomposition (6). The decomposition shows that the decline in the allocation component during credit booms overwhelmingly reflects shifts in employment towards low productivity growth sectors (Table 7). Specifically, the negative correlation between growth in credit to GDP and the allocation component is explained almost exclusively by changes in industry-level employment growth rather than changes in size-weighted productivity growth across sectors.

In other words, credit booms do not reduce the growth rate of productivity of individual sectors but induce labor to shift into lower-productivity growth sectors. In other words, productivity in industries characterized by rapid long-run productivity growth does not grow any more slowly during credit booms, but these industries attract relatively fewer workers. Table 7 shows that more than 90 percent of the effect of credit booms reflects these shifts in employment shares.

Using the credit-to-GDP gap instead of growth in private credit to GDP as a measure of credit expansion provides very similar results. The negative correlation between credit expansions and the allocation component remains largely unchanged and still pertains to changes in the sectoral distribution of employment creation. The relative size of the effect is also very similar.

Table 7. Decomposing the Effect of Credit Booms on the Allocation Component

	(1A)	(2A)	(3A)	(4A)	(1B)	(2B)	(3B)	(4B)
	Allocation Component	**Productivity Driven**	**Employment Driven**	**Jointly Driven**	**Allocation Component**	**Productivity Driven**	**Employment Drive**	**Jointly Driven**
Credit Boom Variable	**–0.045*****	**0.002**	**–0.041*****	**–0.006**	**–0.041***	**0.006**	**–0.044****	**–0.004**
	(0.017)	*(0.007)*	*(0.016)*	*(0.005)*	*(0.023)*	*(0.008)*	*(0.021)*	*(0.007)*
Employment Growth	0.142**	–0.049**	0.190***	6.52e-05	0.120**	–0.049***	0.171***	–0.003
	(0.056)	*(0.019)*	*(0.054)*	*(0.013)*	*(0.058)*	*(0.018)*	*(0.054)*	*(0.014)*
Dummy for Financial Crisis	0.009	–0.003	0.0119*	–0.001	0.007	–0.003	0.011	–0.001
	(0.007)	*(0.002)*	*(0.007)*	*(0.001)*	*(0.007)*	*(0.002)*	*(0.007)*	*(0.001)*
Initial Private Credit to GDP	–0.003	0.021***	–0.024	0.000	0.019	0.021***	–0.006	0.003
	(0.022)	*(0.006)*	*(0.021)*	*(0.005)*	*(0.018)*	*(0.006)*	*(0.017)*	*(0.005)*
Government Consumption to GDP	0.031	–0.001	0.069	–0.037	0.084	0.003	0.110	–0.029
	(0.224)	*(0.089)*	*(0.211)*	*(0.059)*	*(0.223)*	*(0.087)*	*(0.209)*	*(0.057)*
Openness to Trade	–0.058	–0.002	–0.047	–0.009	–0.051	–0.002	–0.042	–0.008
	(0.047)	*(0.016)*	*(0.046)*	*(0.009)*	*(0.048)*	*(0.016)*	*(0.048)*	*(0.009)*
CPI Inflation	–0.199*	–0.162***	0.018	–0.055	–0.237**	–0.155***	–0.023	–0.059
	(0.108)	*(0.049)*	*(0.084)*	*(0.038)*	*(0.116)*	*(0.051)*	*(0.090)*	*(0.040)*
Initial GDP per Person Employed	–0.049	0.048***	–0.113***	0.015	–0.048	0.050***	–0.113***	0.016
(log of)	*(0.041)*	*(0.016)*	*(0.034)*	*(0.012)*	*(0.041)*	*(0.015)*	*(0.036)*	*(0.012)*
Observations	108	108	108	108	108	108	108	108
R-squared	0.695	0.852	0.653	0.692	0.681	0.853	0.644	0.687

Note: This table reports the estimated coefficient for independent variables reported in the first column, the dependent variable being the allocation component (columns 1A and 1B), the allocation component due to productivity shocks (columns 2A and 2B), the allocation component due to employment shocks (columns 3A and 3B), or the allocation component due to both productivity and employment shocks (columns 4A and 4B). Allocation component computed using decomposition (3); last three variables computed using decomposition (6). Credit boom variable in columns 1A–4A is private-credit-to-GDP growth and average private-credit-to-GDP gap in columns 1B–4B. Growth rates and averages computed using five-year windows. Estimation period: 1979–2009. All estimations include country and time fixed effects. Robust standard errors are in parentheses. Statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively, is indicated with ***, **, and *.

3.5 Causality

As a last robustness check, we investigate whether the evidence produced so far is simply a correlation or whether it could represent, even partly, some causality. But before we turn to the estimations designed to address this question, it is worth noting that the evidence produced so far does point, if anything, to causality running from credit expansions to productivity growth rather than the other way round.

Intuitively, reverse causality does not look plausible. It would imply that productivity slowdowns induce either financial intermediaries to supply more credit, or firms and households to demand more of it. True, in the very short term one could imagine, say, households borrowing more to shield their consumption in the face of an unexpected slowdown in productivity and hence income. But it is hard to imagine that such an effect would persist over the relatively long windows we are considering. Moreover, credit tends to be procyclical with respect to output. And since we control for cyclical conditions through employment growth, the response of credit to the real economy is already largely filtered out. Finally, it is hard to envisage that credit would systematically react to productivity slowdowns driven by labor reallocations but not to those driven by the common component.

A first statistical safeguard against reverse causality is that in regressions (5) all right-hand-side variables are pre-determined with respect to the dependent variable, i.e., they are measured at the beginning of the period. The exceptions are employment and credit growth, which are both measured over the same period.[19] Still, in order to lay to rest any residual doubts about the direction of causality even for these two variables, we instrument them. We do so with beginning-of-period values for the nominal long-term interest rate, the ratio of trade balance to GDP, the ratio of current account balance to GDP, as well as the level and change in the financial liberalization index constructed by Abiad, Detragiache, and Tressel

[19] It is also the case that the financial crisis dummy is measured over the same period as productivity growth. However, this variable turns out to have very little influence on the empirical results. We therefore take it out from the IV estimations to ensure all right-hand side variables, except those we instrument, are pre-determined.

(2010). In doing so, we follow Mian, Sufi and Verner (2017), who use spreads on mortgage loans as a predictor of credit to households.[20]

Table 8 provides estimation results using instrumental variables (IV). Credit-to-GDP growth is the proxy for credit booms in the first four columns, and average credit-to-GDP deviation from trend in the last four. As in previous tables, the common and the allocation components sum up to productivity growth and the dependent variable in estimations in 4A and 4B is the part of the allocation component due to shocks to the sectoral distribution of employment, following the variance decomposition presented in Section 3.2.

Estimation results confirm our previous findings. Indeed, the results become even sharper. The estimated coefficient becomes larger in absolute value, suggesting that the OLS estimates may underestimate the effect of credit booms on productivity growth. For example, according to the OLS estimates, a 10 percentage point increase in growth in private credit to GDP over five years reduces productivity growth by 0.8 percent over the same period. But according to the IV estimates, the slowdown in productivity is closer to 1.4 percentage points over five years, which amounts to dampening productivity growth by 0.25–0.30 percentage points per year. In addition, consistent with OLS results, IV estimates confirms that roughly 60 percent of the effect of credit booms on productivity growth reflects labor reallocations across sectors. In other words, labor reallocation is quantitatively the main channel through which credit booms affect productivity. Moreover, these results hold relatively unaltered if credit booms are measured with the credit gap.

4. Sector-Level Evidence

4.1 Econometric Specification

To confirm the findings of the country-level analysis, we can adopt an alternative econometric approach that directly exploits the sector-level dimension of the data. To see this, recall that the allocation

[20] As in Mian, Sufi and Verner (2017), we also face the issue that low interest rates (or interest rate spreads) may reflect improved fundamentals and hence be conducive of higher output and higher productivity growth. But this possibility implies that estimates using interest rates as instrumental variables would tend to under-estimate the negative effect of credit booms on productivity growth.

Table 8. Instrumenting Credit Booms and Employment Growth

	(1A)	(2A)	(3A)	(4A)	(1B)	(2B)	(3B)	(4B)
	Productivity Growth	**Common Component**	**Allocation Component**	**Emp.-Driven Allocation Component**	**Productivity Growth**	**Common Component**	**Allocation Component**	**Emp.-Driven Allocation Component**
Credit Boom Variable	**–0.137*** **	**–0.055**	**–0.082*** **	**–0.080*** **	**–0.188*** **	**–0.081**	**–0.107*** **	**–0.102*** **
	(0.046)	*(0.058)*	*(0.027)*	*(0.031)*	*(0.069)*	*(0.075)*	*(0.036)*	*(0.040)*
Employment Growth	–0.681***	–0.934***	0.253***	0.351***	–0.873***	–1.012***	0.139	0.241**
	(0.158)	*(0.175)*	*(0.094)*	*(0.096)*	*(0.187)*	*(0.178)*	*(0.102)*	*(0.095)*
Initial Private Credit to GDP	0.002	0.039	–0.037	–0.050**	0.0472	0.0556*	–0.0084	–0.0219
	(0.038)	*(0.043)*	*(0.022)*	*(0.024)*	*(0.034)*	*(0.032)*	*(0.018)*	*(0.017)*
Government Consumption	–0.841***	–0.737*	–0.104	–0.020	–0.718*	–0.697*	–0.0210	0.064
to GDP	*(0.353)*	*(0.401)*	*(0.217)*	*(0.225)*	*(0.386)*	*(0.385)*	*(0.227)*	*(0.217)*
Openness to Trade	0.177**	0.259***	–0.082*	–0.090**	0.219**	0.276***	–0.057	–0.066
	(0.090)	*(0.088)*	*(0.042)*	*(0.039)*	*(0.100)*	*(0.086)*	*(0.053)*	*(0.048)*
CPI Inflation	–0.598***	–0.468**	–0.130	0.103	–0.787***	–0.556**	–0.231	0.0098
	(0.215)	*(0.214)*	*(0.141)*	*(0.122)*	*(0.274)*	*(0.246)*	*(0.161)*	*(0.132)*
Initial GDP per Person	–0.155**	–0.019	–0.136***	–0.164***	–0.129*	–0.009	–0.120**	–0.148***
Employed (log of)	*(0.067)*	*(0.071)*	*(0.047)*	*(0.048)*	*(0.074)*	*(0.069)*	*(0.047)*	*(0.045)*
J-stat.	3.477	2.003	1.497	0.526	1.425	1.358	0.741	0.060
p-value	*(0.324)*	*(0.572)*	*(0.683)*	*(0.913)*	*(0.700)*	*(0.715)*	*(0.863)*	*(0.996)*
LM-Test	18.26	18.26	18.26	18.26	14.97	14.97	14.97	14.97
p-value	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.005)*	*(0.005)*	*(0.005)*	*(0.005)*
Observations	102	102	102	102	102	102	102	102
R-squared	0.491	0.503	0.140	0.133	0.346	0.466	0.048	0.138

Note: This table reports the estimated coefficients for independent variables reported in the first column from an IV regression where the dependent variable is aggregate productivity growth (columns 1A and 1B), the common component (columns 2A and 2B), the allocation component (columns 3A and 3B), and the allocation component due to employment shocks (columns 4A and 4B). Common and the allocation components computed based on decomposition (3); employment-driven allocation component computed using decomposition (6). Credit boom variable in columns 1A–4A is private-credit-to-GDP growth and average private-credit-to-GDP gap in columns 1B–4B. Growth rates and averages computed using five-year windows. Credit boom variable and employment growth instrumented using the beginning-of-period values for the long-term interest rate, the short-term interest rate, the current account balance to GDP, the level and change in the financial liberalization index (see Abiad, Detragiache, and Tressel 2010). Estimation period: 1979–2009. All estimations include country and time fixed effects. Robust standard errors are in parentheses. Statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively, is indicated with ***, **, and *.

component of aggregate labor productivity growth—the second term on the right-hand side of (3)—is defined as the covariance between growth in sectoral employment shares and growth of sectoral labor productivity (weighted by sector size). Now, considering a simple bivariate regression, and using the same notation as before, the quantitative relevance of the allocation component can be assessed by regressing sector-level growth in employment shares on sector-level size-weighted productivity growth as follows:

$$\frac{\Delta(l_s/l)}{l_s/l} = \alpha + \theta \cdot \left(1 + \frac{\Delta(y_s/l_s)}{y_s/l_s}\right)\omega_s + \varepsilon_s$$

$$\Rightarrow \quad \widehat{\theta} = \frac{cov\left(\frac{\Delta(l_s/l)}{l_s/l}; \left(1 + \frac{\Delta(y_s/l_s)}{y_s/l_s}\right)\omega_s\right)}{var\left(\left(1 + \frac{\Delta(y_s/l_s)}{y_s/l_s}\right)\omega_s\right)}. \tag{7}$$

The OLS estimate $\widehat{\theta}$ of this bivariate regression is then proportional to the allocation component. Hence using this property, we can test whether credit booms have a negative effect on labor productivity growth by allowing the θ coefficient to depend on measures of credit booms. To do so, we consider a series of regressions of the form:

$$\begin{aligned}\frac{\Delta(l_{s,c,t+n}/l_{c,t+n})}{l_{s,c,t}/l_{c,t}} &= \alpha_{s,c} + \alpha_t + \beta x_{s,c,t} + \beta_F \cdot F^n_{c,t} \\ &\quad + \theta_0 \cdot \left[1 + \frac{\Delta(y_{s,c,t+n}/l_{s,c,t+n})}{y_{s,c,t}/l_{s,c,t}}\right]\omega_{s,c,t} + \theta_1 \cdot F^n_{c,t} \\ &\quad \times \left[1 + \frac{\Delta(y_{s,c,t+n}/l_{s,c,t+n})}{y_{s,c,t}/l_{s,c,t}}\right]\omega_{s,c,t} + \varepsilon_{s,c,t}.\end{aligned} \tag{8}$$

In this extended multivariate specification, the subscripts s and c denote sectors and countries, respectively; $\alpha_{s,c}$ and α_t are country-sector and time fixed effects, x is a vector of control variables, and θ_0 and θ_1 are parameters to be estimated. A negative coefficient θ_1 would then indicate that credit booms coincide with a shift of employment growth from high to low productivity growth sectors, all else equal, and hence with a reduction of the allocation component of labor productivity growth.[21] Here it is important to note

[21]Indeed, we can conclude from (7) and (8) that under OLS estimation, a negative estimate for θ_1 implies that the allocation component of productivity

that the estimated parameters $\widehat{\theta_0}$ and $\widehat{\theta_1}$ differ from $\widehat{\theta}$ estimates based on a bivariate regression, as the former measure the covariance between employment growth and size-weighted productivity growth, after controlling for the variables x included in the regression. That said, estimation results will prove to be very similar across specifications.

Sector-level regressions such as (8) present at least three advantages over the country-level regressions in Section 3. First, the number of observations used in the estimation and the degrees of freedom are substantially larger, making the statistical inference significantly more precise. Second, this approach allows to control for systematic (unobserved) effects not only across countries but also across sectors. For example, if employment were to grow systematically faster in some sectors because of unobserved technological or institutional factors, this effect would be filtered out thanks to the inclusion of the country-sector fixed effects. Third, the possibility that changes in employment or in labor productivity cause credit booms is also less of a concern. Indeed, if aggregate credit growth can affect the sectoral relationship between employment and productivity growth, it is much less likely that changes in this relationship in an individual sector would affect aggregate credit growth.

Table 9 reports various estimates of (8).[22] In addition to country-sector and time fixed effects, we consider three possible control variables: (i) aggregate credit-to-GDP growth (all columns) to control for the direct impact of aggregate credit on employment shares (as opposed to the effect on the slope coefficient, which is what we are interested in); (ii) the beginning of period sectoral output share $\omega_{s,c,t}$ (columns 3–5 and 8–10), which allows to interpret changes in size-weighted labor productivity growth as reflecting fluctuations in labor productivity growth rather than changes in the relative size of sectors; and (iii) the lagged dependent variable to account for

growth is negatively related to the growth rate of credit since we then have $\widehat{\theta_0} + \widehat{\theta_1} \cdot \frac{f_{c,t+n}}{f_{c,t}} = \frac{1}{V} alloc$ where V denotes the variance of size-weighted productivity growth and $alloc$ denotes the allocation component of labor productivity growth.

[22]Results from estimations using sector-level growth in employment as opposed to sector-level growth in employment shares as the dependent variable turn out to be very similar. They are available upon request.

Table 9. Dependent Variable: Growth in Employment Share

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log of Value-Added Share			–0.053***	–0.108***	–0.039			–0.055***	–0.110***	–0.040
			(0.020)	*(0.036)*	*(0.030)*			*(0.020)*	*(0.036)*	*(0.031)*
Lagged Growth in Employment Share				–0.066	–0.299***				–0.063	–0.298***
				(0.060)	*(0.067)*				*(0.059)*	*(0.066)*
Credit Variable	0.129**	0.097**	0.093*	0.088**	0.086**	0.085	0.085*	0.085	0.084	0.113*
	(0.052)	*(0.046)*	*(0.049)*	*(0.035)*	*(0.039)*	*(0.062)*	*(0.050)*	*(0.053)*	*(0.058)*	*(0.061)*
Size-Weighted Labor Productivity Growth	0.055***	–0.097***	–0.068***	–0.054*	–0.170***	0.047***	–0.105***	–0.075***	–0.060*	–0.173***
	(0.009)	*(0.021)*	*(0.024)*	*(0.0301)*	*(0.031)*	*(0.009)*	*(0.021)*	*(0.023)*	*(0.030)*	*(0.032)*
Interaction (Size-Weighted Labor Productivity Growth and Credit Variable)	**–0.074****	**–0.070*****	**–0.062****	**–0.072*****	**–0.073*****	**–0.065**	**–0.080****	**–0.075****	**–0.082****	**–0.109*****
	(0.032)	*(0.026)*	*(0.026)*	*(0.024)*	*(0.023)*	*(0.044)*	*(0.035)*	*(0.035)*	*(0.039)*	*(0.037)*
Country × Sector Fixed Effects	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No
Time Fixed Effects	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Observations	963	963	963	792	621	963	963	963	792	621
R-Squared	0.087	0.097	0.112	0.148	0.252	0.083	0.093	0.108	0.144	0.252
Number of Id.	171	171	171	171		171	171	171	171	

Note: This table reports the estimated coefficients for independent variables reported in the first column, the dependent variable being growth in sectoral employment share. In columns 1–5, the credit growth variable is the growth rate of private credit to GDP. In columns 6–10, the credit growth variable is the average private-credit-to-GDP gap. All variables (growth rates and averages) are computed using non-overlapping five-year periods and all estimations except in columns 1, 5, 6, and 10 include country-sector and time fixed effects. Estimations in columns 5 and 10 are run in first differences and include only time effects. Standard errors, clustered at the country-sector level, are in parentheses. Statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively, is indicated with ***, **, and *.

any time persistence in employment fluctuations (columns 4–5 and 9–10). Furthermore, like in the country-level regressions, we consider two measures of credit booms: growth in the credit-to-GDP ratio (columns 1–5) and the average credit-to-GDP deviation from trend (columns 6–10). Finally, we consider estimations of specification (8) either in levels (columns 1–4 and 6–9) or in first differences (columns 5 and 10). All variables are computed using non-overlapping five-year periods.

Estimates reported in Table 9 confirm the findings of the country-level analysis. The most parsimonious specifications (columns 1 and 6) show that the correlation between growth in employment shares and size-weighted labor productivity growth decreases with credit growth. That is, employment tends to grow more slowly in sectors in which labor productivity grows more quickly when aggregate credit as a share of GDP grows faster, which is consistent with the hypothesis that credit booms tend to go hand-in-hand with stronger employment growth in sectors with weaker productivity growth. This finding holds when controlling for unobservable country-sector characteristics (columns 2 and 7); when controlling for the initial output size of sectors (columns 3 and 8); including lagged growth in employment shares (columns 4 and 8); and estimating the regression in first differences (columns 5 and 10). Moreover, the estimated coefficient on the interaction term is very stable across specifications, particularly when credit booms are measured using growth in credit to GDP.

To compare the results of the sector-level analysis with those of the country-level regressions, we can back out the effect of credit booms on the allocation component from the estimated coefficient $\hat{\theta}_1$. According to bivariate regressions, using (7) and (8), when credit-to-GDP growth changes by $\Delta F^n_{c,t}$, the allocation component component changes by $\Delta\left[(alloc)^n_{c,t}\right]$, with

$$\Delta\left[(alloc)_{c,t+n}\right] = \hat{\theta}_1 \cdot var\left[\left(1 + \frac{\Delta(y_{s,c,t+n}/l_{s,c,t+n})}{y_{s,c,t}/l_{s,c,t}}\right)\omega_{s,c,t}\right] \cdot \Delta F^n_{c,t}. \tag{9}$$

Given that the estimate for the coefficient $\hat{\theta}_1$ is very stable across different specifications at around –0.07, and given that the sample variance $var\left[\left(1+\frac{\Delta(y_{s,c,t+n}/l_{s,c,t+n})}{y_{s,c,t}/l_{s,c,t}}\right)\omega_{s,c,t}\right]$ of size-weighted productivity growth is about 0.7, a one-standard-deviation increase in credit-to-GDP growth of about 3 percentage points per year leads to a drop in the allocation component $\Delta\left[(alloc)_{c,t+n}\right]$ and hence in labor productivity growth of around 0.15 percentage point per year, a figure strikingly similar to the one originally obtained in the country-level analysis.

4.2 Non-linearities

As the country-level evidence suggests, credit could possibly affect the employment-productivity relationship mainly during booms. To test for such potential non-linearities, we create a dummy variable that takes the value of one when growth in credit to GDP (or the average credit-to-GDP deviation from trend) is above the sample median and zero when it is below. With this dummy, we can estimate a richer set of specifications, to test if labor reallocations from high- to low-productivity sectors happen particularly when credit growth is high. Denoting $\mathbf{D}^n_{c,t}$ the dummy that is equal to one when the growth rate (the deviation from trend) of credit to GDP in country c between t and $t+n$ is above the sample median, we estimate the specification:

$$\begin{aligned}\frac{\Delta(l_{s,c,t+n}/l_{c,t+n})}{l_{s,c,t}/l_{c,t}} &= \alpha_{s,c}+\alpha_t+\beta x_{s,c,t}+\beta^d_F\cdot F^n_{c,t}\\ &\quad+\ \theta_0\cdot\left[1+\frac{\Delta(y_{s,c,t+n}/l_{s,c,t+n})}{y_{s,c,t}/l_{s,c,t}}\right]\omega_{s,c,t}+\theta^d_1\cdot F^n_{c,t}\\ &\quad\times\left[1+\frac{\Delta(y_{s,c,t+n}/l_{s,c,t+n})}{y_{s,c,t}/l_{s,c,t}}\right]\omega_{s,c,t}+\varepsilon_{s,c,t}\end{aligned} \tag{10}$$

except that β^d_F and θ^d_1 now depend on the credit dummy variable:

$$\begin{aligned}\beta^d_F &= \mathbf{D}^n_{c,t}\cdot\beta^H_F+\left(1-\mathbf{D}^{n,d}_{c,t}\right)\cdot\beta^L_F\\ \theta^d_1 &= \mathbf{D}^n_{c,t}\cdot\theta^H_1+\left(1-\mathbf{D}^{n,d}_{c,t}\right)\cdot\theta^L_1,\end{aligned} \tag{11}$$

$\left(\beta^H_F;\beta^L_F\right)$ and $\left(\theta^H_1;\theta^L_1\right)$ being parameters to be estimated.

Table 10 presents the estimation results. Overall, the results support the hypothesis that credit matters only during booms. Across all specifications, only above-median credit-to-GDP growth or above-median average credit gap interacts with labor productivity growth with a negative and statistically significant coefficient.

By contrast, there is no regression in which the credit-to-GDP growth variable interacted with the below-median dummy is statistically significant. Another relevant feature from Table 10 is that the negative effects of credit-to-GDP growth on labor productivity growth are likely to be under-estimated. When above the sample median, an increase in credit-to-GDP growth has a statistically significant negative effect on aggregate productivity growth that ranges, depending on the specification, from –0.18 to –0.24 percentage point per year.[23] By contrast, estimates from the linear specifications are generally smaller, ranging from –0.13 to –0.16.

4.3 Instrumenting Labor Productivity Growth

So far we have worked under the assumption that sector-level changes in productivity growth determine sector-level changes in employment shares. However, reverse causation cannot be entirely ruled out, e.g., if labor is characterized by declining marginal productivity. To address this potential problem, we instrument sectoral labor productivity growth with measures of sectoral TFP growth through two distinct approaches.

In the first approach, we assume that the United States is at the technological frontier in all sectors. Thus, an increase in TFP productivity growth in a given U.S. sector would reflect a positive technological shock common to all the identical sectors outside the United States. This suggests using size-weighted sectoral TFP productivity in the United States as our first instrumental variable. In the second approach, we follow Autor and Salomons (2017) and compute for each country-time period observation cross-country averages of sectoral TFP growth (excluding the country under consideration). By averaging out country differences, this variable should capture

[23]To obtain these figures, we compute the effect on labor productivity growth of a one-standard-deviation increase in credit-to-GDP growth (3 percentage points), by using relation (9), where the variance of size-weighted productivity growth is 0.68 and the estimated coefficients $\widehat{\theta}_1$ range from –0.084 to –0.111.

Table 10. Dependent Variable: Growth in Employment Share

	Credit Dummy	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log of Value-Added Share				−0.053***	−0.108***	−0.040			−0.0538***	−0.108***	−0.0380
				(0.020)	*(0.036)*	*(0.030)*			*(0.020)*	*(0.037)*	*(0.031)*
Lagged Growth in Employment Share					−0.071	−0.301***				−0.066	−0.301***
					(0.060)	*(0.068)*				*(0.060)*	*(0.068)*
Credit Variable	Above Median	0.152**	0.124**	0.118*	0.122***	0.114**	0.117	0.131	0.123	0.124	0.193
		(0.058)	*(0.061)*	*(0.063)*	*(0.042)*	*(0.049)*	*(0.107)*	*(0.098)*	*(0.102)*	*(0.115)*	*(0.122)*
	Below Median	−0.010	−0.014	−0.015	−0.045	0.003	0.033	0.012	0.025	0.020	0.011
		(0.091)	*(0.087)*	*(0.089)*	*(0.085)*	*(0.085)*	*(0.125)*	*(0.092)*	*(0.090)*	*(0.107)*	*(0.127)*
Size-Weighted Labor Productivity Growth		0.056***	−0.092***	−0.063***	−0.046	−0.163***	0.049***	−0.100***	−0.072***	−0.053*	−0.164***
		(0.009)	*(0.020)*	*(0.024)*	*(0.028)*	*(0.029)*	*(0.010)*	*(0.022)*	*(0.024)*	*(0.029)*	*(0.031)*
Interaction (Size-Weighted Labor Productivity Growth and Credit Variable)	Above Median	**−0.088****	**−0.091*****	**−0.084*****	**−0.111*****	**−0.097*****	**−0.087**	**−0.131****	**−0.110***	**−0.152****	**−0.204*****
		(0.037)	*(0.032)*	*(0.032)*	*(0.027)*	*(0.024)*	*(0.073)*	*(0.058)*	*(0.061)*	*(0.076)*	*(0.072)*
	Below Median	**0.006**	**0.014**	**0.021**	**0.058**	**−0.003**	**−0.031**	**−0.006**	**−0.021**	**0.0189**	**0.008**
		(0.066)	*(0.050)*	*(0.051)*	*(0.055)*	*(0.052)*	*(0.101)*	*(0.069)*	*(0.069)*	*(0.081)*	*(0.079)*
Country × Sector Fixed Effects		No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No
Time Fixed Effects		No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Observations		963	963	963	792	621	963	963	963	792	621
R-Squared		0.088	0.100	0.115	0.156	0.255	0.081	0.094	0.109	0.147	0.255
Number of Id.		171	171	171	171		171	171	171	171	

Note: This table reports the estimated coefficient for independent variables reported in the first two columns, the dependent variable being growth in sectoral employment share. In columns 1–5, the credit variable is the growth rate of private credit to GDP. In columns 6–10, the credit variable is the average private-credit-to-GDP gap. In the second column, the dummy Above Median (Below Median) is equal to one for observations where the credit growth variable is above (below) the sample median and zero otherwise. All variables (growth rates and averages) are computed using non-overlapping five-year periods and all estimations except in columns 1, 5, 6, and 10 include country-sector and time fixed effects. Estimations in columns 1 and 6 have no fixed effects. Estimations in columns 5 and 10 are run in first differences and include only time effects. Robust standard errors are in parentheses. Statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively, is indicated with ***, **, and *.

sector-specific supply or technological shocks. This suggests using size-weighted TFP growth averaged across countries as our second instrumental variable. To have one more instrument than variables to instrument, we constructed a third instrumental variable by interacting size-weighted TFP growth averaged across countries with private credit-to-GDP growth.[24]

Table 11 reports the estimation of IV regressions. The baseline specification in column 1 confirms the earlier findings. The interaction term has a statistically significant negative sign, indicating that credit-to-GDP growth reduces employment growth in sectors with stronger productivity growth, thereby reducing the allocation component of labor productivity growth. Moreover, the magnitude of the coefficients is similar to that of coefficients estimated under OLS. And controlling for the initial sectoral share in output (column 2) yields very similar estimates. Last, replacing growth in credit to GDP with average credit-to-GDP gap (columns 3 and 4) leaves these conclusions unchanged.

5. A Simple Model of Credit, Reallocation, and Growth

Up to now, we have established that credit booms tend to reduce aggregate labor productivity growth by reallocating the labor force from higher to lower labor productivity growth sectors. In this section, we provide a simple analytical framework that can qualitatively replicate this finding, short of testing a specific channel. In a nutshell, the model rests on the idea that activities with higher returns tend to be relatively less sensitive to credit conditions. The

[24]In constructing the three instrumental variables, we consider the actual size-weights as well as the actual credit growth variable, i.e., those pertaining to the specific country-sector-time observation. For example, the instrument which uses sectoral TFP growth in the United States writes as $\omega_{s,c,t}\left(1+\frac{\Delta A^{US}_{s,t+n}}{A^{US}_{s,t}}\right)$, where $A^{US}_{s,t}$ is TFP in sector s at time t in the United States. Similarly, the instruments which use average sectoral TFP growth across countries write, respectively, as $\omega_{s,c,t}\left(1+\frac{\Delta A_{s,t+n}}{A_{s,t}}\right)$ and $\omega_{s,c,t}\left(1+\frac{\Delta A_{s,t+n}}{A_{s,t}}\right)\cdot\frac{f_{c,t+n}}{f_{c,t}}$ where $\frac{\Delta A_{s,t+n}}{A_{s,t}}$ is average TFP growth in sector s between time t and time $t+1$ across countries and $\frac{f_{c,t+n}}{f_{c,t}}$ is the growth rate of credit to GDP or the average credit-to-GDP gap in country c between time t and time $t+n$.

Table 11. Dependent Variable: Growth in Employment Share

	(1)	**(2)**	**(3)**	**(4)**
Log of Value-Added Share		–0.058***		–0.059***
		(0.021)		*(0.021)*
Credit Variable	0.104**	0.099*	0.095*	0.097*
	(0.047)	*(0.051)*	*(0.051)*	*(0.054)*
Size-Weighted Labor	–0.100***	–0.045	–0.111***	–0.053*
Productivity Growth	*(0.026)*	*(0.030)*	*(0.027)*	*(0.030)*
Interaction (Size-Weighted	**–0.075*** **	**–0.065** **	**–0.090** **	**–0.083** **
Labor Productivity Growth	*(0.028)*	*(0.028)*	*(0.037)*	*(0.037)*
and Credit Variable)				
Country × Sector Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	909	909	909	909
R-Squared	0.067	0.077	0.061	0.072
J-Stat	1.922	0.580	1.992	0.591
p-value	(0.166)	(0.446)	(0.158)	(0.442)
LM-Stat	28.41	27.59	28.53	27.72
p-value	(6.77e-07)	(1.02e-06)	(6.37e-07)	(9.54e-07)

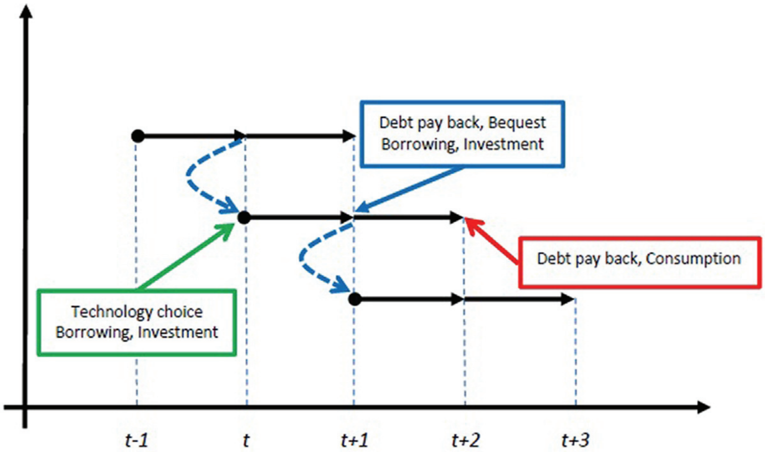
Note: This table reports the estimated coefficient for independent variables reported in the first column from a set of IV regressions, the dependent variable being growth in sectoral employment share. In columns 1–2, the credit variable is the growth rate of private credit to GDP. In columns 3–4, the credit variable is the average private-credit-to-GDP gap. All variables (growth rates and averages) are computed using non-overlapping five-year periods and all estimations include country-sector and time fixed effects. Size-weighted labor productivity growth and the interaction between size-weighted labor productivity growth and the credit variable are instrumented using (i) size-weighted TFP growth in the United States, (ii) size-weighted TFP growth averaged across countries, and (iii) size-weighted TFP growth averaged across countries interacted with the credit variable. Robust standard errors are in parentheses. Statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively, is indicated with ***, **, and *. The statistic for the instrument validity (weak instrument) test is reported on the J-stat row (LM-stat row) while the associated p-value reports the probability that the hypothesis that all instruments are valid (instruments are weak) cannot be rejected.

following sections give more details about how this intuition can fit a simple endogenous growth model.

5.1 Main Assumptions

Consider a small open economy with overlapping generations of entrepreneurs who live for two periods. Entrepreneurs born at date

Figure 4. Timing of the Model



t receive a bequest B_t from the generation born at date $t-1$. Generation-t entrepreneurs combine this bequest with borrowed funds and invest in a project. We denote r_t the cost of capital that lenders charge at date t. At date $t+1$, the project delivers output that is then used for three purposes: (i) paying back date-t borrowing, (ii) bequesting B_{t+1} to generation-$t+1$ entrepreneurs, and (iii) saving S_{t+1}. Entrepreneurs born at date t then combine savings S_{t+1} with some new borrowing to invest in the same project at date $t+1$. See Figure 4.

Finally at date $t+2$, entrepreneurs reap the project's output and use it to (i) pay back liabilities and (ii) consume C_{t+2}. Entrepreneurs can either invest in a type-i (innovative) or a type-h (housing) project. Importantly, they are committed to a single project type for their entire productive life. Realistically, innovative projects carry a higher return, $A_i > A_h$. In addition, the return to housing projects undertaken in the first period decreases with the number of entrepreneurs starting such projects. Denoting n_t the measure of entrepreneurs starting an innovative project at date t, the return to housing projects started at date t is then $A_h(n_t)$ (with $A'_h(n_t) > 0$ and $A''_h(n_t) < 0$) and A_h at date $t+1$. Conversely, the return to investing in an innovative project is A_i both in the first and in the second period. Housing projects therefore face some decreasing returns in the first period, while innovative projects do not.[25] Finally, all projects have positive net present value (NPV), i.e., $A_h > A_h(n) > r_t$ and $A_i > r_t$. Last we assume that agents know at date t the current and the future costs of capital r_t and r_{t+1}. As will be clear later, by running comparative statics on the future cost of capital r_{t+1}, we will be looking at the effect future credit availability, and thereby at the effect of credit growth.[26] Denoting β a positive scalar, we write the utility function of an entrepreneur born at date t as

$$U_t = \log B_{t+1} + \beta \log C_{t+2}. \tag{12}$$

5.2 The Dynamics of the Economy

We denote $\pi_{j,t}(n_t)$ the profit per unit of internal funds for newly born entrepreneurs starting a type-j project at date t, n_t being the number of such entrepreneurs investing in an innovative project at date t. Similarly, $\pi_{j,t+1}$ denotes the profit per unit of internal funds on type-j projects at date $t+1$ for entrepreneurs born at date t. In what follows, we will call $\pi_{j,t}(n_t)$ the "short-run" profit rate and $\pi_{j,t+1}$ the "long-run" profit rate. The utility maximization problem for an entrepreneur born at date t writes as

$$\begin{aligned} &\max_{B_{t+1};C_{t+2}} U_t = \log B_{t+1} + \beta \log C_{t+2} \\ &\text{s.t.} \begin{cases} B_{t+1} + S_{t+1} = \pi_{j,t}(n_t) B_t \\ C_{t+2} = \pi_{j,t+1} S_{t+1}. \end{cases} \end{aligned} \tag{13}$$

Optimal date-$t+1$ bequest B^*_{t+1} and optimal date-$t+2$ consumption C^*_{t+2} then satisfy

$$B^*_{t+1} = \frac{1}{1+\beta}\pi_{j,t}(n_t) B_t \text{ and } C^*_{t+2} = \frac{\beta}{1+\beta}\pi_{j,t+1}\pi_{j,t}(n_t) B_t. \tag{14}$$

The first expression in (14) governs the growth rate of net wealth for entrepreneurs investing in type-j projects. And using (14) we can

[25] This assumption that the number of new housing projects reduces the return to new projects is here to provide an interior solution to the model. Removing it or applying it equally to innovative projects does not change any of our results.

[26] More realistically, agents only know the probabilistic distribution of the future cost of capital. In this case, the comparative static would be made by considering shocks achieving first-order stochastic dominance. Yet, all conclusions would be similar.

write the indirect utility $U_{j,t}$ for entrepreneurs investing in a type-j project, up to a constant, as

$$U_{j,t} = (1+\beta)\log \pi_{j,t}(n_t) + \beta \log \pi_{j,t+1}. \tag{15}$$

5.3 Financial Constraints

Entrepreneurs can borrow from lenders, but they can default strategically. To preclude default, lenders can impose borrowing limits which ensure that entrepreneurs are always worse off defaulting. To determine this no-default level of borrowing, consider an entrepreneur starting with a unit of net wealth, borrowing d_t, the cost of capital being r_t and investing $1+d_t$ in a type-j project. If the entrepreneur chooses to pay back, the profit is then $(1+d_t)A_j - r_t d_t$. Alternatively, suppose the entrepreneur chooses to default. Then in the case of housing projects, the return for entrepreneurs drops to $A_h - \rho_h$, as lenders can always seize $(1+d_t)\rho_h$. The no-default constraint then writes as $r_t d_t \leq (1+d_t)\rho_h$. Assuming the condition $\rho_h \leq r_t$ holds, it simplifies as

$$d_t \leq d_h(r_t) \equiv \frac{\rho_h}{r_t - \rho_h}. \tag{16}$$

Turning to innovative projects, defaulting entrepreneurs incur a deadweight loss $(1+d_t)\rho_i$ and assuming lenders recover a fraction q of their loans, the borrowing limit for entrepreneurs running innovative projects writes as $(1+d_t)A_i - r_t d_t \geq (1+d_t)(A_i - \rho_i) - q r_t d_t$. Then, to recover a fraction q of loans d_t made to an entrepreneur with an innovative project, lenders need to incur a cost $c d_t \ln(1-q)^{-1}$, where where c is a positive scalar. Lenders therefore choose the fraction q of claims to be recovered on defaulted innovative projects to maximize their repayment net of recovering costs:

$$\max_q q r_t d_t - c \ln\left(\frac{1}{1-q}\right) d_t, \tag{17}$$

which yields $(1-q)r_t = c$. Denoting $\lambda_i = \rho_i / c$ and assuming $\lambda_i < 1$, the no-default condition simplifies as

$$d_t \leq d_i \equiv \frac{\lambda_i}{1-\lambda_i}. \tag{18}$$

The key difference in the borrowing limits (16) and (18) lies in the sensitivity to the cost of capital r_t. When an entrepreneur with a housing project defaults, there is no productivity loss and lenders can seize the collateral $(1 + d_t)\,\rho_h$ with no deadweight loss. Lenders therefore choose to increase their lending supply when the cost of capital r_t falls because the face value of their claims $r_t d_t$ falls relative to the value of the collateral $(1 + d_t)\,\rho_h$ they can seize. By contrast, when an entrepreneur with an innovative project defaults, entrepreneurs suffer an output loss $(1 + d_t)\,\rho_i$. But this time, lenders who cannot seize this forgone output, they need to spend extra resources to recover their claims. And given that they choose to spend more—to recover their claims—when the cost of capital r_t is higher, the actual benefit for entrepreneurs to defaulting—$(1 - q)\,r_t d_t$—ends up being independent of the cost of capital r_t. Hence, the maximum level of borrowing for entrepreneurs with an innovative project is also independent of the cost of capital.

Given that projects all have positive NPV, entrepreneurs always borrow as much as possible and both constraints (16) and (18) bind. Short- and long-term profit rates on housing projects hence write as

$$\pi_{h,t}\,(n_t) = \frac{A_h\,(n_t) - \rho_h}{r_t - \rho_h} r_t \text{ and } \pi_{h,t+1} = \frac{A_h - \rho_h}{r_{t+1} - \rho_h} r_{t+1}. \tag{19}$$

And short- and long-term profit rates on innovative projects satisfy

$$\pi_{i,t} = \frac{A_i - \lambda_i r_t}{1 - \lambda_i} \text{ and } \pi_{i,t+1} = \frac{A_i - \lambda_i r_{t+1}}{1 - \lambda_i}. \tag{20}$$

Housing and innovative profits are therefore both decreasing in the cost of capital, but housing profits are also strictly concave in the cost of capital. As a result, when the cost of capital is sufficiently low, a drop in the cost of capital raises proportionally more profits on housing than profits on innovative projects. Now with this framework at hand, we can look at the effect of credit booms, by considering a drop in the future cost of capital r_{t+1}, as it acts to relax future borrowing constraints and hence raise the level of future credit relative to the current one.

5.4 Credit Booms and Reallocation across Sectors

The number of entrepreneurs n_t^* starting at date t an innovative project is such that entrepreneurs should be indifferent between investing in either sector. Using (15), the break-even condition writes as

$$(1+\beta)\log \pi_{h,t}\left(n_t^*\right) + \beta \log \pi_{h,t+1} = (1+\beta)\log \pi_{i,t} + \beta \log \pi_{i,t+1}. \tag{21}$$

Writing $\pi\left(r_{t+1}\right) = \left[\pi_{h,t+1}/\pi_{i,t+1}\right]^{\frac{\beta}{1+\beta}}$, the break-even condition (21) simplifies as

$$\pi_{h,t}\left(n_t^*\right) = \pi\left(r_{t+1}\right) \cdot \pi_{i,t}. \tag{22}$$

In the break-even condition (22), the LHS increases with the number of entrepreneurs n_t investing in innovative projects at date t, while the RHS decreases with the number of entrepreneurs n_t investing in innovative projects at date t. As a result, there is a unique equilibrium which pins down each sector size. In the next proposition, we look at the comparative statics of the equilibrium allocation of entrepreneurs.

PROPOSITION 1. *There exists r^* such that when the cost of capital r_{t+1} satisfies $r_{t+1} < r^*$, then,*
(i) the number of entrepreneurs n_t^* starting innovative projects at date t increases with the future cost of capital r_{t+1};
(ii) equilibrium short-term profits on innovative projects are higher than on housing projects.

Proof. Using the equilibrium condition (22), we have

$$\begin{aligned}&\pi'_{h,t}\left(n_t^*\right)\frac{dn_t^*}{dr_{t+1}}\\ &\quad= \frac{\beta}{1+\beta}\left[\frac{\rho_h}{r_{t+1}-\rho_h}\frac{1}{r_{t+1}} - \frac{\lambda_i}{A_i - \lambda_i r_{t+1}}\right]\left[\frac{\pi_{h,t+1}}{\pi_{i,t+1}}\right]^{\frac{\beta}{1+\beta}}\pi_{i,t}.\end{aligned} \tag{23}$$

The term in brackets is positive if and only if $r_{t+1} \leq \sqrt{A_i \rho_h/\lambda_i}$. Hence given that $\pi'_{h,t}\left(n_t\right) > 0$, a reduction in the cost of capital

r_{t+1} reduces the number of entrepreneurs n_t^* undertaking innovative projects and raises the number of entrepreneurs undertaking housing projects if and only if $r_{t+1} \leq \sqrt{A_i \rho_h / \lambda_i}$. Moreover, long-run profits are larger for housing $\pi_{h,t+1} > \pi_{i,t+1}$ when the cost of capital r_{t+1} is lower than some threshold r, where r satisfies

$$r \equiv \left[\frac{A_i + \rho_h - (1 - \lambda_i) A_h}{2\rho_h A_i} + \sqrt{\left(\frac{A_i + \rho_h - (1 - \lambda_i) A_h}{2\rho_h A_i} \right)^2 - \frac{\lambda_i}{\rho_h A_i}} \right]^{-1}. \qquad (24)$$

Hence, when $r_{t+1} \leq r^* \equiv \min \left\{ \sqrt{A_i \rho_h / \lambda_i}; r \right\}$, then a reduction in the cost of capital r_{t+1} raises the number of entrepreneurs undertaking housing projects, while at the same time, housing projects yield lower short-term profits. ■

As was noted above, profits on housing projects tend to be more sensitive to changes in the cost of capital than profits on innovative projects when $r_{t+1} < r^*$. Hence when this condition is met, a reduction in the cost of capital benefits disproportionately more to housing than to innovative entrepreneurs, which leads a growing number of entrepreneurs to leave the innovative sector and enter the housing sector. Moreover, by the same sensitivity argument, long-run profits on housing projects are higher when $r_{t+1} < r^*$. As a result, equilibrium short-term profits for housing should be lower. Hence, the drop in the cost of capital r_{t+1} leads entrepreneurs to reallocate into housing even if housing is less profitable in the short run.

5.5 Growth

Growth is summarized in this model with the dynamics of entrepreneurs' initial endowment. Given optimal individual choices (14), the growth rate of entrepreneurs' initial endowment writes as

$$\frac{B_{t+1}}{B_t} = \frac{(1 - n_t^*)\, \pi_{h,t}\, (n_t^*) + n_t^* \pi_{i,t}}{1 + \beta}. \qquad (25)$$

It depends on the allocation of entrepreneurs across sectors and short-term profits, but not on long-term profits which only affect consumption. Hence credit growth affects the output growth essentially through two channels: first, through the reallocation channel, as changes in the growth rate of credit affect the distribution of entrepreneurs across sectors; second, through changes in short-term profits, as those determine new entrepreneurs' initial endowment.

PROPOSITION 2. *When $r_{t+1} < r^*$, the growth rate of the economy decreases with the growth rate of credit. This negative relationship is due to entrepreneurs reallocating towards a less profitable housing sector in the short run.*

Proof. A change in credit growth between t and $t+1$ is captured here by an (inverse) change in the cost of capital at date $t+1$. The effect on growth of such a change is summarized in the following expression:

$$\frac{\partial B_{t+1}/B_t}{\partial r_{t+1}} = \frac{\partial n_t^*}{\partial r_{t+1}} \frac{\left(1-n_t^*\right)\pi'_{h,t}\left(n_t^*\right) + \left[\pi_{i,t} - \pi_{h,t}\left(n_t^*\right)\right]}{1+\beta}. \tag{26}$$

From Proposition 1, we know that the first term $\partial n_t^*/\partial r_{t+1}$ is positive: when $r_{t+1} < r^*$, entrepreneurs reallocate into the housing sector when the future cost of capital r_{t+1} goes down. Moreover, as a larger number of entrepreneurs start housing projects, the short-term profit to housing goes down $(\pi'_{h,t}(n_t^*) > 0)$. Last, from Proposition 1, we know that when $r_{t+1} < r^*$, housing is less profitable in the short run; $\pi_{i,t} > \pi_{h,t}(n_t^*)$. Output growth between t and $t+1$ therefore decreases as the cost of capital r_{t+1} goes down, or equivalently as credit growth between t and $t+1$ increases. ■

An increase in the growth rate of credit therefore acts as a drag on aggregate growth through the reallocation channel: When r_{t+1} decreases and credit grows more quickly between t and $t+1$, fewer entrepreneurs start innovative projects in t, while innovative projects happen to provide higher profits in the short run. More resources are hence invested in activities with a lower payoff. This drags down aggregate growth.

6. Conclusion

In this paper we have investigated the relationship between credit growth, productivity growth, and labor reallocations. We find that credit growth tends to reduce aggregate labor productivity growth. Moreover, during credit booms, this reduction occurs through labor reallocations towards lower productivity growth sectors. To reach these conclusions, we have proceeded in four steps. First, we have decomposed aggregate productivity growth into a common and an allocation component, the latter reflecting the covariance between employment and productivity growths across sectors. Second, we have run country fixed-effect panel regressions, showing the existence of a negative and statistically significant relationship between measures of credit growth and the allocation component of aggregate productivity growth, particularly for countries that went through credit boom episodes. Third, we have estimated a series of sector-level regressions showing that when aggregate credit grows more quickly, employment growth tends to slow disproportionately more in sectors with stronger labor productivity growth, thereby confirming the country-level result that labor tends to reallocate into low-productivity growth sectors in periods of rapidly expanding credit. Last, we have developed a simple model, where sectoral differences in credit sensitivities lead entrepreneurs to invest more heavily in low-return sectors, during periods of strong credit growth. While this illustrative framework could provide a case for leaning-against-the-wind policies, i.e., to limit credit expansions with a view to reduce reallocations that hurt productivity growth, making this point formally would require testing this specific channel in the data, in addition to conducting a fully fledged welfare analysis. Both will be the focus of future research.

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