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Please address correspondence to
Banco de Portugal, Economics and Research Department
Av. Almirante Reis, 71, 1150-012 Lisboa, Portugal
Tel.: +351 213 130 000, email: estudos@bportugal.pt

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Bank credit allocation and productivity: stylised facts for Portugal

Nuno Azevedo
Banco de Portugal
School of Economics and Management
(EEG) – Universidade do Minho

Márcio Mateus
Banco de Portugal

Álvaro Pina
Banco de Portugal
ISEG (Universidade de Lisboa)
REM (Research in Economics and Mathematics)
UECE (Research Unit on Complexity and Economics)

Abstract
With a dataset covering 95% of total outstanding credit to non-financial corporations recorded in the Portuguese credit register, we investigate whether outstanding loans by resident banks to 64 economic sectors have been granted to the most productive firms. We find evidence of misallocation, which reflects the joint effects of credit supply and credit demand decisions taken over the course of time, and the adverse cyclical developments following the accumulation of imbalances in the Portuguese economy for a protracted period. In 2008-2016, the share of outstanding credit granted to firms with very low productivity (measured or inferred) was always substantial, peaking at 44% in 2013, and declining afterwards with the rebound in economic activity and the growing allocation of new loans towards lower risk firms and away from higher risk firms. Furthermore, we find that misallocation is associated with slower reallocation. The responsiveness of credit growth to firm relative productivity is much lower in sectors with relatively more misallocated credit and when banks have a high share of such credit in their portfolios.

JEL: D24, G21, O16, O40, O47

Keywords: credit misallocation, credit reallocation, productivity, zombie firms, zombie congestion, evergreening.

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E-mail: ncazevedo@bportugal.pt; mfmateus@bportugal.pt; apina@bportugal.pt

1. Motivation and main findings

In any economy, long-term economic growth largely depends on the ability to channel resources to high-productivity firms, enabling them to invest and upscale. Notwithstanding other forms of financing, including firms' own funds, banks play a prominent role in resource allocation, especially in economies, such as those in the European Union (EU), which are heavily reliant on bank lending (OECD (2016)). The degree of efficiency in the allocation of bank credit, which depends on both credit supply and credit demand, will thus have major consequences both for economic growth and for financial stability. Against this background, this paper analyzes whether, in the case of Portugal, bank credit is going to the most productive firms.

The global financial crisis and the productivity slowdown predating it have rekindled interest in how monetary and financial conditions affect productivity. Tight credit conditions may credit-constrain numerous firms, reducing investment in physical capital and intangible assets and thus weakening productivity growth (Adler *et al.* (2017)). On the other hand, credit booms may harm aggregate productivity growth by inducing resource reallocation towards sectors where productivity growth is lower (Borio *et al.* (2016)). Furthermore, protracted very loose monetary conditions may enable low-productivity, unviable companies – often called zombie firms – to survive, inter alia due to the lower opportunity cost for banks to evergreen loans to such firms.

Resource misallocation, and in particular credit misallocation, is all the more worrying as it can be self-reinforcing. A proliferation of zombie firms tends to congest markets, hampering the entry or growth of more efficient competitors (Caballero *et al.* (2008); McGowan *et al.* (2017)). Evergreening by banks, itself a cause of zombie firm proliferation, also implies long-lasting credit misallocation and may lead to less credit availability for more productive firms.

The linkages between credit allocation and productivity have particular relevance in Portugal. Aggregate productivity levels are low by EU standards, productivity growth has been meagre since the turn of the century and the potential growth of the Portuguese economy remains significantly constrained. Factors like the lower level of qualification of workers and managers and the smaller scale of Portuguese firms, when compared with other EU countries, have certainly played their part but several indicators also provide indirect evidence of an inefficient credit allocation. For instance, the share of the capital stock held by zombie firms is internationally high (McGowan *et al.* (2017)) and, despite substantial reduction over the past two years, the ratio of non-performing loans (NPL) in banks' balance sheets is still among the highest in the euro area (Banco de Portugal (2018a))[1]. Nonetheless, recent positive trends

1. International comparisons of NPL ratios should be approached with care, since the implementation of the EBA (European Banking Authority) definition of NPL requires judgement and, therefore, is not fully harmonized across countries.

are worth underlining. There is evidence of growing credit risk differentiation in the pricing of new bank loans to firms since 2013, in tandem with rising amounts of new bank credit to lower-risk firms, which are often more productive, and decreasing amounts to more risky firms (Banco de Portugal (2017)).

Closely related to this paper are studies which document worsening resource misallocation in the Portuguese economy in the first decade of this century. Dias *et al.* (2016) find a substantial deterioration in within-industry allocative efficiency in 1996-2011, with distortions in capital allocation playing the major role, especially in services. Gopinath *et al.* (2017), who focus mainly on Spain, also find evidence of growing capital misallocation in Portuguese manufacturing in 2006-2012. Reis (2013) emphasizes misallocation of capital inflows across sectors, with an expansion of the low-productivity nontradables sector in 2000-2007. In more recent work with data up to 2015, Dias and Marques (2018) show that the Portuguese crisis had an overall cleansing effect on productivity in 2011-12, mainly through the exit of less productive firms, and a mixed impact on factor reallocation, with firm productivity becoming more correlated with employment growth but (in nontradable services) less with capital growth. Banking system distortions are often mentioned in these studies as potential or likely culprits for capital misallocation, but they are not empirically analysed with credit data.

In this paper, we investigate whether credit extended by the Portuguese banking system has been allocated to the most productive firms within each sector. By matching over 2006-2016 credit register data with firms' balance sheet and income statement data, we are in a position to compute productivity indicators for a given firm, compare them with the average of the respective sector, and relate them to the amount of outstanding credit granted to that firm by each bank resident in Portugal. The ability to explicitly analyse bank credit and link it to variables pertaining to both firms and banks is a novel feature relative to the studies mentioned in the previous paragraph, which largely rely on firm-level or sectoral data alone.

Our dataset includes virtually every firm in a total of 64 sectors, accounting for 95% of total credit to non-financial corporations recorded in the Portuguese credit register. Part of this credit lies with firms for which conventional measures of productivity cannot be defined (e.g. due to negative values for value added), or for which balance sheet and income statement data are missing (e.g. due to non-reporting or firm closure). We define a typology of firms according to data and productivity availability, so that all bank credit can be taken on board in our analysis. It turns out that credit to firms with undefined productivity, or with no accounting data at all, is very sizeable and is associated to slower credit reallocation to more productive firms.

Two main sets of findings should be highlighted. First, a large share of outstanding credit granted by the Portuguese banking system is allocated to firms with very low productivity. This is the joint outcome of credit supply and credit demand decisions taken in those different moments of time when outstanding loans were granted. The share of credit to unproductive firms peaked at 44% in 2013, with the severe downturn experienced by Portugal in the context of the sovereign debt crisis, following a protracted period of accumulation of imbalances, and declined afterwards with the overall recovery in economic activity. Credit to the so-called zombie firms, on which several studies have recently focused, accounts for less than half of this total share. Furthermore, bank credit is more skewed towards unproductive firms than labour and capital. Credit misallocation is particularly high in construction and real estate sectors but also sizeable in a variety of industries across the economy.

Second, a high share of credit sunk in unproductive companies is associated with a slower reallocation of credit towards more productive firms. This effect is felt both at the level of sectors and at the level of banks: reallocation is more sluggish in sectors with a lot of credit allocated to low-productivity firms, and in the case of banks with a high share of such credit in their portfolios. Taking both strands together (sectors and banks), the responsiveness of credit growth to firm productivity could be reduced by a factor of three.

The remainder of this paper is organized as follows. Section 2 describes data sources, productivity measures and the sample used in our analysis. Section 3 characterizes how bank credit is allocated across firms, including those for which conventional productivity indicators cannot be computed. To do so, it identifies groups of firms which have, or are likely to have, very low productivity. Section 4 specifies and estimates econometric models of credit responsiveness to firm productivity. In particular, it investigates to what extent a larger share of credit sunk in unproductive companies affects the reallocation towards more productive firms. Section 5 concludes.

2. Data

Our sample focuses on non-financial corporations (henceforth, firms) and their outstanding loans granted by banks operating in Portugal, and was obtained by matching three different data sources. First, Central de Balanços (CB) of Banco de Portugal, an annual database based on Simplified Corporate Information (IES) reporting which contains detailed balance sheet and income statement data of virtually all companies in Portugal. Second, the Portuguese central credit register (CCR), which provides monthly information on all outstanding loan exposures of credit institutions to Portuguese firms above € 50[2]. Third,

2. Besides bank loans, Central Credit Register data used in this study also covers loans granted by other financial sector entities resident in Portugal including savings banks and mutual agricultural credit banks, non-monetary financial institutions that grant credit, namely credit financial institutions, factoring and financial leasing companies, credit-purchase financing companies and mutual guarantee companies.

supervisory reports collected by Banco de Portugal, containing balance sheet and credit risk data on Portuguese banks, and other internal databases of Banco de Portugal with additional data on firms. These different sources were matched using common identifiers for firms and financial institutions. The period of analysis is 2006-2016.

From the CB database we get information on a number of accounting variables, such as those needed for the computation of gross value added and capital stocks (see below). We also collect data on employment (number of remunerated and non-remunerated employees), which is used inter alia to define classes of firm size. Thus, firms with less than 10 employees were defined as micro corporations; firms with between 10 and 49 employees were classified as small corporations; firms with between 50 and 249 employees were considered as medium-sized corporations; and large corporations were those with 250 or more employees.

Based on CB data we also estimate the capital stock of each firm. The measurement of this stock is widely acknowledged as difficult (Oberfield (2013)). In this paper we follow a simple and common approach in the literature (e.g. Dias *et al.* (2016)) and use the book value of tangible and intangible assets (net of depreciation)[3]. We exclude assets in progress and advances on assets, as in both cases assets are not yet ready for use as productive inputs.

Credit register (CCR) data provides information on all lending relationships between Portuguese credit institutions and firms. For the purposes of our analysis, outstanding credit is defined as the sum of performing, overdue and renegotiated loans. In contrast, written-off loans and potential loans (e.g. unused credit lines) were disregarded. We aggregate (i.e., sum) credit amounts granted to a given firm by different credit institutions belonging to the same banking group. We consider the eight largest banking groups operating in Portugal[4], plus a ninth, residual group comprising all other credit institutions.

From supervisory reports we get the Tier 1 ratio and the credit at risk ratio[5] (for credit granted to non-financial corporations), for each banking group on a consolidated basis. For the time span of this study, data on regulatory capital was first gathered according to the national reporting framework and afterwards, with the entry into force of the Capital Requirements Regulation (CRR), according to the Common Reporting (COREP) at the EU level. To

3. Admittedly, comparability across firms is not perfect as the book value aggregates, without correcting for deflators, different vintages of capital goods. However, alternatives such as the perpetual inventory method are more data-demanding and also face limitations in a small time series as ours.

4. Banif was one of the eight largest banks operating in Portugal until 2015, when a resolution measure was applied to this bank. In 2016, therefore, our sample only includes the seven largest banking groups.

5. We used the credit at risk ratio instead of NPL ratio (EBA definition) because the latter is only available since 2014.

minimize the impact of breaks in the definition of regulatory capital, we chose to use the Tier1 ratio because it was deemed the most comparable capital ratio throughout the period. The Tier1 ratio was computed as Tier 1 capital over Risk Weighted Assets with no corrections being made to either numerator or denominator in any of the periods (i.e., before and after the introduction of the CRR). Credit at risk information was obtained from reporting by banks under Instruction No. 22/2011 of Banco de Portugal.

Finally, from other Banco de Portugal databases we obtain firm features such as age, exporting activity[6], credit rating (measured by the Z-score estimated by Antunes *et al.* (2016)) and activity status (active, inactive or unknown) when not reporting accounting data.

Industry classification is provided by the CB database and follows the European classification of economic activities (NACE Rev. 2.1) at 2-digit level. We exclude from the analysis those industries associated with activities usually not performed by non-financial corporations, such as financial services and insurance activities (NACE sectors 64-66), public administration (sector 84) and activities of households and extraterritorial organizations (sectors 97-99). Additionally, we have merged some industries with a small number of firms, namely mining and quarrying (sectors 5-9), beverages and tobacco (sectors 11-12), coke, refined petroleum and chemicals (sectors 19-20) and sewerage and waste collection (sectors 37-39). These exclusions and mergers leave us with 73 industries.

We use two different concepts of productivity: labour productivity and total factor productivity (TFP). For firm i, (log) labour productivity (LP) is given by

$$LP_i = \ln\left(\frac{GVA_i}{L_i}\right),$$

where GVA_i and L_i are gross value added and the number of employees. Gross value added is defined as output minus intermediate consumption, each of which aggregates a number of firm income statement items, following the criteria adopted by Statistics Portugal. However, our benchmark productivity metric is TFP, which also takes account of the capital stock. Based on a Cobb-Douglas production function,

$$GVA_i = A_i K_i^{\alpha} L_i^{1-\alpha},$$

where K_i stands for firm i's capital stock, (log) TFP is given by

$$TFP_i = \ln(GVA_i) - \alpha \ln(K_i) - (1-\alpha)\ln(L_i).$$

$1-\alpha$ is the industry-level share of labour costs in gross value added averaged over 2008-2015, available from the Integrated Business Accounts System (IBAS)

6. Following the definition adopted by Banco de Portugal (2015), a firm is considered to have an exporting activity if: a) it exports more than 50% of the turnover; or b) it exports more than 10% of the turnover and more than 150 thousand euros.

of Statistics Portugal. We have excluded industries – nine in total[7] – with α below 0.1 or above 0.9, leaving us with a total of 64 different sectors.

Our sample includes a total of 704,141 firms and 9 different banking groups over 2006-2016. In the 64 retained sectors, the sample comprises all firms which report accounting data (IES), regardless of whether they have loans granted by banks operating in Portugal (in 2016, only 42% of those firms had). In the same sectors, the sample also comprises all firms with outstanding loans, regardless of whether those firms are still in activity or not[8] . We thus ensure full coverage of both firms and bank credit in the 64 industries under analysis. The total number of firm-year observations with accounting data is 3,713,481, for 2,206,329 of which TFP can be estimated. The total number of firm-bank-year observations with non-zero outstanding credit is 4,124,974.

We have benchmarked key variables in our database – such as the number of employees, number of firms, gross value added and capital stock – against data from the Integrated Business Accounts System (IBAS) of Statistics Portugal. For the 64 industries as a whole, deviations tend to be small (Table A1 in Appendix A).

3. Characterizing credit allocation in the light of firm productivity

3.1. An overview of credit allocation across all firms

To analyse the link between credit allocation and productivity, we start by an overall characterization of how outstanding bank loans are allocated across firms, comprising both companies for which conventional measures of productivity can be computed, and companies for which they cannot. It turns out that the latter account for a very substantial share of total credit, and are often firms, as far as one can infer given data limitations, with very low productivity. In a second step, focusing on firms for which TFP can be estimated, we propose and compute a summary indicator of the allocation of credit to firms of different productivity within each 2-digit sector.

Our analysis will encompass different classes of firms whose productivity performance raises concerns. Zombie firms are a case in point, and indeed a renowned example of poor credit allocation. Though precise definitions vary across studies, zombie firms are broadly characterized as old, inefficient,

7. The industries excluded based on this criteria were: Food and beverage service activities (sector 56), Scientific research and development (72), Employment activities (78), Security and investigation activities (80), Services to buildings and landscape activities (81), Education (85), Social work activities without accommodation (88), Libraries, archives, museums and other cultural activities (91) and Activities of membership organisations (94). The share of these industries in total CCR credit was about 2.6% at the end of 2015.

8. Firms without IES data are classified into the sector where they were when they last reported.

financially-fragile firms which would normally exit the market, but are kept alive by a number of factors, most prominently different forms of bank support, such as evergreening or subsidized credit. By doing so, banks delay the eventual recognition of capital-depleting losses. The literature has pointed out that the survival of zombie firms may hamper the growth of their more productive competitors through congestion effects, as zombie firms retain a certain market share and use potentially scarce productive inputs (Caballero *et al.* (2008); McGowan *et al.* (2017)).

The share of capital sunk in zombie firms in Portugal is high in international comparison (McGowan *et al.* (2017)), and recent studies do find evidence of congestion effects (Osório de Barros *et al.* (2017); Gouveia and Osterhold (2018)). However, to our knowledge, the importance of zombie firms for credit allocation in Portugal has not been analysed yet.

We classify all firms in our sample into 10 categories, eight of which refer to firms with IES reporting. For firms which report IES, we consider four different configurations of gross value added (GVA), employment (L) and capital stock (K):

- Firms with positive GVA, K and L, for which, as a consequence, TFP can be estimated;
- Firms with $GVA \leq 0$[9];
- Firms with $GVA > 0$, but $K \leq 0$;
- Firms with positive GVA and K, but zero (or missing) L.

For none of the final 3 cases can TFP be estimated, but implications for productivity nonetheless differ. Firms with negative value added tend to be highly unproductive, except when a negative GVA stems from intra-group relationships between efficient firms. As in most of the literature using firm microdata, we treat each firm as an autonomous unit, thus disregarding relationships between firms belonging to the same economic group. In any case, available evidence does not suggest a disproportionate incidence of negative value added among firms belonging to groups[10]. Firms with positive value added but a fully depreciated capital stock may be relatively unproductive, an issue on which the computation of labour productivity (which is possible when $L > 0$) may shed some light. Finally, firms in the last case (positive GVA and K, zero or missing L) may lack TFP estimates simply for technological reasons (a wind farm is an example), implying no prior of poor productivity.

9. Some firms have reported IES but without supplying all the information needed for the computation of GVA. In these cases, their GVA has been set to zero.

10. Over 2014-2016, 9% of firms with negative value added were integrated into groups, only marginally above a share of 8% among all firms (Banco de Portugal (2018b)). Under-reporting of revenue for tax evasion purposes is an alternative explanation for negative value added, and one which is consistent with our prior of low productivity, given the linkages between the latter and semi-informality.

For each of the above four cases, we further distinguish zombie from non-zombie firms. Among the several definitions available in the literature, we follow that of McGowan *et al.* (2017), variants of which have been used in recent studies of Portuguese firms (Osório de Barros *et al.* (2017); Gouveia and Osterhold (2018)). A company is defined as a zombie firm in year t if it is then aged at least 10 years and presents an interest coverage ratio below unity in t, $t-1$ and $t-2$. This latter condition captures persistent financial weakness, while the age criterion avoids capturing young start-ups. The condition on the interest coverage ratio is implemented as EBIT being smaller than interest payments, thus comprising firms with zero interest payments but negative EBIT. As for value added and production factors, the identification of zombies relies on IES data.

Furthermore, to take account of bank credit granted to firms with no IES reporting, we consider two further categories of firms: non-reporting firms known to remain in activity, and non-reporting firms in other situations (e.g. firms which closed down or on which no information is available)[11]. From a productivity viewpoint, the absence of IES reporting raises concerns: firms may linger in a twilight zone between formality and informality, or face difficulties to comply with even routine accounting obligations. Though data for a possible classification as zombie firms is missing, non-reporting firms in activity might likewise congest markets and thus hamper the growth of healthy firms. In contrast, firms having closed down no longer congest markets, but can still affect credit reallocation if their outstanding loans continue to weigh on banks' balance sheets.

Table 1 summarises the distribution of firms among the 10 categories in 2016. For the 8 categories with IES reporting, Table 2 provides further detail on the incidence of zombie firms over 2008-2016, considering all 64 sectors together (2008 is the earliest year for which the identification of zombie firms is possible, since data starts in 2006). Unsurprisingly, the relative incidence of zombie firms is highest among companies with negative value added. In contrast, zombie firm prevalence is lowest among firms with positive value added and capital but zero or missing employment, which lends some support to our previous hypothesis that these firms, as a whole, do not face a particular productivity handicap.

	Firms with IES reporting				Firms without IES reporting	
	$GVA, K, L > 0$	$GVA \leq 0$	$GVA > 0$ & $K \leq 0$	$GVA, K > 0$ $L = 0$ or missing	Firm is active	Firm is not known to be active
Non-zombies	185 584	84 126	44 590	14 597	10 748	37 418
Zombies	9 903	16 983	2 780	745		

Shading is applied to categories deemed unproductive (see text for details).
Firms without IES reporting only include those with outstanding loans.

TABLE 1. Number of firms in each of the 10 categories | 2016

11. We assume that all firms reporting IES are in activity.

	$GVA, K, L > 0$			$GVA \leq 0$			$GVA > 0$ & $K \leq 0$			$GVA > 0$ & $K > 0$ & $L = 0$ **or missing**		
Year	Non–zombies	Zombies	% zombies	Non–zombies	Zombies	% zombies	Non–zombies	Zombies	% zombies	Non–zombies	Zombies	% zombies
2008	206,067	7,648	3.6	70,197	9,746	12.2	18,824	982	5.0	19,107	483	2.5
2009	200,228	8,460	4.1	70,794	11,205	13.7	20,682	1,161	5.3	19,219	627	3.2
2010	196,774	9,552	4.6	67,118	12,072	15.2	24,994	1,485	5.6	12,611	461	3.5
2011	188,881	10,760	5.4	78,803	14,740	15.8	29,956	2,005	6.3	12,944	509	3.8
2012	178,634	11,959	6.3	85,007	16,677	16.4	31,811	2,295	6.7	12,915	590	4.4
2013	176,699	13,374	7.0	85,878	18,212	17.5	34,279	2,515	6.8	13,607	727	5.1
2014	177,113	12,952	6.8	86,126	18,741	17.9	37,385	2,721	6.8	13,727	722	5.0
2015	183,051	11,562	5.9	85,233	17,869	17.3	41,815	2,815	6.3	14,047	782	5.3
2016	185,584	9,903	5.1	84,126	16,983	16.8	44,590	2,780	5.9	14,597	745	4.9

TABLE 2. Relative incidence of zombie firms

Perhaps more surprisingly, the vast majority of firms with negative value added, though presenting an extreme form of negative earnings ($GVA < 0$ implies negative earnings even before wage costs), manages to elude the zombie classification. This is either because of the age criterion (firms less than 10 years old), because firms alternate years with positive and negative earnings (thus avoiding an interest coverage ratio below one for 3 years in a row) or, in rarer cases, because firms achieve an interest coverage ratio above unity through income not considered for value added (some holding companies, which do not have an operational activity, provide an example).

Table 3 compares, when possible, the productivity performance of zombie and non-zombie firms. For each firm we compute the deviation of (log) productivity from the respective 2-digit sector simple average, and then take a simple average of the individual firm deviations across all sectors[12] As one might expect, the average productivity of zombie firms lies far below that of non-zombie firms, regardless of the productivity definition used (TFP or labour productivity). It is also worth noting that firms with positive GVA but non-positive capital stock fare rather poorly in labour productivity. From a productivity perspective, we therefore regard as problematic all firms that are either identified as zombie, have non-positive value added or capital stock, or no longer report IES. For conciseness, we will henceforth refer to these companies as *unproductive firms*. In Table 1, the corresponding categories are shaded.

	TFP		**LP** ($GVA, K, L > 0$)		**LP** ($GVA > 0$ & $K \leq 0$)	
Year	Non–zombies	Zombies	Non–zombies	Zombies	Non–zombies	Zombies
2008	0.02	-0.60	0.06	-0.59	-0.51	-1.33
2009	0.03	-0.65	0.07	-0.62	-0.50	-1.26
2010	0.03	-0.62	0.09	-0.61	-0.50	-1.21
2011	0.03	-0.61	0.11	-0.56	-0.56	-1.25
2012	0.04	-0.64	0.13	-0.57	-0.55	-1.21
2013	0.05	-0.64	0.14	-0.56	-0.51	-1.16
2014	0.05	-0.70	0.14	-0.61	-0.45	-1.18
2015	0.05	-0.77	0.14	-0.68	-0.44	-1.19
2016	0.04	-0.81	0.13	-0.71	-0.41	-1.23

TABLE 3. Productivity performance of zombie vs non–zombie firms: log–deviation from sectoral averages, averaged across all sectors

12. To minimize the impact of outliers, we exclude from these computations firms in the top percentile of the sectoral productivity distributions.

A very large share of the stock of credit granted by resident banks to firms has been allocated to companies with very low productivity (Chart 1 and Table A2 in Appendix A). This share shows a pronounced cyclical pattern, increasing from 2008 to 2013, and declining afterwards (the share in 2016 is likely overestimated, as argued below). The stock of credit sunk in zombie firms largely accounts for the overall cyclicality, peaking at around one fifth of total credit in 2013. However, credit misallocation is not confined to zombie firms: indeed, the share of the stock of credit allocated to the broader concept of unproductive firms is more than twice as large, surpassing 40% in 2012-2014. This much larger figure is mainly explained by outstanding credit to non-zombie firms with negative value added (around 10% in 2015 and 2016), where the impact of the business cycle is also apparent, and credit to firms without IES reporting (12% in 2015).

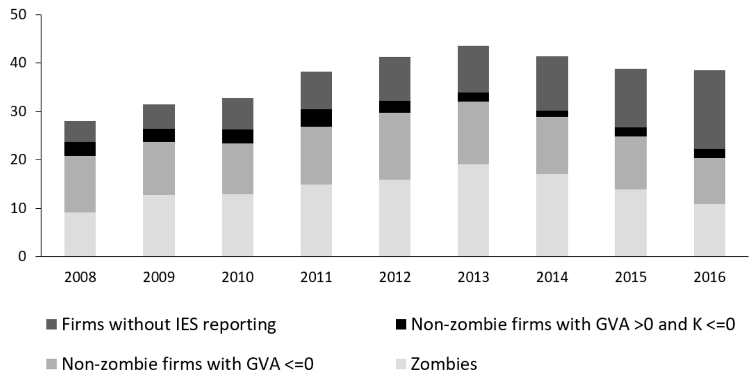


Chart 1: Share of unproductive firms in total bank credit | Per cent

Credit to non-reporting firms displays a marked upward trend over 2008-2016, probably reflecting both the cyclical impact of the global financial and sovereign debt crises, and their subsequent legacy effects. However, in the most recent year of our sample (2016), this share of credit is somewhat overstated, since (i) some firms have likely not complied with the deadline for IES reporting (but will have reported later) and (ii) some other firms have a later deadline due to non-coincidence of their fiscal year with the calendar year, and this later reporting has not been taken into account.

Focusing only on firms with IES reporting, as these are the only ones with data on employment and capital stock, Chart 2 shows that the stock of bank credit is more skewed towards unproductive firms than it is the case for labour and capital[13]. The share of capital sunk in zombie firms, though internationally

13. When analysing capital allocation, firms with negative values for the capital stock are excluded (so as to avoid that some groups of firms, like those with $GVA > 0$ but $K \leq 0$, have a slightly negative share in the total capital stock of the economy). In practice, most firms with $K \leq 0$ have $K = 0$ (cases of $K < 0$ are rare).

high (McGowan *et al.* (2017)), is always smaller than the share of bank credit absorbed by those firms (Panel A). A similar conclusion holds for the broader universe of unproductive firms (Panel B). This could be due to several factors: for instance, highly indebted and poorly capitalized unproductive firms may find it hard to invest, implying that their capital stock shrinks through depreciation. The larger skewness of credit towards unproductive firms would probably be reinforced if one could extend the comparison to firms without IES data, since those having closed down can still have outstanding bank credit but no longer absorb labour or capital.

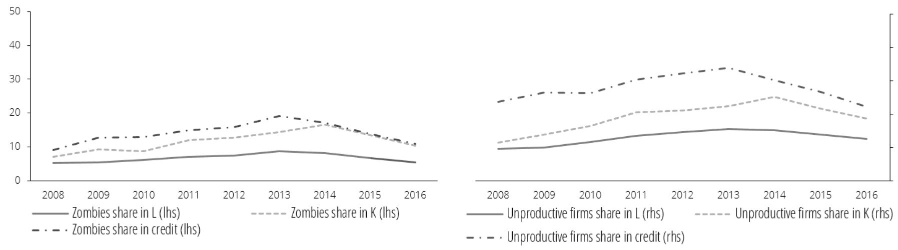


Chart 2: Resource shares allocated to zombie firms (left) and unproductive firms (right)

There is large variability across sectors in the shares of bank credit granted to unproductive firms. Table 4 reports data for broad economic sectors, highlighting the much larger scale of problems in construction and real estate, but also misallocation of credit in the rest of the economy. Chart 3 depicts shares for 2-digit sectors, showing that considerable heterogeneity also exists among non-construction and real estate sectors, such as manufacturing and services[14]. Both for zombie firms and (especially) for the broader set of unproductive firms, shares in sectoral bank credit exceed shares in sectoral capital stocks in a majority of cases.

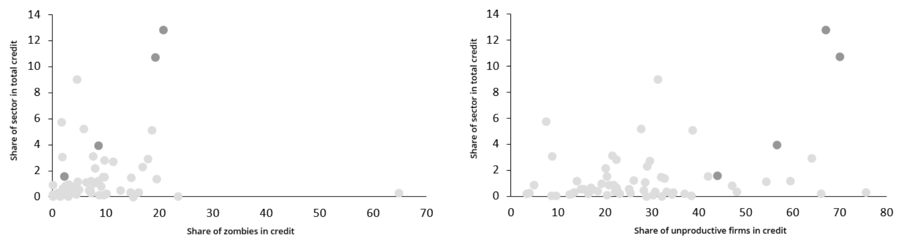
Though to a smaller extent than across sectors, there is also sizeable variation across banking groups in the shares of credit granted to zombie firms and to unproductive firms. Descriptive statistics for some credit shares are provided in Table 5 and will help interpret econometric results in Section 4 below.

14. In an overwhelming majority of 2-digit sectors and years, the average productivity of zombie firms is much smaller than that of non-zombies, and firms with positive value added but a fully depreciated capital stock have on average low labour productivity. Furthermore, in a vast majority of cases, the incidence of zombie firms is smaller among firms with $GVA > 0$, $K > 0$, $L = 0$ (or missing) than among firms with an estimated TFP. Thus, our assumptions for identifying unproductive firms generally continue to hold at the level of 2-digit sectors.

Sectors	Zombies	Unproductive firms
Manufacturing (18.1)	7.7	24.2
Construction & Real estate (29.0)	17.6	65.5
Services except real estate (44.4)	8.5	30.4
Other sectors (8.5)	7.6	19.6

Figures in brackets correspond to the share of each broad sector in total bank credit.

TABLE 4. Share of zombie and unproductive firms in total bank credit by broad economic sector | 2016



Construction and real estate sectors are marked in a darker tone

Chart 3: Share of zombie and unproductive firms in total bank credit by 2-digit sector | 2016

		No. Obs.	Average	St. Dev.	P10	P25	P50	P75	P90
Share of bank credit	Zombie firms	512	10.4	9.7	1.8	3.4	7.4	14	24.2
by 2-digit sector	Unproductive firms	512	25.2	15.2	8.8	14.9	22.8	31.8	46.3
allocated to:	of which: in activity	512	21.9	14.6	6.6	11.9	18.6	27.6	43.9
Share of bank credit	Zombie firms	72	14.2	4.6	8.7	10.6	13.4	16.7	20.5
by banking group	Unproductive firms	72	36.5	8.5	26.2	30.3	36.2	43.4	48.1
allocated to:	of which: in activity	72	32.4	6.8	24.3	27.4	32.2	37.9	41.3

Statistics are given for the period 2008-2015 as this is the relevant period for most regressions in Section 4.
Unproductive firms in activity exclude those without IES reporting which are not known to remain in activity.

TABLE 5. Shares of zombie and unproductive firms in total bank credit | Descriptive statistics, 2008-2015

3.2. A summary indicator of credit allocation across firms with TFP

For the subset of firms for which TFP can be computed, we define at the level of each 2-digit sector s the following summary indicator of credit allocation efficiency, which reflects the joint effects of credit supply and credit demand decisions taken over the course of time and also the broader economic developments. Thus, for a particular sector s in year t, the efficiency of credit allocation is given by:

$$CAE_{st} = \sum_{i=1}^{N_{st}} \left(\frac{C_{ist}}{C_{st}} - \frac{1}{N_{st}} \right) \cdot TFP_{ist}^{d}.$$

N_{st} is the number of firms for which, in a given sector and year, the computation of TFP is possible, after excluding those firms in the top and bottom percentiles of the sectoral TFP distribution. C_{ist} is the outstanding amount of loans granted to firm i by resident banks, and $C_{st} = \sum_{i=1}^{N_{st}} C_{ist}$. The final term ($TFP_{ist}^{d}$) denotes the difference between the log TFP of firm i and the unweighted average of log TFP over the N_{st} firms of the sector.Taking (log) differences to the sector average makes TFP more interpretable, not least by cancelling out sector-specific biases in its computation.

The above indicator is defined along the lines of the allocative efficiency term (or covariance term) in the renowned productivity decomposition by Olley and Pakes (1996). In their decomposition, output shares are used to measure to what extent more productive firms are larger. Instead, our indicator is based on credit shares and thus measures to what extent the outstanding credit granted to a given sector is allocated to the more productive firms within that sector. It is important to note that this indicator does not capture credit reallocation across sectors of activity.

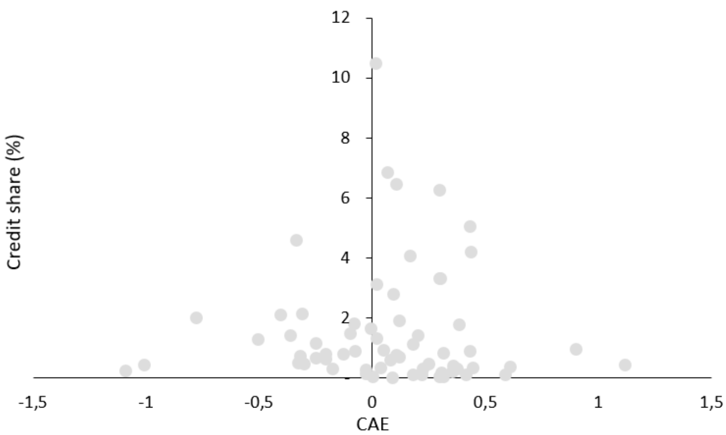
The indicator is a sum of N_{st} terms, one per firm. Companies which are above-average in both productivity and credit share, or which are below-average on both counts, make a positive contribution to the CAE indicator. Conversely, highly productive firms with little credit and low-productivity firms with above-average credit contribute negative terms to CAE. If one partitions N_{st} into groups of companies, as done below for zombie and non-zombie firms, one can also compute the contribution of each group to the indicator.

Chart 4 depicts CAE values for the 64 sectors in 2016, also reported by Table A3 in Appendix A. One observes considerable dispersion, and values for numerous sectors close to or below zero. Similar conclusions would hold if the CAE indicator were computed only for non-zombie firms with TFP (Chart A1). Thus, even when one restricts the analysis to categories of firms with a TFP estimate – arguably among the least problematic categories from a productivity viewpoint, as discussed in the previous subsection – the link between outstanding credit and productivity is often weak.

As a summary indicator for the 64 sectors as a whole, one can write:

$$CAE_{t} = \sum_{s=1}^{64} \frac{C_{st}}{C_{t}} CAE_{st},$$

with $C_{t} = \sum_{s=1}^{64} C_{st}$.



Credit shares in this chart were defined with reference to total credit granted to the subset of firms with $GVA, K, L > 0$.

Chart 4: CAE vs. relative importance of each sector in outstanding credit | 2016

Denoting the contribution of zombie and non–zombie firms to each sectoral indicator by CAE^{z}_{st} and CAE^{nz}_{st} respectively, the above expression can be rewritten as

$$CAE_t = \sum_{s=1}^{64} \frac{C_{st}}{C_t} \left(CAE^{z}_{st} + CAE^{nz}_{st} \right) = \sum_{s=1}^{64} \frac{C_{st}}{C_t} CAE^{z}_{st} + \sum_{s=1}^{64} \frac{C_{st}}{C_t} CAE^{nz}_{st} = CAE^{z}_{t} + CAE^{nz}_{t}.$$

Chart 5 depicts the economy-wide summary indicator in 2008-2016. The contribution of zombie firms is much smaller than that of healthier firms, and sometimes even negative. This is not simply a consequence of zombie firms being much less numerous (recall Table 2, columns 1 and 2): in a majority of sectors, the average individual contribution to CAE_{st} of a zombie firm is smaller than that of a non-zombie. Many zombie firms do not have outstanding bank credit, and hence make positive contributions to CAE_{st} (given their typically below-average productivity). Therefore, it is highly-indebted zombie firms which pull CAE_{st} down.

Finally, it should be noted that year-to-year fluctuations in this summary indicator should be interpreted very carefully. For instance, they are affected by shifts in credit shares across sectors, which have no immediate normative implications. More fundamentally, the slight decrease of the summary indicator in recent years does not contradict the reduction since 2013 in the share of bank credit allocated to unproductive firms (Chart 1). The reason is that the CAE indicator only considers firms for which TFP can be computed, thus providing a partial picture of total credit allocation in a given sector, as most categories of unproductive firms are disregarded.

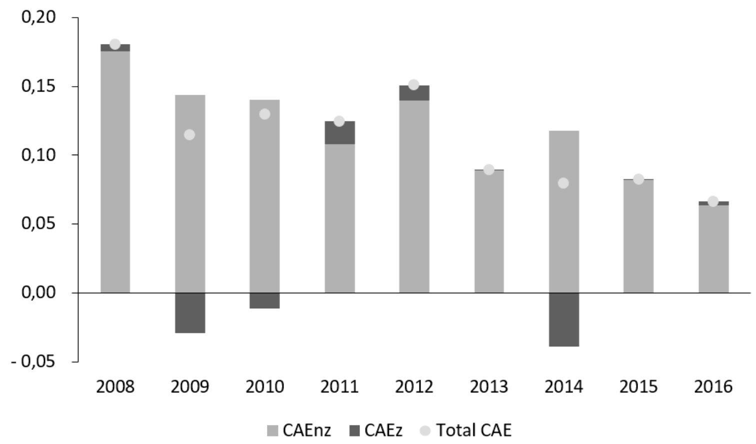


Chart 5: The CAE indicator for the whole economy (64 sectors): contributions of zombie and non-zombie firms

4. The responsiveness of credit to productivity

Section 3 has documented a large share of outstanding credit granted to unproductive firms. We now investigate the dynamics of credit reallocation and how it is affected by misallocation. In particular, we study whether a large share of credit sunk in unproductive corporations is associated with a slower reallocation towards more productive firms.

We proceed in several steps. First, we estimate a baseline, reduced-form model of credit reallocation, where the parameter of interest gives the response of total credit granted to each firm to its level of productivity. Second, we assess how this response is affected by the share of credit allocated to unproductive firms. Third, we redo the analysis with credit granted to each firm *by each banking group*, instead of by the entire banking system, so that bank indicators can be taken on board.

4.1. The response of total credit granted to each firm

We start by the following baseline specification:

$$\Delta C_{ist} = \alpha + \beta_1 TFP^d_{ist-1} + \theta \cdot X_{it-1} + \delta_{st} + \varepsilon_{ist} \tag{S1}$$

where i indexes firm, s sector and t year. The dependent variable ΔC_{ist} denotes the annual change in the total stock of credit to firm i (i.e., credit granted to firm i by all resident banks taken together). It is computed as

$$\Delta C_{ist} = \frac{C_{ist} - C_{ist-1}}{0.5(C_{ist} + C_{ist-1})},$$

which allows us to take account of both intensive and extensive margin credit changes. By construction, $\Delta C_{ist} \in [-2, 2]$, with extensive margin changes at the extremes of this interval.

The coefficient of interest is β_1, which measures the response of credit growth to the lagged deviation of firm-level log TFP from its sector-year unweighted average. Specifications along these lines have been used to study whether the reallocation of labour or capital has been productivity-enhancing (Foster *et al.* (2016); McGowan *et al.* (2017)). Given that firm productivity is only assessed within each sector, our approach is agnostic about productivity differences between sectors. Higher values of β_1 are welcome from a normative perspective since they imply faster credit reallocation towards firms which are among the most productive in their respective sectors, regardless of whether such reallocation is also accompanied by inter-sectoral credit shifts. For instance, a positive β_1 could be driven by credit reallocation from low- to high-productivity firms within the same sector, but also by credit reallocation from low-productivity firms in some sectors to high-productivity firms in different sectors.

Vector X contains a set of firm-specific controls: age, size, exporting activity and credit rating. All take the form of indicator variables and (except for age) are lagged to minimize endogeneity concerns. Firm age is controlled for through a dummy variable equal to one for firms less than 5 years old. Firm size takes four classes based on employment (micro, small, medium-sized and large firms, as detailed in section 2). Exporting activity is given by a dummy variable defined according to the criteria set out in section 2. As for credit rating, we reduce the original 8 credit quality steps (Antunes *et al.* (2016)) to only 6 by merging the top (i.e., least-risk) 3 steps (1-3). Table 6 gives descriptive statistics.

	N	mean	sd	p10	p25	p50	p75	p90
ΔC_{ist}	1086835	-0.10775	0.957263	-1.48842	-0.46434	-0.12902	0.202839	1.261698
TFP^d_{ist-1}	1086835	0.024599	0.933656	-0.97588	-0.38087	0.08009	0.516853	0.98662
LP^d_{ist-1}	1086835	0.183166	0.893098	-0.74959	-0.20004	0.227477	0.66407	1.122014
Micro	833313							
Small	214589							
Medium	34282							
Large	4651							
Young	196399							
Exporter	102814							
Rating CS3	66654							
Rating CS4	160301							
Rating CS5	127144							
Rating CS6	134702							
Rating CS7	268540							
Rating CS8	328343							

Statistics are given for the sample most often used in regressions in this subsection
(e.g. the sample of equation (3) in Table 7 below)

TABLE 6. Summary statistics

Furthermore, specification (S1) contains interacted industry and year fixed effects, thus controlling for unobserved time-varying industry-specific shocks, such as cyclical effects differentiated across sectors. Estimation uses Stata module *reghdfe* (Correia (2016)), which allows for multi-way fixed effects and clustering. Standard errors have been generally clustered at the sector level, with sensitivity analysis on this point referred to below.

The simplest version of specification (S1) – equation (1) in Table 7 – includes only firm-specific controls related to age and size, as common in the related literature (e.g. Foster *et al.* (2016), 2016; McGowan *et al.* (2017)). The coefficient of interest is estimated at 0.05, with very high statistical significance. This estimate implies that, *ceteris paribus*, the difference in credit growth (ΔC_{ist}) between a high-productivity firm (defined as one at the 75th percentile of the distribution of TFP^d_{ist} across all sectors) and a low-productivity firm (one at the 25th percentile) will be 0.045[15] (i.e., about 4,5%). In our reduced-form framework, this reflects the joint effect of credit supply and credit demand – the likely greater willingness of banks to extend credit to high-productivity firms, and the likely greater willingness and ability of these firms to seek more funding (from banks or from other sources) and grow.

Equation (2) adds controls for exporting activity and credit rating. The latter makes the response to productivity decrease by about one third, likely reflecting the positive correlation between higher productivity and better ratings. Equation (3) returns to the simpler, and in our view preferable, equation (1) and restricts the sample in two ways: estimation starts only in 2009 and drops ΔC_{ist} observations for firms that change sector between $t-1$ and t. This is done for comparability with the next step in our analysis (see below), and hardly affects the coefficient of interest. Equation (4) documents a qualitatively similar, though somewhat smaller, credit reallocation effect when labour productivity (LP) replaces TFP (for exactly the same estimation sample). Returning to TFP, equations (5) to (7) show stronger credit responsiveness to productivity differentials in manufacturing or services than in construction and real estate.

15. This equals the coefficient (0.05) times the difference in the TFP deviation between the two percentiles [0.9, i.e., 0.52 – (– 0.38), from Table 6].

	(1) ΔC_{ist}	(2) ΔC_{ist}	(3) ΔC_{ist}	(4) ΔC_{ist}	(5) ΔC_{ist}	(6) ΔC_{ist}	(7) ΔC_{ist}
TFP^d_{ist-1}	0.0500*** (0.00550)	0.0340*** (0.00432)	0.0503*** (0.00541)		0.0629*** (0.00502)	0.0211*** (0.00215)	0.0590*** (0.00247)
LP^d_{ist-1}				0.0409*** (0.00369)			
young	0.322*** (0.00893)	0.332*** (0.00853)	0.331*** (0.00784)	0.333*** (0.00814)	0.364*** (0.0131)	0.347*** (0.00602)	0.321*** (0.00929)
small (lagged)	0.0627*** (0.00724)	0.0441*** (0.0120)	0.0694*** (0.00735)	0.0676*** (0.00826)	0.0637*** (0.00606)	0.116*** (0.00582)	0.0562*** (0.00357)
medium (lagged)	0.0718*** (0.0114)	0.0455** (0.0174)	0.0818*** (0.0114)	0.0749*** (0.0125)	0.0935*** (0.00837)	0.154*** (0.0154)	0.0537*** (0.0116)
large (lagged)	0.0616*** (0.0158)	0.0192 (0.0226)	0.0687*** (0.0170)	0.0576*** (0.0178)	0.0704*** (0.0224)	0.180*** (0.0450)	0.0450** (0.0201)
exporter (lagged)		0.0236*** (0.00581)					
rating CS4 (lagged)		-0.0108 (0.0183)					
rating CS5 (lagged)		-0.0316 (0.0224)					
rating CS6 (lagged)		-0.0362* (0.0211)					
rating CS7 (lagged)		-0.0573** (0.0218)					
rating CS8 (lagged)		-0.140*** (0.0247)					
Years	2007–2016	2007–2016	2009–2016	2009–2016	2009–2016	2009–2016	2009–2016
Sectors	All	All	All	All	Manufacturing	Construction & RE	Services except RE
Sector × year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1410660	1409495	1086835	1086835	179373	172270	691393
R^2	0.029	0.031	0.030	0.029	0.032	0.032	0.028

Standard errors in parentheses, clustered by sector
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 7. Credit reallocation and firm productivity

We now bring possible effects from misallocation into the picture by estimating

$$\Delta C_{ist} = \alpha + \beta_1 TFP^d_{ist-1} + \beta_2 TFP^d_{ist-1} S_{st-1} + \theta \cdot X_{it-1} + \delta_{st} + \varepsilon_{ist}, \quad \text{(S2)}$$

where TFP is interacted with the share S of bank credit to sector s allocated to zombie or unproductive firms.

Equation (1) in Table 8 reports results for S defined with reference to zombie firms only. Estimation starts in 2009 since S is only defined from 2008 onwards; furthermore, since S refers to a given sector, we drop from the sample observations for firms which change sector between $t-1$ and t. The estimate for β_2 is negative, as expected, but of only marginal statistical significance. To assess the economic impact of this estimate, let us compare a sector with a high share of credit sunk in zombie firms (e.g. 24%, the 90^{th} percentile in the cross-sector distribution of S over 2008-2015 – see Table 5) and a sector with a low share (2%, the 10^{th} percentile). Moving from the former to the latter will increase the difference in credit growth between a high-productivity firm and a low-productivity firm (respectively at the 75^{th} and 25^{th} percentiles of the distribution of TFP^d_{ist}, as above) from 0.036[16] to 0.052, a sizeable impact.

Sizeable though it is, it pales by comparison with estimates from equation (2), where S is defined for the broader universe of unproductive firms in activity. The coefficient on the interaction term is now highly significant, and implied impacts on credit reallocation are much larger. Redoing the exercise above, the 90^{th} and 10^{th} percentiles of credit sunk in unproductive firms are 44% and 7% (Table 5). Moving from the former to the latter will increase the difference in credit growth between a high-productivity firm and a low-productivity firm (defined as before) from 0.032 to 0.061, almost twice as much.

	(1) ΔC_{ist}	(2) ΔC_{ist}	(3) ΔC_{ist}	(4) ΔC_{ist}	(5) ΔC_{ist}	(6) ΔC_{ist}
TFP^d_{ist-1}	0.0591***	0.0740***			0.0587***	0.0648***
	(0.00389)	(0.00433)			(0.00325)	(0.00421)
$TFP^d_{ist-1} \times S_{st-1}$ (zombies)	-0.0771*				-0.00343	
	(0.0399)				(0.0221)	
$TFP^d_{ist-1} \times S_{st-1}$ (unproductive)		-0.0868***				-0.0291**
		(0.0152)				(0.0131)
LP^d_{ist-1}			0.0475***	0.0565***		
			(0.00367)	(0.00452)		
$LP^d_{ist-1} \times S_{st-1}$ (zombies)			-0.0594***			
			(0.0215)			
$LP^d_{ist-1} \times S_{st-1}$ (unproductive)				-0.0590***		
				(0.0116)		
Firm age and size controls	Yes	Yes	Yes	Yes	Yes	Yes
Sectors	All	All	All	All	Excluding Const. & RE	Excluding Const. & RE
Sector × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1086835	1086835	1086835	1086835	914565	914565
R^2	0.030	0.030	0.029	0.029	0.029	0.029

Standard errors in parentheses, clustered by sector
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 8. Credit reallocation and firm productivity: impacts from misallocation

We thus find strong evidence that credit reallocation towards high-productivity firms is slower in sectors where a high share of bank credit is sunk in inefficient firms. This echoes similar results obtained for capital stock shares and reallocation by McGowan *et al.* (2017), Andrews and Petroulakis (2017) and Gouveia and Osterhold (2018). Evidence is much stronger, numerically and statistically, for the broader category of unproductive firms in activity than for the narrower definition of zombie firms.

Equations (3) and (4) resort to labour productivity (LP) instead of TFP. Parameter β_2 is again more precisely estimated for credit sunk in unproductive firms. Implied economic impacts are not out of line with those obtained with TFP, though somewhat smaller: moving from the 90^{th} to the 10^{th} percentile of S would increase the difference in credit growth between a high-productivity firm and a low-productivity firm (defined as before) from 0.029 to 0.040 with

16. This equals the estimated coefficient account taken of the interaction term $(0.059 - 0.077 \times 0.24)$ times the difference in the TFP deviation between the two percentiles (0.9).

S referring to zombie firm shares, and from 0.026 to 0.045 with S referring to unproductive firm shares.

Equations (5) and (6) exclude firms from construction and real estate sectors, where the share of misallocated credit is disproportionately large (recall Table 4). The coefficient on the interaction with credit shares allocated to zombie firms is no longer statistically different from zero, but the interaction defined for unproductive firms remains significant. The difference in credit growth between a high-productivity firm and a low-productivity firm increases by about 1 percentage point when moving from the 90^{th} to the 10^{th} percentile of the distribution of S.

We have performed a battery of sensitivity analysis tests, re-running the equations yielding the main findings – equations (2) and (6) of Table 8 – with a different sample (Appendix B, Tables B1 and B2). In this vein, we have excluded observations pertaining to zombie firms, removed productivity outliers, and dropped dependent variable observations corresponding to small absolute changes in credit or to extensive margin credit changes. Furthermore, we have computed S_{st-1} with alternative delimitations of unproductive firms, either enlarging our baseline perimeter to include firms not known to be in activity or restricting it by excluding non-zombie firms with $GVA \leq 0$ (on account of possible intra-group relationships). Finally, we have experimented with different clustering of standard errors. For all sectors considered, the significance of β_2 remains extremely robust, while without construction and real estate it sometimes falters.

4.2. The response of credit granted to each firm by each banking group

At firm-bank level, the dependent variable becomes the growth rate of the stock of credit granted by banking group b to firm i, defined as:

$$\Delta C_{isbt} = \frac{C_{isbt} - C_{isbt-1}}{0.5(C_{isbt} + C_{isbt-1})}.$$

We first estimate

$$\Delta C_{isbt} = \alpha + \beta_1 TFP^d_{ist-1} + \theta \cdot X_{it-1} + \delta_{st} + \gamma_{bt} + \varepsilon_{isbt}, \tag{S3}$$

which adds interacted bank and year fixed effects to specification (S1) above, thus controlling for unobserved time-varying bank heterogeneity.

Table 9 essentially confirms for this richer panel previous results. In equation (1), the estimate for β_1 is virtually identical to the one of equation (3) in Table 7. Results for labour productivity also turn out very similar (equation (2), Table 9 *versus* equation (4), Table 7). Furthermore, it remains the case that credit responsiveness to productivity differentials is weaker in construction and real estate (last three equations of Tables 7 and 9).

	(1) ΔC_{isbt}	(2) ΔC_{isbt}	(3) ΔC_{isbt}	(4) ΔC_{isbt}	(5) ΔC_{isbt}
TFP^d_{ist-1}	0.0496***		0.0633***	0.0186***	0.0587***
	(0.00575)		(0.00447)	(0.00190)	(0.00216)
LP^d_{ist-1}		0.0443***			
		(0.00439)			
Firm age and size controls	Yes	Yes	Yes	Yes	Yes
Years	2009–2016	2009–2016	2009–2016	2009–2016	2009–2016
Sectors	All	All	Manufacturing	Const. & RE	Services except RE
Sector × year FE	Yes	Yes	Yes	Yes	Yes
Bank × year FE	Yes	Yes	Yes	Yes	Yes
Observations	2050618	2050618	391616	319443	1258023
R^2	0.033	0.033	0.030	0.038	0.033

Standard errors in parentheses, clustered by sector (except in column (4))
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 9. Credit reallocation by each bank and firm productivity

We next investigate the empirical relevance of interactions with TFP, by estimating:

$$\Delta C_{isbt} = \alpha + \beta_1 TFP^d_{ist-1} + \beta_2 TFP^d_{ist-1} S_{st-1} + \beta_3 TFP^d_{ist-1} B_{bt-1} + \theta X_{it-1} + \delta_{st} + \gamma_{bt} + \varepsilon_{isbt}. \quad \text{(S4)}$$

Considering outstanding loans at the level of each banking group enables us to study a richer set of interaction terms, including sectoral credit shares (S), as before, but also bank-specific variables (B) characterizing the quality of credit portfolios. Hence, we consider for each bank the share of outstanding credit granted to zombie firms and to unproductive firms (taking the 64 sectors under analysis together). Variable B can also refer to other bank variables, such as credit at risk ratios or Tier1 ratios.

Equations (1) and (2) in Table 10 show coefficients of interest which are very similar to their counterparts in Table 8, again with sectoral shares S defined for unproductive firms yielding statistically stronger impacts than shares defined for zombie firms. Equations (3) and (4) add interactions with the credit shares of each banking group (B) granted respectively to zombie firms and to unproductive firms, which turn out highly significant, especially in the latter case. For credit to all unproductive firms (i.e., in activity or not)[17], 26% is the 10^{th} percentile of the cross-bank distribution of B over 2008-2015, and 48% is the 90^{th} percentile (Table 5). Moving from the former to the latter will decrease the difference in credit growth between a high-productivity firm and

17. This is broader than in the definition of S, which considered only unproductive firms in activity. The difference has to do with the possible interpretation of S as capturing the intensity of congestion effects, which can only be ascribed to firms in activity (the final section of the paper further discusses this interpretation), while B refers to the quality of credit portfolios, which is best assessed on the basis of the full portfolio.

a low-productivity firm (respectively at the 75^{th} and 25^{th} percentiles of the distribution of TFP^d_{ist}, as above) from 0.058 to 0.043[18].

Equations (3) and (4) therefore illustrate that, in the case of banks with a higher share of credit granted to unproductive firms, reallocation towards high-productivity companies tends to be more sluggish. Taken together, effects from misallocation at the sector and at the bank level can significantly weigh on productivity-responsive credit reallocation. Moving from the 90^{th} to the 10^{th} percentile in *both* the cross-bank distribution of B and the cross-sector distribution of S will multiply the difference in credit growth between a high-productivity firm and a low-productivity firm by a factor of three (from 0.022 to 0.067)[19] .

Interestingly, the interaction of credit-at-risk ratios with TFP is not statistically significant (equation (5) in Table 10)[20]. The interaction of Tier1 ratios with TFP has a positive coefficient, as expected, but is not statistically significant either (equation (6)).

When firms in construction and real estate sectors are excluded, the interaction $TFP.S$ loses significance, but the interaction $TFP.B$ retains it (equation (7))[21]. Similar conclusions hold when replacing TFP by labour productivity, as done in equations (8) and (9).

Tables B3 and B4 (Appendix B) report sensitivity analysis, conducted along the lines of the previous subsection. We have added the exclusion of observations pertaining to the residual banking group given its internal heterogeneity, and experimented with a similar perimeter of unproductive firms for computing S and B (firms in activity only in both cases, or all unproductive firms in both cases). Re-running variants of equation (4) in Table 10, the significance of both interaction terms (with S and with B) is generally preserved. Likewise, the significance of the coefficient on $TFP.B$ in variants of equation (7) of the same table continues to hold.

18. This assumes S at the median of its cross-sector distribution.

19. Admittedly, moving from the 90^{th} to the 10^{th} percentiles in both distributions is a more extreme exercise than a similar move in just one of them.

20. There are fewer observations in the regression with the credit-at-risk ratio, since this ratio is only available from 2009 onwards (i.e., one year later than the shares of credit allocated to zombie or unproductive firms) and has not been computed for the ninth (residual) banking group. One might wonder whether this different sample is behind the non-significance of the interaction coefficient. However, re-estimating equation (4) with the same sample of equation (5) yields a statistically significant coefficient on the interaction $B.TFP$ (though only at the 10% significance level).

21. Variable B is defined with reference to all 64 sectors, and hence also takes account of credit allocated to unproductive firms in construction and real estate.

	(1) ΔC_{isbt}	(2) ΔC_{isbt}	(3) ΔC_{isbt}	(4) ΔC_{isbt}	(5) ΔC_{isbt}	(6) ΔC_{isbt}	(7) ΔC_{isbt}	(8) ΔC_{isbt}	(9) ΔC_{isbt}
TFP^d_{ist-1}	0.0605***	0.0755***	0.0764***	0.101***	0.0724***	0.0619***	0.107***		
	(0.00380)	(0.00415)	(0.00870)	(0.00876)	(0.00439)	(0.00809)	(0.00727)		
$TFP^d_{ist-1} \times S_{st-1}$ (zombies)	-0.0962**		-0.0854**						
	(0.0398)		(0.0426)						
$TFP^d_{ist-1} \times S_{st-1}$ (unproductive)		-0.0959***		-0.0907***	-0.0937***	-0.104***	-0.00384		
		(0.0167)		(0.0191)	(0.0194)	(0.0177)	(0.0134)		
$TFP^d_{ist-1} \times B_{bt-1}$ (zombies)			-0.125**						
			(0.0582)						
$TFP^d_{ist-1} \times B_{bt-1}$ (unproductive)				-0.0762***			-0.133***		
				(0.0280)			(0.0165)		
$TFP^d_{ist-1} \times B_{bt-1}$ (credit at risk ratio)					-0.00854				
					(0.0387)				
$TFP^d_{ist-1} \times B_{bt-1}$ (Tier 1 ratio)						0.119			
						(0.0789)			
LP^d_{ist-1}								0.0995***	0.104***
								(0.00768)	(0.00763)
$LP^d_{ist-1} \times S_{st-1}$ (unproductive)								-0.0670***	-0.0248
								(0.0144)	(0.0181)
$LP^d_{ist-1} \times B_{bt-1}$ (unproductive)								-0.106***	-0.138***
								(0.0197)	(0.0162)
Firm age and size controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Years	2009–2016	2009–2016	2009–2016	2009–2016	2010–2016	2009–2016	2009–2016	2009–2016	2009–2016
Sectors	All	All	All	All	All	All	Excluding Const. & RE	All	Excluding Const. & RE
Sector × year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank × year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2050618	2050618	2050618	2050618	1297115	1509647	1731175	2050618	1731175
R^2	0.033	0.033	0.033	0.033	0.036	0.033	0.032	0.033	0.032

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 10. Credit reallocation by each bank and firm productivity: impacts from misallocation

5. Concluding remarks

This study has examined two related questions. First, how outstanding loans granted by the Portuguese banking system are allocated across firms of different levels of productivity. Second, how changes in the stock of credit respond to firm productivity, and how that response is affected by the existing allocation.

We have obtained two main sets of findings. First, there is a large share of outstanding credit granted by resident banks to non-financial corporations which is allocated to categories of firms with very low measured or inferred productivity (referred to as unproductive firms). This credit share rose from 2008 to 2013, when it peaked at 44%. Since then, the share of misallocated credit started to decline with the rebound in economic activity and the growing allocation of new bank loans towards lower risk firms (which tend to have higher productivity) and away from higher risk firms (Banco de Portugal (2017)). Credit misallocation is particularly high in construction and real estate but not confined to these sectors. Furthermore, the share of bank credit allocated to unproductive firms exceeds the corresponding shares of labour and capital, one possible explanation being that highly indebted and poorly capitalized unproductive firms may find it hard to invest and thus prevent that their capital stock shrinks through depreciation. Even among firms not deemed as unproductive, the link between credit allocation and productivity is often tenuous.

Second, the reallocation of bank loans is hampered by misallocation: a high share of credit sunk in unproductive companies is associated to a smaller responsiveness of credit growth to firm productivity. This effect is felt both at sector and bank levels: reallocation is slower in sectors with a higher share of the stock of credit granted to unproductive firms, and in the case of banks with a higher share of such credit in their portfolios.

Our analysis is mainly descriptive, and a structural interpretation is complex and largely beyond the scope of this paper. In particular, it is tempting, but wrong, to fully attribute the prevailing allocation of loans to the credit supply decisions of banks. They undoubtedly played their part, but so did borrowers. For instance, recent years have seen stronger capitalization of Portuguese SMEs through retained earnings and increasing resort to international capital markets by some large firms (Banco de Portugal (2018c)), both of which could lower the demand for loans granted by resident banks. Furthermore, in addition to credit supply and demand decisions at the time of loan origination, subsequent events, such as cyclical developments, also weigh on the prevailing credit allocation at a given point in time.

The dampening impact of past credit misallocation on current reallocation is also the joint effect of multiple supply and demand influences. While no attempt is made at structural identification, it is worth recalling the main forces likely to be at play, both at bank level and at sectoral level.

At the level of bank credit portfolios, a larger weight of unproductive firms may hamper reallocation through supply-side evergreening incentives or by making banks postpone write-offs of loans unlikely to be ever repaid. However, this behaviour has been tackled by stepped up supervisory action, especially since 2016, which inter alia has required that some large banks comply with NPL reduction plans submitted to supervisory authorities (Banco de Portugal (2018a)). In a second strand of explanation, banks with worse portfolios could also face higher funding costs (European Systemic Risk Board (2017)), reducing their ability to grant loans to the best performing firms at competitive interest rates. But the plausibility of this second strand in the Portuguese case is weakened by the fact that bank funding from securities, arguably the funding item most cost-sensitive to portfolio quality, has strongly declined since early 2010.

At sectoral level, congestion effects may lie behind hampered reallocation. In a sector where unproductive firms abound, healthy competitors find it harder to grow (e.g. since surviving inefficient firms take some market share) and hence demand less funding, be it from banks or from other sources. Banks, aware of congestion and of its negative impact on firm profitability, could also be less inclined to further extend credit to that sector.

The recomposition of the financing structure of Portuguese firms, observed since 2012, has favoured equity and intra-group loans to the detriment of bank loans, particularly in SMEs. Despite these recent positive trends, the indebtedness ratio of non-financial corporations remains high, which may deter investment and is an important vulnerability from a financial stability perspective (Banco de Portugal (2017); Farinha and Prego (2013)). In addition, the NPL ratio of banks is still among the highest in the euro area, despite substantial reduction over the past two years. In this context, credit reallocation to the most productive firms should proceed in tandem with further rebalancing of the financing structure of non-financial corporations as a whole towards own funds and away from debt. Banks play a key role in this reallocation path, as many firms are heavily reliant on bank lending.

Bank credit allocation in the Portuguese economy remains a topic where further research is much needed. Even without venturing into structural modelling, the avenues for reduced-form analysis are far from exhausted. For instance, it would be interesting to study whether patterns of credit allocation or reallocation differ by the quality and quantity of loan collateral.

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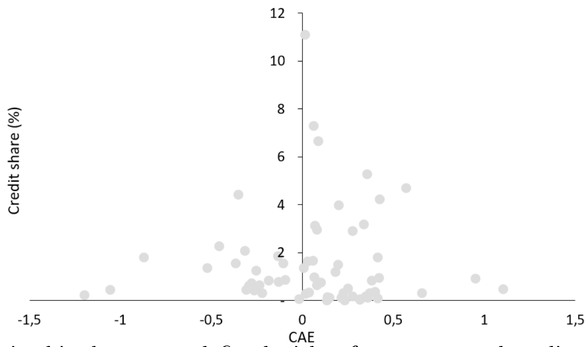
Appendix A

Variable	Our database	Statistics Portugal (IBAS)	Deviation (%)
Number of firms	356,449	331,752	7.4[a]
Number of employees	2,173,289	2,266,069	-4.1
GVA (€ millions)	69,883	69,688	0.3
Capital stock (€ millions)	149,858	$169,003^{(b)}$	-11.3

Unpublished data from IBAS (disaggregated at 2-digit level) has been kindly provided by Statistics Portugal. (a) If we excluded from our dataset those firms with zero employees, GVA and capital stock, we would obtain a number of firms very close to that of IBAS. (b) Capital stock of IBAS include fixed tangible assets, property and biological assets and intangible assets. Our database, unlike data from IBAS, excludes assets in progress and advances on assets, which helps explain lower values.

Table A.1. Key variables benchmarking (our database versus IBAS) | 2015



Credit shares in this chart were defined with reference to total credit granted to the subset of non-zombie firms with GVA, K, $L > 0$. The CAE indicator was computed for each sector considering only non-zombie firms for which the computation of TFP was possible.

Chart A1: CAE for non-zombie firms vs. relative importance of each sector in outstanding credit | 2016

	GVA, K, L > 0		GVA ≤ 0		GVA>0 & K≤ 0		GVA>0 & K >0 & L=0 or missing		Firms without IES reporting	
Year	Non–zombies	Zombies	Non–zombies	Zombies	Non–zombies	Zombies	Non–zombies	Zombies	Firm is active	Firm is not known to be active
2008	63,4	6,1	11,7	2,1	2,8	0,3	8,6	0,5	1,7	2,6
2009	61,4	7,3	11,0	3,3	2,8	0,4	7,1	1,8	2,8	2,2
2010	60,7	7,7	10,5	4,0	2,8	0,4	6,5	0,8	3,9	2,6
2011	56,1	8,2	12,1	5,3	3,5	0,5	5,8	0,9	4,4	3,3
2012	53,0	8,5	13,9	5,7	2,4	0,7	5,7	1,0	5,1	4,0
2013	51,4	10,2	12,9	6,8	1,9	0,7	5,1	1,4	4,7	4,9
2014	53,6	9,3	11,8	6,2	1,3	0,5	5,1	1,0	4,8	6,4
2015	56,5	6,8	10,9	5,9	1,9	0,4	4,8	0,8	5,1	6,9
2016	56,3	5,2	9,5	4,5	1,8	0,6	5,1	0,6	9,0	7,3

Table A.2. Share of different groups of firms in total bank credit | Per cent

Industry number	Industry name	Credit exposure (€ millions)	CAE
1	Crop and animal production, hunting and related service activities	1 447	0,30
2	Forestry and logging	120	-0,03
3	Fishing and aquaculture	185	0,36
5-9	Mining and quarrying	219	-0,33
10	Manufacture of food products	1 764	0,17
11-12	Beverages and tobacco	785	-0,08
13	Manufacture of textiles	720	-0,01
14	Manufacture of wearing apparel	496	0,18
15	Manufacture of leather and related products	403	0,05
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	576	0,02
17	Manufacture of paper and paper products	350	-0,21
18	Printing and reproduction of recorded media	295	-0,25
19-20	Coke, refined petroleum and chemicals	388	-0,08
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	206	-0,30
22	Manufacture of rubber and plastic products	511	-0,25
23	Manufacture of other non-metallic mineral products	833	0,12
24	Manufacture of basic metals	271	-0,21
25	Manufacture of fabricated metal products, except machinery and equipment	1 364	0,02
26	Manufacture of computer, electronic and optical products	156	0,44
27	Manufacture of electrical equipment	266	0,08
28	Manufacture of machineryand equipment n.e.c.	314	-0,32
29	Manufacture of motor vehicles, trailers and semi-trailers	343	-0,13
30	Manufacture of other transport equipment	56	0,18
31	Manufacture of furniture	334	0,10
32	Other manufacturing	132	-0,17
33	Repair and installation of machinery and equipment	135	0,22
35	Electricity, gas, steam and air conditioning supply	921	-0,41
36	Water collection, treatment and supply	621	-0,36
37-39	Sewerage and waste collection	563	-0,51
41	Construction of buildings	2 193	0,43
42	Civil engineering	1 221	0,09
43	Specialised construction activities	615	0,20
45	Wholesale and retail trade and repair of motor vehicles and motorcycles	1 829	0,43
46	Wholesale trade, except of motor vehicles and motorcycles	4 560	0,01
47	Retail trade, except of motor vehicles and motorcycles	2 801	0,11
49	Land transport and transport via pipelines	1 441	0,30
50	Water transport	46	0,41
51	Air transport	877	-0,78
52	Warehousing and support activities for transportation	2 972	0.07
53	Postal and courier activities	11	0,09
55	Accommodation	2 720	0,30
58	Publishing activities	163	0,61
59	Motion picture, video and television programme production, sound recording and music publishing activities	69	-0.03
60	Programming and broadcasting activities	44	0,59
61	Telecommunications	187	-1,01
62	Computer programming, consultancy and related activities	358	0,32
63	Information service activities	24	0,31
68	Real estate activities	1 992	-0,34
69	Legal and accounting activities	207	0,25
70	Activities of head offices; management consultancy activities	772	0,38
71	Architectural and engineering activities; technical testing and analysis	390	0,43
73	Advertising and market research	197	1,12
74	Other professional, scientific and technical activities	76	0.31
75	Veterinary activities	27	0.00
77	Rental and leasing activities	647	-0,10
79	Travel agency, tour operator reservation service and related activities	129	0,37
82	Office administrative, office support and other business support activities	304	0,12
86	Human health activities	933	-0,31
87	Residential care activities	152	0,04
90	Creative, arts and entertainment activities	54	0,22
92	Gambling and betting activities	105	-1,09
93	Sports activities and amusement and recreation activities	413	0,90
95	Repair of computers and personal and household goods	15	0,29
96	Other personal service activities	88	0,35

Credit exposure refers to total credit granted to the subset of firms with $GVA, K, L > 0$.

TABLE A.3. CAE by industry | 2016

Appendix B

Table B1: Sensitivity analysis: variants of equation (2), Table (8) (all sectors)

	(1) ΔC_{ist}	(2) ΔC_{ist}	(3) ΔC_{ist}	(4) ΔC_{ist}	(5) ΔC_{ist}	(6) ΔC_{ist}	(7) ΔC_{ist}	(8) ΔC_{ist}	(9) ΔC_{ist}	(10) ΔC_{ist}
TFP^d_{ist-1}	0.0684***	0.0578***	0.0840***	0.100***	0.0741***	0.0664***	0.0740***	0.0740***	0.0740***	0.0740***
	(0.00416)	(0.00334)	(0.00481)	(0.00649)	(0.00435)	(0.00471)	(0.00711)	(0.00393)	(0.00211)	(0.00682)
$TFP^d_{ist-1} \times S_{st-1}$	-0.0814***	-0.0745***	-0.0868***	-0.118***	-0.0754***	-0.0904***	-0.0868***	-0.0868***	-0.0868***	-0.0868***
	(0.0140)	(0.0137)	(0.0133)	(0.0204)	(0.0137)	(0.0334)	(0.0193)	(0.0136)	(0.00685)	(0.0178)
Exclusions	zombies	extensive margin	TFP outliers	small credit changes						
Unproductive firms	in activity	in activity	in activity	in activity	in activity or not	in activity, with exceptions	in activity	in activity	in activity	in activity
S.E. Clustering by	Sector	Sector	Sector	Sector	Sector	Sector	Sector & year	Sector × year	Firm	Firm & year
Observations	1008052	930495	1065099	815146	1086835	1086835	1086835	1086835	1086835	1086835
R^2	0.029	0.023	0.030	0.044	0.030	0.030	0.030	0.030	0.030	0.030

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All equations include firm age and size controls, and interacted sector and year fixed effects. Equation (1) excludes observations from firms which are classified as zombies in either t or $t-1$. Equation (2) excludes observations with $\Delta C_{ist} = 2$ or $\Delta C_{ist} = -2$. Equation (3) excludes observations in the top and bottom percentiles of TFP^d_{ist-1}. Equation (4) excludes observations in the bottom quartile of $C_{ist} - C_{ist-1}$, taken in absolute terms. Equation (5) includes among unproductive firms (for purposes of computing S_{st-1}) all those not reporting IES, regardless of their activity status; all other equations exclude non-reporting firms not known to be in activity, and equation (6) further excludes non-zombie firms with non-positive GVA.

Table B2: Sensitivity analysis: variants of equation (6), Table (8) (excluding construction and real estate)

	(1) ΔC_{ist}	(2) ΔC_{ist}	(3) ΔC_{ist}	(4) ΔC_{ist}	(5) ΔC_{ist}	(6) ΔC_{ist}	(7) ΔC_{ist}	(8) ΔC_{ist}	(9) ΔC_{ist}	(10) ΔC_{ist}
TFP^d_{ist-1}	0.0606***	0.0482***	0.0800***	0.0859***	0.0630***	0.0603***	0.0648***	0.0648***	0.0648***	0.0648***
	(0.00415)	(0.00326)	(0.00569)	(0.00633)	(0.00435)	(0.00410)	(0.00810)	(0.00426)	(0.00284)	(0.00810)
$TFP^d_{ist-1} \times S_{st-1}$	-0.0303**	-0.0209	-0.0545**	-0.0275	-0.0178	-0.0131	-0.0291	-0.0291*	-0.0291**	-0.0291
	(0.0120)	(0.0133)	(0.0209)	(0.0192)	(0.0138)	(0.0210)	(0.0164)	(0.0150)	(0.0119)	(0.0180)
Exclusions	zombies	extensive margin	TFP outliers	small credit changes						
Unproductive firms	in activity	in activity	in activity	in activity	in activity or not	in activity, with exceptions	in activity	in activity	in activity	in activity
S.E. Clustering by	Sector	Sector	Sector	Sector	Sector	Sector	Sector & year	Sector × year	Firm	Firm & year
Observations	846808	784888	896275	685926	914565	914565	914565	914565	914565	914565
R^2	0.028	0.023	0.029	0.043	0.029	0.029	0.029	0.029	0.029	0.029

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Same notes as in Table B1.

Table B3: Sensitivity analysis: variants of equation (4), Table 10 (all sectors)

	(1) ΔC_{isbt}	(2) ΔC_{isbt}	(3) ΔC_{isbt}	(4) ΔC_{isbt}	(5) ΔC_{isbt}	(6) ΔC_{isbt}	(7) ΔC_{isbt}	(8) ΔC_{isbt}	(9) ΔC_{isbt}	(10) ΔC_{isbt}	(11) ΔC_{isbt}
TFP^d_{ist-1}	0.0963***	0.0574***	0.123***	0.116***	0.0927***	0.106***	0.0998***	0.101***	0.101***	0.101***	0.101***
	(0.00846)	(0.00539)	(0.00954)	(0.0115)	(0.00973)	(0.00835)	(0.00911)	(0.00800)	(0.0171)	(0.00440)	(0.0157)
$TFP^d_{ist-1} \times S_{st-1}$	-0.0807***	-0.0449***	-0.0869***	-0.123***	-0.0974***	-0.0901***	-0.0804***	-0.0907***	-0.0907***	-0.0907***	-0.0907***
	(0.0174)	(0.0126)	(0.0200)	(0.0269)	(0.0187)	(0.0188)	(0.0175)	(0.0150)	(0.0103)	(0.00630)	(0.0171)
$TFP^d_{ist-1} \times B_{bt-1}$	-0.0864***	-0.0607***	-0.116***	-0.0468	-0.0559*	-0.101***	-0.0702**	-0.0762***	-0.0762*	-0.0762***	-0.0762*
	(0.0272)	(0.0160)	(0.0283)	(0.0380)	(0.0281)	(0.0283)	(0.0297)	(0.0220)	(0.0419)	(0.0115)	(0.0340)
Exclusions	zombies	extensive margin	TFP outliers	small credit changes	residual banking group						
Unproductive firms (S)	in activity	in activity	in activity	in activity	in activity	in activity	in activity or not	in activity	in activity	in activity	in activity
Unproductive firms (B)	in activity or not	in activity or not	in activity or not	in activity or not	in activity or not	in activity	in activity or not	in activity or not	in activity or not	in activity or not	in activity or not
S.E. Clustering by	Sector	Sector	Sector	Sector	Sector	Sector	Sector	Sector × year	Bank × year	Firm	Firm & year
Observations	1903001	1576622	2009612	1538024	1520364	2050618	2050618	2050618	2050618	2050618	2050618
R^2	0.032	0.020	0.033	0.041	0.033	0.033	0.033	0.033	0.033	0.033	0.033

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

All equations include firm age and size controls, and interacted sector and year fixed effects. Equation (1) excludes observations from firms which are classified as zombies in either t or $t-1$. Equation (2) excludes observations with $\Delta C_{ist} = 2$ or $\Delta C_{ist} = -2$. Equation (3) excludes observations in the top and bottom percentiles of TFP^d_{ist-1}. Equation (4) excludes observations in the bottom quartile of $C_{ist} - C_{ist-1}$, taken in absolute terms. Equation (5) excludes observations from the ninth (residual) banking group. All equations except (6) and (7) include among unproductive firms for purposes of computing S_{st-1} only those in activity, and for purposes of computing B_{bt-1} also firms without IES reporting not known to be in activity.

Table B4: Sensitivity analysis: variants of equation (7), Table 10 (excluding construction and real estate)

	(1) ΔC_{isbt}	(2) ΔC_{isbt}	(3) ΔC_{isbt}	(4) ΔC_{isbt}	(5) ΔC_{isbt}	(6) ΔC_{isbt}	(7) ΔC_{isbt}	(8) ΔC_{isbt}	(9) ΔC_{isbt}	(10) ΔC_{isbt}	(11) ΔC_{isbt}
TFP^d_{ist-1}	0.102***	0.0580***	0.132***	0.125***	0.0962***	0.110***	0.105***	0.107***	0.107***	0.107***	0.107***
	(0.00711)	(0.00493)	(0.00977)	(0.00778)	(0.00972)	(0.00748)	(0.00717)	(0.00755)	(0.0187)	(0.00508)	(0.0178)
$TFP^d_{ist-1} \times S_{st-1}$	-0.00470	0.000901	-0.0143	0.00979	-0.0106	-0.00423	0.00758	-0.00384	-0.00384	-0.00384	-0.00384
	(0.0122)	(0.0105)	(0.0182)	(0.0183)	(0.0165)	(0.0135)	(0.0156)	(0.0137)	(0.0147)	(0.0112)	(0.0149)
$TFP^d_{ist-1} \times B_{bt-1}$	-0.138***	-0.0862***	-0.171***	-0.136***	-0.107***	-0.160***	-0.136***	-0.133***	-0.133***	-0.133***	-0.133**
	(0.0177)	(0.0109)	(0.0214)	(0.0187)	(0.0206)	(0.0191)	(0.0172)	(0.0189)	(0.0471)	(0.0130)	(0.0464)
Exclusions	zombies	extensive margin	TFP outliers	small credit changes	residual banking group						
Unproductive firms (S)	in activity	in activity	in activity	in activity	in activity	in activity	in activity or not	in activity	in activity	in activity	in activity
Unproductive firms (B)	in activity or not	in activity or not	in activity or not	in activity or not	in activity or not	in activity	in activity or not	in activity or not	in activity or not	in activity or not	in activity ot not
S.E. Clustering by	Sector	Sector	Sector	Sector	Sector	Sector	Sector	Sector × year	Bank × year	Firm	Firm & year
Observations	1605078	1333943	1696553	1298408	1286223	1731175	1731175	1731175	1731175	1731175	1731175
R^2	0.031	0.019	0.032	0.040	0.033	0.032	0.032	0.032	0.032	0.032	0.032

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Same notes as in Table B3.

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