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Credit Misallocation During the European Financial Crisis*

Fabiano Schivardi† Enrico Sette‡ Guido Tabellini§

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Abstract

Do banks with low capital extend excessive credit to weak firms, and does this matter for aggregate efficiency? Using a unique data set that covers almost all bank-firm relationships in Italy in the period 2004-2013, we find that, during the Eurozone financial crisis: (i) Under-capitalized banks were less likely to cut credit to non-viable firms. (ii) Credit misallocation increased the failure rate of healthy firms and reduced the failure rate of non viable firms. (iii) Nevertheless, the adverse effects of credit misallocation on the growth rate of healthier firms were negligible, and so were the effects on TFP dispersion. This goes against previous influential findings that, we argue, face serious identification problems. Thus, while banks with low capital can be an important source of aggregate inefficiency in the long run, their contribution to the severity of the great recession via capital misallocation was modest.

Keywords: Bank capitalization, zombie lending, capital misallocation

JEL classification number: D23, E24, G21

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1 Introduction

An important dimension of financial crises is a weakened banking sector. There is a widespread perception in the policy debate that under-capitalized banks can prolong depression by misallocating credit to weaker firms in the verge of bankruptcy and restraining credit to healthy borrowers ("zombie lending"). This perception is supported by evidence for Japan during the "lost decade" (Caballero et al., 2008) and, more recently, for the Euro area during the financial crisis (Acharya et al., 2016). Due to data and methodological challenges, however, assessing the consequences of a weakened banking sector on credit allocation and real economic activity is difficult. Moreover, during a recession not all economic effects of zombie lending are necessarily bad for the healthy part of the economy. Extending credit to very weak firms keeps them alive and may prevent layoffs. This in turn can mitigate the adverse aggregate demand externalities that are so important during a recession (Mian et al., 2015). Firms closures can disrupt input-output relationships that, at least in the short run, can be difficult to substitute for (Barrot and Sauvagnat, 2016). In this paper, we add to the literature by improving both in terms of data quality and of identification framework. As we show below, these modifications lead to conclusions that differ substantially from the received wisdom.

We explore the extent and consequences of credit misallocation in Italy during and after the Eurozone financial crisis. We ask two main questions. First, what bank characteristics are more conducive to zombie lending? Second, what is the cost of zombie lending in terms of lost economic activity and misallocation of real resources? Italy is an ideal testing ground for these issues, because the financial crisis induced a very deep and long recession, that left a cumulative drop in GDP of almost 10%. This caused a very large increase in non-performing loans (from 5.8% of outstanding bank loans in December 2006 to 16% in December 2013), and a prolonged contraction in bank credit (see Figure 1). Moreover, unlike other Eurozone countries, Italy did not inject public funds to recapitalize its banking system nor it created a bad bank to absorb the non-performing loans. As a result, Italian banks remained saddled with a large fraction of bad loans, and several banks struggled to meet the stricter capital requirements imposed by regulators in the aftermath of the crisis. The problem persists today, and it is one of the major current policy challenges in Italy.

In short, these are our main findings. Under-capitalized banks are more likely to keep lending to zombie firms during the financial crisis, compared to stronger banks. This affects firms survival and exit: in the areas-sectors where lending is predominantly done by weaker banks, zombie firms are more likely to survive while non zombies are more likely to go bankrupt. Nevertheless, and contrary to previous findings, we do not find evidence that bank under-capitalization hurts the growth rate of healthy firms.

We use a unique data set that covers almost all bank-firm relationships in Italy for the period 2004-2013. We observe all incorporated firms, including small ones. Most of the previous literature instead considered only listed firms. In addition to detailed information on firm-bank relationships, we also have access to firms and banks balance sheets. We focus on the most extreme form of credit misallocation, namely, loans granted to firms that clearly are no longer viable – *zombie firms*. We define as zombie a firm that is highly indebted and for which the returns on assets have been systematically below the cost of capital of the safest firms (we experiment with alternative definitions to assess robustness). As shown in figure 2, credit to zombie firms dropped faster than credit to healthier firms during the first part of the crisis, but the opposite was true from 2011 onwards, when low capital became a pressing problem for several Italian banks. This suggests that credit was not reallocated away from zombie firms.

To study what bank characteristics are conducive to zombie lending we regress the growth rate of granted credit at the firm-bank level on various indicators of banks' solidity, using the regulatory capital ratio as the preferred one. The identification challenge in this type of regressions is that the observed granted credit is the result of both demand and supply of credit. To single out the supply effects, we exploit the fact that Italian firms typically borrow from more than one bank. This enables us to compare banks with different degrees of capitalization that lend to the same firm, controlling for firm-year fixed effects. As first argued by Khwaja and Mian (2008), this allows to control for any effect coming from firms' credit demand, such as a higher demand from zombie firms, and to interpret the coefficients in terms of credit supply effects.

We depart from the previous literature when we analyze the consequences of zombie lending on healthy firms. Typically, this question is addressed by regressing indicators of firm performance on the share of zombie firms in the sector in which the firm operates. The main challenge to identification is that an adverse sectoral shock both increases the share of zombies and affects firms performance. Following Caballero et al. (2008), the standard approach is to include fixed effects at the sector-year level in the regression, so as to fully control for aggregate shocks, and to allow zombie and healthy firms to be differentially affected by a larger share of zombies in the sector. This approach can only estimate the *relative* effect of the share of zombies on healthy firms compared to zombies, however, as the share of zombies itself is absorbed by the dummies. Estimating a relative effect is not very informative, because we care about the absolute effect on healthy firms, and zombie lending is likely to improve the performance of zombie firms. Moreover, while it accounts for aggregate shocks, this approach neglects a second, and more subtle, identification problem. A negative correlation between the share of zombies in a sector and the relative performance of healthy vs zombie firms is interpreted as evidence of adverse spillovers from zombies to healthy firms. But this rests on the assumption that, in the absence of spillovers from zombies to healthy firms, aggregate shocks have the same effect on the two groups of firms. We show that this assumption is violated in very standard settings with heterogeneous firm performance. For example, when performance follows a normal distribution, aggregate shocks that shift the entire distribution to the left mechanically generate a negative correlation between the share of zombies and the relative performance of healthy vs zombie firms, even in the absence of any spillover effects.

To cope with these issues, we replace the share of zombies with a measure of banks capitalization. Since both bank lending and production are geographically concentrated, we take the relevant market to be the province-sector in which a firm is located, and study how the average capitalization of banks active in a given province-sector affects firms performance within the same province-sector. Banks are typically active in several province-sectors, and exposure to a single province-sector is very low: on average banks are active in about 48% of sector-provinces (the median is very similar). Thus, bank capitalization is unlikely to be correlated with shocks in the province-sector, and we can take it as exogenous with respect to shocks that shift the distribution of firms. Moreover, given the exogeneity of banks capitalization, we can estimate regressions without province-sector-year fixed effects and recover the absolute (and not just relative) effect of bank capitalization on the performance of healthy firms.

These are our main results. In terms of lending, we find that low-capital banks engaged in significantly more zombie lending, compared to other banks. This effect is only present from 2008 onwards, possibly because before the financial crisis capital ratios were not yet a concern. More precisely, between 2008 and 2013 bank credit drops by almost 8% every year on average. But banks with a capital ratio below the median provide 2 percentage points of additional yearly credit growth to zombie firms, compared to stronger banks (a 25% increase relative to the average). The result is robust to the definition of zombie firm and to the measure of bank capital. There is also evidence that the effect is non-linear and it is larger for the much weaker banks. Results are similar if we look at the extensive margin: from 2008 onwards, the probability of closing a credit relationship with any firm drops by 1 percentage point if the bank regulatory capital ratio is below the median, and it drops by a further 0.7 percentage point if the firm is a zombie and bank capital is below the median. Low-capital banks are also less likely to classify their loans as bad, whether they are loans to zombie firms or to any firm; again, this effect is only apparent from 2008 onwards. All these results point to the conclusion that weak banks misallocate credit, because they are more likely to keep lending to non viable firms.

We next explore the adverse real effects of credit misallocation on healthier firms and on aggregate economic activity. We start by considering the intensive margin, namely how zombie lending affects the growth of existing non-zombie firms. Our central result here is that bank under-capitalization has only negligible (absolute) effects on the growth of healthy firms during the recession. This holds for several indicators of economic activity, such as the wage bill (a proxy for employment), the capital stock and revenues. The reason is that, although bank under-capitalization hurts the relative performance of healthy vs zombie firms, it also improves the growth rate of zombies. As a result, the absolute effect on healthy firms is negligible. This finding may seem surprising, in light of the received wisdom from the previous literature. A priori, it is argued, weak banks that engage in zombie lending hurt healthy firms in two ways: first, by reducing bank credit available to the rest of the economy; second, because lending to non-viable firms is equivalent to a subsidy, it hurts their competitors in product and input markets. But zombie lending may also have positive economic effects during a recession: because it does not force inefficient firms to shrink or to exit, it could mitigate adverse aggregate demand and input/output externalities. This last mechanism has generally been neglected by the literature, but the data suggests that it may be empirically relevant.

We then explore the extensive margin, namely the effect of bank capitalization on the survival rates of zombie and non zombie firms. In line with the results on credit allocation, we find that weak banks influence the composition of bankruptcies. Zombies are more likely to survive, and healthy firms are more likely to fail, in province-sectors where lending is predominantly done by banks with a capital ratio below the median. To assess the magnitude, consider an injection of capital in the weak banks so as to bring their capital ratio to the median level. This counterfactual exercise would increase the failure rate of zombies by 0.4% and reduce the failure rate of non zombies by 0.4% (an absolute effect). This is a non trivial effect, as it represents a reduction of one fifth in the failure rate of healthy firms in the period.[1]

Finally, we ask whether bank under-capitalization is positively correlated with (revenue based) TFP dispersion in the province-sector. As shown by Hsieh and Klenow (2009), in the absence of frictions in the inputs market, revenue TFP should be equalized across firms. Thus TFP dispersion can be interpreted as revealing the presence of some frictions or misallocations in the input markets The data show that there is a positive association between low bank capitalization and aggregate TFP dispersion, but only in the presence of a large fraction of zombie firms.

A weak banking sector is often identified as one of the key causes of low economic

[1]Our finding that low bank capital has much larger effects on the extensive than on the intensive margin is in line with the findings of Midrigan and Xu (2014), who study the impact of credit frictions on TFP through both margins.

growth in Southern Europe and in Italy in particular, since the onset of the financial crisis (e.g., Acharya et al., 2016). This inference is only partially supported by our findings. There is clear evidence that, during the crisis, weaker banks have kept lending to non-viable firms to a greater extent than stronger banks. But the adverse economic consequences of this credit misallocation are only evident on the exit rates of non zombie firms, and not on their growth rate. To quantify the aggregate effects, consider an injection of capital of 4 billions Euros in the weaker banks. This is the amount that, as of 2012, would bring their capital ratio to the median level. Inserting our estimates in a simple evaluation scheme, this injection would increase the yearly output growth by between 0.2% and 0.35% during 2008-13, depending on the relative productivity of zombies vs non zombies. During this period, output in our sample on average shrank by almost 2 percent per year. The contribution of zombie lending to this negative performance is therefore between 10 and 20%, and comes almost entirely from the extensive margin and the composition of firms exits.

These findings contribute to the current policy debate on the importance of bank capital and on the consequences of a large stock of non-performing loans on credit supply and its allocation (IMF 2016). They suggest that the main reason for injecting capital into a weak banking sector is not so much to alleviate the recession or shorten its duration, but rather to prevent productive inefficiencies and possibly to facilitate the recovery once it is in place.

The outline of the paper is as follows. Section 2 outlines the related literature. Section 3 describes the data and our methodology to define zombie lending. Section 4 describes the empirical strategy and asks which types of banks engage in zombie lending, while the real consequences of zombie lending are explored in section 5. Section 6 evaluates the aggregate implications of low bank capitalization, and section 7 concludes.

2 Related literature

Misallocation of credit has been proposed as an explanation for the prolonged stagnation of the Japanese economy after the real estate crisis of the early 90s. Following Hoshi (2000), a large literature attempted to quantify the phenomenon of "zombie lending". Peek and Rosengren (2005) document that under-capitalized banks kept lending to weak firms during the Japanese crisis. Caballero et al. (2008) study zombie lending during Janpan's "lost decade". They find evidence of lending to zombie firms by weaker banks. They also investigate the effect of zombie lending on the growth of healthy firms relative to zombies, finding a large relative effect. Subsequent studies of the Japanese case have used different definitions of zombie firms and often a longer time span. Results are mixed, suggesting that the impact of zombie lending on economic performance may have been overstated (Ahearne and Shinada, 2005; Fukao and Ug Kwon, 2006; Fukuda and Nakamura, 2011). More recent work explores the effectiveness of bank bailouts during the Japanese crisis, finding that capital injections that are too small both fail to increase the supply of credit and encourage the evergreening of nonperforming loans (Giannetti and Simonov, 2013).

With reference to the European crisis, it is often argued in the financial press that banks weakness and an inefficient allocation of credit may have prolonged the stagnation and delayed the recover. Yet, surprisingly little evidence on zombie lending in Europe is available. Acharya et al. (2016) use syndicated loan data to study banks behavior after the "whatever it takes" announcement by Mario Draghi. This policy turn led to a drop in yield on sovereign bonds, generating an increase in trading profits for banks. Under-capitalized banks used the extra profits to lend to industries with a higher share of zombie firms. Acharya et al. (2016) also find that a larger share of zombies hurt the growth of healthy firms in the same industry and country, relative to zombie firms. McGowan et al. (2017) show that the resources sunk in zombie firms have risen since the mid 2000s in OECD countries, with negative consequences on the performance of non-zombies. Albertazzi and Marchetti (2010) identify zombie firms as those with low TFP, and look at the dynamics of credit supply in the year following the default of Lehman Brothers. They find no evidence of zombie lending or of loan evergreening.

A large literature has discussed the relevance of credit frictions as a driver of the misallocation of factors of production. Hsieh and Klenow (2009) propose a standard model of Cobb-Douglas production with monopolistic competition in which the dispersion of (revenue) TFP measures the extent of the misallocation of resources. They estimate a large effect of misallocation on aggregate productivity in India and China compared to the United States. While they do not explicitly measure the impact of credit frictions, these are among the most likely sources of frictions that drive the misallocation. Other works suggest a more mixed picture. On the one hand, Moll (2014) shows that the impact of financial frictions on TFP are large and persistent, i.e. they cannot be undone by self-financing of firms, and Yang (2011) shows that micro-level frictions, including credit frictions, can generate sizeable aggregate TFP losses by distorting the selection of new entrant firms. On the other hand, Midrigan and Xu (2014) suggest that financial frictions affect aggregate TFP by inducing an inefficient entry and exit of firms, while the impact on the intensive margin is small. Borio et al. (2016) use a long time series of at the country-industry level and show that credit booms tend to undermine productivity growth by inducing reallocation of labor towards sectors with low productivity growth. A growing literature studies the impact of misallocation of resources on GDP and TFP growth after financial crises, and generally finds large negative effects (Barnett et al., 2014;

Di Nola, 2015). Two recent papers have studied misallocation of resources in the Europe. Gopinath et al. (2015) document a significant increase in productivity losses from capital misallocation in Southern European countries, most notably Spain. They show that the drop in real interest rates following the introduction of the Euro led to a misallocation of capital inflows toward firms that have higher net worth but are not necessarily more productive. Gamberoni et al. (2016) use industry-level data from 5 European countries and find that restrictive bank lending standards and heightened demand uncertainty led to capital misallocation, but the allocative efficiency of both capital and labor improved during the Great Recession.

Our work contributes to this literature in several ways. First, we use a comprehensive dataset representative of the whole population of banks and firms, that includes both listed and unlisted firms. This is important when it comes to quantifying the relevance of zombie lending. Data covering only listed firms, or only syndicated loans can hardly provide a good basis to quantify the relevance of zombie lending and its impact on the real economy. Second, thanks to the richness of our data set, we can identify the presence of zombie lending by exploiting firms that borrow from more than one bank. This allows us to quantify the extent of zombie lending after controlling for firm demand for credit and more generally for firm unobserved characteristics. Third, we propose a new and more reliable definition of zombie firm, that takes into account both efficiency (return on assets) and financial fragility (indebtedness before the crisis). Fourth, when assessing the consequences of bank under-capitalization on aggregate economic efficiency and growth, we can distinguish between the intensive margin (growth of existing firms) and the composition of bankruptcies, documenting how the most important aggregate effects of bank weakness operate through the latter channel. Last, and perhaps most important of all, we estimate the *absolute* effect of bank under-capitalization on the growth of healthy firms, and not just a relative effect on the growth of healthy vs zombie firms. This is a significant departure from the most influential papers in the literature, because we find that, while the relative effect is negative and highly significant, the absolute effect is negligible. We also show that the identification approach used in the literature to estimate the real effects of zombie firms is weak, because common shocks to firm performance that increase the share of zombie firms typically have differential effects on zombie and non-zombie firms.

3 The Data

The paper uses two samples. In the first one we study what types of banks engage in zombie lending, exploiting data on bank-firm relationships. Only firms that borrow from at least two banks are included in this sample. In the second sample we explore the consequences of zombie lending. Here all firms are included, irrespective of their borrowing status. In both samples, we restrict attention to non-financial firms excluding agriculture. Both samples are obtained matching three data sources: the Firm Register (Cerved), that contains balance sheet information of *all* – as opposed to listed firms only, typically used in the literature – limited liability companies incorporated in Italy; the Credit Register, that contains information on all loans by Italian banks; and the Supervisory Reports collected by the Bank of Italy, that contains balance sheet data on all Italian banks. In this section we describe the first sample. The variables used in the second sample are defined and described in Section 5.

We match the three data sources using the firms and banks tax identifier. We therefore obtain loan-level information on all relationships between Italian banks and firms, matched with balance sheet information of both firms and banks. The Credit Register lists all loans granted by banks operating in Italy to borrowers for which the overall exposure of the bank is above 75,000 Euros (this reporting threshold was lowered to 30,000 in 2009).[2] The overall exposure of the bank includes both loan granted and guarantees provided to the borrower. Loans are divided into three broad categories: overdraft loans (uncommitted credit lines), term loans (these include leasing, mortgages and committed credit lines), loans backed by receivables.

We select the sample as follows. We start the bank-firm relationships for which; i) we have detailed information on firm balance sheets, in particular leverage, profits, interest expenses; ii) we have bank balance sheet data on capital ratio; iii) the relationships are in place for at least one full year so as to be able to compute the yearly change in credit. This sample includes 5,113,468 bank-firm-year observations (in what follows "observations"). From it, we drop three categories of observations. First, we drop mutual banks, as these are subjected to specific regulations: in particular, they mainly operate within a pre-determined geographical area ("zona di competenza territoriale", ZCT).[3] Mutual banks, to be identified as such, must concentrate at least 95% of their risky assets (loans and mortgages) to counterparties located in their ZCT. Moreover they must grant credit primarily (at least 50%) to their shareholders. Firms or households may become shareholder of a mutual bank only if they are based in the ZCT of the bank. These features are especially relevant for our work because mutual banks' lending choices are constrained by the pool of borrowers of their ZCTs, independently from the bank's financial solidity. Instead, we are interested in how banks lending policies change as their

[2] To maximise coverage, in our analysis we do not adjust for the change in the threshold. We have repeated all the estimations imposing the 75,000 euro threshold throughout the whole period, finding similar results.

[3] This is the municipality where the bank has its headquarter or its branches including neighboring municipalities. These municipalities must be contiguous to each other.

financial ratios change, provided that that face alternative pools of potential borrowers. This is clearly the case for banks that operate in multiple areas. This reduces the sample to 4,522,722 observations. Second, to avoid drawing inferences from very small loans, we drop credit relationships with granted amounts below 30,000 euros. This reduces the sample to 4,497,269 observations. Third, we select firms that have credit relationships from at least two banks in a year. We do this because identification is based on comparing loans to the same firm from banks with different characteristics, controlling for firm-year fixed effects, as in Khwaja and Mian (2008). After this last step, we are left with 3,656,203 observations.

The sample spans the period from 2004 to 2013 (we use firm balance sheet data back to 2002 to compute moving averages of certain indicators of firms financial conditions). Thus, we observe 4 years before the crisis and, more importantly, both the great recession (2007-2009) and the sovereign debt crisis (2011-2013). Overall, the sample includes 242,506 firms (for 1,097,673 firm-year couples borrowing from 163 banks. Note that this is a very comprehensive sample, especially in terms of firm size. Median firm assets are 2.3 million euros, indicating that a large fraction of small firms is included. Summary statistics are described in the next subsection.

3.1 What is a zombie firm?

We are interested in determining if certain bank's characteristics are conducive to lending to zombie firms. Our first challenge is therefore the definition of a zombie firm. We define as zombie a firm for which the expected marginal return of capital is below the risk adjusted market cost of capital. Lending to zombie firms thus results in misallocation of capital, that could earn higher returns (and produce more output) elsewhere. Since we don't observe the expected marginal return of capital nor the risk of each firm, we rely on alternative measures of what is a zombie firm, and check that our results are robust to these alternative definitions. All these alternative measures combine indicators of low profitability and of high default risk. From a lender's perspective, both the debtor's expected profits conditional on surviving and default risk matter, since both determine the expected return on the loan.[4]

Our preferred indicator of profitability is the return on assets, defined as Earnings Before Interest, Taxes, Depreciation and Amortization (EBITDA) over total assets. EBITDA is what is left of revenues after paying labor and intermediates, so that its ratio to capital

[4]Our procedure of identifying zombies from balance sheets information has benefited with discussions with several practitioners in the corporate banking and private equity sector. We are particularly grateful to Galeazzo Scarampi, a private equity operator with a long experience in firms' turnaround.

invested is the average gross return on capital.[5] Ideally, we would like to measure expected future profitability. Since this is not available, we rely instead on a three year moving average of the return on assets. We thus define the variable *return on assets* (ROA) as the three year moving average of EBITDA over total assets. We compare ROA to a measure of the cost of capital for the safest borrowers in the sample. This is computed as the average interest rate charged on the credit lines to the safest firms. To reduce time series fluctuations related to changes in the policy rates, here too we use a three years moving average. The safest firms are defined as those having an Altman Z-Score of either 1 or 2 - the Z-score varies from 1 (safest) to 9 (riskiest). This measure of the cost of capital is called *prime rate* (PRIME).

As a measure of default risk, we rely on leverage. Highly indebted firms are obviously more at risk of default, so that a lender should be less willing to extend them credit, controlling for expected returns. We define *leverage* as total financial debt over total assets. Total financial debt excludes debt towards shareholders, typically more akin to equity.

In our first definition, we classify a firm as zombie in any given year if, in that year, ROA is below PRIME, and if leverage exceeds a time invariant threshold L. As we vary L, we enlarge or shrink the set of firms defined as zombies. To determine whether leverage is so high as to imply a significant risk of default, we consider the distribution of leverage in the year 2005 for firms that exited the market in 2006 or 2007 (i.e. just before the beginning of the crisis), and that also had a low return on assets (defined as ROA $<$ PRIME) in 2004 and/or 2005.[6] Figure 3 illustrates the distribution of leverage in our overall sample (panel a) and in the comparison sample of firms that exited and had ROA $<$ PRIME in 2004 and/or 2005 (panel b). Clearly the two distributions are very different. The latter has more mass to the right, i.e. on higher values of leverage.

Our preferred definition of zombie takes L to be the median of the distribution in panel b, namely 40%. Thus a firm is defined a zombie in year t if in that year ROA is below PRIME and leverage is above 40%, where 40% is the median value of leverage in 2005 in the sample of firms that exited during 2006-2007 and that during the previous two years had ROA$<$ PRIME at least once. We checked that the share of zombies varies little and continuously as we vary L between the 40-th and the 60-th percentile of the

[5] For the Cobb-Douglas technology with constant returns to scale, this is exactly equal to the marginal product of capital.

[6] From the firm register we observe the reason for the exit of the firm, so we can precisely identify firms that exited the market because of default or liquidation, from firms that exited the market for other reasons. We consider a firm as "exited" if its status is "in liquidation". This information is available since 2006, and this is why we computed leverage in 2005. Note that, since our sample starts in 2002, we can compute the three year moving average of ROA from 2004 onwards.

distribution depicted in panel b of Figure 3, implying that our definition of zombie is not particularly sensitive to the numerical value of the selected threshold L. Unless otherwise noted, this is the definition of zombie that we use throughout the paper.

Table 1 shows the distribution of the main firm characteristics according to zombie status of the firm, distinguishing between the pre-crisis (panel A) and the crisis (panel B) periods. Not surprisingly, zombie firms are more leveraged, have lower ROA, and a lower EBITDA to interest expenses ratio. Zombies are also somewhat larger than non-zombies. This is explained by the high leverage of zombie firms. If leverage is used to increase assets, it is almost "mechanical" that more highly leveraged firms are also larger.[7]

Figure 4 shows the time evolution of the share of zombies together with the evolution of GDP growth. The share of zombies is negatively correlated with GDP growth. The higher value of the share of zombies in 2004 as opposed to 2005 is explained by the fact that the Italian economy experienced a recession in 2001 and 2002, so the higher share of zombies is likely a legacy of that recession. The share of zombies reaches a maximum in 2009, when GDP contracted by almost 6%. It declines slightly in the following two recovery years and it increases again in 2012, when GDP growth turns negative again, dropping only slightly in 2013 as the contraction in GDP gets smaller.

We also experiment with a different measure of profitability, comparing EBITDA to interest expenses to determine creditworthiness. Clearly, debt is unsustainable if interest expenses exceed EBITDA for a prolonged period of time. Specifically, we define the variable $RATIO$ as the ratio between the three year moving average of EBITDA and the three year moving average of interest expenses. A firm is defined as a zombie in a given year if in that year the variable $RATIO$ is below 1 and if its leverage is above a threshold L. For consistency, in this alternative definition of zombie the threshold L is computed as the median of leverage in 2005 in the sample of firms that exited during 2006-2007 (as for the main definition of zombie firm) and that had $RATIO < 1$ in 2004 and/or 2005.

The two definitions overlap significantly, although the second one is more stringent: about 18% of firms are classified as zombie in the first definition, and about 10% in the second one. The definition based on the ratio of EBITDA to Interest Expenses (Zombie 2) is almost a strict subset of that based on the comparison between ROA and the prime rate. Only 0.2% of firms are classified as zombies according to definition 2 and non-zombie according to definition 1. The opposite occurs instead in 7.1% of the cases. Overall, we prefer definition 1 since it is based on an economic notion of credit misallocation, namely low returns on capital, but we check the robustness of our results to the more restrictive

[7]The positive correlation between firm size and leverage has been documented extensively in the corporate finance literature (see, among others, Titman and Wessels, 1988; Rajan and Zingales, 1995; Fama and French, 2002).

definition 2.[8]

These two definitions classify as zombies firms that pass the established thresholds of low profitability and high leverage. While useful from a descriptive viewpoint and easy to interpret, there is some arbitrariness in the choice of the thresholds. Moreover, one could argue that the status of zombie would be better described by a continuous rather than a dichotomic variable. For this reason, we also construct two continuous indicators of zombie firms, by taking the first principal component of the two variables on which the dichotomic indicators are constructed. Specifically, *PC ROA Leverage* is measured as the first principal component of ROA and leverage, while *PC EBITDA/INT Leverage* is measured by the first principal component of the ratio of EBITDA over interest payments and leverage. For the continuous variables, the share of variance accounted for by *PC ROA Leverage* is 62%, while that accounted for by *PC EBITDA/INT leverage* is 54%.

Observable outcomes associated with zombie firms are very different from those of healthy firms, confirming the plausibility of our definitions. First, the status of zombie firm is highly persistent. If a firm is classified as a zombie in period t, it has 72% probability of still being a zombie next period, and there is little difference between the pre-crisis and the crisis years. Second, credit to zombies is much more likely to be cut by the average bank: the proportion of terminated relationships with zombies is 14%, against 9% for non-zombies. Third, the share of zombie firms that exited because of default and bankruptcy is 12.8%, that of non-zombies 3.3%. Fourth, revenue growth is much slower for zombie firms than for non-zombies. The 3-year average growth rate of revenues (weighted by firms' assets) is -3.53% for zombies, while it is 1.70% for healthy firms. This is important to reduce concerns that we may be classifying high-growth firms as zombies. For example, a start-up might have high leverage and negative profits because of high investment, but this might be due to high growth opportunities. It turns out that this is not the case in our data, indicating that our definition of zombie is effectively identifying firms with grim prospects.

3.2 Variables used in the credit regressions

In Table 2 we report descriptive statistics of the variables used in the credit regressions, distinguishing between the pre-crisis period (Panel A) and the crisis period (Panel B). In terms of dependent variables, we use the growth of credit, a dummy for the break-up of the credit relationship and various indicators of the decision of the bank to classify a loan as problematic. Credit conditions clearly deteriorate during the crisis. In particular, the growth rate of credit goes from 5.3% to -8.06%. The share of zombies tend to increase,

[8] In definition 2 the threshold L for leverage is slightly larger than for definition 1, 42.5, so the difference between the two criteria is due entirely to the different indicators of profitability.

although modestly: for example, according to the preferred definition of zombies, 17% of firms were zombies before the crisis and 19% during the crisis.

Our key regressors are indicators of banks strength. The main measure of bank strength is the regulatory capital ratio. This is defined as the ratio of total capital (the sum of Tier 1 and Tier 2 capital) to risk-weighted assets. Regulation prescribes that banks maintain this ratio above 8%. Higher capital identifies financially stronger banks. Table 2 shows that average capital ratio is around 11%, and it is actually lower before the crisis, reflecting the efforts at rebuilding bank capital after the onset of the crisis. The median of the capital ratio over the period has remained stable at around 11%. Figure 5 illustrates how zombie firms are distributed between banks, according to their capital ratio. Banks with a capital ratio in the bottom quartile of the distribution have a substantially higher share of zombies out of total borrowers. Banks in the second quartile have a share that is lower than that in the first by still higher than that of last two quartiles, which have similar values. This suggests that the relationship between zombie lending and capital ratio is non-linear: weak banks are more likely to engage in zombie lending, but as the capital ratio increases substantially above the regulatory threshold, the relationship between capital ratio and zombie lending vanishes. To capture this non linearity, we use as the preferred indicator of a weak bank a dummy which is equal to 1 if the capital ratio is below the median capital ratio in the sample, equal to 10.99%. Given that the median is stable over time, using year-specific medians delivers the same results.

Table 2 shows that the dummy for banks with the capital ratio below the median (LowCap) is one in 58% of the observations before the crisis and in 46% during the crisis. This suggests that banks with fewer borrowers (smaller banks) suffered a more severe capital shortfall during the crisis. We experiment with alternative indicators based on the capital ratio, such as the level of the capital ratio itself or a dummy for banks very close to the regulatory threshold, that is, with a capital ratio below 9. We also use an alternative measure of financial strength, that is the ratio between Tier 1 capital, the capital with the highest risk-absorption capacity, and risk weighted assets. Descriptive statistics for all these variables are in Table 2.

Other bank characteristics may be relevant for lending. For this reason, in the regressions we include a set of standard controls for lending regressions (Khwaja and Mian, 2008; Iyer et al., 2014): the liquidity ratio, namely the ratio of cash plus government securities to total assets; the ratio of interbank deposits to total asset; bank profits divided by total assets; and bank size, measured by the log of total assets. The return on bank assets was 0.7% before the crisis and dropped to about 0 during the crisis.[9] Table 2 also shows that on average a firm borrows from any single bank over one quarter of the total

[9]Due to their large assets, ROA is typically lower in banking than in other sectors.

bank credit that it receives and that approximately one quarter of total credit is granted through credit lines.

4 Who lends to zombie firms?

4.1 Empirical strategy

In this section we test what bank characteristics are more conducive to zombie lending. We focus on capital adequacy. Low capital banks may be particularly averse to absorb losses, especially during a recession, and may therefore be relatively more willing to keep lending to weak firms that otherwise would not be able to service their debt. Hence, our goal is to determine whether banks with low capital ratios are more likely to extend credit (or slower to cut credit) to zombie firms in the crisis period. We expect zombie lending to be more related to capital ratio during the crisis than before, for several reasons. First, the onset of the crisis caused bank losses and an initial erosion of bank capital. Second, raising capital was much more difficult during the crisis: on the one hand, banks experienced a drop in profits (lower lending volumes, higher losses on loans, lower income from services and securities trading), which reduced their ability to increase capital through retained earnings; on the other hand, issuing new equity was extremely costly, as the market was very concerned with banks' solvency and was willing to buy banks equity issuances only at a very large discount. Third, bank supervision became much stricter during the crisis.

We test this hypothesis based on the following regression framework:

$$\Delta b_{ijt} = \beta_0 + \beta_1(Z_{it} * LowCap_{jt} * crisis_t) + \beta_2\mathbf{X_{ijt}} + Dummies + \eta_{ijt} \quad (1)$$

where Δb_{ijt} is the log difference in total lending of bank j to firm i between year t and $t+1$; Z_{it} is the zombie 0/1 indicator; $LowCap_{jt}$ is a dummy equal to one if the capital ratio of bank j at time t is below the median in the sample; $crisis_t$ is a dummy equal to one from 2008 onwards; $\mathbf{X_{ijt}}$ are other controls at the firm and bank level (that always include all the lower-level interactions between Z_{it}, $LowCap_{jt}$ and $crisis_t$); $Dummies$ are different sets of dummy variables used in different specifications. Our coefficient of interest is β_1, that captures the effect of a bank's capital ratio on the propensity to lend to zombies in the post crisis period. A positive coefficient would indicate that weaker banks lend relatively more to zombies in the crisis years when compared to stronger banks, relative to the pre-crisis years. To account for potential correlation in the residuals at the level both of the bank and of the firm, standard errors are always double clustered at the bank and firm level.

The main identification issue that we face is that credit granted to firms depends not only on banks supply decisions, but also on firms' demand. In fact, firms are not randomly matched to banks. The correlation measured by β_1 could be due to some matching between weak banks and weak firms for reasons other than the banks' capital ratio. For example, it could be that some banks specialized in lending to firms that were more severely hit by the crisis, which in turn led to a deterioration in the banks' financial position. These are also the firms that are more likely to be classified as zombies. In this case, the causality chain would actually go from firms to banks rather than the other way around. The richness of our data allows us to properly address this issue. First, we use changes in credit granted, rather then levels, so as to consider the dynamics of credit evolution rather than a stock measure of exposure. Still, one could argue that even changes in credit might be driven by demand effects on the firms side, and in the presence of non random matching this would challenge the causal interpretation of our estimates. For instance, zombie firms, possibly more likely to be matched to weak banks, might demand more credit during the crisis, compared to healthy firms. To tackle this criticism, we follow the identification strategy proposed by Khwaja and Mian (2008). A well-known feature of the Italian lending market is that firms tend to borrow from different banks simultaneously (Detragiache et al., 2000). In our data borrowing firms have 3.3 lending relationships on average. This allows us to include a full set of firm-year dummy variables. These dummy variables control for any potential effect coming from firm-level time varying shocks to credit demand and therefore account for all the unobserved heterogeneity[10] at the firm-year level. Our estimates are only based on within firm-year variations in credit growth across banks with different degrees of financial strength. Thus, the inclusion of firm-year dummy variables rules out any demand driven potential correlation between unobservable determinants of credit growth and measures of capital intensity of banks.

The remaining identification concern is that the bank capital ratio could be correlated with unobserved bank features that may influence zombie lending during crisis years, such as management practices or other features of the banks' balance sheet. To address this concern, we include other observable banks' characteristics, potentially correlated with the capital ratio and with lending policies, such as measures of bank profitability, of its liquidity and of its liability structure (more details are provided in context). We also include a full set of bank dummies, to account for all potential fixed unobserved heterogeneity at the level of the bank. In the most saturated specification, we also include a full set of bank*time dummies, to account for time varying bank level unobserved heterogeneity, too. Finally, we also include some observable features of the bank-firm match, such as the importance of the individual bank in the total bank debt of the firm, and the share of credit granted through a credit line.

[10]Firm-year dummies also account for all observed heterogeneity, making firm controls redundant.

4.2 Basic results

The results of estimating equation (1) are reported in Table 3. In the first column we report a specification with separate year and firm fixed effects. We find a negative coefficient on the triple interaction, significant at the 5% level. The estimated coefficient of 1.9 implies that, during the crisis, the yearly growth of credit to zombie firms was almost 2 percentage points higher in banks with a capital ratio below the median, compared to banks with capital ratio above the median. Average yearly credit growth was about -8% during the crisis, so this corresponds to a 25% increase in credit growth to zombies (relative to average credit growth) due to low bank capital. Two other estimated coefficients are statistically significant: those on the zombie dummy variable alone (-3.1) and interacted with *crisis* (-4.6); thus, zombies record a substantially lower rate of growth of credit, particularly during the crisis. All other coefficients are not statistically significant.

These results have interesting implications. First, before the crisis weaker banks were not more likely to extend more credit to zombies. If anything, in some specifications we find that weak banks tend to reduce credit with respect to strong banks, although the result is not robust. This could be interpreted as indicating that, during a period of substantial credit expansion and generally healthier banks' balance sheet, solvency ratios were not a concern and therefore had little impact on the lending policies of banks. Second, in the pre-crisis period the low capital ratio dummy has no explanatory power even for non-zombie firms, further supporting the hypothesis that bank capital concerns affect lending only in troubled periods. Finally, there is also no effect of the low capital ratio on credit growth in the crisis period for non-zombies (the estimated coefficient is positive but not significant). This indicates that, in this specification, the only effect of capital ratio emerges in terms of zombie lending in the crisis period.

As argued above, the specification of Column 1 is vulnerable to criticisms in terms of unobserved heterogeneity, non random matching and reverse causality. Column 2 displays our preferred specification with firm-year fixed effects, which address these issues. The coefficient of the triple interaction drops only marginally and maintains the same significance level, suggesting that time varying shocks to credit demand are not driving the correlation between zombie lending and bank fragility during the crisis. As before, all other coefficients are statistically insignificant.[11]

One potential issue is that credit growth granted by a bank to a firm might depend on pre-existing conditions, such as the share of the total firm's credit a bank accounts for or the composition of credit across different credit facilities. For example, it might be easier

[11] When we include firm-year effects we cannot estimate the coefficient of the zombie dummy and the zombie dummy interacted with the crisis dummy, as these variables are absorbed by the firm-year dummies. We can only estimate the relative effect of low capital bank with respect to high capital banks.

to change the amount of credit granted if a bank extends a large portion of credit through credit lines, whose conditions can be modified unilaterally by the bank at any time. In column 3 we therefore include as additional regressors the share of credit granted by the bank over total bank credit received by the firm: $share\ bank_{ijt} = credit_{ijt}/\sum_j credit_{ijt}$ where $credit_{ijt}$ is the total amount of credit granted by bank j to firm i in year t and the amount granted through a credit line: $share\ credit\ line_{ijt} = credit\ line_{ijt}/credit_{ijt}$. The inclusion of these additional variables does not affect our coefficient of interest, which rises slightly and now becomes statistically significant at 1%. Credit growth is negatively related to the share of credit that a bank extends to a firm and positively related to the share extended through credit lines.

In column 4 we introduce further banks controls: the *liquidity ratio* (the ratio of cash and government bonds to total assets), the *interbank ratio* (the ratio of interbank deposits and repos with banks–excluding those with central banks–and total assets) and *ROA* (the ratio of bank profits to bank total assets). These indicators are meant to capture other bank characteristics that might influence lending policies and that might be correlated with the capital ratio. We find that they do influence credit growth, without however affecting our coefficient of interest.

In column 5 we add a set of bank fixed effects, to account for fixed unobserved characteristics at the bank level that might be related to lending policies. Again, our basic result turns out to be remarkably robust to the introduction of this additional control. Finally, in column 6 we include a full set of bank*year dummies, to account for any bank level, time-varying shock that might affect credit supply. The coefficient of interest again is not affected and remains close to 1.9 with a p-value below 1%.

The dummy variable for the crisis years is defined to include the whole period between 2008 and 2013. There were two legs to the financial crisis, however, with the sovereign debt crisis beginning in 2011. Moreover, after 2011 bank supervision became more demanding in terms of capital requirements. We thus split the crisis period in two subperiods, estimating the usual interactions with two dummy variables, one for the years 2008-2010, and one for 2011-2013. Although the results are stronger for the second subperiod, we cannot reject equality of the estimated coefficients of the two dummy variables (results not reported).

4.3 Robustness

We next address the issue of the robustness of our results to various modifications of the basic setting. To save on space, we only report regressions based on our preferred and most comprehensive specification that always includes firm-year dummies, and then either includes bank fixed effects plus the time varying bank controls, or it includes bank-year fixed effects. Throughout we also control for the variables *share bank* and *share credit line* defined above.

Definition of zombies. One key issue relates to the definition of zombie firms. In Table 4 we repeat the estimations using alternative definitions of zombie firms. In columns (1) and (2) we use the measure of zombies based on the ratio between EBITDA and interest expenses. As seen in Section 3, this is a more restrictive definition of zombies. For example, in the crisis years 11% of firms are classified as zombies according to this definition, against 19% of the previous one. Notwithstanding this difference, the results are extremely similar to those obtained with the basic definition of zombies.

Another issue is the binary nature of our zombies indicators, that classify as zombies firms that pass the established thresholds of profitability and leverage. Given the possible arbitrariness of the thresholds defining the zombies, columns (3)-(6) of Table 4 replace the variable *Zombie2* with the continuous indicators measured by the corresponding principal components (see above). They confirm the findings based on the dummy for the preferred definition of zombie: again, we find that banks with a capital ratio below the median record a higher growth of credit to weaker firms during the crisis. To give a sense of the magnitude of the effect, consider two firms with a difference in the value of *PC EBITDA/INT leverage* of one standard deviation (0.9). Using the estimate of 1.6 in column 6, during the crisis banks with low capital allow credit to grow by almost 1.5% more to the weaker firm than to the stronger firm, compared to banks with capital above the median. Results are similar when we use the other principal component, *PC ROA leverage* (columns 3 and 4).

As noted before, we find some evidence that weak banks were extending less credit to zombie firms before the crisis. The estimated coefficient of the interaction of *Zombie* with *LowCap* is often statistically significant and with a negative coefficient ranging from -0.1 to -0.82, indicating that before the crisis banks with low capital were cutting credit to zombies more than banks with a capital ratio above the median (although by a rather small magnitude). Finally, again we find no effects of banks capitalization on credit supply to non zombies.

Definition of banks capital structure. We next experiment with alternative definitions of bank under-capitalization. Throughout we use the specification in Column 5 of Table 3, that is, with firm-year fixed effects, bank fixed effects and controls for share of credit of the bank over the total credit and the share of credit that is granted through a credit line. Results are robust to using the other specifications.

In Table 3 we define a bank with low capital if its capital ratio is below the sample median (about 11%). We experiment with other thresholds to check the sensitivity of the results to this choice. In column (1) of Table 5, we redefine the threshold for having low capital as being below the median by year (rather than the overall sample median). This is a more demanding definition of having adequate capital, because the median capital ratio increased over time. Results are qualitatively similar to the baseline. The coefficient of the triple interaction with the dummy zombie and the dummy crisis is positive and significant at the 6% level. The effect is somewhat smaller: the yearly growth of credit to zombie firms was almost 1.2 percentage points higher in banks identified as low capital according to this definition, compared to the other banks. This is not surprising as using a time-varying distribution of capital implies that banks may be well capitalized in absolute terms (or with respect to the regulatory minimum) but less capitalized in relative terms in a given year.

Figure 5 shows that banks closer to the regulatory threshold are more likely to lend to zombies. To test if the intensity of the effect changes with a more stringent definition of weak bank, we construct a dummy variable equal to 1 if the bank capital ratio is below 9, a value below which the bank's capitalization becomes particularly at risk. The banks with a capital ratio in this danger zone tend to be small banks: about 20% of all banks in our sample had a capital ratio below 9% in at least one year,[12] but these banks only account for about 5.3% of all the bank-firm relationships in our sample. In fact, the dummy is one for around 7% of observations in the pre-crisis period, and for 4% in the crisis years. Column (2) of Table 5 reports a coefficient of 2.45, highly statistically significant, and higher than the value of about 2 that we estimated for capital below the median. This confirms that the effects of capital requirements on lending policies are likely to be non linear, and stronger closer to the regulatory threshold. At the same time, the change is rather limited when modifying the threshold. This estimate implies that, during the crisis, banks with a capital ratio below 9 recorded a growth rate of credit to zombies about 2.5% higher than banks above this threshold.

Column (3) uses instead the continuous capital ratio indicator, rather than dummy variables for whether this same variable is below a given threshold. The estimated coefficient is negative and significant, as expected. Its numerical value of -0.4 implies that an increase of one standard deviation in the capital ratio (2.4% in the crisis period) would imply a reduction in credit growth to zombie firms of slightly more than 1%.

We next experiment with an alternative indicator of bank capital structure, that is, the Tier 1 ratio, defined as the ratio between Tier 1 capital and risk weighted assets. The regulatory threshold for this ratio is 4%. When we use the continuous indicator (Column 5), we get a negative coefficient, implying that banks with a high Tier 1 ratio

[12] Over the whole period, thus including both the crisis and the pre-crisis years.

reduced credit to zombies more than those with a low ratio, although the estimate is not statistically significant. When we use the dummy variable for low capitalized banks, however, we get a very precise estimate. In Column 4 we report the estimate when defining a weak bank as having a Tier 1 ratio below 5%. Even if only a small share of banks are below this threshold, we obtain a value of 3.4, higher than for a capital ratio below 9, and highly significant.

We also considered the composition of assets, measured by the ratio of risk weighted assets to toal assets (the higher is the ratio, the larger are the capital requirements). Banks with a higher ratio of high risk weighted assets to totalassets are more likely to extend credit to zombie firms during the crisis (results not reported).

We replaced the measures of capital structure with indicators of bank profitability, such as an inverse leverage ratio or the return on assets, but these interactions were generally not statistically significant. We also used the ratio of loan-charge-offs to total assets or to total loans as a measure of bank fragility. We find little evidence of an effect on lending to zombie firms. While this may be due to the backward-looking nature of these variables, it is also noteworthy that they are not directly related to regulatory indicators of bank strength. In other words, the bank variables that are significantly correlated with zombie lending during the crisis reflect features of the bank that are subject to regulation. This, together with the finding that capital shortages are associated with zombie lending only after 2008, namely when both regulators and markets started paying more attention to banks capital, suggests that zombie lending may have been an attempt of weaker banks to avoid requests by regulators to boost capital.

All in all, this analysis allows us to draw three conclusions. First, our results are robust to alternative measures of capital structure. Second, there is evidence of non-linearity in the effects of capital ratios on lending policies. Third, other indicators of bank weakness are less related to zombie lending compared to regulatory indicators.

Other lending policies. So far, we have focused on the intensive margin of credit, that is, changes in the amount of credit granted, conditional on the continuation of the credit relationship. Another channel through which credit can be decreased is by completely shutting down a credit relationship, something that cannot be captured by our credit growth indicator. To get a complete picture of the effect of bank solidity on zombie lending, we therefore also explore the extensive margin through a survival analysis of the credit relationship.

We construct a dummy for the year in which the relationship is terminated, namely if the bank is lending to a firm in year t and not in year $t + 1$, and 0 otherwise. We then regress it on the same set of controls as in our basic regressions. We set the dependent variable to 100 when the relationship is severed, so that the coefficients can be readily interpreted as percentage points. Throughout we control for firm-year fixed effects to account for firm's shocks to credit demand.[13] The specification and the structure of the table are identical to those in columns (2-6) of Table 3.

Results are reported in Table 6. First of all, banks with capital ratio below the median are less likely to severe any type of credit relationship during the crisis, compared to stronger banks - the estimated coefficient of $LowCap * crisis$ is always negative and significant. The point estimate -1 (or higher in absolute value) means that the probability of termination is lower by at least 1 percentage point if bank capital is below the median. This compares with an overall share of relationships that are terminated every year of 5.6% and implies a reduction of about 20% in that probability. However, banks with low capital are even less likely to terminate credit to zombie firms during the crisis, compared to stronger banks. The point estimate of the triple interaction $LowCap * Z * crisis$ varies between -0.7 and -0.8 depending on the specification, implying a further reduction in the probability of termination during the crisis of about 13%, although statistical significance here is less strong. Note that, before the crisis, banks with low capital were more likely to terminate a credit relationship (by about 1/2 a percentage point), compared to healthier banks, and there was no significant difference between zombies and healthy firms.

Next, we consider an additional effect that a low credit ratio might have on banks' incentives to extend credit to zombies. In addition to credit decisions, banks also decide if to classify a loan as non-performing. There are different classes of non-performing loans, involving different degrees of discretion by banks. The first class is "past-due". If a repayment of a loan is late by more than 180 days, the bank has to classify the loan as past-due. Banks may avoid classifying the old loan as past-due by providing a new loan to the borrower or by restructuring the existing one, for example by replacing the original loan with a new one with longer maturity. Otherwise, a past-due involves little discretion by the bank. The other two categories are "substandard loans" and "bad loans" and both involve some form of subjective evaluation by banks. In fact, a loan can be classified as substandard when the firm is "facing temporary difficulties - defined on the basis of objective factors - that are expected to be overcome within a reasonable period of time". The latter part of the definition entails a degree of discretion in credit evaluation which is a natural part of the activities performed by banks. Bad loans are loans for which banks expect to recover only a small fraction of the nominal value. The decision to classify a loan as bad is to some extent arbitrary, as banks must come to the conclusion that a borrower is not able to repay and classify the loan as a defaulted loan.

Classifying a loan as substandard or bad has two consequences. First, it forces the

[13]Given the very large number of fixed effects, we cannot estimate logit or probit models, so that we run linear probability models (OLS).

bank to set aside a provision for future losses, thus reducing current profits. Banks with a weak capital structure may be reluctant to do this. Second, a bad loan classification has a very negative effect on the firm's access to credit. The classification is signalled to the Centrale dei Rischi and all banks are notified of the event. As a result, the firm is basically excluded from the loan market. Therefore, if a bank has the incentive to keep a zombie alive, it will be reluctant to classify its loans as substandard or bad. For both reasons, we expect that under-capitalized banks will be more reluctant to do so.

To test this hypothesis, we run a set of regressions in which the dependent variable is a dummy variable BAD_{ijt} equal to 100 (again, to easy interpretation) if a loan to firm i from bank j is classified as bad between t and $t+1$. We construct a dummy variable for the three different types of procedures: Bad loans, sub-standard loans and past due. Note that this is a demanding test, for two reasons. First, our firm-year fixed effects specification identifies the estimated coefficient from differences in the bad loan classification across banks. Only about 4.7% of all bad loans in our sample are not classified as such by all banks.[14] Second, the benefit for a bank of delaying to classify a loan as substandard or bad may not be long lasting, as supervisors may require banks to do so when they identify these loans, or they may require banks to perform writedowns to increase their coverage ratios, i.e. the ratio between write-downs and the overall stock of non-performing exposures, resulting in lower profits and capital.[15].

With these caveats in mind, we show results in Table 7. The first column uses the bad loan dummy. We find that low capital banks are 0.5 percentage points less likely than better capitalized banks to classify a loan to a zombie as bad. Compared to an overall share of bad loans of 1.48 percent, this represents a drop of more than one third. Interestingly, we also find that the coefficient of the low capital-crisis interaction is positive, indicating that low capitalized banks are more likely to start a bad loan procedure on non-zombie firms. Before the crisis, instead, bank capital had no effect on such likelihood. Note that our estimates include firm-year effects. This means that these results are not due to assortative matching of firms to banks or to specific shocks to firm credit demand. Rather, we are comparing the decisions of different banks over the same firm, as we are only using within firm-year, across banks variability to identify the parameters. Finally, classification of the loan as bad is lower if the bank is a more important lender for that firm (the estimated coefficient on *share bank* is negative and highly significant).

[14] For this paper we are using yearly data from the Credit Register. It is possible that a bank classifies a borrower as a bad loan, say in June and the other banks follow, say, in September, so that as of December, the borrower has been classified as a bad loan by all banks.

[15] In 2012 and 2013 the Italian supervisor conducted targeted inspections on 20 major banks with the aim of verifying credit risk and increase coverage ratios. This resulted in banks increasing writedowns by 50%

The next column uses sub-standard loans as dependent variable. We find a similar effect, somewhat higher. The decision to classify a loan as sub-standard is more arbitrary than the decision to classify a loan as bad. Interestingly, low capital banks are less likely to classify the loan of any firm as sub-standard during the crisis, although the effect is one third that on loans to zombie firms. Finally, low capital banks are more likely to classify a loan as past-due. On the one hand, this reflects the very low degree of arbitrariness in turning these flags on. On the other, it might be that firms strategically decides to delay payments to weak banks, aware of the fact that these are less likely to turn on a substandard or bad loan flag. This interpretation is consistent with Schiantarelli et al. (2016), who show that firms strategically decide to pay late more often when borrowing from a weak bank, because such banks are more likely to tolerate delayed payments.

All in all, the evidence indicates that, during the crisis, weak banks cut credit to zombie firms less than stronger banks. This is evidence of zombie lending. Nevertheless, this does not happen at the expenses of credit supply to non zombies: we find no clear-cut evidence on the relationship between bank capitalization and lending to non zombies. In terms of the extensive margins, compared to stronger banks, weak banks are less likely to stop a credit relationship to both zombies and non zombies, although the effect is stronger for zombies. Overall, therefore, this result confirms previous evidence of banks behavior on zombie survival, but zombie lending does not seem to reduce credit availability to healthy firms.

5 The economic consequences of zombie lending

In the previous sections we have shown that, during the crisis, weak banks were more reluctant to cut credit to very weak firms and to terminate a credit relationship, in general and with zombie firms in particular. The magnitude of this effect of low bank capital is economically relevant: 2 percentage points of additional yearly credit growth going to zombie firms if bank capital is below the median, corresponding to a 25% increase relative to the average yearly contraction of credit of -8% during the crisis. We now ask how this phenomenon affected real economic activity. Since we found an effect of bank capital on zombie lending only during the crisis years, throughout this analysis we restrict the sample to the period 2008-2013.

We break the question in three parts. First, following Caballero et al. (2008), we study the effects of zombie lending on the growth of healthy firms. Prior research based on different episodes or different samples has concluded that lending to unprofitable firms hurts their healthy competitors, slowing down their rate of growth (Caballero et al. 2008, Acharya et al. 2016). This is because the supply of bank credit available to healthy firms is reduced, and also because the subsidy received by zombies distorts competition in the product and input markets. During a sharp recession, however, this negative effect on healthy firms could be mitigated by the positive aggregate demand externalities of reducing firm bankruptcies (Mian et al., 2015). In the next subsection we explore which of these effects prevails in our sample. Second, zombie lending affects the composition of bankruptcies: more zombies are kept alive, and possibly more healthy firms are pushed into bankruptcy. We explore this issue in Subsection 5.2. Third, building on the insight of the literature on misallocation (Hsieh and Klenow, 2009), we consider the implications of zombie lending for the dispersion of productivity across firms. In a frictionless economy, factors of production would be allocated to firms so that the marginal value product of inputs – and thus revenue productivity – is equalized across firms. Zombie lending reduces the efficiency of the allocative process, both because inefficient firms are kept alive (or prevented from shrinking), and because healthy firms find it more difficult to grow. As a consequence, zombie lending should increase the dispersion of productivity across firms. We address this implication in Subsection 5.3.

A key issue is how to define the group of firms within which these effects take place. Caballero et al. (2008) study Japanese listed firms only, for which the relevant markets are national (or even international). Accordingly, they use the sector as the reference group. Acharya et al. (2016) follow this approach and, given that they have a sample of firms from different European countries, they use the country-sector. Our sample instead consists of all incorporated firms, including very small firms. For this reason, we also consider geography. Many firms in our sample have access only to the local lending market. Since banks tend to be geographically specialized, and often competing firms are also geographically concentrated, we aggregate zombie lending at the province-sector level. Provinces are administrative units roughly comparable to a US county. As argued by Guiso et al. (2013), they constitute an ideal geographical unit to define the credit market: in fact, according to the Italian Antitrust authority, the "relevant market" in banking for antitrust purposes is the province. Moreover, provinces are also a natural boundary to define a local labor market, within which firms compete for workers.[16] In terms of sector, we exclude agriculture and finance and divide the other firms in 18 sectors.[17]

[16]The national institute for statistics define local labor markets using census data on workers' commuting patterns. It turns out that local labor markets so defined are smaller than provinces. However, for our study the most relevant market is the banking one, so that we decided to keep the province as our preferred geographical unit.

[17]Specifically, the sectoral classification is: Food and tobacco; Textile and leather; Wood; Paper; Chemicals; Minerals; Metals; Machinery; Vehicles, Manufacturing n.e.c.; Electricity gas, water; Constructions; Wholesale and retail trade; Hotels and restaurants; Transport, storage, communication; Real estate, renting and business activities; Professional, scientific and technical services; Business services.

5.1 Firm growth

How does zombie lending affect different growth indicators of individual firms operating in the same province-sector? This is the question addressed in this subsection.

5.1.1 Identification

The typical framework used in the literature to assess the effects of zombie lending on non zombie firms entails to regress firms performance on the incidence of zombies:

$$\Delta y_{ipt} = \beta_0 + \beta_1 ShZ_{pt} + \beta_2(1 - Z_{ipt}) * ShZ_{pt} + \beta_3 Z_{ipt} + Dummies_{ipt} + \eta_{ipt} \qquad (2)$$

where i denotes the firm, p the area-sector, and t the year. The dependent variable Δy_{ipt} is a measure of firm performance, such as the growth rate of inputs or output and ShZ_{pt} is the share of zombies in area-sector p at t. The coefficient β_1 captures the average effect of ShZ_{ipt} on the performance of zombie firms, while β_2 captures the effect of ShZ_{pt} on healthy firms, in deviation from that on zombies. The hypothesis that zombies hurt non zombies is formalized as $\beta_2 < 0$. In particular, when the dependent variable measures the growth rate of inputs, the coefficient β_2 captures both the crowding out channel and the implicit subsidy channel discussed above. Both channels reinforce each other and slow down input growth. When the dependent variable measures the growth of output, instead, the coefficient β_2 mainly reflects the implicit subsidy channel, hence its expected sign is still negative.

The key identification problem in estimating (2) is that the share of zombies is correlated with shocks affecting the performance of non zombies, such as demand shocks. An adverse demand shock in area-sector p is bound to increase the share of zombies and also negatively affect the performance of healthy firms operating in the same area-sector. This problem is well understood by the literature and is addressed by focussing on the *relative* performance of non zombies vs zombies. In particular, Caballero et al. (2008), Acharya et al. (2016) and McGowan et al. (2017) specify the vector of dummy variables as a full set of country-sector-year dummies (in our setting this is a set of province-sector-year dummies). In this regression, the area-sector-year dummies perfectly control for any aggregate shock. The coefficient β_1 is not identified, however, because the variable ShZ_{pt} is absorbed by the dummies. So the regression estimates β_2 as the effect of more zombies on non zombies, in deviation from the effect on zombies themselves. This coefficient should capture the implicit subsidy and the crowding out effects. Note that β_2 cannot capture aggregate demand externalities, since these are likely to affect both non-zombies and zombies.

The literature neglects a second identification problem with this approach, however, due to firm heterogeneity. This problem is illustrated in Figure 6, where the lighter curve depicts an hypothetical distribution of firms in an area-sector. The horizontal axis is a measure of firm "quality", such as growth prospects. Zombie firms are those below a given threshold, T_Z in the Figure. Healthy firms are those to the right of T_Z. We are interested in the difference between the average performance of healthy vs. zombie firms, namely $\mu^{NZ} - \mu^Z$, where $\mu^{NZ} \equiv E(x|x > T_Z)$ and $\mu_s^Z \equiv E(x|x \leq T_Z)$ denote the mean of healthy and zombie firms respectively. In particular, we want to know how random changes in ShZ_{pt}, the share of zombies in area-sector p at t, affect $\mu^{NZ} - \mu^Z$ through the spillover effects described above (distortions of competition and lower credit supply to healthy firms). According to the prevalent interpretation in the literature, this can be assessed by the estimate of β_2 in equation (2).

The implicit identifying assumption behind this approach is that, in the absence of spillover effects, shocks that change the share of zombies have the same effect on the performance of zombies and healthy firms, that is, they do not affect $\mu^{NZ} - \mu^Z$. Unfortunately, this assumption is unlikely to hold in the data and, therefore, β_2 cannot identify the effects of zombies on non zombies even if one includes area-sector-year dummy variables in equation (2). To see this, suppose that the area-sector is hit by a negative shock that shifts the whole distribution of firms to the left, to the darker curve depicted in Figure 6. Three things happen. First, the share of zombie firms, ShZ_{pt}, increases (the area to the left of T_Z rises, as illustrated by the shaded area in Figure 6). Second, both conditional means μ^{NZ} and μ^Z change, and presumably drop.[18] This is the standard identification problem discussed above, addressed in the literature by the inclusion of area-sector-year dummy variables. Third, the difference between the conditional means, $\mu^{NZ} - \mu^Z$, could also be affected, in a manner that depends on the shape of the distribution. This identification problem is neglected in the literature, but it is relevant for a large class of distributions.

Specifically, in the appendix we show that, under a simple condition on the distribution of performance, a shift to the left in the distribution induces a drop in the difference $\mu^{NZ} - \mu^Z$. We illustrate this with a numerical simulation. Consider the case of the normal distribution with unit variance and mean equal to 5 (the choice of the mean is inconsequential for the results). Assume that a firm is classified as zombie if its quality is below 3. We perform the following experiment. We generate negative shocks $s = 0.01, 0.02, ..., 3$ that progressively shift the distribution to the left, $\mu(s) = 5 - s$, and compute $\mu^{NZ}(s) - \mu^Z(s)$, that is, the difference in the average quality of non zombies and zombies, for each value of s. Panel A of figure 7 plots this difference and shows that it is decreasing for $s < 2$, that is, as long as the zombie threshold is to the left of the mean of

[18]Note that, for some distributions, a leftward shift might actually increase μ^{NZ}, the conditional mean above the threshold. However the mean surely decreases for log-concave distributions (Barlow and Proschan, 1975), a family that includes many commonly used distributions, such as the normal, the Laplace and the logistic.

the distribution (for $s = 2, \mu(s) = 3$, equal to the zombie threshold). Panel B of the figure plots $\mu^{NZ}(s) - \mu^{Z}(s)$ against the share of zombies (the latter obviously increases with s). Here too we find a negative relationship, as long as the share of zombies is below 50%. This condition is generally met in the papers on zombie lending. For example, in Acharya et al. (2016) the share of zombies varies between 3% in Germany and 20% in Italy, while in Caballero et al. (2008) it varies between sector and over time, but it exceeds 20% only in a few years in Services and Real Estate (see their Figure 3). In our case, we classify as zombies 19% of firms during the crisis years. Thus, in this very standard setting and without any negative spillovers occurring from zombies to non zombies, the estimation of equation 2 would deliver a negative coefficient β_2. But this simply reflects a property of the distribution of firms, and has nothing to do with the hypothesis that a larger share of zombies hurts healthy firms through spillovers in credit, product or input markets.[19]

To cope with this problem, we need a variable that moves the shares of zombies in a province-sector-year but that is orthogonal to local-sectoral shocks. In what follows we use a measure of under capitalization of the banks that lend in the province-sector. As a measure of banks weakness, we construct the credit-weighted average value of the variable $LowCap_{pt}$ used in the previous section:

$$\overline{LowCap}_{pt} = \frac{\sum_j LowCap_{jt} * Credit_{jpt}}{\sum_j Credit_{jpt}} \tag{3}$$

where $Credit_{jpt}$ is the amount of credit granted by bank j to province-sector p in year t. Thus, $\overline{LowCap}_{pt}$ is the share of loans granted in each province-sector-year that originate from banks with a capital ratio below the median. We have shown in Section 4 that this indicator captures zombie lending. We expect that, in sector-province where banks are weaker, the tendency to engage in zombie lending hurts healthy firms through the two channels described above. But these spillover effects could be mitigated by reduced adverse aggregate demand externalities, if zombie lending also reduces bankruptcies and layoffs.

While endogeneity concerns are first order when using the share of zombies in equation (2), they are much less likely to be a problem with $\overline{LowCap}$. The exclusion restriction is that bank capital is exogenous with respect to the conditions prevailing in a province-sector-year: that is, it is orthogonal to shifts of the distribution. The banks in our sample

[19] Note that in our simulation we are likely to underestimate the extent to which $\mu^{NZ}(s) - \mu^{Z}(s)$ decreases with s. The reason is that very low quality firms could exit the market. This would limit the drop in performance of (surviving) zombies (and hence the drop in $\mu^{Z}(s)$) when shocks hit. This can be seen again in Figure 6, where we also added an exit threshold T_D. When we shift the distribution to the left, the drop in the average quality of zombies is reduced by the fact that extremely low quality zombies drop out of the market. At the same time, as long as the density is higher at the zombie threshold T_Z than at the exit threshold T_D, we still obtain that a leftward shift in the distribution increases the mass of zombies.

are typically active in several province-sectors, so that capital shortages are not due to adverse conditions in one particular province-sector-year. Indeed, on average banks are active in about 48% of sector-provinces (the median is very similar). Moreover, the 95-th percentile of the distribution of the share of of lending is 1.39%. The share reaches 6.46% only at the 99-th percentile. The distribution is therefore extremely skewed towards zero, the lower bound. Shares of banks' loan portfolio above 5% are concentrated in a handful of sectors, such as construction and wholesale and retail trade, characterized by the presence of some very large firms, and in the provinces in which these large firms have their headquarter (the great majority of these are in Milan, Rome and Turin, the largest cities in the country). Large concentrations of a banks' portfolio also occur in the case of small banks whose operations are geographically concentrated. For banks with assets valued more than 50 billion euros, the share of the loan portfolio is above 5% in only 55 province-sector-year cells (out of 18,809 year-sector-province cells). As a further robustness check, we also run our tests excluding province-sector-year cells in which at least one bank has a share of its loan portfolio above 5%, as well as the whole province-sector in which at least one bank has a share of its loan portfolio above 5% in any year. Although the number of observations drops substantially in the two exercises, the results are very similar to those based on the whole sample. We therefore maintain that bank capital is exogenous with respect to the conditions prevailing in a province-sector-year; in terms of Figure 6, it is orthogonal to shifts of the distribution.

An additional endogeneity concern is that the shares of credit might be correlated with local-sectoral shocks. For example, when a negative shock hits a province-sector, low-capital banks might expand their credit shares. To account for this possibility, we also construct an alternative measure of banks weakness based on the share of loans in the pre-crisis period. Specifically, we compute

$$\widehat{LowCap}_{pt} = \frac{\sum_j LowCap_{jt} * Credit_{jp04-07}}{\sum_j Credit_{jp04-07}}, \tag{4}$$

where $Credit_{jp04-07}$ is the total credit that bank j extended to province-sector p in the period 2004-2007. For this variable, credit shares are fixed at their pre-crisis average values, so that they are by construction exogenous with respect to shocks that occur during the crisis. In what follows, we use $\overline{LowCap}_{pt}$ as our main variable, as it represents a more accurate description of the credit condition at the sectoral-local level during the crisis. It turns out that the shares are fairly stable: the correlation between $\widehat{LowCap}_{pt}$ and $\overline{LowCap}_{pt}$ is 0.83. To make sure that the potential endogeneity of credit shares is not driving our conclusions, in the appendix we report the tables that replicate all the regressions using $\widehat{LowCap}_{pt}$ instead of $\overline{LowCap}_{pt}$ as regressor. We find very similar results.

We again use Figure 6 to illustrate the possible effects of $\overline{LowCap}$ on firms performance. Consider first zombie firms. We have seen that weak banks provide more credit to them. This can have two effects. On one hand, it keeps very low quality zombies alive: the failure threshold T_D in Figure 6 shifts to the left. This implies that the performance of zombies should deteriorate (extensive margin effect: weaker selection). On the other hand, with more credit, zombies can expand operations (or contract less): the intensive margin effect implies that their performance improves. Which effect dominates is an empirical question.

Next consider healthy firms. First, their performance can be negatively affected by bank weakness, because of the spillover effects induced by zombie lending (implicit subsidy to inefficient competitors and reduced credit availability). Second, in the opposite direction, zombie lending could mitigate the adverse aggregate demand externalities, through reduced layoffs and bankruptcies. Third, there might be a negative direct effect of $\overline{LowCap}$ on healthy firms, if low capitalized banks supply less credit independently from the presence of zombies. So any effect we find is an upper bound to the pure zombie channel. Note that this is not necessarily a limit of our analysis: we estimate the total effect of banks low capitalization on the growth performance of healthy firms, rather than the partial effect going through the zombie lending channel. From a policy perspective, the total effect is as important, if not more important, than the partial one.

Finally, it is important to stress the difference between the relative effect of $\overline{LowCap}_{pt}$ on healthy firms with respect to zombies, β_1, and the absolute one, measured by $\beta_1 + \beta_2$. We have seen that $\overline{LowCap}_{pt}$ is likely to affect the performance of zombies. In this case, β_2 identifies the differential effects on non zombies, but in itself it is not enough to assess the total effect. For example, it might be that the performance of zombies improves and that of non zombies is unaffected: in this case, the relative effect would be negative but the total effect would be zero. Our approach has an important advantage over the previous literature. Because the variable $\overline{LowCap}_{pt}$ is unlikely to be correlated with shocks at the sector-province level, we can also estimate equation (2) without including province-sector-year dummies and still obtain consistent estimates of of β_1 and β_2 and hence of the total effect $\beta_1 + \beta_2$.

5.1.2 Results

As a first exercise, we have replicated the regressions run by the previous literature of firm performance on the share of zombies at the province-sector-year levels. We find results in line with the previous literature. The first two columns of Table 9 report a regression of employment growth at the firm level, measured by the growth rate of the wage bill,[20] on the share of zombie firms at the province-sector-year level, by itself and interacted with a dummy for non zombie firms. In column (1) we control for province-sector and year fixed effects, so we can estimate both β_1 and β_2 in equation (2). We find that employment growth of zombie firms decreases as the share of zombie increases, but that it does so even more for non zombies: the interaction is negative and statistically significant. This result survives the inclusion of a full set of province–sector-year dummies (column 2), in which case we can only identify the relative effects on non zombies. As the previous literature, we also find a negative and significant coefficient.

Despite the substantial differences in the settings, particularly in terms of firms included in the exercise (listed firms for the other papers, all firms in our case) and definition of reference group (country-sector-year vs. province-sector-year), the magnitudes are also comparable, particularly with Caballero et al. (2008). They find a β_1 of -0.0454, very similar to ours, and a β_2 of -0.0232 (-0.0188 in the specification with sector-year fixed effects), smaller than our estimates of around -0.07. This might be due to the much finer geographical definition of our analysis.[21]. The results in Columns 1 and 2 of Table 9 are clear cut: the negative relationship between the share of zombies and the relative performance of non zombies is a very robust empirical finding also in our setting. Unfortunately, given our discussion above, it is likely to be a mechanical consequence of the leftward shift in the distribution and cannot in itself be interpreted as evidence of negative spillovers from zombies to non zombies.

We next move on to estimating our preferred regression, where ShZ is replaced by $\overline{LowCap}$. As argued above, our credit supply indicator is less subject to the endogeneity issue compared to ShZ_{pt}, because the banks' capital ratio is unlikely to be affected by shocks at the province-sector level. We use three performance indicators (all expressed in rates of growth): the growth in employment, in the capital stock and in sales.

The remaining columns (3)-(8) of Table 9 report the estimates. For labor, the estimated coefficient β_2 is negative and highly significant: under-capitalized banks reduce labor expansion of healthy firms, *compared to zombies.* Using the estimated coefficient of -0.028 on $\overline{LowCap}_{pt} * (1 - Z_{ipt})$ in column (3), increasing the capitalization of the weak banks so that they are all above the threshold used to define a weak bank (i.e. so

[20] We have experimented with capital and sales growth, obtaining similar results.

[21] Comparisons with Acharya et al. (2016) are less straightforward. In fact, they further split non-zombies into high and low quality firms and include firm fixed effects. They find no relative effect for low quality healthy firms, while a very large coefficient, of -0.5, for high quality healthy firms. But introducing a second threshold that distinguishes low and high quality healthy firms further exacerbates the identification problems in interpreting the relative coefficient (see our previous discussoin of Figure 6). Results are available upon request.

that $\overline{LowCap}_{pt} = 0$) would imply that non-zombie firms would increase the growth of their wage bill by 2.8% *relative to zombies*. While the relative effect is substantial, the *absolute one* is basically zero. In fact, the whole relative effect comes from the fact that zombies growth improves with weak banks: $\beta_1 = 0.027$. This means the all the drop in relative performance of non zombies is due to an increase in the performance of zombies: in absolute terms, healthy firms performance is unaffected. In fact, we fail to reject the hypothesis that $\beta_1 + \beta_2 = 0$. To assess if our estimates are robust to the presence of local-sectoral shocks, Column (4) of Table 9 estimates a specification that also includes province-sector-year dummy variables. The estimate of β_2 is unaffected, suggesting that local shocks are not a major concern. Of course, we cannot infer anything about the size of the absolute effect, since $\overline{LowCap}_{pt}$ on its own is absorbed by the dummy and β_1 cannot be estimated.

The remaining columns of Table 9 repeat the same exercise for the other measures of firm performance, For capital, we find that neither β_1, nor β_2 or their sum are significantly different from zero. This might be due to the fact that measurement error is likely to be a more important concern for capital, measured at book values, than for labor or sales. In fact, for the the latter we find effects that are similar to those for labor, although the relative effect is somehow smaller in absolute value. For all all indicators, we fail to reject the hypothesis that $\beta_1 + \beta_2 = 0$: healthy firms' absolute performance is unaffected by banks capitalization.

We have performed several robustness checks. First, we have experimented with different set of dummy variables. Our preferred specification controls for sector-province and year fixed effects. We have also experimented with sector-year and province-year fixed effects. In general, we confirm the overall results, with the only noticeable difference that, for employment growth, when we increase the set of dummies we find some evidence of a negative absolute effect on non-zombies. Second, we have run a different specification. As argued above, $\overline{LowCap}_{pt}$ captures the total effect of low capitalization on firm performance. We have also run an IV estimate in which healthy firm performance is regressed on the share of zombies, and the latter is instrumented with $\overline{LowCap}_{pt}$. The sample only includes non zombie firms. The idea is that, by moving the T_D threshold of Figure 6, changes in the degree of capitalization induce changes in the share of zombies unrelated to local sectoral shocks that shift the distribution. As expected, we find a positive and statistically significant first stage coefficient. The second stage results confirm the previous analysis: exogenous shifts in the share of zombie firms have no effects on the performance of healthy firms. Although in line with the overall results, this analysis should be taken with a grain of salt, both because the first stage is not very powerful (F-test of around 6) and because the exclusion restriction might fail if, as discussed above, bank capitalization has direct effects on healthy firms performance through credit availability (although the previous results suggest that this is not the case). Finally, as explained above, we have used a measure of banks weakness based on the share of credit in the pre-crisis period (see equation 4). Results, reported in appendix Table A9, are very similar.

Overall, these results indicate that banks' capitalization does not affect the absolute performance of healthy firms. The fact that low bank capital induces a higher growth of zombie firms is consistent with the findings of the previous section, that weaker banks lend more to zombies. From this perspective, zombie lending does affect outcomes. However, this does not hurt the healthy firms. This finding too is consistent with the fact that we found no negative effects of banks capitalization on the supply of credit to healthy firms. Our results therefore confirm one finding of the previous literature, that weaker banks extend credit to zombie firms. But they contradict the other finding, arguably more important, that this has negative consequences for healthy firms and, through this, on aggregate growth.

Note that our sample ends in 2013, and thus does not include the recovery years. This may be relevant, because some of the negative economic consequences of zombie lending are more likely to be felt when the recession is over, and healthy firms increase their demand for credit. During the recession, instead, keeping firms alive (even if non-viable) can cushion the negative general equilibrium effects of aggregate demand failures, and through this channel mitigate the adverse economic effects of an inefficient allocation of credit.

5.2 Firm failure

The previous regressions focus on the intensive margins, that is, firm's growth conditional on survival. But zombie lending also affects the extensive margin, since the banks' financing decisions determines firms' survival.[22] In fact, the term "zombie" is meant to indicate a non viable firm that survives only thanks to bank lending. To analyze the effects on the survival probability, we estimate the following regression:

$$F_{ipt} = \gamma_0 + \gamma_1 \overline{LowCap}_{pt} + \gamma_2 (1 - Z_{ipt}) * \overline{LowCap}_{pt} + \gamma_3 Z_{ipt} + Dummies_{ipt} + \nu_{ipt} \quad (5)$$

where F_{ipt} is a dummy variable equal to 1 if firm i in sector-province p exits through a bankruptcy procedure in year t.

[22] An additional channel could occur through entry, if zombie lending depresses firms' entry. Differently from the exit analysis, that can be carried out at the firm level accounting for the zombie status, we do not observe potential entrants. In a series of unreported regressions, we have performed the analysis at the aggregate province-year-sector level, regressing observed entry rates on $\overline{LowCap}$. We did not find any robust correlation between entry and banks capital ratios.

The Firms Register reports the status of firms, signaling those failed or undergoing a legal procedure due to financial distress, typically leading to failure. We focus on failure, rather than overall exit, because the latter also includes voluntary firm closures without financial distress, ie., paying out all liabilities. These are cases in which the entrepreneur decides to close the firm, rather than being forced to shut down due to lack of credit. Instead, we want to focus on episodes in which the closure event is related to financial distress, and therefore to access to credit. We use as year of failure the last year in which we observe the firm in the dataset, that is, the last year in which the firm compiles its balance sheets. One problem is that the failure date is often after this year, as legal procedures take time to be implemented. For example, of the firms for which we last observe the balance sheets in 2008 and that exit through failure, 20% report as year of failure 2010, 10% 2011 and 7.6% 2012. This implies that, for the most recent years, we are underestimating the number of true failures, as we only have information up to 2013 To have a uniform definition of failure, independently from the year in which we last observe balance sheets, we only consider firms for which failure is within two years of the last year in which we observe the balance sheets and use data up to 2011. During the crisis years the overall failure rate is 2.9%; it decreases to 2% for non-zombies and increases to 7% for zombies. We expect that low capitalized banks reduce the failure rate of zombies ($\gamma_1 < 0$) at the expenses of healthy firms ($\gamma_2 > 0$).

We start with a linear probability model, as probit models are problematic to estimate with a large number of fixed effects. As before, we cluster standard errors at the province-sector level. Table 10 reports the results. In column (1) we use separate year and province-sector fixed effects. We find that $\gamma_1 = -0.877$ and highly significant, which implies that a larger share of undercapitalized banks reduces the failure rate of zombies. The effect is opposite for non-zombies: $\gamma_2 = 1.682$. Moreover, we reject the null hypothesis that $\gamma_1 + \gamma_2 = 0$, meaning that low capitalized banks increase not only the relative but also the absolute failure probability of non zombies.[23] The relative effect on non-zombies is very similar (statistically identical) in column (2), where we control for province-sector-year fixed effects, signalling that reverse causality is not likely to be an issue. Finally, in column (3) we estimate a probit model using the more parsimonious dummy specification, that is, with separate year and province-sector dummies. The marginal effects are slightly smaller in absolute value than those in the linear probability models, but they fully confirm the results. In terms of the magnitude of the effects, the estimates of column (1) imply that increasing the capital ratio of all banks above the median would increase the failure rate of zombies by 0.4%. Relative to zombies, healthy firms would record a drop in failure rate of 0.8%. The *absolute* (as opposed to relative) effects on healthy firms is therefore -0.4%.

[23]Results are confirmed when we add sector-year and province-year fixed effects.

This is a non-trivial effect, as it represents a reduction of approximately one fifth in the failure rate of healthy firms in the period.

As before, we have performed the analysis replacing $\overline{LowCap}_{pt}$ with $\widehat{LowCap}_{pt}$ as defined in equation refeq:lowcaphat). Table A10 in the appendix shows that the results change only marginally.

5.3 Productivity dispersion

We now turn to a third implication of zombie lending: the misallocation of credit increases the dispersion of productivity across firms. In fact, when banks lend relatively more to zombies, they increase both the relative chance of survival and the size of their operations, possibly at the expenses of heathy firms. TFP dispersion has become the standard measure of misallocation since the seminal contribution of Hsieh and Klenow (2009) who, following Foster et al. (2008), distinguish between physical TFP (computed on physical quantities) and revenue TFP (computed on revenues). In their model, monopolistic competition implies that, even if firms are heterogeneous in their physical TFP, revenue TFP should be equalized across firms, as more efficient firms expand their scale of operation, thus decreasing pricing and, through this, revenue TFP. This process is inhibited by frictions that prevent the efficient allocation of inputs of production: the higher the frictions, the more dispersed is revenue TFP. In our case, the friction is an inefficient allocation of credit to low productivity firms. We thus assess whether zombie lending is associated with an increase in (revenue) TFP dispersion.

We compute TFP at the firm level assuming a constant return to scale Cobb-Douglas production function of the form $Y = TFP * L^{\alpha} * K^{1-\alpha}$ where Y is value added, L labor and K the capital stock. We estimate the labor coefficient as the labor share at the sectoral level: $\alpha = \frac{wL}{Y}$, which varies between a maximum of 0.66 in Vehicles to a minimum of 0.35 in Electricity, gas and water. The labor input is measured as the wage bill and the capital input is computed using the permanent inventory method. We fist compare the TFP of zombies and non zombies. As expected, we find that the average log TFP is substantially higher in healthy firms, with a log difference of almost 0.5. There is also evidence that the dispersion is higher among zombies firms: 0.71 against 0.61 for non zombies. Reallocating inputs from zombies to non zombies, therefore, should reduce the dispersion.

We start by analyzing the relationship between the share of zombies and TFP dispersion. Specifically we estimate the following regression:

$$SD(TFP)_{pt} = \lambda_0 + \lambda_1 ShZ_{pt} + \lambda_2 \Delta TFP_{pt} + Dummies_{pt} + \eta_{pt} \tag{6}$$

The dependent variable, $SD(TFP)_{ipt}$, is the standard deviation of TFP at the sector-province-year level, where TFP is computed as explained above. If zombies are a source of misallocation, we should expect that the higher their share the higher TFP dispersion. In this specification we can only include separate dummy variables for the province-sector and for the year, since in the fully saturated model with province-sector-year fixed effects the coefficient of interest λ_1 cannot be identified. To control for shocks at the province-sector-year level, we include average TFP growth at that level, ΔTFP_{ipt}. Descriptive statistics for TFP dispersion and average TFP growth at the province-sector-year level are in Table 8, Panel B.

Table 11 reports the estimates. To account for measurement error due to the fact that in some province-sector-years we have a small number of firms, in column (1) we exclude observations in which the standard deviation is computed on less than 10 firms. In column (2) we keep all province-sector-years, but weight them according to the number of firms contained in it. Consistent with the view that zombies are a source of misallocation, we find a positive correlation between the share of zombies and TFP dispersion. In terms of magnitude, taking the estimate of Column (2), an increase in the share of zombies of one standard deviation (0.191) would increase the standard deviation of the province-sector by 0.015, approximately 2.6% of it average value.

The problem with this regressions is that the causal interpretation rests on the assumption that changes in the share of zombies are orthogonal to the dispersion of TFPR. This is not an uncontroversial assumption. For example, since the seminal work by Lilien (1982), a large literature has argued that negative shocks can affect both the first and the second moment of the productivity distribution and that recessions are periods in which the dispersion of performance increases (Davis and Haltiwanger, 1992; Bloom, 2009). Moreover, we are interested in the extent of misallocation due to banks' lending choices, rather than to zombies in general. To directly test for the impact of banks' weakness on misallocation, we substitute ShZ with is the share of credit originated by banks with capital ratio below the median, $\overline{LowCap}_{ipt}$. As argued above, this variable is likely to be exogenous with respect to local conditions, and directly capture the health of the banking sector at the local-sectoral level. The estimates, reported in column (3) and (4) of Table 11, yield no evidence that banks' capital had any impact on misallocation during the crisis: the coefficient λ_1 is always negative, but very small and statistically insignificant. As an additional check, we have also run IV regressions in which the share of zombies is instrumented with $\overline{LowCap}$. As before, the first stage is weak so that in the second stage no significant effect of the share of zombies emerge. A weak first stage signals that the effects that we found on the extensive margins are too small to induce sufficient variation in the share of zombies to estimate the parameter.

Nevertheless, one can argue that what really matters is the interaction between the banks' capital ratio and the presence of zombies. That is, weak banks misallocate credit only if a market is populated by zombies: in sector-province with strong firms, there is no scope for diverting credit to unhealthy firms. To test this implication, we run the following regression:

$$SD(TFP)_{pt} = \lambda_0 + \lambda_1 \overline{LowCap}_{pt} + \lambda_2 \Delta TFP_{pt} + \lambda_3 \overline{LowCap}_{pt} * ShZ_{pt} + \\ + \lambda_4 ShZ_{pt} + Dummies_{pt} + \eta_{pt} \tag{7}$$

and test the hypothesis that the interaction coefficient λ_3 is positive. Of course, this specification has to be taken with some caution, as it is subject to the endogeneity issues of the share of zombies explained above. The results are in the last two columns of Table 11. First, the share of zombies itself is not significant anymore while that of $\overline{LowCap}_{pt}$ is negative and significant, implying that, in the absence of zombies, low capitalization decreases TFP dispersion. The interaction between $\overline{LowCap}_{pt}$ and the share of zombies always has a positive and significant impact on the dispersion of TFP, as expected. This means that, during the crisis, the combination of a larger population of zombies and of weaker banks was positively related to the dispersion of TFP. Given that $\partial SD(TFP)_{pt}/\partial \overline{LowCap}_{pt} = \lambda_1 + \lambda_3 ShZ_{pt}$, using the estimate of the last column we find that an increase in $\overline{LowCap}$ increases dispersion if the share of zombie firms is above 21%, which happens in around 43% of the province-sector-years. This indicates that low bank capitalization increases TFP dispersion only in the presence of a fairly large population of zombies.[24] All in all, therefore, we conclude that banks low capitalization is responsible for only a modest misallocation of resources, measured in terms of TFP dispersion. This is in line with some recent analyses of the evolution of misallocation in Italy at the aggregate level, which find that, if anything, it has slightly decreased during the crisis (Calligaris et al., 2016; Linarello and Petrella, 2016). Again, all results are confirmed when using the indicator of banks weakness based on the pre-crisis credit shares (see appendix Table A11).

6 An Evaluation of the Aggregate Effects of Low Capitalized Banks

Putting all the pieces together, what would be the aggregate effects of recapitalizing the banking system so as to reduce the extent of zombie lending? In this section we propose a simple, stylized framework that allows us to compute some bounds on the answer to this question. The thought experiment is to inject capital in weaker banks, so that all banks

[24]The weak correlation between bank capitalization and TFP dispersion is confirmed by the fact that, when we increase the set of dummies including sector-year and province-year fixed effects, we tend to loose statistical significance.

with a capital ratio below the median reach the median itself. In other words, following the exercises of the previous section, we inject capital so that the value of the variable $\overline{LowCap}$ goes from an average of 0.453 to zero. Taking the level of banks' capitalization as of December 2012, this amounts to a capital injection of approximately 4 billions. We want to quantify the effect of this capital injection on aggregate growth during the crisis, based on the previous estimates.

6.1 A Simple Evaluation Scheme

Define Y^{NZ} as the average product of one unit of input in non-zombie firms. The units can be both firms (extensive margin) or workers/capital (intensive margin). Assume that a zombie's average product is $Y^Z = \theta Y^{NZ}, \theta \in [0,1]$, where $\theta = 0$ is the case in which zombies are totally unproductive and $\theta = 1$ if zombies are as productive as non-zombies.

Consider first the case in which the unit is a firm, so that Y^{NZ} is the average output of non-zombies. Assume that there are n^{NZ} non-zombies and n^Z zombies. Total output is then

$$Y = Y^{NZ} * n^{NZ} + Y^Z * n^Z = Y^{NZ} * (n^{NZ} + \theta * n^Z). \tag{8}$$

We want to compute the effect of recapitalizing banks so that they are all above the median level of the capital ratio in terms of firms' failure using the estimates of equation (5), as we are focusing on the extensive margin. The counterfactual output is

$$Y^{CF} = Y^{NZ} * (n^{NZ}(1 - \delta^{NZ}) + \theta * n^Z(1 - \delta^Z)) \tag{9}$$

where, δ^S, $S = Z, NZ$ is the effect of bank recapitalization on the failure rate of zombies and non-zombies respectively (so that $(1-\delta^S)$ is the effect on their survival rate). Using the notation of equation 5 we have: $\delta^Z = -\hat{\gamma}_1 * \Delta\overline{LowCap}$ and $\delta^{NZ} = -(\hat{\gamma}_1 + \hat{\gamma}_2) * \Delta\overline{LowCap}$, and by the previous computations $\Delta\overline{LowCap} = -0.432$. When δ^S is negative, the number of surviving firms in the counterfactual scenario increases relative to the actual number, and vice versa if positive. In particular, we found that recapitalizing banks decreases the failure rate of non-zombies and increases that of zombies.

Define $sh^{NZ} = n^{NZ}/(n^{NZ} + n^Z)$ as the share of non-zombies firms and symmetrically for sh^Z. The growth rate of output in the counterfactual scenario relative to actual output is:

$$\frac{Y^{CF} - Y}{Y} = \frac{-sh^{NZ}\delta^{NZ} - \theta * sh^Z\delta^Z}{sh^{NZ} + \theta * sh^Z} \tag{10}$$

The first term in the numerator is the percentage increase in output coming from the increase in the number of non-zombie firms (provided that δ^{NZ} is negative), while the second term is the decrease coming from the exit of zombie firms, weighted by their relative productivity. The increase is maximal, and equal to δ^{NZ} itself, when $\theta = 0$, i.e., when zombies are totally unproductive, and minimal when $\theta = 1$. Even in this case, however, the increase in the capital ratio of banks can have a positive effect as long as $-sh^{NZ}\delta^{NZ} > sh^{Z}\delta^{Z}$. In particular, the fact that the share of non-zombies is four times as large as that of zombies magnifies the effect: even when the treatment has perfectly symmetric effects ($\delta^{NZ} = -\delta^{Z}$), output increases because there are more non-zombies so that the contraction in output due to zombies exit is more than compensated by the expansion in non-zombies.

From the descriptive statistics in Table 2, we have that the share of zombies during the crisis is $sh^{Z} = 0.19$; regression results in the first column of Table 10 deliver $\hat{\gamma}_1 = -0.877$ and $\hat{\gamma}_2 = 1.682$, so that $\delta^{Z} = 0.0038$; and $\delta^{NZ} = 0.0035$. The increase in output for $\theta = 0$ is 0.35% and for $\theta = 1$ is 0.18%. So, according to these numbers, the lower failure rate of healthy firms and the higher failure rate of zombies that would result from the capital injection increases output growth by between 0.2% and 0.35% during the crisis.

For the intensive margin, we have shown that the effects on the growth of non-zombies are rather modest. Consistently, if we take the estimates for employment growth in the first column of Table 9, we obtain $\delta^{Z} = 0.012$ and $\delta^{NZ} = 0.0004$, so the increase in output is negligible for $\theta = 0$ and slightly negative for $\theta = 1$. We obtain similar results, if not even more negative, when we use capital and sales growth. Overall, the effect coming from the intensive margin is, int the best of cases, rather limited.

6.2 Discussion

Overall, this quantitative exercise suggests that recapitalizing the weaker banks would have a positive effect on output growth mainly or almost exclusively through the extensive margin. In our counterfactual exercises, a capital injection of 4 billions in the weaker banks would have increased yearly output growth by between 0.2 and 0.35 during the crisis period 2008-2013. The mechanism operates by increasing the survival rate of healthy firms and increasing the failure rate of zombie firms. The reallocation effects on surviving firms are instead small.

During this same crisis period, yearly output growth was on average -3.7% in our sample of firms. Even under the most extreme assumption of zero productivity of zombies, therefore, zombie lending can explain less than 1/10 of this value. Thus, taken at face value, these results suggest that, while zombie lending played a role in aggravating the deep GDP contraction recorded by the Italian economy during the great recession, it is unlikely to be the key factor. Other developments, such as the drop in aggregate demand and the overall contraction of credit –rather than its misallocation to weak firms– are likely to be at the heart of the recession.

This result does not rule out the possibility that zombie lending could have a larger effect in slowing down the recovery after the recession. First, most of the effects play out through the extensive margins suggesting that credit misallocation might take time to display its full consequences. Failures and closures (as well as firm opening), require years to be implemented and our time span might be too short to capture these medium to long run effects. Second, in a deep recession such as the one that characterizes our period of analysis, zombie lending might be less harmful to growth than during a recovery. Mian et al. (2015) show that, in US states where foreclosures were easier to implement, the foreclosure rate was higher and the decline in aggregate demand stronger. This effect might be present for firms too. Reallocating productive factors from low productivity firms requires that there are more productive firms willing to use such assets. During the deep recessionary period we analyze, however, even healthy firms suffered large demand drops and, therefore, their demand for inputs might have been unable to absorb those freed up by zombies. In such a scenario, hoarding factors in zombies might be less detrimental to growth than during "normal" times. If this were the case, the negative effects of zombie lending would be much larger during the recovery period, when good firms face more expansion opportunities and therefore express a higher demand for credit.

7 Concluding remarks

This paper explored the consequences of under-capitalization of Italian banks during the Eurozone financial crisis, in the period 2008-13. We find that banks with low capital are more reluctant to cut credit to non-viable firms. The effect is only present during the crisis years and its aftermath, and it only concerns regulatory capital (and not other indicators of bank weakness). Capital requirements became more demanding during and after the crisis years, also in association with the transition of bank supervision from national to European authorities. Hence our results suggest that the misallocation of credit towards non-viable firms may have been a reaction to the tighter regulatory environment, as weaker banks attempted to reduce the risk of supervisory requests to boost their capital.

This misallocation of credit has important effects on the real economy. During the crisis years, bank capitalization affects the composition of bankruptcies. In province-sectors where lending is predominantly done by weaker banks, zombie firms are more likely to survive, and healthy firms are more likely to fail. We also observe a greater dispersion of TFP if banks are weaker, although this effect is present only if the share of zombie firms in the province-sector-year is sufficiently large.

Nevertheless, we find no evidence that the growth of existing healthy firms is hurt by bank weakness. We do find that bank weakness induces a lower growth rate of healthy firms relative to zombies, in line with the previous literature. But this happens because weak banks allow zombies to grow faster (or more precisely to contract less). When this higher growth of zombies is taken into account, the absolute effect of bank undercapitalization on the growth rate of healthy firms is close to zero. There is also no evidence that bank weakness reduced the entry of new firms. A plausible interpretation of this finding is that weak banks lend more to non-viable firms, and this mitigates the local adverse aggregate demand externalities, partly offsetting the other negative spillovers effects of zombie firms. This interpretation is also consistent with our finding that undercapitalized banks extend more credit to zombies (compared to stronger banks), but do not reduce credit to healthy firms.

All in all, this suggests that bank-undercapitalization may be costly in terms of misallocation of capital and productive efficiency in the medium term, but cannot be blamed for aggravating or prolonging the recession induced by the Eurozone financial crisis. Of course, this conclusion cannot be extrapolated to the recovery phase, since our sample ends in 2013 and Italian GDP growth was negative until the last quarter of 2014.

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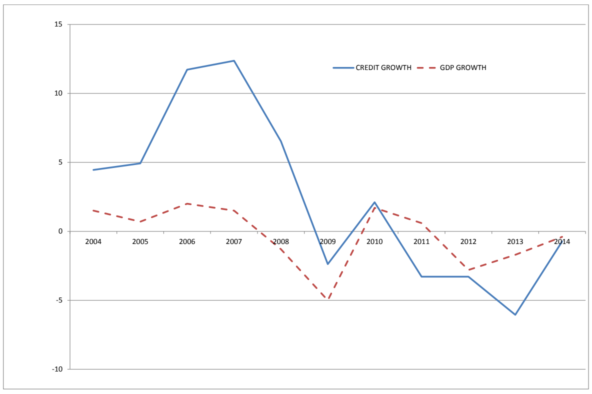
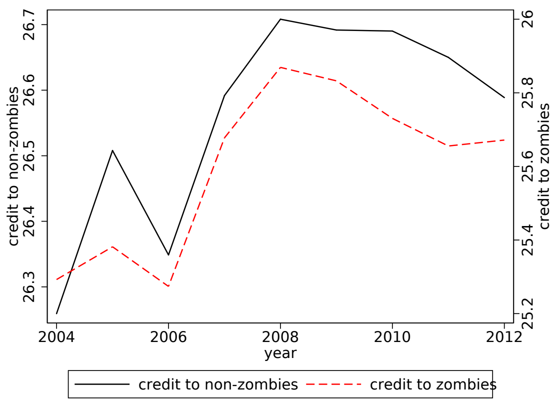
Figures and Tables

Figure 1: Credit Growth and GDP Growth in Italy



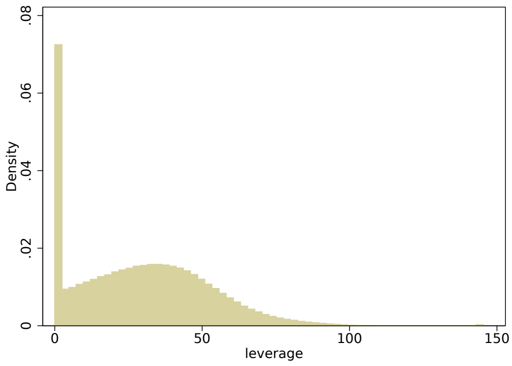
The figure shows the growth of credit by banks to non-financial firms and GDP growth in Italy between 2004 and 2014. Credit is from Supervisory reports, GDP growth is from National Statistics (ISTAT).

Figure 2: Credit to Zombie and to Non-Zombie Firms

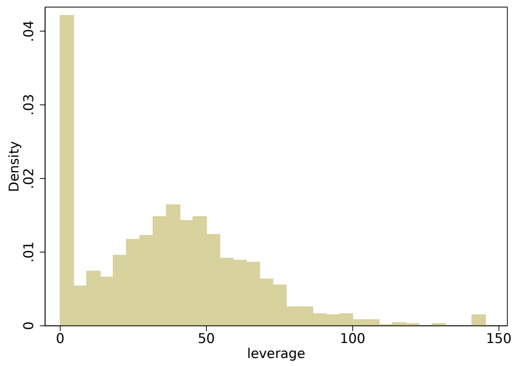


The figure shows log of granted credit to zombie and to non zombie firms used in our sample. Zombie firms are defined as those that in a given year has the 3 years moving average of ROA below PRIME, and leverage above the median leverage in year 2005 of firms that had the moving average of ROA below the prime rate in at least one year between 2004 and 2005 and that exited the market in 2006 or 2007 due to default or liquidation. The sample include non-financial firms borrowing from at least two Italian banks between 2004 and 2013. Data on credit are from the Credit Register. Data on firm characteristics are from the Firm register.

Figure 3: Leverage of Firms



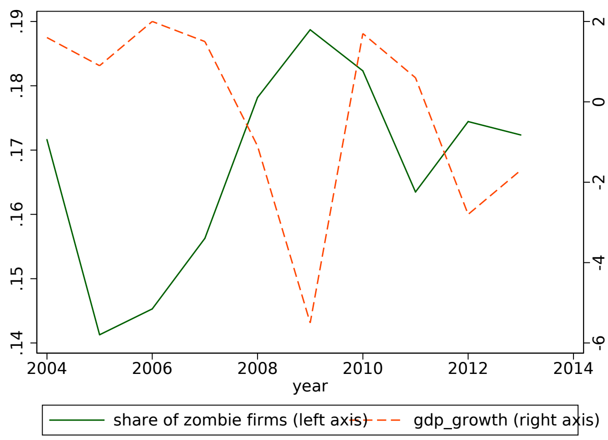
(a) Whole sample



(b) Firms Exiting and with Roa<Prime Rate

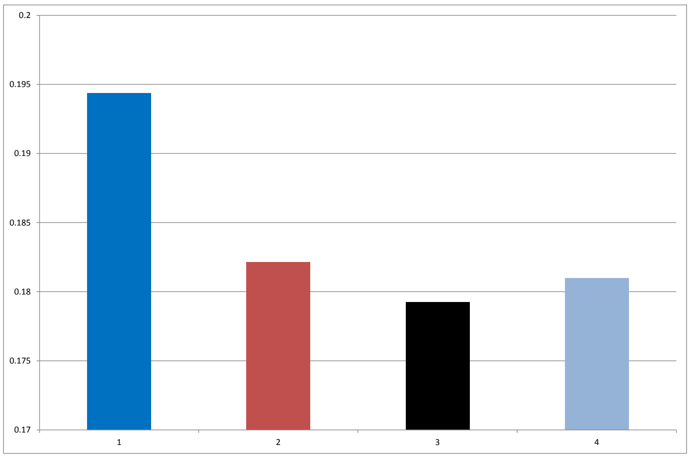
Panel a shows the distribution of leverage (the ratio of debt from banks and from other financiers, excluding trade debt and debt towards shareholders, to total assets) for the whole sample of firms included in the firm register. Panel b shows the distribution of leverage of firms with the moving average of ROA below the prime rate in at least one year between 2004 and 2005 and that exited the market in 2006 or 2007 due to default or liquidation. The threshold on leverage used to define zombie firms is the median of this distribution. Data are from the year 2005.

Figure 4: Share of zombie firms and GDP growth



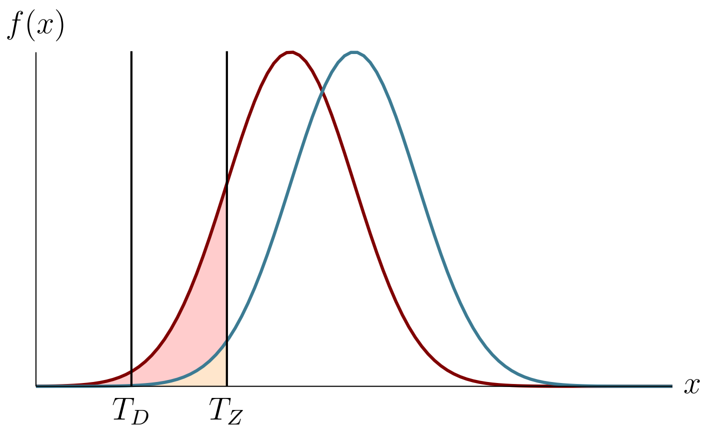
The figure plots the share of zombie firms (left scale) and GDP growth (right scale). Zombie firms are those with the 3 years moving average of ROA below PRIME, and leverage above 40% (see the main text and Figure 3). Data on firms are from the firm register (CERVED), GDP growth is from National Statistics (ISTAT).

Figure 5: Share of zombie firms by quartiles of bank capital



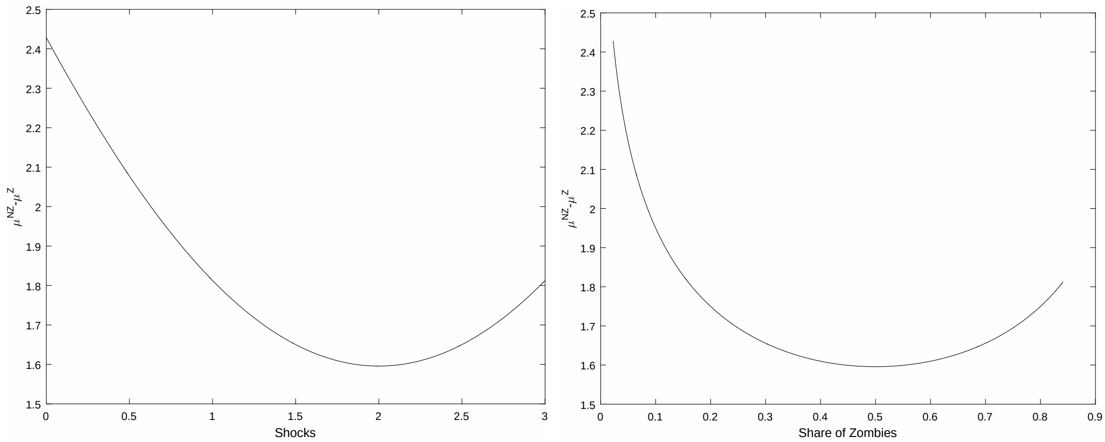
The figure shows the share of zombie firms by quartiles of bank capital. The share is computed using bank-firm relationships from the Italian Credit Register. Bank capital is the ration of regulatory capital to risk weighted assets. Data cover the period 2004-2013.

Figure 6: The effect of a common shock on zombies and non zombies



The figure plots two normal distributions with unit variance and mean $\mu_L = 4$ and $\mu_H = 5$, respectively. T_Z is the threshold to be classified zombie and T_D is the threshold for exit.

Figure 7: Difference in non zombies vs. zombies average performance



(a) Relative performance and aggregate shocks (b) Relative performance and share of zombies

The graphs report the difference in the conditional mean of zombies and non zombies, $\mu^{NZ} - \mu^{Z}$. In Panel a it is plotted against the aggregate shock $s = 0, 0.01..., 3$, which determines the leftward shift in the performance distribution, as illustrated in Figure 6. In Panel b it is plotted against the share of zombies implied by the leftward shift in the distribution shown in Panel a.

Table 1: Descriptive statistics of firms

	Mean	Median	25pct	75pct	S.D.	N
			Panel A: Pre-Crisis			
Non-Zombie Firms						
Leverage	24.01	23.22	4.57	37.37	19.79	337,940
ROA	7.01	6.52	3.18	10.72	8.20	337,940
EBITDA/Int Exp	6.14	2.85	1.41	6.57	10.58	333,389
Cash Hold / Assets	7.08	3.02	0.70	9.19	10.06	321,642
Liquidity / Assets	8.72	4.70	1.95	10.16	39.25	337,892
Assets (000 Euros)	9,936	2,509	1,198	5,900	95,220	33,7940
Zombie Firms						
Leverage	55.89	52.67	45.79	62.44	13.38	57,839
ROA	-0.21	1.78	-2.16	3.90	7.03	57,839
EBITDA/Int Exp	0.03	0.69	-0.78	0.15	3.26	57,666
Cash Hold / Assets	3.85	1.25	0.29	4.25	6.98	54,042
Liquidity / Assets	5.68	2.25	0.83	5.79	51.67	57,832
Assets (000 Euros)	16,408	4,300	1,777	11,023	174,572	57,839
			Panel B: Crisis			
Non-Zombie Firms						
Leverage	23.92	23.05	6.71	36.36	19.09	582,406
ROA	5.54	5.26	1.77	9.46	8.50	582,406
EBITDA/Int Exp	6.10	2.71	0.11	0.67	12.28	569,568
Cash Hold / Assets	6.96	2.71	0.62	8.85	10.27	551,970
Liquidity / Assets	13.18	6.07	2.33	14.14	62.10	582,265
Assets (000 Euros)	9,414	1,999	896	5,049	119,134	582,406
Zombie Firms						
Leverage	56.84	52.89	45.88	63.58	15.06	119,488
ROA	-1.34	1.09	-3.35	3.35	7.98	119,488
EBITDA/Int Exp	-0.45	0.48	-1.36	1.44	4.16	118,875
Cash Hold / Assets	3.18	0.94	0.23	3.30	6.15	109,909
Liquidity / Assets	9.11	3.20	1.05	8.62	65.19	119,463
Assets (000 Euros)	12,896	3,156	1,245	8,653	79,031	119,488

The table shows descriptive statistics of firms according to “Zombie” status, before the crisis (2004-2008 - Panel A) and after the crisis (2009-2012- Panel B). A zombie firm in a given year has the 3 years moving average of ROA below PRIME, and leverage above the median leverage in year 2005 of firms that exited the market in 2006 or 2007 due to default or liquidation. Data are from the Firm Register (Cerved) available at annual frequency from firms' balance sheets. Leverage is total financial debt over total assets; ROA is profits to assets ratio; Ebitdta/Int Exp is the ratio of Earnings before interest taxes depreciation and amortization to interest expenses; Cash Holdings to Assets is the ratio of cash and cash equivalents to total assets; Liquidity to Assets is the share of liquidity and short term assets to total assets.

Table 2: Descriptive Statistics of the variables used in the credit regressions

	Mean	Median	25pct	75pct	S.D.	N
	Panel A: Pre-crisis					
Dependent variables:						
Delta Log Credit	5.30	0.00	-7.09	12.93	51.43	1,368,513
D cut=1	8.00	0.00	0.00	0.00	0.27	1,750,220
D Bad Loans	0.89	0.00	0.00	0.00	9.40	1,400,662
D Non-Per	1.34	0.00	0.00	0.00	11.49	1,400,662
D Past Due	2.46	0.00	0.00	0.00	15.49	1,400,662
Firms regressors:						
Zombie 1	0.17	0.00	0.00	0.00	0.37	1,368,513
Zombie 2	0.10	0.00	0.00	0.00	0.29	1,346,260
PC ROA-leverage (PC 1)	-0.00	0.05	-0.56	0.55	0.83	1,368,513
PC EBITDA/Int.-leverage (PC 2)	0.09	0.26	-0.44	0.71	0.91	1,346,260
Banks regressors:						
LowCap	0.58	1.00	0.00	1.00	0.49	1,368,513
Capital Ratio	10.91	10.79	9.84	11.16	3.37	1,368,513
D Cap Ratio< 9	0.07	0.00	0.00	0.00	0.26	1,368,513
LowCap yby	0.43	0.00	0.00	1.00	0.49	1,368,513
Tier 1 Ratio	7.56	7.15	6.59	7.94	3.42	1,368,513
D Tier 1 Ratio< 5	0.01	0.00	0.00	0.00	0.11	1,368,513
Liquidity ratio	5.64	5.11	3.77	7.22	3.13	1,368,513
Interbank Ratio	11.91	11.55	7.89	14.49	7.37	1,368,513
ROA	0.74	0.66	0.52	0.93	0.72	1,368,513
Bank size	11.19	11.36	10.07	12.51	1.74	1,368,513
Bank-firm regressors:						
Share bank	26.24	20.73	10.77	37.21	19.79	1,368,513
Share credit line	23.31	11.76	4.35	29.26	28.65	1,368,513
	Panel B: Crisis					
Dependent variables:						
Delta Log Credit	-8.06	0.00	-15.77	0.00	50.13	2,287,690
D cut=1	10.36	0.00	0.00	0.00	30.48	2,668,861
D Bad loans	1.78	0.00	0.00	0.00	13.22	2,698,744
D Non-Per	3.72	0.00	0.00	0.00	18.93	2,698,744
D Past Due	2.14	0.00	0.00	0.00	14.48	2,698,744
Firm regressors:						
Zombie 1	0.19	0.00	0.00	0.00	0.39	2,287,690
Zombie 2	0.11	0.00	0.00	0.00	0.31	2,224,741
PC ROA-leverage (PC 1)	0.07	0.11	-0.47	0.60	0.84	2,287,690
PC EBITDA/Int.-leverage (PC 2)	0.09	0.28	-0.38	0.73	0.99	2,224,741

Table continues on the next page

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	Mean	Median	25pct	75pct	S.D.	N
Banks regressors:						
LowCap	0.46	0.00	0.00	1.00	0.50	2,287,690
Capital Ratio	11.32	11.09	10.16	12.09	2.36	2,287,690
D Cap Ratio< 9	0.04	0.00	0.00	0.00	0.20	2,287,690
LowCap yby	0.44	0.00	0.00	1.00	0.50	2,287,690
Tier 1 Ratio	8.09	7.78	7.15	8.70	2.51	2,287,690
D Tier 1 Ratio< 5	0.02	0.00	0.00	0.00	0.14	2,287,690
Liquidity ratio	7.14	6.66	4.20	10.15	4.56	2,287,690
Interbank Ratio	7.92	5.94	3.56	9.06	8.14	2,286,616
Bank ROA	0.03	0.22	0.07	0.44	0.66	2,286,616
Bank Size	11.58	11.80	10.40	13.30	1.82	2,287,690
Bank-firm regressors:						
Share Bank	29.39	23.94	12.28	42.35	21.45	2,287,690
Share credit line	24.16	11.11	3.50	30.71	30.50	2,287,690

The table shows descriptive statistics of the variables used in the regressions, relative to the estimating sample. The statistics are taken over the distribution of firm-bank-year observations. Data on credit and on bank-firm relationships are from the Italian Credit Register. Data on firm characteristics are from the Firm Register. Data on bank characteristics are from the Supervisory Reports. The sample period includes bank-firm relationships at the year frequency between 2004 and 2013. Delta log credit is the yearly difference in log credit granted; D cut= 1 is a dummy equal to one if a credit relationship is severed in the next year; D Bad Loans is a dummy equal to 1 if the bank classifies a loan as bad loan between year t and $t+1$; D Non-Per if a dummy equal to 1 if the bank classifies a loan as non performing between year t and $t+1$; D Past Due is a dummy equal to 1 if the bank classifies a loan as past due between year t and $t+1$; LowCap is a dummy equal to 1 if the capital ratio is below the median capital ratio in the sample; Capital Ratio is the ratio of regulatory capital to risk weighted assets; D Cap Ratio< 9 is a dummy equal to 1 if the capital ratio is below 9 (the regulatory threshold is 8); LowCap yby is a dummy equal to 1 if the capital ratio is below the median capital ratio computed year by year; Tier 1 ratio is the ratio of Tier 1 capital to risk weighted assets; D Tier 1 Ratio < 5 is a dummy equal to 1 if the Tier 1 Ratio is below 5 (the regulatory threshold is 4); D Tier 1 Ratio <Median is a dummy equal to 1 if the Tier 1 Ratio is below the median Tier 1 ratio in the sample; Liquidity ratio is the ratio of cash plus government securities to total assets; Interbank ratio is the ratio of interbank deposits to total assets; ROA is the ratio of bank profit to total assets; Bank size is the log of total assets; Zombie 1 is a dummy equal to 1 if the firm's ROA (2 years moving average) is below the prime rate (2 years moving average) and the firm's leverage is above the median leverage, as of the end of 2005, computed on the sample of firms that had ROA below prime rate in at least 1 year between 2004 and 2005 and which exited in 2006 or 2007. Zombie 2 is a dummy equal to 1 if the firm EBITDA to interest expenses ratio (2 years moving average) is below 1 and the firm's leverage is above the median leverage, as of the end of 2005, computed on the sample of firms that the ebit to interest expenses ratio below 1 in at least 1 year between 2004 and 2005 and which exited in 2006 or 2007; PC ROA-leverage (PC 1) is the principal components of the moving average of ROA and leverage, PC EBITDA/Int-Leverage is the principal component of the moving average of the EBITDA to interest expenses ratio and leverage. Share bank is the share of total credit to the firm by the bank; Share credit line is the share of overdraft loans out of total loans within the bank-firm relationship.

Table 3: Growth of credit, baseline regressions

	(1)	(2)	(3)	(4)	(5)	(6)
LowCap*Z*crisis	1.906**	1.745**	1.957***	2.042***	1.982***	1.893***
	(0.790)	(0.703)	(0.694)	(0.704)	(0.680)	(0.671)
LowCap*Z	-1.150	-0.845	-0.857	-0.993*	-0.864	-0.830*
	(0.745)	(0.614)	(0.593)	(0.581)	(0.580)	(0.492)
LowCap*crisis	2.156	2.790	2.658	2.281	0.514	
	(1.911)	(1.715)	(2.007)	(1.672)	(1.866)	
LowCap	-1.766	-2.189	-2.300	-1.597	-0.817	
	(1.790)	(1.598)	(1.664)	(1.606)	(1.960)	
Z*crisis	-4.578***					
	(0.637)					
Z	-3.088***					
	(0.468)					
Share bank			-0.276***	-0.290***	-0.303***	-0.297***
			(0.015)	(0.016)	(0.014)	(0.013)
Share credit line			0.143***	0.141***	0.125***	0.129***
			(0.009)	(0.009)	(0.008)	(0.008)
Liquidity ratio				0.209***	0.190**	
				(0.063)	(0.086)	
Interbank ratio				-0.112**	0.115**	
				(0.051)	(0.056)	
ROA				1.297**	0.386	
				(0.518)	(0.447)	
Bank size				1.097***	-3.849**	
				(0.098)	(1.813)	
Firm FE	Y	N	N	N	N	N
Time FE	Y	N	N	N	N	N
Firm*year FE	N	Y	Y	Y	Y	Y
Bank FE	N	N	N	N	Y	N
Bank*year FE	Y	N	N	N	N	Y
Observations	3,656,203	3,656,203	3,656,203	3,654,795	3,654,794	3,656,184
R-squared	0.112	0.358	0.377	0.379	0.382	0.390

The table shows regressions of the change in the log of credit granted (credit commitments) on the dummy for "zombie" firms (Z), the dummy for banks with capital ratio below the median (LowCap) and the dummy for the crisis period (crisis), and their interactions. The change in the log of credit granted is computed as the difference between total credit granted to the firm by the bank in period t and period $t+1$. Firm and bank level controls are measured as of year t. The dummy for a zombie firm equals one if both a) the firm's ROA (2 years moving average) is below the prime rate (2 years moving average); and b) the firm's leverage is above the median leverage, as of the end of 2005, computed on the sample of firms that had ROA below the prime rate in at least 1 year between 2004 and 2005 and which exited in 2006 or 2007. The capital ratio is the ratio of bank regulatory capital and risk weighted assets. The dummy crisis equals 1 if the period t is year 2008 or later. Liquidity ratio is the ratio of cash and government bonds to total assets; Interbank ratio is the ratio of interbank deposits and repos with banks (excluding those with central banks) and total assets; ROA is the ratio of profits to total assets. Bank size is the log of total assets. The sample includes years between 2004 and 2012 (the change in log credit in the last year is computed between 2012 and 2013). Standard errors double clustered at the bank and firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Growth of credit, Robustness to the definition of zombie firm

	(1)	(2)	(3)	(4)	(5)	(6)
	Definition of zombie firm					
	Zombie 2		PC 1		PC 2	
LowCap*Z*crisis	1.746***	1.855***	1.437***	1.527***	1.567***	1.648***
	(0.564)	(0.601)	(0.394)	(0.413)	(0.387)	(0.412)
LowCap*Z	-0.112	-0.239*	-0.574*	-0.652***	-0.741**	-0.819***
	(0.348)	(0.127)	(0.330)	(0.106)	(0.325)	(0.068)
LowCap*crisis	0.690		0.787		0.669	
	(1.953)		(1.936)		(1.919)	
LowCap	-0.965		-0.947		-0.871	
	(2.044)		(2.031)		(2.019)	
Share bank	-0.305***	-0.298***	-0.303***	-0.297***	-0.305***	-0.298***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)
Share credit line	0.125***	0.129***	0.125***	0.129***	0.125***	0.129***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Liquidity ratio	0.191**		0.190**		0.190**	
	(0.087)		(0.086)		(0.087)	
Interbank ratio	0.116**		0.115**		0.116**	
	(0.057)		(0.056)		(0.057)	
ROA	0.381		0.385		0.380	
	(0.449)		(0.448)		(0.450)	
Bank size	-3.829**		-3.847**		-3.826**	
	(1.831)		(1.812)		(1.835)	
Bank FE	Y	N	Y	N	Y	N
Bank-year FE	N	Y	N	Y	N	Y
Observations	3,569,638	3,570,983	3,654,794	3,656,184	3,569,638	3,570,983
R-squared	0.379	0.388	0.382	0.390	0.3780	0.388

The table replicates the regressions in columns (5) (with firm*year and bank fixed effects) and (6) (with firm-year and bank-year fixed effects) of Table 3 using alternative definitions of "zombie" firms. In columns (1) and (2) the dummy for a zombie firm (Zombie 2) equals one if both a) the firm EBITDA to interest coverage ratio (2 years moving average) is below 1; and b) the firm's leverage is above the median leverage, as of the end of 2005, computed on the sample of firms with EBITDA to interest coverage ratio below 1 in at least 1 year between 2004 and 2005 and which exited in 2006 or 2007; in columns (3) and (4) the continuous indicator for zombie firms (PC 1) is the principal component of the moving average of ROA and leverage, in columns (5) and (6) (PC 2) is the principal component of the moving average of the EBITDA to interest coverage ratio and leverage. See the note to Table 3 for the definition of the other variables. Standard errors double clustered at the bank and firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Growth of credit, Robustness on the definition of banks strength

	(1) Capratio<median yby	(2) Capratio<9	(3) Capratio	(4) T1 Ratio<5	(5) T1 Ratio
BankCap*Zombie*Crisis	1.190*	2.452***	-0.398**	3.366***	-0.098
	(0.630)	(0.807)	(0.167)	(0.827)	(0.117)
BankCap	2.187*	0.691	-0.440	-8.326***	-0.464
	(1.319)	(1.345)	(0.494)	(2.791)	(0.505)
BankCap*Zombie	0.252	0.160	0.123	-0.877	0.100
	(0.557)	(0.629)	(0.138)	(0.822)	(0.114)
BankCap*Crisis	-3.387***	-1.368	0.796**	5.835***	0.764***
	(1.090)	(1.257)	(0.382)	(2.164)	(0.247)
Share bank	-0.304***	-0.303***	-0.303***	-0.303***	-0.303***
	(0.014)	(0.014)	(0.015)	(0.014)	(0.015)
Share credit lines	0.125***	0.125***	0.125***	0.126***	0.125***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Liquidity ratio	0.232**	0.203**	0.208**	0.202**	0.210**
	(0.095)	(0.089)	(0.090)	(0.088)	(0.085)
Interbank funding	0.143**	0.121*	0.127*	0.127**	0.115*
	(0.064)	(0.063)	(0.065)	(0.063)	(0.067)
ROA	0.455	0.383	0.366	0.466	0.335
	(0.431)	(0.465)	(0.432)	(0.421)	(0.436)
Bank size	-3.564**	-3.947**	-3.910**	-4.268**	-3.657**
	(1.735)	(1.753)	(1.755)	(1.934)	(1.729)
Observations	3654794	3654794	3654794	3654794	3654794
R-squared	0.382	0.382	0.382	0.382	0.382

The table replicates the regression in column (5) (with firm*year and bank fixed effects) of Table 3 using alternative definitions of ‘banks strength. In column (1) the indicator of banks strength is a dummy equal to one if the capital ratio in a year is below the median capital ratio in that year; in column (2) is a dummy equal to one if the capital ratio is below 9 (the minimum regulatory threshold is 8%); in column (3) is the continuous capital ratio; in column (4) is a dummy if the Tier 1 capital ratio is below 5% (the minimum regulatory threshold is 4%); in column (5) is the continuous Tier 1 capital ratio indicator (the ratio between Tier 1 capital and risk-weighted assets). The sample includes years between 2004 and 2012 (the change in log credit in the last year is computed between 2012 and 2013). Standard errors double clustered at the bank and firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Extensive Margin

	(1)	(1)	(3)	(4)	(5)
LowCap*Z*crisis	-0.831**	-0.661*	-0.703*	-0.726*	-0.760*
	(0.414)	(0.390)	(0.401)	(0.393)	(0.391)
LowCap*Z	-0.073	-0.134	-0.076	-0.107	-0.094
	(0.169)	(0.175)	(0.177)	(0.163)	(0.163)
LowCap*Crisis	-1.041**	-1.056***	-1.351***	-1.213***	
	(0.428)	(0.371)	(0.385)	(0.315)	
LowCap	0.611*	0.713**	0.475	1.051***	
	(0.319)	(0.302)	(0.329)	(0.289)	
Share bank		-0.230***	-0.222***	-0.212***	-0.211***
		(0.011)	(0.010)	(0.008)	(0.008)
Share credit line		-0.055***	-0.051***	-0.040***	-0.037***
		(0.006)	(0.005)	(0.003)	(0.003)
Liquidity ratio			-0.046	-0.088***	
			(0.049)	(0.025)	
Interbank ratio			0.143***	0.062*	
			(0.038)	(0.035)	
ROA			-0.659	-0.658***	
			(0.418)	(0.226)	
Bank size			-0.452***	0.473***	
			(0.102)	(0.123)	
Bank FE	N	N	N	Y	N
Bank*year FE	N	N	N	N	Y
Observations	4,331,355	4,331,355	4,329,493	4,329,493	4,331,341
R-squared	0.465	0.481	0.483	0.492	0.495

The table shows OLS regressions of a dummy equal to 100 if a firm has credit from a bank in period t and has no credit from the same bank in period t+1 (i.e. the credit relationship has been severed) on the dummy for "zombie" firms (Z), the dummy for banks with capital ratio below the median (LowCap) and the dummy for the crisis period (crisis), and their interactions. The regressors are defined in the note to table 3. All regressions include firm*year fixed effects. The sample includes yearly data between 2004 and 2012 (the change in log credit in the last year is computed between 2012 and 2013). Standard errors double clustered at the bank and firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Banks' decision to classify a loan as non-performing

	(1) Bad Loan	(2) Sub-Standard	(3) Past due
LowCap*Z*crisis	-0.538**	-0.597***	0.535***
	(0.255)	(0.171)	(0.188)
LowCap*Z	-0.009	0.201**	-0.140
	(0.056)	(0.081)	(0.111)
LowCap*Crisis	0.139**	-0.218**	-0.085
	(0.067)	(0.108)	(0.151)
LowCap	-0.076	0.031	0.116
	(0.048)	(0.067)	(0.194)
Share bank	-0.003***	0.005***	0.028***
	(0.000)	(0.002)	(0.004)
Share credit line	-0.000	0.006***	-0.004***
	(0.001)	(0.002)	(0.001)
Liquidity ratio	-0.001	-0.051***	-0.023
	(0.011)	(0.018)	(0.020)
Interbank funding	0.005	-0.021**	0.028**
	(0.004)	(0.010)	(0.012)
Roa	-0.018	0.025	0.183***
	(0.069)	(0.100)	(0.060)
Bank size	-0.143	-0.400*	0.632**
	(0.129)	(0.221)	(0.276)
Observations	4,099,406	4,099,406	4,099,406
R-squared	0.747	0.561	0.374

The table shows regressions of a dummy equal to 100 if the bank classifies the loan as non-performing on the dummy for "zombie" firms (Z), the dummy for banks with capital ratio below the median (LowCap) and the dummy for the crisis period (crisis), and their interactions. The dummy Bad Loan, column (1), equals 100 if the bank classifies the loan as a bad loan, and zero otherwise, between year t and year t+1; the dummy Non-Per, column (2), equals 100 if the bank classifies the loan as non-performing and zero otherwise, between year t and year t+1; the dummy Past-Due, column (3), equals 100 if the bank classifies the loan as past-due and zero otherwise, between year t and year $t+1$. All regressions include firm*year fixed effects and bank fixed effects (the same specification as in column (5) of Table 3), the share of total credit to the firm grant by the bank and the share of credit line out of total credit to the firm by the bank. Bank level controls are defined in the notes to table 3. The sample includes yearly data between 2004 and 2012 (for the classification of loans as bad, non performing, past-due, we consider data from 2005 to 2013). Standard errors double clustered at the bank and firm level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Summary Statistics for the Effects of Zombie Lending

	Mean	Median	25pct	75pct	S.D.	N
	Panel A: Firm level variables					
Non-zombie Firms						
Δ labor	0.002	0.012	-0.097	0.115	0.274	850,486
Δ capital	-0.016	-0.058	-0.206	0.079	0.390	805,291
Δ sales	-0.039	-0.023	-0.164	0.102	0.270	850,766
Failure	0.026	0	0	0	0.158	950,679
Zombie Firms						
Δ labor	-0.045	-0.020	-0.155	0.087	0.290	116,482
Δ capital	-0.022	-0.048	-0.148	0.036	0.339	111,268
Δ sales	-0.086	-0.058	-0.230	0.080	0.301	114,989
Failure	0.077	0	0	0	0.266	199,982
	Panel B: Sector-province year variables					
Capital ratio below median ($\overline{\text{LowCap}}$)	0.453	0.427	0.261	0.643	0.254	11,008
Share of zombies (ShZ)	0.209	0.191	0.107	0.277	0.159	11,008
Standard Deviation of TFP	0.596	0.563	0.484	0.656	0.203	10,900
TFP growth	-0.020	-0.017	-0.084	0.046	0.177	10,972

The table shows descriptive statistics of the variables used in regressions of the effects of zombie lending. Panel A reports growth rate of the wage bill, the capital stock, sales and TFP, all at constant prices, and a dummy equal to 1 if a firm fails. Panel B report indicators at the province-sector-year levels. Share of credit to zombie Firms is the share of credit that is granted to zombies in a given province-sector-year; CR below median is the share of credit extended by banks with a capital ratio below the median value of the banks' capital ratio; Share of zombies is the share of firms classified as zombies according to our preferred definition; Standard deviation of TFP and TFP growth are again computed at the province-sector-year level. Variables refer to the years 2008-2013.

Table 9: Firms growth and zombie lending

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ΔLabour				ΔCapital		ΔSales	
ShZ	-0.042**							
	(0.018)							
ShZ*(1-Z)	-0.067***	-0.058***						
	(0.013)	(0.013)						
$\overline{\text{LowCap}}$			0.027***		0.011		0.026***	
			(0.007)		(0.007)		(0.010)	
$\overline{\text{LowCap}}$*(1-Z)			-0.028***	-0.028***	-0.007	-0.001	-0.013**	-0.016***
			(0.004)	(0.004)	(0.006)	(0.006)	(0.005)	(0.005)
Z	-0.062***	-0.060***	-0.060***	-0.060***	-0.015***	-0.012***	-0.053***	-0.055***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
$\beta_1 + \beta_2$	-0.109		-0.001		0.004		0.013	
Test $\beta_1 + \beta_2 = 0$ (p-val)	0.000		0.878		0.4154		0.162	
Province-Sector FE	YES	NO	YES	NO	YES	NO	YES	NO
Year FE	YES	NO	YES	NO	YES	NO	YES	NO
Prov-sect-year FE	NO	YES	NO	YES	NO	YES	NO	YES
Observations	966,968	966,968	966,968	966,968	916,559	916,559	965,755	965,755
R-squared	0.036	0.058	0.036	0.058	0.019	0.029	0.083	0.122

The table shows regressions of different measures of firm growth on the share of zombies (columns 1-2) and banks' capital ratio (columns 3-8). Specifically, ShZ is the share of firms that are classified as zombies in a sector-province-year; $\overline{\text{LowCap}}$ is the average at the province-sector-year of a dummy equal to one for banks with a capital ratio below the median capital ratio. The average is computed using the share of credit in the province-sector-year as weights. The dependent variable is the delta log of the wage bill in column 1-4, of the book value of the capital stock in columns 5-6, of sales in columns 7-8. Odd columns include province-sector and year fixed effects, while even columns include province-sector-year fixed effects. $\beta_1 + \beta_2$ is the sum of the coefficients in the first two rows in the column. The sample includes yearly data form 2008 to 2013. Standard errors clustered at the province-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Firm failure and banks capital ratio

	(1)	(2)	(3)
	Linear probability		Probit
$\overline{\text{LowCap}}$	-0.877***		-0.620***
	(0.376)		(0.233)
$\overline{\text{LowCap}}$*(1-Z)	1.682***	1.732***	1.413***
	(0.374)	(0.383)	(0.210)
Z	6.079***	6.010***	4.686***
	(0.256)	(0.260)	(0.131)
$\gamma_1 + \gamma_2 = 0$	0.805***		0.792***
Test $\gamma_1 + \gamma_2 = 0$ (p-val)	0.000		0.000
Province-sector FE	Y	N	Y
Year FE	Y	N	Y
Prov-sect-year FE FE	N	Y	N
Obs	1,150,661	1,150,661	1,150,661
R-squared	0.016	0.020	0.038

The table shows regressions of a dummy equal to 100 for firms that go bankrupt on banks' capital ratio, so that all coefficients can be red as percentages. $\overline{\text{LowCap}}$ is the average at the province-sector-year of a dummy equal to one for banks with a capital ratio below the median capital ratio. The average is computed using the share of credit in the province-sector-year as weights. Z is a dummy for zombie firms. Odd columns include province-sector and year fixed effects, while even columns include province-sector-year fixed effects. The first two columns are OLS estimates, while column (3) is a probit estimate, with marginal effects reported. $\gamma_1 + \gamma_2$ is the sum of the coefficients in the first two rows in the column. The sample includes yearly data form 2008 to 2011. Standard errors clustered at the province-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: TFP dispersion and credit to zombies

	(1)	(2)	(3)	(4)	(5)	(6)
ShZ	0.040**	0.082***			-0.038	0.013
	(0.018)	(0.014)			(0.025)	(0.022)
$\overline{\text{LowCap}}$			-0.001	-0.001	-0.038***	-0.030***
			(0.008)	(0.006)	(0.010)	(0.008)
$\overline{\text{LowCap}}$ *ShZ					0.158***	0.141***
					(0.039)	(0.030)
Tfp growth	-0.055***	-0.075***	-0.054***	-0.076***	-0.054***	-0.073***
	(0.013)	(0.008)	(0.013)	(0.008)	(0.013)	(0.008)
Observations	9,194	10,886	9,194	10,886	9,194	10,886
R-squared	0.825	0.872	0.824	0.871	0.826	0.872

The table shows regressions of the standard deviation of TFP at the province-sector-year level on the share of zombies and banks' capital ratio. Specifically, ShZ is the share of firms that are classified as zombies in the province-sector-year and $\overline{\text{LowCap}}$ is the average at the province-sector-year of a dummy equal to one for banks with a capital ratio below the median capital ratio. The average is computed using the share of credit in the province-sector-year as weights. Tfp growth is Delta log of the average TFP at the province-sector level. Columns 1, 3 and 5 exclude province-sector-years with less than 10 firms. Columns 2, 4 and 6 include all province-sector-years but weight them according to the number of firms. All regressions include year and province-sector fixed effects. The sample includes yearly data form 2008 to 2013. Standard errors clustered at the province-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A Appendix

Consider the effect of a shift to the left in the distribution $F(X)$ depicted in Figure 6. We want to know how this shift affects the difference between conditional means, $\mu^{NZ} - \mu^{Z}$, where:

$$\begin{aligned} \mu^{NZ} &= \frac{1}{1 - F(T_z)} \int_{T_z}^{\infty} x dF(x) \\ \mu^{Z} &= \frac{1}{F(T_z)} \int_{-\infty}^{T_z} x dF(x) \end{aligned} \tag{11}$$

Note that this question is equivalent to asking how $\mu^{NZ} - \mu^{Z}$ is affected by a change in the threshold T_z. By (11) we have:

$$\begin{aligned} \frac{\partial \mu^{NZ}}{\partial T_z} &= \frac{f(T_z)}{1 - F(T_z)} (\mu^{NZ} - T_z) \\ \frac{\partial \mu^{Z}}{\partial T_z} &= \frac{f(T_z)}{F(T_z)} (T_z - \mu^{Z}) \end{aligned}$$

so that

$$\text{Sign } \frac{\partial(\mu^{NZ} - \mu^{Z})}{\partial T_z} = \text{Sign } \left\{ F(T_z)\mu^{NZ} + [1 - F(T_z)]\mu^{Z} - T_z \right\} \tag{12}$$

Let $\mu = F(T_z)\mu^{Z} + [1 - F(T_z)]\mu^{NZ}$ denote the unconditional mean of x. Equation (12) can then be rewritten as:

$$\text{Sign } \frac{\partial(\mu^{NZ} - \mu^{Z})}{\partial T_z} = \text{Sign } \left\{ (\mu^{NZ} - \mu) - (T_z - \mu^{Z}) \right\}$$

It is easy to verify that for a uniform distribution this implies $\frac{\partial(\mu^{NZ} - \mu^{Z})}{\partial T_z} = 0$. More generally, a necessary and sufficient condition for $\frac{\partial(\mu^{NZ} - \mu^{Z})}{\partial T_z} < 0$ is that

$$(\mu^{NZ} - \mu) < (T_z - \mu^{Z}) \tag{13}$$

B Appendix tables: using the 2004-2007 credit shares to compute the average capital ratio

In this appendix we re-run the regressions of Tables 9, 10 and 11 using $\widehat{\text{LowCap}}$ as defined in equation 4 as measure of banks weakness.

Table A9: Firms growth and zombie lending with the alternative definition of banks' capital ratio

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔLabour		ΔCapital		ΔSales	
$\widehat{\text{LowCap}}$	0.026***		0.018**		0.018*	
	(0.007)		(0.008)		(0.010)	
$\widehat{\text{LowCap}}$*(1-Z)	-0.028***	-0.030***	-0.010	-0.003	-0.009	-0.015***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)	(0.005)
Z	-0.060***	-0.060***	-0.016***	-0.013***	-0.051***	-0.053***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
$\beta_1 + \beta_2$	-0.002		0.008		0.009	
Test $\beta_1 + \beta_2 = 0$ (p-val)	0.753		0.191		0.338	
Province-Sector FE	YES	NO	YES	NO	YES	NO
Year FE	YES	NO	YES	NO	YES	NO
Prov-sect-year FE	NO	YES	NO	YES	NO	YES
Observations	966,975	966,680	916,555	916,283	965,764	965,465
R-squared	0.036	0.058	0.019	0.029	0.083	0.122

The table shows regressions of different measures of firm growth on banks' capital ratio, $\widehat{\text{LowCap}}$, computed as the average at the province-sector-year of a dummy equal to one for banks with a capital ratio below the median capital ratio. The average is computed using the share of credit in the province-sector for the period 2004-2007 as weights. The dependent variable is the delta log of the wage bill in column 1-2, of the book value of the capital stock in columns 3-4, of sales in columns 5-6. Odd columns include province-sector and year fixed effects, while even columns include province-sector-year fixed effects. $\beta_1 + \beta_2$ is the sum of the coefficients in the first two rows in the column. The sample includes yearly data form 2008 to 2013. Standard errors clustered at the province-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Firm failure and banks alternative definition of capital ratio

	(1)	(2)	(3)
	Linear probability		Probit
$\widehat{\text{LowCap}}$	-1.333***		-0.687***
	(0.400)		(0.244)
$\widehat{\text{LowCap}}$*(1-Z)	1.936***	1.980***	1.320***
	(0.384)	(0.392)	(0.213)
Z	6.121***	6.138***	4.571***
	(0.250)	(0.254)	(0.128)
$\gamma_1 + \gamma_2 = 0$	0.603***		0.633***
Test $\gamma_1 + \gamma_2 = 0$ (p-val)	0.0036		0.0020
Province-sector FE	Y	N	Y
Year FE	Y	N	Y
Prov-sect-year FE FE	N	Y	N
Observations	1,150,681	1,150,623	1,150,684
R-squared	0.016	0.020	0.038

The table shows regressions of a dummy equal to 100 for firms that go bankrupt on banks' capital ratio, so that all coefficients can be red as percentages. $\widehat{\text{LowCap}}$is the average at the province-sector-year of a dummy equal to one for banks with a capital ratio below the median capital ratio. The average is computed using the share of credit in the province-sector for the period 2004-2007 as weights. Z is a dummy for zombie firms. Odd columns include province-sector and year fixed effects, while even columns include province-sector-year fixed effects. The first two columns are OLS estimates, while column (3) is a probit estimate, with marginal effects reported. $\gamma_1 + \gamma_2$ is the sum of the coefficients in the first two rows in the column. The sample includes yearly data form 2008 to 2011. Standard errors clustered at the province-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: TFP dispersion and credit to zombies

	(1)	(2)	(3)	(4)	(5)	(6)
ShZ	0.040**	0.082***			-0.046*	0.011
	(0.018)	(0.014)			(0.027)	(0.023)
$\widehat{\text{LowCap}}$			-0.003	0.001	-0.043***	-0.030***
			(0.008)	(0.005)	(0.011)	(0.009)
$\widehat{\text{LowCap}}$ *ShZ					0.184***	0.154***
					(0.046)	(0.034)
TFP Growth	-0.055***	-0.075***	-0.054***	-0.076***	-0.053***	-0.073***
	(0.013)	(0.008)	(0.013)	(0.008)	(0.013)	(0.008)
Observations	9,194	10,886	9,191	10,870	9,191	10,870
R-squared	0.825	0.872	0.824	0.871	0.826	0.872

The table shows regressions of the standard deviation of TFP at the province-sector-year level on the share of zombies and banks' capital ratio. Specifically, ShZ is the share of firms that are classified as zombies in the province-sector-year and $\widehat{\text{LowCap}}$is the average at the province-sector-year of a dummy equal to one for banks with a capital ratio below the median capital ratio. The average is computed using the share of credit in the province-sector for the period 2004-2007 as weights. Tfp growth is Delta log of the average TFP at the province-sector level. Columns 1, 3 and 5 exclude province-sector-years with less than 10 firms. Columns 2, 4 and 6 include all province-sector-years but weight them according to the number of firms. All regressions include year and province-sector fixed effects. The sample includes yearly data form 2008 to 2013. Standard errors clustered at the province-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.