Bank Specialization and Zombie Lending *

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Abstract

We study whether banks internalize congestion externalities when lending to zombie firms. We conjecture that banks should be better informed about the presence of zombie borrowers and the congestion externalities they exert on healthy borrowers in industries where they are specialized. We show that credit supply to zombie firms relates negatively to banks' industry specialization. This relation is stronger when congestion externalities are likely to have stronger adverse effects; namely, when zombie firms take a higher fraction of resources in the industry or when the industry is expected to grow faster. Additionally, this relation is weaker in industries with higher asset specificity, as zombie firms' default (and potential asset fire sales) could reduce healthy borrowers' collateral.

Keywords: Credit misallocation, Zombie lending, Bank specialization, Soft industry information
JEL classification: G21, G3, L2

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1. Introduction

Zombie firms are poorly performing firms that are unable to service their debt from operating cash flows over a prolonged period of time, but survive thanks to lax credit supply by lenders. Such zombie lending is known to have contributed to the "lost decade" of Japan's economy (Caballero et al., 2008) and can thus have a large economic impact. Banerjee and Hofmann (2020) show that zombie firms have become much more prevalent over the last decades in many European countries. This emergence of zombie firms has been put forward as an explanation for Europe's low productivity (McGowan et al., 2018; Gouveia and Osterhold, 2018), low innovation and patenting activity (Schmidt et al., 2020), and lack of inflation during the recovery from the financial and sovereign debt crisis (Acharya et al., 2020).

The literature has mainly proposed strategic motivations for zombie lending rooted in either (i) avoiding bank capital shortfalls (Blattner et al., 2022, e.g.), (ii) gambling for resurrection (Bruche and Llobet, 2014, e.g.), or (iii) taking advantage of asymmetric information to offload bad borrowers to market-based lenders (Hu and Varas, 2021). The literature on zombie lending mitigation has so far only documented on-site inspections of bank regulators (Bonfim et al., 2022; Passalacqua et al., 2020). In this paper, we look into a novel, information-based mechanism that might induce banks to *reduce* credit supply to zombie firms, namely bank specialization.

The mechanism has two ingredients. First, zombie firms can create negative congestion externalities on healthy borrowers. Such externalities arise when zombie firms are not forced to downsize, therefore take too much market share in the input and output market (Caballero et al., 2008), and hence put pressure on healthy borrowers by keeping wages high and mark-ups low (Acharya et al., 2020). If so, keeping zombie firms alive will deteriorate the bank's lending portfolio, not only directly through zombie lending, but also indirectly because the performance of the bank's healthy borrowers will deteriorate if they have to compete with zombie firms. Second, to understand whether congestion externalities are likely to occur or not, banks need to have industry-specific knowledge. This type of knowledge cannot be inferred through firm-specific hard or soft information, but can be learned through having many interactions with borrowers from the same industry, i.e. through specializing (Berger et al., 2017; De Jonghe et al., 2020). Banks thus have an incentive to internalize congestion externalities created by zombie firms, but are only likely to do so if they are informed about the presence of zombie firms and especially their impact on healthy borrowers.

To investigate this mechanism, we use a unique dataset that combines three data sources of the National Bank of Belgium (Belgium's Central Bank). We draw firm-bank level credit information for the universe of banks and firms in Belgium from the Corporate Credit Register, and augment this data with firms' and banks' balance sheets and income statements. As banks are most informed about industries where they grant most loans, banks' industry specialization is often proxied by an industry's share in the bank's lending portfolio (De Jonghe et al., 2020; Blickle et al., 2021). The richness of the data enables us to use a comprehensive set of fixed effects. Building on Khwaja and Mian (2008), we disentangle credit demand from credit supply using firm×year fixed effects. Thus, in all our specifications, our identification is based on comparing how multiple banks with different levels of industry specialization adjust their credit supply to the *same* firm/zombie. Our final dataset runs from 2004 to 2018, and covers 614,320 firm-bank-year observations for 54 banks and more than 50,000 firms.

Our results at the extensive margin show that, holding credit demand constant, zombie firms are less likely to receive a new loan from a bank that is specialized in lending to the zombie's industry than from a bank that is not specialized. Results at the intensive margin confirm this. For a given level of demand, a zombie firm sees its credit supply significantly more reduced from the bank that is relatively more specialized in lending to the zombie's industry. Our specifications also include bank×year fixed effects to absorb bank-time specific shocks as well as time-invariant bank characteristics. Our results can thus also be interpreted as follows: banks reduce their credit supply significantly more to zombie firms in industries in which they are specialized than to zombie firms in industries in which they are not specialized. Both interpretations, however, are in line with the idea that banks are more aware and concerned about congestion externalities of zombie lending in industries where they are specialized.

A possible concern is to what extent the information captured in industry specialization is really distinct from borrower-specific hard or soft information. To look at this, we augment our baseline model with bank-firm relationship characteristics (e.g., relationship length, bank's share in firm's borrowing) and their interaction with firms' zombie status, as well as with interactions between banks' industry specialization and firms' financial characteristics (e.g., profitability, leverage). These controls have little to no impact on the baseline results, confirming that our results are not driven by specific firm-related information as opposed to wider industry-specific knowledge.

Another possible concern is that specialization may be capturing a bank's industry market share. If so, it could be that a bank's power to avoid cascade effects and industry-wide distress is driving the mechanism (as in Giannetti and Saidi (2019)). However, this is not the case. First, the correlation between banks' industry specialization and industry market share is weak (-0.08 at the NACE 2-digit sector level).[1] Second, we add banks' industry market share and its interaction with firms' zombie status to our baseline model to further look into this. We find that high-market-share banks are more likely to internalize zombie congestion externalities. However, and more importantly, our baseline results on industry specialization and zombie lending remain entirely unaffected. This confirms that bank industry specialization is about gaining industry-specific knowledge and this information mechanism is orthogonal to the one by Giannetti and Saidi (2019).

Next, we shed further light on the extent to which this specialization mechanism informs banks about the negative (and positive) externalities of lending to zombie firms. Healthy borrowers compete with zombie firms for resources and market share. This competition is likely only distorted if zombie firms make up a significant fraction of the industry, and hence only leads to congestion externalities in those cases. We show that the effect of bank specialization on zombie lending is significantly stronger in industries where the share of labor employed at zombie firms is higher.[2] Furthermore, congestion externalities are likely to be more costly for healthy borrowers in fast-growing industries. We show that the negative relation between banks' industry specialization and zombie lending is significantly stronger in industries that are expected to exhibit higher sales growth. In contrast, in some industries zombie firms' default and asset fire sales pose contagion risk for the collateral value of healthy borrowers' assets. We show that the effect of bank specialization on zombie lending is less pronounced in industries with higher asset specificity, as these assets are less redeployable outside the industry and therefore have lower liquidation and collateral values (Giannetti and Saidi, 2019; Almeida et al., 2011; Acharya et al., 2007).

In addition, to identify zombie firms using firms' financial statements, our paper proposes some important modifications to the widely-used OECD definition. The OECD measure (McGowan et al., 2018) defines zombie firms as mature firms whose EBIT-to-interest expense ratio is below one for three consecutive years. Our first modification is to start from firms' recurring cash flows rather than from firms' EBIT. This implies

[1]This is not specific to our data. See, e.g. Giannetti and Saidi (2019), De Jonghe et al. (2020), and Blickle et al. (2021).

[2]We get equivalent results when we look at the competition for other resources, like for instance the share of credit in an industry going to zombie firms or the share of tangible capital.

adding back depreciation and amortization as well as including recurring financial revenues (e.g., from liquid assets or intercompany loans). This modification avoids wrongly classifying as zombies: i) firms with recent large investments and hence large depreciation, ii) firms with high cash levels, and iii) firms that grant many intercompany loans. Our second modification is to not look at three consecutive years, but to look at whether the three-year cumulative recurring cash flows fail to cover the three-year cumulative interest expenses (where also minimum two of the three individual years fail). This brings more persistence to zombies identified at the margin as otherwise one (exceptional) year where the ratio>1, implies that a firm will be considered healthy for the next three years.

Compared to the OECD definition, our definition estimates a much smaller and less cyclical share of zombie borrowers in the economy: 3.4% instead of 10.4%. This difference is the result of 8% of borrowers that are zombies according to the OECD measure but not ours, and 1% that are zombies according to our measure but not the OECD's. The average zombie identified according to our definition is of significantly lower quality and less viable than the average zombie identified according to the OECD definition. Specifically, the differences in quality pertain to firm profitability, leverage, having negative equity, past firm growth, future sales growth, investments in tangible assets, etc. These modifications not only show a more credible picture of zombie firms, but we show that they are also important to identify the role that bank specialization plays in zombie lending.

Unlike Caballero et al. (2008) and Acharya et al. (2019, 2020), our zombie measure does not require zombie firms to be charged interest rates below that of the best-rated (AA-rated) firms. The zombie firms in our sample pay an (implicit) interest rate that is on average 114 basis points higher than the healthy firms.[3] However, we believe that this is still in line with receiving an interest rate subsidy. Using supervisory data from Norway, Müller et al. (2021) show that the difference in interest rates between firms with the lowest (p5) and highest (p95) default probability corresponds to 250-300 basis points. Nonetheless, we perform two robustness tests related to this. First, we split our zombie firms into two groups based on the zombies' median implicit interest rate and rerun our baseline model. The results hold equally for both groups of zombie firms, irrespective of whether their interest rates are the most subsidized or not. Second, we identify zombie firms

[3]Note that this is in line with recent theoretical evidence on zombie lending from Faria-e-Castro et al. (2021), who conclude that "*most evergreening is associated with riskier firms that are paying relatively higher interest rates. Attempts to empirically identify zombies as those with funding costs below benchmark risk-free rates may underestimate the extent of this phenomenon.*"

as in Acharya et al. (2019) and rerun our baseline model. Also here, the effect of bank specialization on zombie lending is confirmed.

Lastly, as industry specialization implies higher exposure to an industry, it also creates concentration risk. However, we deem it unlikely that our specialization results can be explained by this alone. With concentration risk, banks care about downside risk, which does not resonate with our results being stronger in industries with higher expected sales growth.

We contribute to the academic literature in at least three ways. First of all, we contribute to the literature on zombie lending. Most studies focus on the role of bank capital (Caballero et al., 2008; Giannetti and Simonov, 2013; Acharya et al., 2019, 2020) or overall bank health (e.g., Andrews and Petroulakis, 2017; Storz et al., 2017). Recently, Bonfim et al. (2022) and Passalacqua et al. (2020) show that on-site regulatory inspections also significantly determine banks' incentives to renew loans to zombie firms. We show a novel determinant that alleviates zombie lending, namely bank specialization.

Secondly, we contribute to the literature on bank industry specialization. One view is that banks should diversify their lending portfolio (e.g., Diamond, 1984). However, recent theoretical arguments and empirical evidence claim substantial benefits of specialization. Industry specialization gives banks an information advantage which may reduce screening and monitoring costs (Berger et al., 2017), and allows banks to offer loans with more generous terms (Blickle et al., 2021) and less restrictive covenants (Giometti and Pietrosanti, 2019). Banks have incentives to protect borrowers in specialized industries to maintain their information advantage (Müller, 2020), and indeed, did so during the interbank freeze after the Lehman Brothers collapse (De Jonghe et al., 2020). Bank specialization has also been shown to correlate with lower credit risk (Jahn et al., 2016), higher performance (Acharya et al., 2006), higher distance-to-default (Beck et al., 2022) and higher financial stability (Acharya et al., 2006; Beck et al., 2022). Our results are in line with this recent evidence and show that bank specialization leads to lower zombie lending to reduce the risk of negative congestion externalities onto healthy borrowers.

Finally, we add to the debate on the definition of zombie firms (Caballero et al., 2008; McGowan et al., 2018; Acharya et al., 2019; Schivardi et al., 2020; Bonfim et al., 2022). Although the firms identified as zombies according to our definition pay a higher interest rate than healthy firms, there does seem to be some subsidization (Caballero et al., 2008; Acharya et al., 2019) as the difference in interest rates is less than what the difference in firm risk would imply (Müller et al., 2021). Moreover, while we do not impose a solvency criterion in our zombie definition, we are picking up firms with higher leverage (Acharya et al., 2020), that are more likely to have negative equity (Bonfim et al., 2022), and have lower growth potential (Banerjee and Hofmann, 2020) due to lower investment in physical and human capital and lower future sales growth. Also importantly, we end up with a more moderate size of the zombie population. This is in line with recent studies showing that zombie firms in certain countries are not as prevalent as previously believed (see, e.g. Rodano and Sette (2019) for evidence on Italy or Favara et al. (2021) for the U.S.)

2. Data

We draw data from three unique data sources available at the National Bank of Belgium. The first source is the Corporate Credit Register. It records, at a monthly frequency, all loans granted by Belgian financial institutions to firms operating in Belgium. This database allows us (i) to compute credit growth at the intensive and extensive margin, (ii) to isolate credit supply from credit demand by (mainly) focusing on multiple-bank borrowers, and (iii) to compute banks' industry specialization in the corporate credit market. We aggregate the credit exposures at the firm-bank-year level before matching them with the second data source.

The second data source is the Central Balance Sheet Office. It collects balance sheets and income statements of *the universe* of Belgian enterprises. All firms, irrespective of their size, have to file financial statements on an annual basis. This dataset also contains a firm's date of incorporation, legal form, and the main economic industry a firm operates in. The richness and completeness of this database allow us to construct our new zombie definition. Finally, we obtain balance sheets and income statements of financial institutions. Banks report these data following the so-called Scheme A, and we use the latest financial statement reported in a given year.

We apply the following filters. Since we analyze bank lending to the real economy, we exclude firms from the financial and insurance industry, public administration and education industries, activities of extraterritorial entities, and activities of households as employers (NACE industries K, O, P, T, U). Additionally, we exclude micro-firms from the analysis due to different reporting requirements. Micro firms are defined as firms who have, on average over the sample period, less than 10 FTEs and less than 350,000 euro in total assets. We also exclude rare and highly specific legal forms.[4] Finally, as there was a reporting threshold of 25,000 Euro before April 2012, we exclude credit exposures below 25,000 Euro to be consistent throughout all sampled years (2004-2018). Note, however, that these excluded exposures account for just over 1% of total corporate credit.

Merging these three sources and applying the aforementioned filters results in a dataset containing *54* banks lending to more than *50,000* multiple-bank firms over the sample period 2004 to 2018. All tables and figures in this paper are based on this sample of multiple-bank borrowers unless explicitly stated otherwise. Table A.1 in Appendix provides information on the definition and construction of variables used throughout the paper, whereas Table B.1 contains summary statistics of these variables.

3. Who Are the Zombie Firms?

A zombie firm is a mature, consistently underperforming, and unproductive firm that is not able to repay its debt. These firms have a marginal return on capital that is below the risk-adjusted market cost of capital (Schivardi et al., 2022), and would -barring external support- exit the market in a frictionless economy. Due to market failures, zombie firms can stay alive and banks are often blamed for helping them. While there is more or less agreement on the definition of zombie firms, there is an abundance of empirical proxies.

Caballero et al. (2008) identify zombie firms as those who received subsidized credit, which is being defined as a lower interest rate than the interest rate paid by the highest quality (AA-rated) borrowers. Andrews and Petroulakis (2017) and McGowan et al. (2018) define zombies as firms that are at least 10 years old and have an interest coverage ratio (earnings before interests and taxes (EBIT) to financial expenses) below one for three consecutive years. We refer to this as the OECD definition. Other researchers have identified zombie firms using (a combination of) firm performance measures, such as: (i) firm profitability (e.g., Schivardi et al., 2022), (ii) negative equity (Bonfim et al., 2022), (iii) low interest coverage ratio (e.g., Andrews and Petroulakis, 2017), or (iv) leverage (Acharya et al., 2020).

[4]Specifically, we keep the following legal forms in the sample in the descending order based on the frequency in the sample (in Dutch): Besloten Vennootschap met Beperkte Aansprakelijkheid, Naamloze Vennootschap, Besloten Vennootschap, Coöperatieve Vennootschap, Commanditaire Vennootschap op Aandelen, Coöperatieve Vennootschap, Gewone Commanditaire Vennootschap, Coöperatieve Vennootschap met Onbeperkte Aansprakelijkheid, Vennootschap onder Firma, Coöperatieve Vennootschap met Beperkte Aansprakelijkheid, bij wijze van Deelneming, Besloten Vennootschap van publiek recht. These legal forms account for 99% of the total population of enterprises.

3.1. New approach to classify zombie firms

We suggest a new approach to identify zombie firms. Our approach is based on *recurring cash flows* and *longer term, structural underperformance*, and builds on the OECD definition. A firm is classified as a zombie if three conditions are met: (i) the firm's 3-year accumulated recurring cash flows fail to cover 3-year accumulated interest expenses, (ii) minimum two of the three individual years (i.e. not accumulated) also fail, and (iii) the firm is at least 10 years old.

We focus on *recurring cash flows*, which implies two departures from the OECD definition. The first difference is the use of EBITDA rather than EBIT to measure recurring operational income. As interest expenses are a cash outflow, operational earnings (EBIT) is not a good indicator of a firm's ability to service its debt due to its inclusion of components that do not generate cash-flows, in particular depreciation and amortization. Furthermore, deprecation and amortization practices are highly industry-specific (see Figure C.1 in Appendix where we plot the industry-average share of depreciation and amortization in EBITDA). This distorts comparisons across industries and countries (to the extent that countries differ in their industrial composition). Finally, firms with high depreciation in the current period (and thus low EBIT relative to EBITDA) tend to have invested heavily in the previous years, which is counter-intuitive as zombie firms are expected not to be able to invest (Storz et al., 2017).

The second difference is that we add recurring financial income to operating income to measure a firm's recurring cash flows. Recurring financial income (of which dividends and income earned on current assets are the most important sources) can also be used to service interest expenses. In addition, recurring financial revenues are more prevalent in large firms, and excluding these revenues might induce biases as well as inflate the share of capital and labor stuck in zombies. Finally, recurring financial revenues are industry-specific and should thus be properly accounted for (Figure C.1 in Appendix plots the industry-average share of recurring financial revenues in EBITDA.).

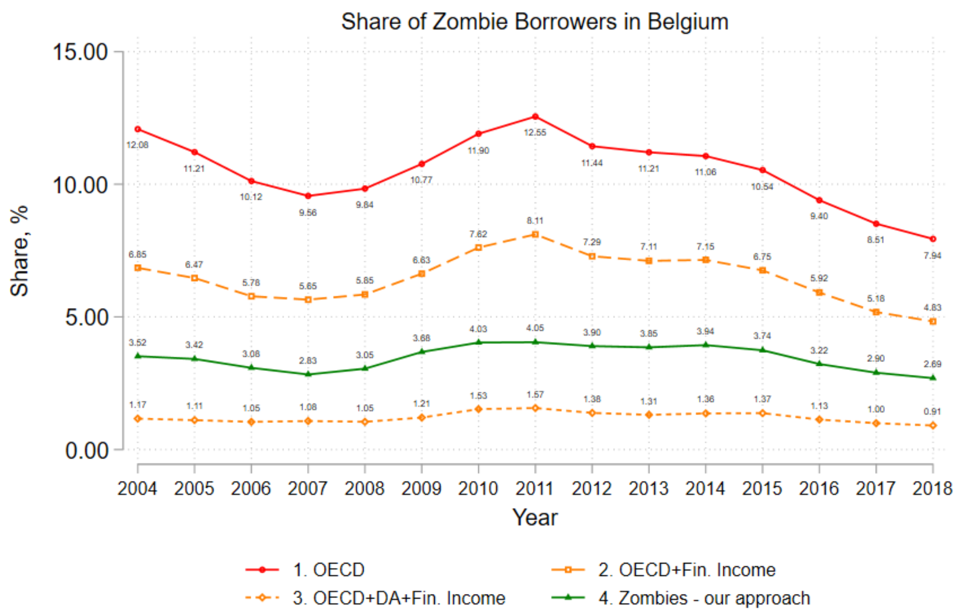
Further, our identification requires that recurring cash flows are *structurally* insufficient to meet interest expenses. Rather than assessing the condition year-by-year over a 3-year horizon (as in the OECD concept), we assess whether 3-year cumulative recurring cash flows are insufficient to cover 3-year cumulative interest expenses. Using cumulative recurring cash flows and interest expenses over a period of three years is akin to Schivardi et al. (2022), who suggest using a moving-average-based approach for the numerator and denominator of the interest coverage ratio. With this adjustment, we avoid incorrectly classifying firms as healthy, if they (possibly by luck) have a one-off improvement in cash flows or one-off reduction in interest expenses.[5] Moreover, in zombie definitions that require a threshold not to be breached for three consecutive years, one (exceptional) year that does breach it implies that a firm will not be considered as a zombie for the next three years. To avoid, on the other hand, incorrectly classifying firms as zombies due to one exceptionally bad year, we additionally impose that recurring cash flows should be less than interest expenses in at least two of the three years.

Each adjustment may have important consequences for classifying a firm as a zombie or not. To shed light on the impact of these adjustments, we plot in Figure 1, the impact of each of these adjustments on the share of zombies borrowers. Starting from the OECD definition (red line on top), we see that adding financial revenues (orange, long-dash) already has a sizeable impact on the number of firms identified as zombies. Further, using cash flows (EBITDA) rather than EBIT substantially reduces the number and importance of zombies (see also Rodano and Sette (2019) for a similar impact when applied to Italian firms). Finally, assessing cash flow deficiencies over a three-year horizon, rather than on a year-by-year basis, leads to a substantial increase in the number of zombie firms (but still substantially less than using the OECD definition). It is important to mention that these adjustments mainly lead to a level shift in the number of zombies, while the time series evolution of our measure (green line) and the OECD measure (red line) is very similar. Prior to the global financial crisis, the share of zombie borrowers was decreasing, followed by a run-up leading to a peak in 2011 and a gradual decrease afterward. The amplitude of the cycle is, however, smaller when using our definition.

[5] An example of the latter are debt moratoria installed by countries during the COVID-19 pandemic, which led financial institutions to allow for temporary debt renegotiation and reducing financial expenses.

Figure 1: Fraction of zombie borrowers: step-by-step definition adjustments

This figure depicts the impact of every adjustment made to the original OECD definition on the fraction of zombie borrowers. The red solid line shows the fraction of zombie borrowers identified by the OECD definition. The long-dashed orange line shows the impact of accounting for recurrent financial income. The short-dashed line shows the impact of accounting for recurrent financial income and adding back depreciation and amortization. The solid green line shows the fraction of zombie borrowers identified after introducing all adjustments. The sample includes yearly data of firms borrowing from more than one bank between 2004 and 2018.



3.2. Zombie firms versus low quality firms

In the previous subsection, we introduced our zombie definition and showed what the adjustments implied for the number of firms identified as zombies (vis-à-vis the OECD definition). In this subsection, we document what these adjustments imply for the type of firms identified as zombies. Comparing zombies according to our definition (Z) with the OECD definition (Z^{OECD}) partitions the sample into four groups: (i) firms identified as zombies under both definitions, (ii) firms identified as zombies according to our definition but as healthy according to the OECD definition, (iii) firms identified as zombies using the OECD definition, but as healthy according to our definition, (iv) healthy firms under both approaches. The number of firms in each group is respectively, 2.4%, 1.0%, 8.0%, and 88.6% of the sample (275,122 firm-year observations).

Using regression analysis, we are comparing whether and how firms in each of these four groups differ in terms of solvency and risk, profitability, growth of tangible assets and employment, future sales growth, and implicit interest rates. The regression analysis includes industry×Year and Location×Year fixed effects to net out industry or regional differences in firm characteristics and performance. The results are reported in Table 1 and the reported coefficients should be interpreted as deviations from the baseline group, i.e., firms identified as zombies under both definitions (Z=1 and Z^{OECD}=1).

Table 1: Firm characteristics and firm growth: differences across zombie types

This table shows the results of regression analysis comparing four groups of zombie and healthy firms across several dimensions. The dependent variables are equity to total assets ratio (Column 1), a dummy equal to 1 if firm's equity is negative and 0 otherwise (Column 2), EBITDA to total assets ratio (Column 3), Altman Z score (Column 4), growth of tangible assets (Column 5), growth of employment (Column 6), the one-year ahead growth of sales (Column 7), and cost of debt (Column 8). The independent variables are dummies that identify one of the four groups of firms. Z=1 & Z^{OECD}=0 equals 1 if a firm is identified as a zombie according to our definition but not according to the OECD definition, and 0 otherwise. Z=0 & Z^{OECD}=1 equals 1 if a firm is identified as a zombie according to the OECD definition but not according to our definition, and 0 otherwise. Z=0 & Z^{OECD}=0 equals 1 if a firm is not identified as a zombie according to either definition, and 0 otherwise. The omitted reference category includes firms that are identified as zombies according to both definitions. The sample includes yearly data of firms borrowing from more than one bank between 2004 and 2018. industry-year and location-year fixed effects absorb time-varying industry- or location-specific differences in the dependent variables. Industries are defined at the two-digit NACE level. Location is defined at the two-digit postcode level. Standard errors are clustered at the industry-year level. ***, ** and * denote p<0.01, p<0.05, and p<0.1, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\frac{\text{Equity}}{\text{Assets}}$	Negative Equity	$\frac{\text{EBITDA}}{\text{Assets}}$	Altman Z	TangAssets Growth	Employment Growth	Future Sales Growth	Cost of Debt
Z=1 & Z^{OECD}=0	0.60	-2.53**	1.15***	0.19***	-0.57	-0.14	0.81	0.44
	(0.61)	(1.07)	(0.28)	(0.02)	(0.98)	(0.43)	(1.15)	(0.27)
Z=0 & Z^{OECD}=1	11.81***	-21.51***	6.81***	0.51***	4.55***	3.93***	5.78***	-0.98***
	(0.41)	(0.75)	(0.20)	(0.02)	(0.55)	(0.27)	(0.70)	(0.19)
Z=0 & Z^{OECD}=0	16.33***	-26.44***	12.15***	0.93***	9.64***	6.83***	8.27***	-1.14***
	(0.47)	(0.80)	(0.26)	(0.02)	(0.54)	(0.34)	(0.70)	(0.16)
Observations	275,121	275,121	275,121	275,121	275,121	275,121	231,917	265,230
R-squared	0.06	0.07	0.17	0.11	0.02	0.02	0.03	0.06
N. of clusters	1087	1087	1087	1087	1087	1087	1078	1081
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

First of all, our approach picks up a set of firms (Z=1 & Z^{OECD}=0), representing 1% of the sampled firms, which are very similar (both economically and statistically) to the baseline group, i.e. zombies under both definitions. However, under the OECD definition, these firms would be pooled together with the set of healthy firms (last row), from which they differ substantially and significantly.

Secondly, and importantly, a sizeable number of firms (8.0% of the sample) are classified as zombies according to the OECD definition, but not according to ours (Z=0 & Z^{OECD}=1). We find that these firms substantially outperform the benchmark group in terms of solvency, profitability, investment, employment growth as well as future sales growth, and have a lower cost of debt (i.e. pay 98 basis points lower implicit interest rates). In fact, their characteristics are much closer to those of healthy firms than those of zombie firms. They could thus be considered as lower-quality healthy firms, much rather than zombie firms.

Thirdly, compared to the baseline group, firms that are classified as healthy under both definitions (i.e., Z=0 & Z^{OECD}=0) are substantially better capitalized, have a much lower incidence of firms with negative equity and are substantially more profitable; resulting in much higher Altman Z scores. These healthy firms also invest more in physical and human capital, exhibit better future performance (as measured by sales growth), and have a lower cost of debt.

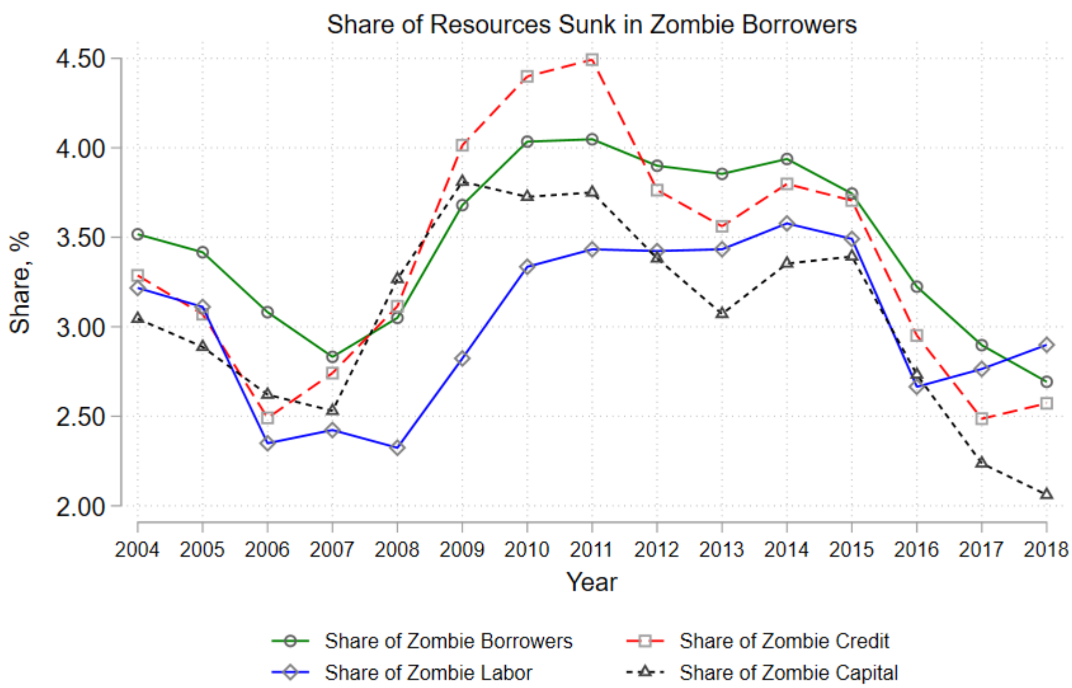
The results in Table 1 also allow us to make some qualitative comparisons with studies using alternative concepts to identify zombies. First, we show that the zombie definition used by the OECD mixes zombie firms with low-quality, but still healthy firms. Interestingly, the ratio of zombies (Z=1) to zombies and low-quality firms (Z=1 + Z^{OECD}=1) is about 30%. Using a different zombie measurement approach, Acharya et al. (2020) obtain a similar conclusion using a European sample of firms. Second, without imposing a solvency criterion in our zombie definition, we are picking up firms with higher leverage (Acharya et al., 2020), that are more likely to have negative equity (Bonfim et al., 2022), and have lower growth potential (Banerjee and Hofmann, 2020), due to lower investment in physical and human capital and lower future sales growth. Third, while our zombie measure does not require zombie firms to be charged interest rates below that of the best-rated (AA-rated) firms (Caballero et al., 2008; Acharya et al., 2019, 2020), we do believe that our zombie firms are being charged too low interest rates (and hence receive an interest rate subsidy from their bank). Using supervisory data from Norway, Müller et al. (2021) show that the difference in interest rates between firms with the lowest (p5) and highest (p95) default probability corresponds to 250-300 basis points. The zombie firms in our sample pay an (implicit) interest rate that is on average 114 basis points higher than the healthy firms. This difference thus seems too low to compensate for the difference in firm risk and hence suggests some subsidization.

3.3. Resources sunk in zombies and impact on healthy firms

Figure 1 already showed the dynamics of the fraction of zombie borrowers in Belgium between 2004 and 2018. In Figure 2, we plot the evolution of resources allocated to (or 'sunk' in) zombies and depict three lines (in addition to the fraction of zombie borrowers): the share of capital (fixed tangible assets), labor force (FTEs), and bank credit sunk in zombie borrowers.

Figure 2: Share of zombie firms in Belgium

This figure plots the evolution of the fraction of (i) zombie borrowers (solid green line); (ii) capital sunk in zombie borrowers (dashed red line); (iii) labor force sunk in zombie borrowers (solid blue line); (iv) bank credit granted to zombie borrowers (dashed black line). Capital is proxied by fixed tangible assets. Labor is proxied by FTEs. The sample includes yearly data of firms borrowing from more than one bank between 2004 and 2018.



We can see an increase in the zombie population during and after the financial crisis in the years 2008-2011. After that, the zombie population started to decline slowly. The rise of zombies during the crisis has also been found in other European countries (McGowan et al., 2018). The share of credit sunk in zombies exhibit similar dynamics as the share of zombie borrowers but with a larger amplitude. In most years, the share of capital and labor sunk in zombies is less than the share of credit allocated to zombies. On the one hand, it is reassuring that less real resources than financial resources are sunk in zombies. On the other hand, the credit sunk in zombies (although less used for investments in physical and human capital) may negatively affect the performance of healthy firms competing with these zombies (for credit and market share); a phenomenon called *zombie congestion*. Zombie congestion may happen through at least two channels. Firstly, a larger amount of credit granted to zombie borrowers limits the amount of credit available to healthy firms that are willing to take a bank loan. Secondly, as bank credit helps zombie firms to stay alive and take up the market share, it slows down business dynamism and negatively affects competition (e.g., McGowan et al., 2018) and mark-ups (Acharya et al., 2020).

Prior research shows a robust, negative relationship between the growth of healthy firms and the share of zombie firms in their industry (see, e.g., Caballero et al. (2008) who show this for Japan and McGowan et al. (2018) who document it for EU firms). In Table E.1 of Appendix, we document that such relationships are present in the Belgian data as well. Healthy borrowers exhibit higher growth in tangible assets, in employment, in current sales and in future sales. However, the growth of healthy borrowers will be smaller if they operate in industries where a larger fraction of credit is granted to zombie firms. Note that Schivardi et al. (2020) document a serious, and difficult to solve, identification problem in such regressions. They even conclude that the correlation between healthy firms' performance and zombie presence might be mechanical and biased. Solving this identification problem is not the purpose of the paper and therefore, the results in Table E.1 are indicative and only present correlations and not causal evidence. Moreover, as the direction and magnitude of the bias are unclear and context-specific (Schivardi et al., 2020), assessing the economic magnitude of the coefficients is meaningless.

4. Bank specialization and credit supply to zombie firms

4.1. Empirical specification

Our goal is to analyze the role of bank specialization in zombie lending. To be more specific, we are investigating whether the effect of bank specialization on credit supply is different for zombie firms than for healthy firms. Econometrically, we estimate the following baseline equation:

$$y_{ibt} = \beta_1 \; Specialization_{bjt-1} + \beta_2 \; Z_{it} \times Specialization_{bjt-1} + \nu_{it} + \upsilon_{bt} + \epsilon_{ibt} \quad (1)$$

The dependent variable y_{ibt} is one of three measures of credit growth. First, *New Loan* is a dummy variable that equals one if credit growth for a firm i with bank b in year t is positive, and zero otherwise. It measures, for existing borrowers, whether a new loan has been added or an existing limit has been increased. Next, we measure intensive margin credit growth in two alternative ways. Δ*Ln(Credit)* is the annual credit growth, defined as the logarithmic difference between the outstanding credit amount, at the firm-bank level, in year t and year *t-1*. Δ*Credit/Assets* is the absolute change in the outstanding credit amount, at the firm-bank level, from year *t-1* to year t scaled by the borrower's total assets in *t-1*. With these measures, we only focus on the *intensive* margin of lending, i.e., changes in the volume of lending to existing borrowers, as the concern is that banks keep zombie firms alive (rather than starting new relationships with zombie firms).

Z_{it} is a zombie identifier, which equals one if a firm i is identified as a zombie according to our definition in year t. Bank specialization, $Specialization_{bjt-1}$, or industry lending concentration, is the fraction of bank b's credit granted to an industry j in bank b's total corporate lending portfolio, measured in year $t-1$. An industry j is measured at the two-digit level of the NACE classification. We interact the zombie identifier with bank specialization to grasp whether the effect of specialization on credit supply differs for zombie firms. Table B.1 and Figure F.1 in Appendix show that there is sizeable variation in industry specialization across the sample, but also between banks within an industry-year. Given the inclusion of a large set of fixed effects, see infra, it is the latter source of variation that is relevant for estimating and identifying the effect of specialization on credit supply to zombie firms.

The baseline specification in Equation 1 includes an extensive set of fixed effects. We resort to the most stringent specification using the methodology of Khwaja and Mian (2008). Firm×year fixed effects (ν_{it}) capture any observed and unobserved firm-specific credit demand effects. Doing so, we only include firms that simultaneously borrow from two or more banks. This is stringent in the setting of Belgium, as many firms in Belgium borrow from only one bank. However, as credit demand might differ substantially between zombie firms and healthy firms, it is crucial to isolate demand from supply and therefore resort to the approach of Khwaja and Mian (2008). Note that this Firm×year fixed effect also absorbs the direct effect of Z_{it} on y_{ibt} and is therefore not separately included in Equation (1). Additionally, we include bank×year fixed effects (v_{bt}) to capture all observed and unobserved bank-specific determinants of lending.

The coefficients of interest are β_1 and β_2. β_1 is expected to be positive. Banks tend to provide more credit to firms operating in industries in which the bank is specialized (De Jonghe et al., 2020). The coefficient β_2 of the interaction between specialization and the zombie identifier is expected to be negative. A negative sign indicates that zombie firms benefit less (or are penalized) in terms of credit supply due to bank specialization. Alternatively, a zombie firm borrowing from two banks will experience a lower credit supply from its specialized lender vis-à-vis its uninformed lender.

4.2. Main results

Table 2 presents the results of estimating Equation 1 on the sample of multiple-bank borrowers over the period 2004-2018. The sample includes *614,320* bank-firm-year observations. Bank specialization has been standardized to facilitate the interpretation and economic impact assessment. We find, first of all, a positive and statistically significant coefficient of industry specialization. This is in line with existing evidence and suggests that banks are on average more likely to increase lending to firms in industries they specialize in. Secondly, and of crucial interest for our analysis is the negative coefficient on the interaction term between industry specialization and the zombie indicator, in each of the three columns.

In the first column, the coefficient on the interaction term is smaller (in absolute value) than the main effect of specialization, indicating that the beneficial effect of specialization on credit supply is much less pronounced for zombie borrowers. Zombie borrowers are less likely to receive a new loan from their specialized lender compared to their less specialized lender. The effects of specialization are also economically significant. A one standard deviation increase in specialization leads, for a healthy firm, to a 2.01 percentage point higher probability of obtaining a new loan (from its current lenders). This is sizeable, given that the average probability of receiving a new loan in the sample is 25.61% (see the summary statistics in Table B.1). However, the results in Column 1 of Table 2 also suggest that a one standard deviation increase in specialization reduces the probability of receiving a new loan for a zombie borrower by 1.53 percentage points. This is economically meaningful as it corresponds to a 6% lower probability compared to the unconditional mean, and thus shows that zombie borrowers face stricter credit supply at the extensive margin from specialized banks .

Table 2: Average effect of bank specialization on zombie lending

This table shows the effect of bank specialization on the credit growth of healthy firms and zombies. The dependent variables are a dummy variable that equals 1 if the outstanding credit amount increases and 0 otherwise (Column 1), the logarithmic difference between the outstanding credit amount in year *t* and year *t-1* (Column 2), and absolute change in the outstanding credit amount scaled to the borrower's total assets (Column 3). The independent variables are bank specialization and the interaction between bank specialization and a dummy indicator for zombie firms. The sample includes yearly bank-firm level data between 2004 and 2018. The sample includes firms borrowing from more than one bank. We control for firm demand and bank-specific effects using firm-year and bank-year fixed effects, respectively. Bank specialization has been standardized. Standard errors are clustered at the bank-industry level. ***, ** and * denote p<0.01, p<0.05, and p<0.1, respectively.

	(1) New Loan	(2) ΔLn(Credit)	(3) $\frac{\Delta \text{Credit}}{\text{Assets}}$
Specialization	2.01***	0.51**	0.11***
	(0.40)	(0.21)	(0.04)
Z×Specialization	-1.53***	-0.85***	-0.34***
	(0.31)	(0.24)	(0.08)
Observations	614,320	614,320	614,320
R-squared	0.47	0.45	0.46
N. of clusters	1774	1774	1774
Firm×Year FE	Yes	Yes	Yes
Bank×Year FE	Yes	Yes	Yes

In the second and third column, the coefficients on the interaction term are again negative and statistically significant. This implies that an increase in industry specialization also reduces credit for zombie borrowers on the intensive margin. The results in Column 2 show that a one standard deviation increase in a bank's industry specialization reduces the credit growth by 0.85 percentage points. This is economically meaningful as it increases the unconditional average annual credit growth of -1.91 percentage points by 44%. In the case of the credit growth relative to firm size (Column 3), while a one standard deviation increase in bank specialization leads to an average increase in relative credit amount of almost 0.11 percentage points (which is well above the sample mean of credit growth), a zombie borrower from the same industry faces a credit reduction, which is twice larger in magnitude (-0.23=0.11-0.34).

Overall, our findings reveal an important role of bank industry specialization in zombie lending. On the one hand, more credit is granted to borrowers operating in industries in which banks are more specialized. This finding is in line with the existing literature (e.g., Paravisini et al., 2017; De Jonghe et al., 2020), which shows that banks expand lending to industries where they are more specialized. On the other hand, we shed light on a novel aspect of bank industry specialization that has not been discussed before. We find that bank specialization is associated with lower zombie lending. Using our sample of firms borrowing from multiple banks, we show that a zombie firm faces a lower credit supply at the bank that is more specialized in the borrower's industry.

These main results are in line with the interpretation that banks gain an informational advantage from specialization. By concentrating lending in a certain industry, banks obtain more proprietary industry-specific information (Berger et al., 2017), which leads to a reduction in the cost of monitoring (Diamond, 1984) and better screening abilities (Dell'Ariccia et al., 1999). As a result, banks specialized in a certain industry are (i) better able to identify zombie borrowers and distinguish them from healthy firms and firms who temporarily perform poorly, (ii) better able to assess the long-term financial prospects of their borrowers, and (iii) understand better the impact that zombie firms have on the long-term financial prospects of their healthy borrowers.

In section 6, we document in detail that this baseline specification is **robust** to (i) firm-bank matching and credit demand, (ii) aggregate (size-weighted) analysis, (iii) alternative measures of specialization, (iv) confounding factors related to bank health and financial crises, (v) alternative clustering of standard errors, and (vi) alternative measures of zombie firms (based on interest rate subsidization).

4.3. Zombies versus low-quality firms

Acharya et al. (2020) document that zombie firms constitute less than 25% of all low-quality firms. Likewise, we find that only 30% of the firms identified as zombies according to the commonly used OECD definition are still labeled zombies after our adjustments. Moreover, comparing these along many relevant dimensions (see Table 1) indicates that low-quality, non-zombie firms (Z^{OECD}=1 & Z=0) are more akin to healthy firms than to zombie firms. Hence, we would expect that the impact of information acquisition (through specialization) on credit supply to low-quality firms is more similar to the baseline effect (i.e., for healthy firms) than the effect for zombie borrowers.

In Table 3, we show results of augmenting the baseline specification with an interaction term of bank specialization and a dummy that is one for low-quality, non-zombie firms, and zero otherwise (i.e., a dummy capturing the firms for which Z^{OECD}=1 & Z=0). We find that the coefficient in the second line has the expected negative sign, but is only significant in the first column. Moreover, even in the first column, the moderating effect is substantially weaker for the lower quality firms (-0.53) than for the zombie firms (-1.58).

An important insight from this additional analysis is that using measures that pool low-quality firms with zombie firms might lead to biased results and incorrect conclusions on how banks use their information advantage to reallocate credit from zombies towards healthier firms in industries in which they are specialized.

Table 3: Average effect of bank specialization on zombie lending: zombies vs. low-quality firms

This table shows the effect of bank specialization on the credit growth of healthy firms, low-quality firms, and zombies. The dependent variables are a dummy variable that equals 1 if the outstanding credit amount increases and 0 otherwise (Column 1), the logarithmic difference between the outstanding credit amount in year *t* and year *t-1* (Column 2), and absolute change in the outstanding credit amount scaled to the borrower's total assets (Column 3). The independent variables are bank specialization and the interactions between bank specialization and two dummy indicators. First, an indicator for low-quality firms, which equals 1 if a firm is identified as a zombie according to the OECD definition but not according to ours and 0 otherwise. Second, an indicator for zombie firms, which equals 1 if a firm is identified as a zombie according to our definition and 0 otherwise. The sample includes yearly bank-firm level data between 2004 and 2018. The sample includes firms borrowing from more than one bank. We control for firm demand and bank-specific effects using firm-year and bank-year fixed effects, respectively. Bank specialization has been standardized. Standard errors are clustered at the bank-industry level. ***, ** and * denote p<0.01, p<0.05, and p<0.1, respectively.

	(1) New Loan	(2) ΔLn(Credit)	(3) $\frac{\Delta \text{Credit}}{\text{Assets}}$
Specialization	2.07***	0.52**	0.12***
	(0.40)	(0.22)	(0.04)
Z=0 & Z^{OECD}=1×Specialization	-0.53**	-0.12	-0.06
	(0.25)	(0.26)	(0.04)
Z×Specialization	-1.58***	-0.86***	-0.34***
	(0.31)	(0.25)	(0.08)
Observations	614,320	614,320	614,320
R-squared	0.47	0.45	0.46
N. of clusters	1774	1774	1774
Firm×Year FE	Yes	Yes	Yes
Bank×Year FE	Yes	Yes	Yes

5. Characteristics of the Specialization Channel

In this section, we explore various characteristics that help to understand how the bank specialization channel works in reducing zombie lending.

5.1. *Specialization and information advantage*

We argue that specialization-induced information advantages allow banks to better screen and monitor their borrowers and understand industry dynamics. Not only are specialized banks thus better able to identify zombie borrowers, but they may also better understand zombies' impact on healthy borrowers. However, industry specialization need not be the only source of superior information. Soft information acquired by banks throughout the relationship with borrowers (Petersen and Rajan, 1994) is also an important determinant of firms' access to credit (Bolton et al., 2016; Petersen and Rajan, 1995). If banks lack expertise in an industry and are therefore deprived of industry-specific information, they may invest more in firm-specific information. The two sources of information could thus act as substitutes and not adequately controlling for firm-specific soft information might bias our main finding.

Our strategy for testing whether the industry-specific soft information obtained through specialization drives the effect of specialization on zombie lending is to horse-race our baseline model in Equation 1 against specifications enriched with alternative sources of information that may affect the bank's decision to roll over zombie loans. If the impact of additional variables on the interaction term between the zombie identifier and specialization is limited, it would serve as evidence that the relationship between industry specialization and zombie lending is indeed driven by the industry-specific information that banks learn about the borrowers in specialized industries.

First, we augment the baseline model with firm-bank-specific soft information that banks learn over the course of the relationships with their borrowers. On the one hand, by having closer and stronger relationships with their borrowers, banks are better able to screen the quality of the borrowers (e.g., Bolton et al., 2016). On the other hand, by having a long relationship with their borrowers, banks may even continue to lend to poorly performing firms such that they can extract more profits from them later on (Sharpe, 1990; Schäfer, 2019). Hence, we introduce to the specification a variable *Ln(Relationship)* measuring the relationship length since the first time a bank lent to a given borrower. Additionally, we control for private information that can be learned by the primary lender (e.g., Ioannidou and Ongena, 2010) by adding a variable *Bank's Share in Firm Credit* that measures the share of the bank in the borrower's total outstanding credit. Finally, we also control for a bank's market share in a given industry (*Market Share*) to account for a bank's pricing power as well as for a bank's willingness to internalize losses in markets where the bank is more present (Giannetti and Saidi, 2019). To rule out that banks reduce credit supply to zombie firms in specialized industries because they have more firm-specific soft information about their borrowers in specialized industries or because they have more market share in specialized industries[6], we also interact our zombie indicator with the above-defined variables.

Second, besides controlling for soft information, we introduce interaction terms between bank specialization and hard information on risk (at the firm-year level). What is important to note here is that these interaction terms are not to be interpreted as whether banks adjust credit supply differently to firms according to these firm characteristics (because we already include firm×year fixed effects which absorb this). It should, however, enable us to assess whether banks' industry specialization incentivizes banks to reduce credit to zombie borrowers because banks learn more about them and their impact on healthy borrowers, or whether specialization simply enables banks to better understand firm-specific risk. If the latter is true, then the interaction between industry specialization and our zombie indicator in the baseline regression was spurious due to the zombie indicator being related to hard firm characteristics that reveal high risk. If the former is true, then adding the interactions between specialization and the hard firm characteristics should not affect the interaction between zombie and specialization. The hard-information variables include the firm's lagged total assets, leverage, return on assets, current ratio, and age.

The results of this exercise are presented in Table 4. In columns 1 to 3, we include only the soft information controls; in columns 4 to 6, we include only the hard information controls; in columns 7 to 9, we include both soft and hard information controls. The results of this test show that bank specialization remains an important and significant determinant of zombie lending, even when we explicitly account for other common sources of soft and hard information. The results of this exercise support the conclusion that higher industry specialization provides the bank with a separate source of proprietary information, which is bank-industry specific and soft in nature.

[6]The correlation between industry market share and industry specialization is rather modest ($corr = -0.08$). While the former measures how important a bank is for an industry, the latter measures how important an industry is for a bank. As De Jonghe et al. (2020) show, both have important, yet distinct implications for bank lending.

Table 4: Industry specialization and information advantage: controlling for soft and hard information

This table shows the effect of bank specialization on the credit growth of healthy firms and zombies when controlling for various hard and soft information proxies. The dependent variables are a dummy variable that equals 1 if the outstanding credit amount increases and 0 otherwise (Columns 1, 4, and 7), the logarithmic difference between the outstanding credit amount in year t and year $t\text{-}1$ (Columns 2, 5, and 8), and absolute change in the outstanding credit amount scaled to the borrower's total assets (Columns 3, 6, and 9). The independent variables are bank specialization, the interaction between bank specialization and a dummy indicator for zombie firms, the interactions between the zombie indicator and measures of soft information, and the interactions between bank specialization and measures of hard information. We capture soft information by the length of a firm-bank relationship, a share of a bank in a firm's total credit, and bank market presence. We capture hard information by the firm's total assets, leverage ratio, return on assets, current ratio, and age. The sample includes yearly firm-bank level data between 2004 and 2018. The sample includes firms borrowing from more than one bank. We control for firm demand and bank-specific effects using firm-year and bank-year fixed effects, respectively. Continuous independent variables have been standardized. Standard errors are clustered at the bank-industry level. ***, ** and * denote $p<0.01$, $p<0.05$, and $p<0.1$, respectively.

	(1) New Loan	(2) ΔLn(Credit)	(3) $\frac{\Delta Credit}{Assets}$	(4) New Loan	(5) ΔLn(Credit)	(6) $\frac{\Delta Credit}{Assets}$	(7) New Loan	(8) ΔLn(Credit)	(9) $\frac{\Delta Credit}{Assets}$
Specialization	2.31***	1.24***	0.26***	1.92***	0.52**	0.10**	2.18***	1.19***	0.24***
	(0.47)	(0.19)	(0.05)	(0.34)	(0.21)	(0.04)	(0.39)	(0.20)	(0.05)
Z×Specialization	-1.67***	-1.09***	-0.36***	-1.98***	-0.82***	-0.37***	-2.14***	-1.11***	-0.40***
	(0.31)	(0.27)	(0.08)	(0.39)	(0.31)	(0.05)	(0.37)	(0.32)	(0.07)
Soft information									
Ln(Relationship)	-3.02***	-3.41***	-0.55***				-3.02***	-3.42***	-0.55***
	(0.13)	(0.14)	(0.03)				(0.13)	(0.14)	(0.03)
Z×Ln(Relationship)	1.08**	1.20***	0.17**				1.09**	1.20***	0.17**
	(0.49)	(0.39)	(0.08)				(0.49)	(0.39)	(0.08)
Bank's Share in Firm Credit	-1.11***	-4.32***	-0.82***				-1.11***	-4.32***	-0.82***
	(0.21)	(0.21)	(0.03)				(0.21)	(0.21)	(0.03)
Z×Bank's Share in Firm Credit	0.95***	0.06	-0.43***				0.96***	0.06	-0.43***
	(0.34)	(0.27)	(0.07)				(0.34)	(0.27)	(0.07)
Market Share	0.39	0.56***	0.04				0.45	0.57***	0.05
	(0.28)	(0.19)	(0.04)				(0.28)	(0.19)	(0.04)
Z×Market Share	-0.89**	-1.42***	-0.25***				-0.89**	-1.42***	-0.25***
	(0.38)	(0.34)	(0.06)				(0.38)	(0.34)	(0.06)
Hard information									
Specialization×Ln(Assets)				0.05	-0.06	0.01	0.14	0.14	0.05
				(0.25)	(0.10)	(0.05)	(0.27)	(0.13)	(0.05)
Specialization×Equity/Assets				-0.08	-0.14	-0.08***	-0.11	-0.19*	-0.09***
				(0.13)	(0.11)	(0.02)	(0.13)	(0.11)	(0.02)
Specialization×EBITDA/Assets				-0.34*	0.05	-0.00	-0.34**	0.05	-0.00
				(0.18)	(0.16)	(0.04)	(0.17)	(0.13)	(0.04)
Specialization×Current Ratio				0.11	0.11	0.01	0.09	0.09	0.00
				(0.19)	(0.13)	(0.02)	(0.20)	(0.15)	(0.02)
Specialization×Age				0.27**	-0.04	0.01	0.30**	0.04	0.02*
				(0.11)	(0.07)	(0.01)	(0.12)	(0.08)	(0.01)
Observations	614,320	614,320	614,320	614,192	614,192	614,192	614,192	614,192	614,192
R-squared	0.48	0.47	0.48	0.47	0.45	0.46	0.48	0.47	0.48
N. of clusters	1774	1774	1774	1774	1774	1774	1774	1774	1774
Firm×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

5.2. Fear of missing out: risk of zombie congestion externalities

The existing literature provides ample evidence of negative externalities created by zombies. Zombie firms hamper growth (Caballero et al., 2008), business dynamism (Andrews and Petroulakis, 2017) and innovation (Schmidt et al., 2020) of healthy firms operating in congested industries. If bank specialization provides banks with superior information about the industry, they should have more incentives to limit zombie lending when the scope and cost of such externalities on healthy borrowers are larger.

First of all, the *scope* for congestion externalities will likely be larger, the more important zombie firms are in the industry and the more resources they lock up (such as labor, capital, and credit). It is rather unlikely that healthy firms endure negative effects from competing with zombie firms if these zombies take up only a marginal fraction of resources and market share. Specialized banks should be more aware of this and are therefore expected to curb zombie lending, especially in industries where zombies take up a meaningful share of resources.

Second, not only the scope for congestion externalities but also the opportunity costs of those externalities may matter. By granting additional credit and enabling zombie firms to stay afloat, banks impose a higher risk of negative zombie congestion externalities on healthy borrowers. The cost of these externalities increases with the industry's growth prospects as the growth distortion due to zombie congestion is more palpable in those industries. Hence credit reallocation from zombies to healthy firms induced by superior industry information is going to be especially valuable in industries with better growth prospects. Moreover, by allocating more credit to productive firms, banks further contribute to the industry productivity boost (Bai et al., 2018) and help to sustain the industry growth and benefit from it as it widens the pool of high-quality borrowers that would bring more positive-NPV projects for a bank.

To test each of these two conjectures, we modify the baseline Equation 1 and add a triple interaction. First, we interact the $Z \times Specialization$ term with the share of labor sunk in zombies in the industry[7] when testing the scope for congestion hypothesis. Second, we interact the $Z \times Specialization$ with the industry's

[7]Labor is our preferred measure of zombie market share for two reasons. Firstly, labor is more sticky than capital (i.e., tangible assets) or credit and is, therefore, less endogenous with respect to changes in bank credit supply. Secondly, labor is more scarce than capital and credit within the economy. Hence, if more labor is trapped in zombie firms, less labor is available to healthy firms. Therefore, the industry share of zombie labor is more correlated with the negative externalities of resource misallocation inflicted on healthy firms. However, we get equivalent results as the ones presented here if we would look at the share of credit or tangible assets in an industry that is going to zombie firms.

expected turnover growth (proxied by the industry's median firm turnover growth in *t+1*) when testing the opportunity cost of congestion externalities.

The coefficient on the triple interaction term is expected to be negative in both tests. Together with the baseline effect, this would indicate that banks tend to reduce zombie lending in industries where they are more specialized, and especially so if zombie firms lock up a higher fraction of labor in that industry and/or if the growth prospects of the firms in that industry are better.

Table 5: Scope for zombie congestion externalities: labor sunk in zombies

This table shows the effect of bank specialization on the credit growth of healthy firms and zombies allowing for heterogeneity due to industry differences in zombie congestion. The dependent variables are a dummy variable that equals 1 if the outstanding credit amount increases and 0 otherwise (Column 1), the logarithmic difference between the outstanding credit amount in year *t* and year *t-1* (Column 2), and absolute change in the outstanding credit amount scaled to the borrower's total assets (Column 3). The independent variables are bank specialization, a dummy indicator for zombie firms, the share of labor sunk in zombies at the industry-year level, as well as their possible interactions. The sample includes yearly bank-firm level data between 2004 and 2018. The sample includes firms borrowing from more than one bank. We control for firm demand and bank-specific effects using firm-year and bank-year fixed effects, respectively. Continuous independent variables have been standardized. Standard errors are clustered at the bank-industry level. ***, ** and * denote p<0.01, p<0.05, and p<0.1, respectively.

	(1) New Loan	(2) ΔLn(Credit)	(3) $\frac{\Delta \text{Credit}}{\text{Assets}}$
Specialization	2.02***	0.52**	0.12***
	(0.40)	(0.21)	(0.04)
Z×Specialization	-1.51***	-0.77***	-0.32***
	(0.32)	(0.24)	(0.08)
Specialization×Z^{Labor} Share	0.15	0.30	0.08
	(0.32)	(0.24)	(0.06)
Z×Specialization×Z^{Labor} Share	-0.21	-0.52**	-0.13**
	(0.35)	(0.25)	(0.06)
Observations	614,320	614,320	614,320
R-squared	0.47	0.45	0.46
N. of clusters	1774	1774	1774
Firm×Year FE	Yes	Yes	Yes
Bank×Year FE	Yes	Yes	Yes

The results in Table 5 suggest that banks, indeed, tend to reduce lending relative more to zombie firms operating in industries where banks are more specialized (the baseline effect), and this effect amplifies with a higher share of zombie labor in that industry. In other words, relative to a healthy borrower in the same industry, a zombie faces an even more limited credit supply from a specialized bank if the industry is more congested by zombie firms. This channel is more pronounced at the intensive margin of credit growth (Columns 2 and 3).

Likewise, the results in columns 2 and 3 of Table 6 also reveal that ceteris paribus, specialization induces banks to curb zombie lending proportionally more in industries that are expected to grow faster in terms of turnover (negative triple interaction term).

Table 6: Opportunity costs of congestion externalities: industry growth

This table shows the effect of bank specialization on the credit growth of healthy firms and zombies allowing for heterogeneity due to industry differences in sales growth. The dependent variables are a dummy variable that equals 1 if the outstanding credit amount increases and 0 otherwise (Column 1), the logarithmic difference between the outstanding credit amount in year t and year t-1 (Column 2), and absolute change in the outstanding credit amount scaled to the borrower's total assets (Column 3). The independent variables are bank specialization, a dummy indicator for zombie firms, the share of labor sunk in zombies at the industry-year level, as well as their possible interactions. The sample includes yearly firm-bank level data between 2004 and 2018. The sample includes firms borrowing from more than one bank. We control for firm demand and bank-specific effects using firm-year and bank-year fixed effects, respectively. Continuous independent variables have been standardized. Standard errors are clustered at the bank-industry level. ***, ** and * denote p<0.01, p<0.05, and p<0.1, respectively.

	(1) New Loan	(2) ΔLn(Credit)	(3) $\frac{\Delta \text{Credit}}{\text{Assets}}$
Specialization	2.03***	0.52**	0.12***
	(0.40)	(0.20)	(0.04)
Z×Specialization	-1.52***	-0.88***	-0.34***
	(0.30)	(0.24)	(0.07)
Specialization×Industry Growth	0.45	0.22	0.06
	(0.28)	(0.25)	(0.04)
Z×Specialization×Industry Growth	0.26	-0.65***	-0.12**
	(0.40)	(0.22)	(0.05)
Observations	614,320	614,320	614,320
R-squared	0.47	0.45	0.46
N. of clusters	1774	1774	1774
Firm×Year FE	Yes	Yes	Yes
Bank×Year FE	Yes	Yes	Yes

Overall, these two tests indicate that the negative relationship between bank specialization and zombie lending in a given industry becomes more apparent when the scope and opportunity cost of zombie congestion is larger. Banks tend to 'de-zombify' economic industries, in which they are more specialized, when the resources sunk in zombies increase and when the growth prospects of that industry are better. Bank specialization and information acquisition hence facilitate a more efficient resource reallocation.

5.3. Loss aversion motive

In the previous section, we have shown that the information advantage induces banks to cut zombie lending more if the potential benefit to healthy firms is larger. In this section, we document the presence of an alternative channel, *loss (given default)-aversion*, which induces banks to cut zombie lending less because triggering default of zombies is likely to hurt (collateral values of) healthy firms.

Firms pledge collateral to reduce the loss given default. However, if this collateral consists of less re-deployable assets (more firm- or industry-specific assets), it may not only affect the repossession value of the claims on the defaulting firm. If assets are more difficult to sell, and especially outside their original industry, then selling them at a substantial discount (fire-sale prices) drives down the market value of the collateral of other firms in the same industry (e.g., Giannetti and Saidi, 2019; Almeida et al., 2011; Acharya et al., 2007)[8]. A specialized bank might therefore be less willing to cut credit to zombie firms if the bank expects the firm's assets to be liquidated at a significant discount, with spillover effects to healthy firms. Put differently, thanks to the information advantage due to specialization, a specialized bank is better aware of the consequences of collateral liquidation[9] on its other borrowers, which may affect the bank's decision to lend to zombie borrowers.

To test this conjecture we again add a triple interaction to our baseline regression model in Equation 1, this time with a measure of industry asset specificity. More specifically, we follow Giannetti and Saidi (2019) and Acharya et al. (2007) and measure industry asset specificity as the ratio of the total value of machinery and equipment in a given two-digit industry relative to the total value of total assets in the industry.[10] The coefficient of interest is the triple interaction between the zombie indicator, bank specialization, and industry asset specificity. If the sign of the coefficient is positive, it means that if a bank is more aware (thanks to

[8]Benmelech and Bergman (2011) introduce the "collateral channel" to explain the negative externalities of bankrupt firms on nonbankrupt competitors. According to this channel, bankruptcies reduce the collateral value of the nonbankrupt firms within an industry, and the higher illiquidity of assets amplifies this effect.

[9]Gopal (2021) also provides evidence of banks specializing in different types of collateral. This collateral specialization reduces information asymmetry and facilitates better credit access of firms that pledge collateral, in which a bank is more specialized.

[10]The reasoning for proxying for asset specificity with machinery and equipment ratio is the following. Being movable collateral, machinery and equipment are less valuable than immovable real estate. Furthermore, machinery is deemed as more industry-specific and often custom-made, which makes it more difficult to sell at fair value in the case of liquidation.

higher specialization) of the lower redeployability of the assets in an industry and hence the larger impact on healthy borrowers, the bank is less willing to cut zombie credit in that industry. The results of this exercise are presented in Table 7.

Table 7: Loss aversion motive: the role of industry asset specificity

This table shows the effect of bank specialization on the credit growth of healthy firms and zombies allowing for heterogeneity due to industry differences in asset specificity. The dependent variables are a dummy variable that equals 1 if the outstanding credit amount increases and 0 otherwise (Column 1), the logarithmic difference between the outstanding credit amount in year *t* and year *t-1* (Column 2), and absolute change in the outstanding credit amount scaled to the borrower's total assets (Column 3). The independent variables are bank specialization, a dummy indicator for zombie firms, the ratio of aggregate machinery and equipment to aggregate total assets (at the industry-year level), as well as their possible interactions. The sample includes yearly firm-bank level data between 2004 and 2018. The sample includes firms borrowing from more than one bank. We control for firm demand and bank-specific effects using firm-year and bank-year fixed effects, respectively. Continuous independent variables have been standardized. Standard errors are clustered at the bank-industry level. ***, ** and * denote p<0.01, p<0.05, and p<0.1, respectively.

	(1) New Loan	(2) ΔLn(Credit)	(3) $\frac{\Delta \text{Credit}}{\text{Assets}}$
Specialization	2.02***	0.50**	0.11***
	(0.38)	(0.21)	(0.04)
Z×Specialization	-1.29***	-0.38	-0.24***
	(0.43)	(0.27)	(0.08)
Specialization×Specificity	-0.28	0.05	-0.04*
	(0.21)	(0.12)	(0.02)
Z×Specialization×Specificity	0.60	1.04***	0.23***
	(0.59)	(0.39)	(0.09)
Observations	614,320	614,320	614,320
R-squared	0.47	0.45	0.46
N. of clusters	1774	1774	1774
Firm×Year FE	Yes	Yes	Yes
Bank×Year FE	Yes	Yes	Yes

The results of the test show that specialized banks tend to provide relatively more credit to zombie firms operating in industries with more specific assets. This effect is more evident at the intensive margin of credit growth. Interesting to note here is the (mostly) insignificant, negative interaction term between bank specialization and industry assets specificity in Table 7. Specialized banks do not treat healthy firms in low or high-asset specificity industries differently, as these firms have a substantially lower probability of default (and hence the risk of contagious revaluation due to asset fire sales is lower).

5.3.1. Loss aversion motive: large zombies

Zombie lending is argued to be pervasive in order to avoid an impact on bank solvency. Zombies that account for a large share in the bank's total lending (and are thus important to the bank) might be protected more as their default would have a larger impact on bank solvency. We would therefore expect zombie firms that are larger from the bank's perspective, to enjoy a more generous credit supply.

The role that bank specialization might play for credit supply to large zombies is ex-ante less clear. On the one hand, large zombies –by definition– take up a large fraction of industry resources and thereby increase the scope for negative congestion externalities. If this effect is dominant, we would expect the reduction in zombie lending from specialized banks to be stronger for larger zombies. On the other hand, the default of a large zombie is more likely to have an impact on industry asset values, and hence be contagious for healthy borrowers, than a default of a small zombie. If this effect is dominant, we would expect the reduction in zombie lending from specialized banks to be weaker for larger zombies.

To investigate this, we add a triple interaction to our baseline regression model in Equation 1. This time we add an interaction term with the lagged share that the credit granted to a firm takes in the bank's total corporate credit in a given year, *Firm Share*. The latter proxies for the firm's importance to a bank. Note that, because *Firm Share* is varying at the bank-firm level, we also include it separately in this regression model, as well as its interactions with Z and *Specialization*. Also note that, in previous triple interaction models, the stand-alone inclusion of the characteristic under study and its interaction with Z were subsumed by the firm$\times$year fixed effects.

Firstly, given the positive sign of the interaction term Z$\times$Firm Share, zombie firms seem to enjoy a more generous credit supply when they make up a bigger share of the bank's total credit. Thus, banks tend to protect important zombie borrowers from a credit dry-up. This finding suggests that banks seem to avoid larger write-offs by providing more liquidity to zombie borrowers that account for a larger share of the bank's total credit portfolio.

The effect of the triple interaction term is negative, and therefore suggests that specialized banks reduce zombie lending even more if the zombie borrower is large. This is in line with specialized banks being more

Table 8: Loss aversion motive: interaction with firm's share in bank portfolio

This table shows the effect of bank specialization on the credit growth of healthy firms and zombies allowing for heterogeneity due to the importance of a firm to a bank. The dependent variables are a dummy variable that equals 1 if the outstanding credit amount increases and 0 otherwise (Column 1), the logarithmic difference between the outstanding credit amount in year *t* and year *t-1* (Column 2), and absolute change in the outstanding credit amount scaled to the borrower's total assets (Column 3). The independent variables are bank specialization, a dummy indicator for zombie firms, the share of firm credit in the banks' corporate credit portfolio, as well as their possible interactions. The sample includes yearly firm-bank level data between 2004 and 2018. The sample includes firms borrowing from more than one bank. We control for firm demand and bank-specific effects using firm-year and bank-year fixed effects, respectively. Continuous independent variables have been standardized. Standard errors are clustered at the bank-industry level. ***, ** and * denote p<0.01, p<0.05, and p<0.1, respectively.

	(1) New Loan	(2) ΔLn(Credit)	(3) $\frac{\Delta\text{Credit}}{\text{Assets}}$
Specialization	2.00***	0.52**	0.12***
	(0.40)	(0.22)	(0.04)
Z×Specialization	-1.44***	-0.79***	-0.32***
	(0.34)	(0.25)	(0.07)
Firm Share	-0.11	-0.83***	-0.20***
	(0.17)	(0.18)	(0.04)
Z×Firm Share	1.22**	1.34***	0.26***
	(0.52)	(0.41)	(0.09)
Specialization×Firm Share	0.02	0.09***	0.02***
	(0.03)	(0.03)	(0.01)
Z×Specialization×Firm Share	-0.18**	-0.18***	-0.04***
	(0.07)	(0.06)	(0.01)
Observations	614,320	614,320	614,320
R-squared	0.47	0.45	0.46
N. of clusters	1774	1774	1774
Firm×Year FE	Yes	Yes	Yes
Bank×Year FE	Yes	Yes	Yes

concerned and aware of the negative impact that (large) zombie firms have on healthy borrowers. Note, however, that the net effect of being a large zombie borrower is still positive. Hence, while the motive of banks to protect more important zombie borrowers remains strong for an average bank, it is weaker for banks with better industry information.

6. Robustness tests of the baseline specification

In this section, we revisit the baseline specification (i.e., Equation 1 and Table 2) and discuss several robustness checks. For space and clarity, we keep this section intentionally focused and put all tables in Appendix G. We focus on six potential concerns with the baseline specification: (i) firm-bank matching and credit demand, (ii) aggregate effects (iii) measurement of bank specialization, (iv) the role of bank health and crisis episodes, (v) clustering of standard errors, and (vi) subsidized credit.

6.1. Firm-bank matching and credit demand

The baseline Equation 1 includes firm$\times$year fixed effects and thus controls for any observed and unobserved heterogeneity at the firm-year level. However, that does not rule out potential distortions due to (historic) firm-bank matching.[11] Moreover, we look at total credit at the firm-bank level, which pools together various products that differ in the degree to which they are callable by the bank (due to differences in maturity, covenants, etc.). Biases in the estimation results might thus also occur if the choice of bank products by firms is correlated with bank specialization (and would result in bank-specific credit demand, as in Paravisini et al. (2017)).

To mitigate these concerns, we proceed in two steps. We first redo the analysis on one specific product that is homogeneous across banks and firms, namely *overdraft facilities*. At the expense of sample size and generalizability, we increase identification. The results in columns 1, 3, and 5 of Table G.1 show that our results also apply for this homogeneous product and a much smaller sample of firms that have such a product with at least two banks.

[11] In Table 4, we already included some variables at the firm-bank level (such as relationship length and the share of the bank in firm's credit) that might account for biases due to the firm-bank matching. Here, we provide further tests using a homogeneous product.

Subsequently, we add two other sets of fixed effects to this specification applied to this homogeneous product (overdraft facilities). Like Paligorova and Santos (2017); Altavilla et al. (2020); Schivardi et al. (2022), we include firm×bank fixed effects to control for non-random matching between firms and banks. In addition, we also include bank×industry×year fixed effects, to further strengthen identification (e.g., capturing bank-industry specific credit supply shocks, such as capital requirements due to concentration risk). Columns 2, 4, and 6 of Table G.1 show that the impact of specialization on credit supply to zombie firms is negative and significant (at the intensive margin) in a specification on a homogeneous product with fixed effects that control for bank-firm matching.

6.2. Aggregate effects

The baseline results come from an unweighted regression that gives equal weight to each observation. To account for the importance of each observation and get closer to the aggregate impact, we estimate weighted regressions (ceteris paribus) using the firm's total assets as weights. The coefficients of the interaction effect are slightly smaller but are still significantly different from zero.

The inclusion of firm×year fixed effects is common practice in studies that use credit register data as it allows separating demand and supply effects. However, it implies that we restrict the sample to multiple-bank firms. In the Belgian credit market, most borrowers have a single-bank relationship, which may cast doubt on the generalizability of the results. Following Degryse et al. (2019), we bin together single-bank firms in sets of firms that can be assumed to have similar credit demand. In particular, we create, for each year, triplets based on the firm's location, firm's industry, and zombie status. Using these location×industry×zombie×year fixed effects to control for single-bank borrowers' credit demand expands the sample with a factor of 2.5. Trading of identification with representativeness, we still find quantitatively and qualitatively similar results.

6.3. Measuring specialization

In Table G.3, we present results using alterations of the independent variable of interest *Bank Specialization*. In panel A, we use a dummy variable approach to measure specialization. The dummy takes the value of one if $Specialization_{bjt-1}$ is in the top decile of that industry j in year *t-1*, and zero otherwise. As in Berthou et al. (2021), we find that the 90% cutoff is akin to using the cutoff as in Paravisini et al. (2017). We find that our main results remain and even become larger in economic magnitude.

Second, specialization is a proxy for the industry-specific soft information that banks acquire. However, theoretically, a large exposure to an industry could be driven by a handful of large borrowers, limiting the scope of learning through repeated interaction with firms in a given industry. Therefore, we alternatively compute specialization based on the number of borrowers in an industry, rather than the volume lent to an industry. More specifically, in panel B, we compute specialization as the fraction of the number of borrowers a bank has in a given industry relative to the total number of borrowers a bank has in a given year. We obtain similar results, which is not surprising as this measure is strongly correlated with the baseline specification measure ($corr = 0.8$).

Third, using two-digit NACE codes might be too granular, and acquired information might be useful for making decisions in related industries (sharing the first digit). Measuring specialization in bank lending at the one-digit NACE level (16 industries) in panel C, we show again that our main findings are robust to this alteration. Fourth and finally, utilities (electricity, water supply, and waste collection) and commercial real estate play a central role as input for many other industries and may be more affected by state regulation or subsidies. As such, learning and knowledge acquisition may play a lesser role in credit allocation towards these firms. The results in panel D document that excluding these industries from the sample and recomputing the specialization measure also does not affect our main results.

6.4. Bank health and crisis periods

We are the first to focus on the role of information acquisition (through industry specialization) on the credit supply to zombie firms. Previous research mainly focused on bank health and bank crises as a crucial factor in heterogeneous lending decisions towards healthy, less productive, and zombie firms. For example, Albertazzi and Marchetti (2010) and Schivardi et al. (2022) document that undercapitalized banks in Italy were more likely to keep lending to low-quality borrowers during the financial crisis in 2008. Likewise, Giannetti and Simonov (2013) show that bank undercapitalization fosters lending to zombie firms in Japan. The rationale here is that banks that struggle to meet regulatory capital requirements will be less willing to recognize losses on bad loans.

Next to bank capital, also profitability (Bonfim et al., 2022) and bank size (Albertazzi and Marchetti, 2010) have been shown to affect zombie lending. As bank specialization might be correlated with bank capital, profitability, and size (see Beck et al., 2022), it is important to test whether bank specialization remains an important channel affecting zombie lending despite including an interaction with the other important drivers of zombie lending.

Similarly, the recovery from a (financial) crisis usually features an increasing share of zombies, a strategic reorientation by banks, and a credit contraction. It is thus important to verify whether our results are time-varying and episode-specific. We use a fairly long time period to make the results as general as possible, but are able to analyze whether there is a differential impact in (i) the period prior to the global financial crisis (2004-2007), (ii) the period spanning the global financial crisis and the sovereign debt crisis (2008-2013), and (iii) the post-crisis period (2014-2018).

Including interactions of the zombie dummy with various bank characteristics and triple interactions between bank specialization, zombie status, and (post-)crisis period dummies leave the coefficients of interest largely unaffected. If anything, we even notice an economically larger effect.

6.5. Clustering of standard errors

The baseline results come from clustering standard errors at the bank-industry level, and thus at the cross of banks and industries. A potential issue is that observations within the same industry across banks are likely related to each other. To address this issue, we re-estimate the baseline equation (1) and double-cluster standard errors at the industry and bank levels.

Table G.5 presents the results of the estimation using this double clustering of standard errors. The standard errors (and hence significance of the point estimates) differ little from those presented in Table 2.

6.6. Subsidized zombie credit

The results presented in Table 1 suggest that zombie firms pay a higher interest rate than healthy, higher-quality firms. This is in line with the theoretical and empirical evidence from, respectively, Faria-e-Castro et al. (2021) and Favara et al. (2021), but different from Caballero et al. (2008) and Acharya et al. (2019) who rely on a strong concept of subsidized credit to identify zombie firms. However, as argued above, we believe that our interest rate results are still consistent with a weaker concept of subsidized credit, whereby zombie firms pay an interest rate that is higher than healthy firms, but lower than what would be justified by their default probability.

Nonetheless, we show that our main results hold even when we use alternative zombie definitions. First, we take our preferred zombie definition and split zombie firms defined by our definition into two equal groups based on the median value of the (implicit) interest rate paid by the zombies. This way we assume that it is more likely that zombie firms with the cost of debt below the median level are benefiting from subsidized credit. We then re-estimate our baseline model (1) and compare the two groups of zombie borrowers with the healthy borrowers. Estimates presented in Table G.6 suggest that the negative relationship between bank specialization and zombie lending is equally strong for all zombie companies no matter the cost of debt.

Second, we follow Acharya et al. (2019, 2020) and compute an alternative zombie definition. According to this approach, a firm needs to satisfy two conditions in order to be considered a zombie. The first one is that it needs to be a low-quality firm (BB-rated or worse), which is defined as a firm whose interest coverage ratio (ICR = EBIT/Interest Expenses) is below 3.5. The second condition states that the firm needs to pay an interest rate that is below the interest rate paid by the best firms in the economy (AA-rated or better), and hence enjoys subsidized credit. These best firms are defined as firms whose ICR equals or exceeds 9.5; and the benchmark interest rate is computed at the industry-year level.

We then use this alternative zombie definition to re-estimate baseline model (1) and present the results in Table G.7. As one can see, the point estimates for the effect of bank specialization on zombie lending are also negative with this zombie definition. At the intensive margin, the relationship becomes statistically insignificant (although with a p-value of 0.102 for the effect on $\Delta Ln(Credit)$), but at the extensive margin it remains strongly statistically significant. The results of this robustness test thus confirm that the relationship between bank industry specialization and zombie lending holds when using alternative zombie definitions.

7. Conclusion

This paper contributes to the discussion of zombie congestion and zombie lending using loan-level data for the universe of firms and banks in Belgium between 2004 and 2018. We develop a new approach to identify zombie firms and uncover a previously unexplored determinant of zombie lending, namely bank specialization.

Overall, our findings convey two interesting and important messages. First of all, the choice of how zombie firms are identified is important, as it may lead to substantial differences in the estimated zombie population, both in terms of the number of zombie firms and the quality of zombie firms. Compared to the widely-used OECD definition (McGowan et al., 2018), our approach identifies much fewer firms as zombies (3.4% of the population instead of 10.4%) and they are of much lower quality than healthy firms. Nonetheless, despite documenting that there are relatively fewer zombie firms in Belgium than what other studies have found, we find that i) some industries have significant, above average amounts of zombie firms; and ii) having more resources stuck in zombie firms still exerts negative externalities onto healthy firms.

Secondly, we provide evidence on the effect that bank industry specialization has on zombie lending. We show that bank specialization is associated with lower and even reduced credit supply to zombie borrowers. Banks that are specialized in lending to a certain industry have gained an information advantage that makes them more aware of zombie firms in the industry as well as more knowledgeable about the negative impact that zombie firms have on healthy borrowers.

Our analysis shows that this information channel is indeed industry-specific and different from borrower-specific hard or soft information. Moreover, specialized banks reduce zombie lending even more when the scope and opportunity cost of negative externalities on healthy borrowers is larger; namely, when the fraction of industry labor stuck in zombie firms is larger or when the industry is expected to grow faster. Additionally, specialized banks reduce zombie lending more in industries with low asset specificity than with high specificity. In industries with high asset specificity, it is relatively more likely that a zombie firms' default would lead to its assets being sold at a significant discount and hence more likely to contaminate the value of healthy borrowers' collateral.

Our results imply that bank specialization can benefit financial stability as it reduces zombie lending. As such, it not only improves the quality of the bank's lending portfolio by increasing the relative share of credit going to healthy borrowers, it also improves the business climate for the healthy borrowers who then compete with fewer or smaller zombie firms. Our study, however, does not claim that a lending specialization of 100% should be preferred for banks as we only provide a partial analysis rather than a general equilibrium approach. Our results merely show that there are also benefits to divert from a full diversification.

Our findings are particularly relevant in the current turbulent times. The COVID-19 pandemic as well as the rise in energy and commodity prices put severe strain on the liquidity of various corporation. In such circumstances, an increase in non-performing loans (NPLs) can be expected. However, it is important to differentiate between viable, yet illiquid firms and zombie firms. Therefore, banks' expertise and screening abilities become especially important to identify truly viable firms and negotiate the term of debt restructuring in a way that supports the economic recovery.

Finally, while 'killing' zombie firms would improve resource allocation and bring about productivity gains, this should likely not happen overnight (Schivardi et al., 2022). Despite the economic gains that will follow in the long run when zombie firms exit the market, a sudden closure of multiple enterprises may have a negative effect on the economy. Firstly, it may cause capital destruction and negative spillovers to firms both within and outside the economic industry, where a mass shut-down is happening. Sudden mass closure of businesses may lead to fire sales (e.g., Shleifer and Vishny, 1992) of assets and collateral below the fair prices, which drives down the collateral value of other firms in the industry and exacerbates their financial constraints (Kiyotaki and Moore, 1997). Additionally, fire sales harm firms' creditors (Acharya et al., 2007) and may have a negative spillover to other industries via the supply chain channel (e.g., Giannetti and Saidi, 2019). Moreover, the costs of worker displacement should be taken into account as discussed by Andrews and Saia (2016). A large and sudden business shut-down may increase unemployment. Hence, banks and policymakers need to take the economic side effects into account when developing a strategy to reduce the population of zombie firms.

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Appendix A. Definitions of Variables

Table A.1: Variable definitions

Credit Variables	
New Loan	A dummy = 1 if authorized credit L_{bft} granted by bank b to firm f in year t exceeds the authorized credit amount in year *t-1* and 0 otherwise, multiplied by 100.
ΔLn(Credit)	$= Ln(L_{bft}) - Ln(L_{bft-1})$, multiplied by 100
$\frac{\Delta \text{Credit}}{\text{Assets}}$	$= \frac{L_{bft} - L_{bft-1}}{TotalAssets_{ft-1}}$, multiplied by 100
Bank-Industry Variables	
Specialization	$= \frac{\sum_{f=1}^{F} L_{bfst}}{\sum_{s=1}^{S}\sum_{f=1}^{F} L_{bfst}}$, the fraction of bank's b credit L_{bfst} granted to all firms in industry s in year t in the bank's total credit granted to all industries in that year.
Market Share	$= \frac{\sum_{f=1}^{F} L_{bfst}}{\sum_{b=1}^{B}\sum_{f=1}^{F} L_{bfst}}$, the fraction of bank's b credit L_{bfst} granted to all firms in industry s in year t in the total credit granted to that industry by all banks.
Industry Variables	
Z^{Credit} Share	$= \frac{\sum_{f=1}^{F} \text{Credit}_{fs} \mid Z=1}{\sum_{f=1}^{F} \text{Credit}_{fs}}$, the fraction of credit granted to zombie borrowers in the total amount of credit granted to all firms in industry s.
Industry Growth	Median turnover[12] growth of firms operating in an industry in year *t+1*.
Z^{Labor} Share	$= \frac{\sum_{f=1}^{F} \text{FTE}_{fs} \mid Z=1}{\sum_{f=1}^{F} \text{FTE}_{fs}}$, the fraction of labor force (FTEs) sunk in zombie borrowers in the total number of FTEs employed by all firms in industry s.
Specificity	$= \frac{\sum_{f=1}^{F} Machinery_{fs}}{\sum_{f=1}^{F} Assets_{fs}}$, the share of total machinery and equipment in total assets in industry s.

[12] Small and medium-sized enterprises do not have to report the turnover figures in the income statement. Therefore, we draw the turnover data from monthly VAT filings.

Variable definitions: continued

Firm Variables	
Equity/Assets	Firm's leverage ratio
Negative Equity	A dummy = 1 if firm's equity is negative and 0 otherwise
EBITDA/Assets	Return on Assets
Altman Z	$= 0.717 \times \frac{WorkingCapital}{TotalAssets} + 0.847 \times \frac{RetainedIncome}{TotalAssets} +$ $3.107 \times \frac{EBIT}{TotalAssets} + 0.42 \times \frac{Equity}{Debt} + 0.998 \times \frac{GrossMargin}{TotalAssets}$
TangAssets Growth	Current growth of fixed tangible assets (TangA): $Growth_t = (TangA_t - TangA_{t-1})/(0.5 \times (TangA_t + TangA_{t-1}))$
Employment Growth	Contemporaneous growth of FTE
Sales Growth	Contemporaneous growth of turnover
Future Sales Growth	Future growth of turnover (Sales): $Growth_t = (Sales_{t+1} - Sales_t)/(0.5 \times (Sales_{t+1} + Sales_t))$
Cost of Debt	Interest Expenses/Total Financial Debt
Z	A dummy = 1 if a firm is identified as a zombie according to the our zombie definition described in section 3 and 0 otherwise
Healthy	A dummy = 1 if a firm a firm is *not* identified as a zombie according to the adjusted zombie definition and 0 otherwise
Ln(Assets)	Logarithm of firm's total assets
Current Ratio	= Current Assets/Current Liabilities
Age	Number of years since firm's year of incorporation
Bank-Firm Variables	
Firm Share	$= \frac{L_{bft-1}}{\sum_{f=1}^{F} L_{bft-1}}$, the fraction credit granted by bank b to firm f relative to the total credit granted by the bank to all firms.
Ln(Relationship)	Logarithm of the number of months since the first time firm f obtained a loan from bank b.
Bank's Share in Firm Credit	$= \frac{L_{bft-1}}{\sum_{b=1}^{B} L_{bft-1}}$, the fraction credit granted by bank b to firm f relative to the total credit granted to that firm by all banks.
Bank Variables	
Ln(Assets)	Logarithm of bank total assets
Capital Ratio	Common Equity/Total assets
Liquidity Ratio	(Cash + Interbank Assets)/Total assets
ROE	Return on Equity = Net income/Common Equity

Appendix B. Summary Statistics

Appendix B.1. Summary statistics of the main sample

Table B.1: Summary statistics

This table presents summary statistics of the variables used the analysis presented in section 4 onward. The sample includes yearly bank-firm level data between 2004 and 2018. The sample includes firms borrowing from more than one bank.

	N	Mean	SD	p1	p25	p50	p75	p99
Credit Variables								
New Loan	614320	25.61	43.65	0.00	0.00	0.00	100.00	100.00
ΔLn(Credit)	614320	-1.91	36.89	-92.95	-15.90	-3.17	0.50	119.46
ΔCredit/Assets	614320	0.04	6.79	-19.58	-2.25	-0.32	0.05	28.49
Bank-Industry Variables								
Specialization	614320	0.07	0.08	0.00	0.01	0.04	0.10	0.27
Market Share	614320	0.20	0.10	0.00	0.13	0.22	0.27	0.40
Industry Variables								
Industry Growth	614320	0.03	0.03	-0.08	0.01	0.03	0.04	0.10
Z^{Labor} Share	614320	0.04	0.03	0.00	0.02	0.04	0.05	0.14
Specificity	614320	0.04	0.03	0.00	0.02	0.03	0.05	0.14
Firm Variables								
Zombie	614320	0.03	0.18	0.00	0.00	0.00	0.00	1.00
Ln(Assets)	614192	14.46	1.09	12.53	13.62	14.32	15.20	16.72
Equity/Assets	614192	0.29	0.21	-0.19	0.14	0.26	0.42	0.83
EBITDA/Assets	614192	0.13	0.10	-0.07	0.07	0.12	0.18	0.43
Current Ratio	614192	1.54	1.36	0.03	0.88	1.23	1.75	8.22
Age	614192	20.27	11.47	2.00	11.00	19.00	28.00	47.00
Bank-Firm Variables								
Firm Share	614320	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Ln(Relationship)	614320	4.26	1.01	0.69	3.83	4.51	4.98	5.48
Bank's Share in Firm Credit	614320	0.45	0.27	0.02	0.21	0.42	0.67	0.97
Bank Variables								
Ln(Assets)	611151	11.50	1.43	6.30	11.66	11.95	12.21	13.20
Capital Ratio	611151	0.05	0.03	0.01	0.04	0.05	0.07	0.10
Liquidity Ratio	611151	0.16	0.08	0.02	0.10	0.15	0.19	0.36
ROE	611151	0.08	0.18	-1.01	0.06	0.11	0.14	0.33

Appendix B.2. Summary statistics of the firm-year sample

Table B.2: Summary statistics

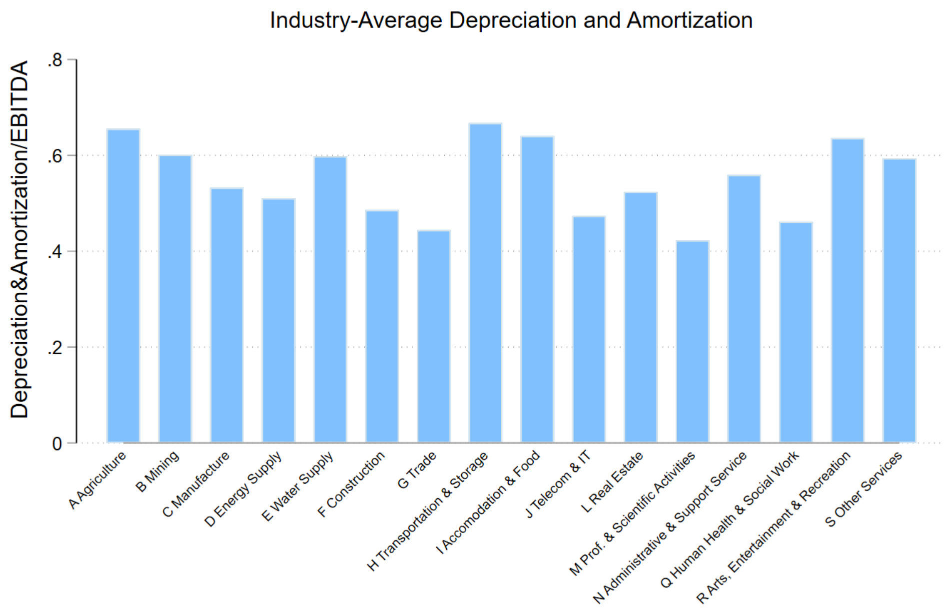
This table presents summary statistics of the variables used the analysis presented in section 3.2 and Appendix E. The sample includes yearly data of firms borrowing from more than one bank between 2004 and 2018.

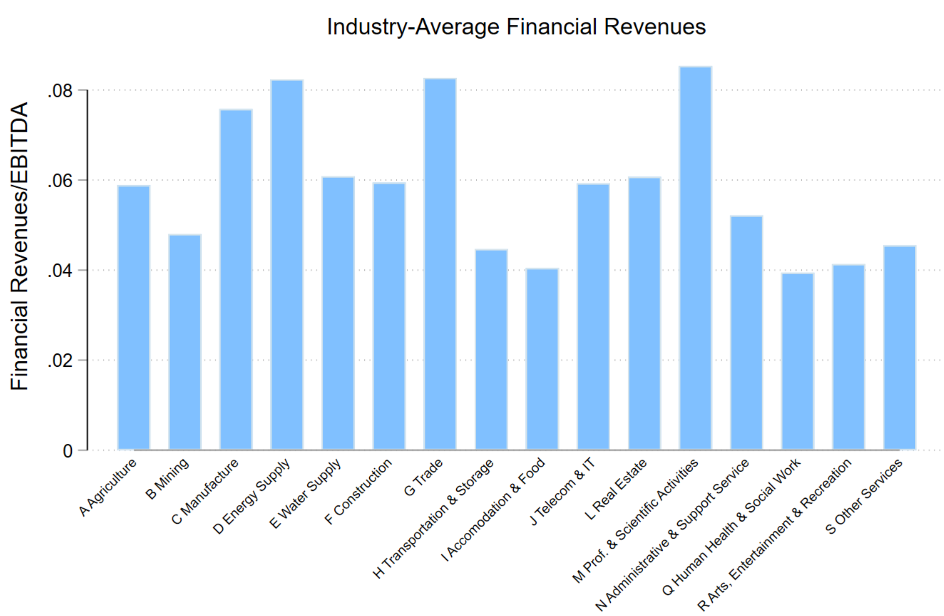
	N	Mean	SD	p1	p25	p50	p75	p99
Dependent Variables in Tables 1 and E.1								
Equity/Assets	275121	29.63	21.91	-23.45	14.14	26.97	43.48	83.23
Negative Equity	275121	4.95	21.69	0.00	0.00	0.00	0.00	100.00
EBITDA/Assets	275121	13.28	9.68	-8.22	6.92	11.70	18.29	42.14
Altman Z	275121	0.89	0.82	-0.93	0.37	0.76	1.27	3.76
TangAssets Growth	275121	1.49	33.60	-83.53	-12.25	-4.04	9.23	127.85
Employment Growth	275121	1.09	15.32	-46.58	-2.33	0.00	5.41	43.90
Sales Growth	243691	1.93	28.13	-104.53	-7.68	2.91	13.80	76.71
Future Sales Growth	231917	0.11	29.28	-113.43	-8.68	2.20	12.67	74.83
Cost of Debt	265234	8.44	9.40	1.27	4.24	5.91	8.80	55.19
Controls Variables in Table E.1								
Healthy	275121	0.97	0.18	0.00	1.00	1.00	1.00	1.00
Z^{Credit} Share	275121	0.04	0.03	0.00	0.02	0.04	0.05	0.11
Equity/Assets	275121	0.29	0.20	-0.10	0.14	0.26	0.42	0.76
EBITDA/Assets	275121	0.13	0.09	-0.05	0.07	0.12	0.18	0.37
Ln(Assets)	275121	14.40	1.09	12.68	13.57	14.24	15.08	17.05
Age	275121	20.09	11.70	3.00	11.00	18.00	27.00	49.00

Appendix C. Share of Depreciation and Amortization and Recurring Financial Income in EBITDA

Figure C.1: Share of depreciation and amortization and financial income in EBITDA

The figures below plot the share of depreciation and amortization in EBITDA (upper graph) and the share of recurring financial revenue in EBITDA (lower graph) for various economic industries defined at the first digit of the NACE classification. The reported shares are time-average values. The sample includes yearly data of firms borrowing from more than one bank between 2004 and 2018.

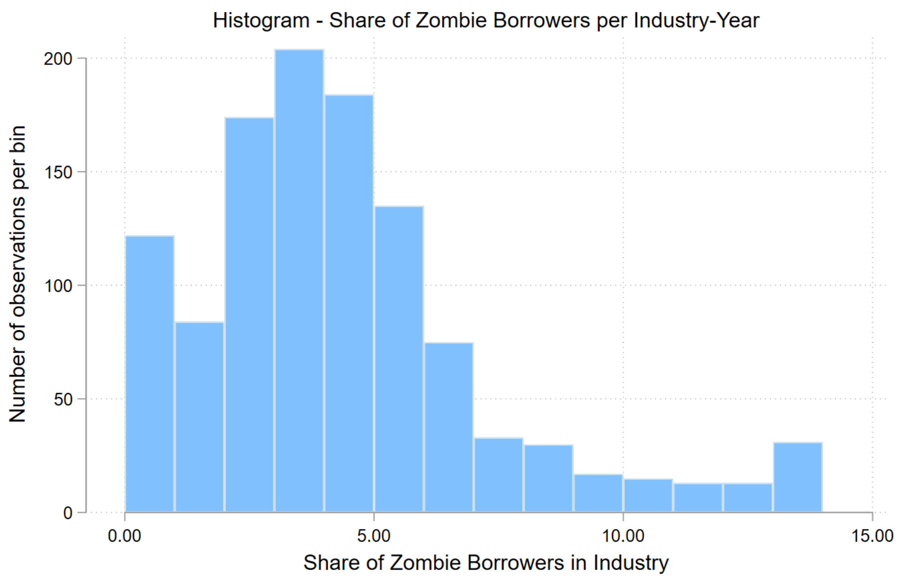


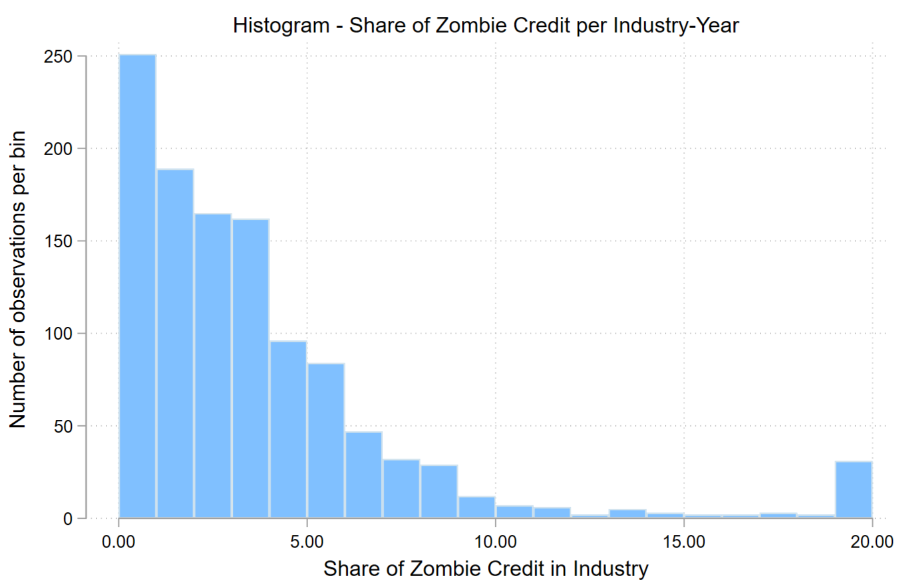


Appendix D. Shares of Zombie Borrowers and Zombie Credit per Industry

Figure D.1: Zombie shares per industry

The plots below present distributional information on the shares of zombie borrowers (upper graph) and shares of zombie credit (lower graph). We compute these two shares for every industry (defined at the two-digit NACE classification) and every year in the sample (i.e., 2004-2018). The histogram shows on the X-axis the shares (binned in ranges of 1%) and on the Y-axis the number of industry-year combinations in that specific bin. Large values in the right tail have been binned together for clarity of presentation.





Appendix E. Zombie Congestion

Prior research shows a robust, negative relationship between the growth of healthy firms and the share of zombie firms in their industry (see, e.g., Caballero et al. (2008) who show this for Japan and McGowan et al. (2018) who document it for EU firms). However, Schivardi et al. (2020) document a serious, and difficult to solve, identification problem and even conclude that the correlation between healthy firm performance and zombie presence might be mechanical and biased. Solving this identification problem is not the purpose of the paper, but we nevertheless present empirical evidence of zombie congestion in our sample of Belgian firms. The results below present correlations and not causal evidence. Moreover, as the direction and magnitude of the bias are unclear and context-specific (Schivardi et al., 2020), we refrain from assessing the economic magnitude of the coefficients.

Table E.1 contains the results of estimating the following specification with the firm-year level data:

$$y_{it} = \beta_1 Healthy_{it} + \beta_2 Healthy_{it} \times Z^{Credit}\, Share_{jt-1} + \gamma\, X_{it-1} + \nu_{jt} + \upsilon_{st} + \epsilon_{ijt} \tag{E.1}$$

Where y_{it} is either growth of tangible fixed assets, employment, current sales, or future sales. The coefficient of interest is β_2, which is the interaction between a healthy firm dummy and the share of zombie credit in an industry. To be precise, *Healthy* is a dummy equal to 1 if a firm is not identified as a zombie, and 0 otherwise. Z^{Credit} *Share* is the share of credit sunk in zombie firms in industry j in a given year[13]. If a higher level of industry credit granted to zombie firms harms the growth of healthy borrowers operating in the same industry, the coefficient β_2 is expected to be negative.

The results of the estimation[14] are presented in Table E.1. Healthy borrowers exhibit higher growth in tangible assets, employment as well as current and future sales. However, the growth of healthy borrowers will be smaller if they operate in industries where a larger fraction of credit is granted to zombie firms. The

[13]Importantly, there is substantial variation in the share of zombie borrowers and zombie credit across years and industries as can be seen in the histogram plot in Figure D.1. While the share of zombie credit in most industries is relatively low, certain industries suffer from more severe credit misallocation. For example, the industries of the mining support service activities (NACE code 09), manufacture of motor vehicles (NACE code 29), waste collection (NACE code 38), and air transport (NACE code 51) are representing the right tail of the histogram.

[14]Firm-level controls include firm age, leverage, profitability, and total assets. Industry-year and firm location-year fixed effects absorb all observed and unobserved time-varying impacts of industry-specific and locational characteristics such as product and credit demand.

effects are statistically significant in three of the four columns. For reasons mentioned above, we mainly see this as suggestive evidence of zombie congestion as well as an exercise to show consistency (with prior research) in the Belgian context and using our zombie definition.

Table E.1: Effect of zombie congestion on growth

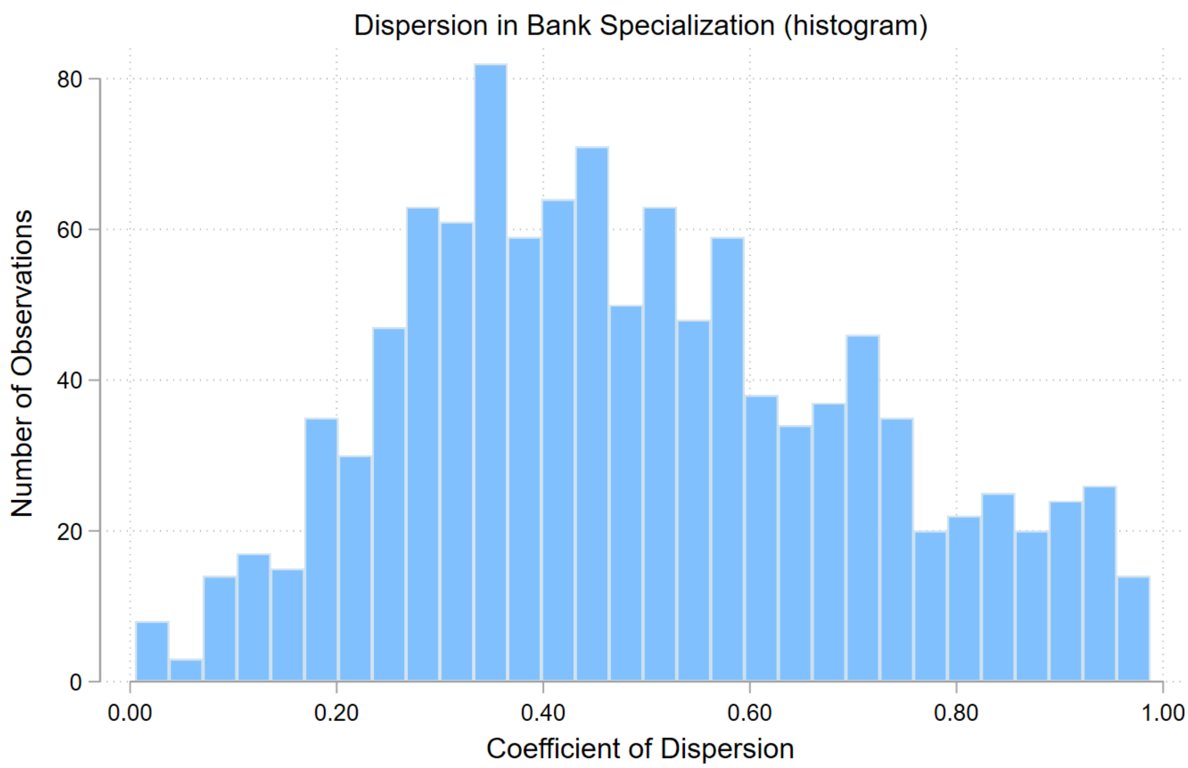
This table shows the relative effect of the share of credit granted to zombie firms (Z^{Credit} *Share*) on the growth of the healthy (*Healthy*) firms relative to zombie firms operating in the same industry. The dependent variables are contemporaneous growth of tangible assets (Column 1), employment (Column 2), sales (Column 3) in period t, and future growth of sales in period $t+1$ (Column 4). The independent variables of interest are the healthy firm indicator, which equals 1 if a firm is identified as a non-zombie and 0 otherwise, and the interaction term between the dummy for healthy firms and the share of credit granted to zombie borrowers in a given industry. Firm control variables include the leverage ratio, return on assets, the logarithm of total assets, and firm age in years. The sample includes yearly data of firms borrowing from more than one bank between 2004 and 2018. Industry-year and location-year fixed effects absorb time-varying industry- or location-specific differences in the dependent variables. Industries are defined at the two-digit NACE level. Location is defined at the two-digit postcode level. Continuous independent variables are standardized. Standard errors are clustered at the industry-year level. ***, ** and * denote p<0.01, p<0.05, and p<0.1, respectively.

	(1) TangAssets Growth	(2) Employment Growth	(3) Sales Growth	(4) Future Sales Growth
Healthy	5.74***	4.46***	11.73***	5.78***
	(0.47)	(0.21)	(0.47)	(0.56)
Healthy×Z^{Credit} Share	-0.55	-0.71***	-1.12**	-1.30**
	(0.38)	(0.22)	(0.48)	(0.57)
Control Variables				
Equity/Assets	1.34***	-0.33***	-0.58***	0.14**
	(0.09)	(0.03)	(0.07)	(0.07)
EBITDA/Assets	2.03***	1.55***	-0.61***	1.41***
	(0.09)	(0.05)	(0.10)	(0.07)
Ln(Assets)	0.12	0.81***	0.64***	0.51***
	(0.08)	(0.04)	(0.08)	(0.08)
Age	-1.53***	-1.31***	-1.45***	-0.88***
	(0.08)	(0.04)	(0.07)	(0.07)
Observations	275,121	275,121	243,691	231917
R-squared	0.02	0.04	0.04	0.03
N. of clusters	1087	1087	1080	1078
Industry×Year FE	Yes	Yes	Yes	Yes
Location×Year FE	Yes	Yes	Yes	Yes

Appendix F. Distribution of Bank Specialization

Figure F.1: Bank specialization: histogram of coefficient of variation

This plot presents distributional information on within industry dispersion in bank specialization. For each industry and each year, we compute a modified quartile coefficient of dispersion*, as the ratio of the difference and the sum of the 90th and 50th percentile of bank specialization. The larger the coefficient of dispersion, the larger the within industry differences in bank specialization, and thus the larger the scope for informational advantages for the specialized banks. We compute this coefficient of dispersion for every industry (defined at the two-digit NACE classification) and every year in the sample (i.e., 2004-2018). The histogram shows on the X-axis bins of this coefficient of dispersion and on the Y-axis the number of industry-year combinations in that specific bin.



* The quartile coefficient of dispersion is usually computed based on the 75th and 25th percentile. Compared with the coefficient of variation, it is a robust measure of scale as it is not affected by outliers. We modify the percentiles to document the scope for information advantages of the most specialized banks in an industry.

Appendix G. Robustness Tests

Appendix G.1. Robustness of the baseline results: firm-bank matching and credit demand

Table G.1: Robustness: firm-bank matching and credit demand

This table shows the effect of bank specialization on the credit growth of healthy firms and zombies for a standardized and homogeneous credit contract. In particular, we only consider one credit product, namely overdraft facilities. The dependent variables are a dummy variable that equals 1 if the outstanding credit amount increases and 0 otherwise (Column 1), the logarithmic difference between the outstanding credit amount in year *t* and year *t-1* (Column 2), and absolute change in the outstanding credit amount scaled to the borrower's total assets (Column 3). The independent variables are bank specialization and the interaction between bank specialization and a dummy indicator for zombie firms. The sample includes yearly bank-firm level data between 2004 and 2018. The sample includes firms borrowing from more than one bank. In all specifications, we control for firm demand and bank-specific effects using firm-year and bank-year fixed effects, respectively. Additionally, specifications in Columns 2, 4 and 6 include bank-firm and bank-industry-year fixed effects. Bank specialization has been standardized. Standard errors are clustered at the bank-industry level. ***, ** and * denote p<0.01, p<0.05, and p<0.1, respectively.

	(1) New Loan	(2) New Loan	(3) ΔLn(Credit)	(4) ΔLn(Credit)	(5) $\frac{\Delta \text{Credit}}{\text{Assets}}$	(6) $\frac{\Delta \text{Credit}}{\text{Assets}}$
Specialization	1.96***		1.35***		0.09***	
	(0.48)		(0.33)		(0.02)	
Z×Specialization	-1.74***	-0.23	-1.73***	-1.24**	-0.21***	-0.11*
	(0.53)	(0.89)	(0.49)	(0.55)	(0.04)	(0.06)
Observations	112,973	102,570	112,973	102,570	112,973	102,570
R-squared	0.53	0.68	0.54	0.67	0.52	0.65
N. of clusters	875	456	875	456	875	456
Firm×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank×Firm FE		Yes		Yes		Yes
Bank×Industry×Year FE		Yes		Yes		Yes

Appendix G.2. Robustness of the baseline results: aggregate effects

Table G.2: Robustness: aggregate effects

This table shows the effect of bank specialization on the credit growth of healthy firms and zombies. The dependent variables are a dummy variable that equals 1 if the outstanding credit amount increases and 0 otherwise (Column 1), the logarithmic difference between the outstanding credit amount in year *t* and year *t-1* (Column 2), and absolute change in the outstanding credit amount scaled to the borrower's total assets (Column 3). The independent variables are bank specialization and the interaction between the bank specialization and a dummy indicator for zombie firms. The sample includes yearly bank-firm level data between 2004 and 2018. We present two approaches to get at aggregate effects. In Panel A, the sample includes firms borrowing from more than one bank. We run a weighted regression with weights linked to each firm's total assets. In this panel, we control for firm demand and bank-specific effects using firm-year and bank-year fixed effects, respectively. In Panel B, the sample includes all borrowing firms regardless of the number of bank relationships. In this panel, we control for firm demand and bank-specific effects using industry-location-zombie-year and bank-year fixed effects, respectively. In both panels, bank specialization has been standardized. Standard errors are clustered at the bank-industry level. ***, ** and * denote p<0.01, p<0.05, and p<0.1, respectively.

	(1) New Loan	(2) ΔLn(Credit)	(3) $\frac{\Delta \text{Credit}}{\text{Assets}}$
Panel A: baseline specification – weighted regression			
Specialization	1.79***	0.13	0.06*
	(0.35)	(0.29)	(0.03)
Z×Specialization	-1.36***	-0.57*	-0.30***
	(0.42)	(0.30)	(0.08)
Observations	614,320	614,320	614,320
R-squared	0.47	0.45	0.46
N. of clusters	1774	1774	1774
Firm×Year FE	Yes	Yes	Yes
Bank×Year FE	Yes	Yes	Yes
Panel B: full sample – firm-cluster fixed effects			
Specialization	1.60***	0.42***	0.16***
	(0.19)	(0.13)	(0.03)
Z×Specialization	-1.01***	-0.36**	-0.19***
	(0.23)	(0.18)	(0.06)
Observations	1,568,563	1,568,563	1,568,563
R-squared	0.24	0.22	0.17
N. of clusters	2017	2017	2017
ILZ×Year FE	Yes	Yes	Yes
Bank×Year FE	Yes	Yes	Yes

Appendix G.3. Robustness of the baseline results: alternative specialization measures

Table G.3: Robustness: alternative specialization measures

This table shows the effect of bank specialization on the credit growth of healthy firms and zombies. The dependent variables are a dummy variable that equals 1 if the outstanding credit amount increases and 0 otherwise (Column 1), the logarithmic difference between the outstanding credit amount in year *t* and year *t-1* (Column 2), and absolute change in the outstanding credit amount scaled to the borrower's total assets (Column 3). The independent variables are various measures of bank specialization and the interaction between the bank specialization and a dummy indicator for zombie firms. We show the robustness of the results with respect to the construction of the specialization measure. In Panel A, we measure specialization as a dummy variable that takes the value of one if $Specialization_{bjt-1}$ is in the top decile of that industry j in year *t-1*, and zero otherwise. In Panel B, we compute specialization as the fraction of the number of borrowers a bank has in a given industry relative to the total number of borrowers a bank has in a given year. In Panel C, we measure volume-based specialization at the one-digit NACE level. In Panel D, we exclude electricity, water supply, waste collection, and commercial real estate from the sample and re-compute our baseline measure of bank specialization. The sample includes yearly bank-firm level data between 2004 and 2018. The sample includes firms borrowing from more than one bank. We control for firm demand and bank-specific effects using firm-year and bank-year fixed effects, respectively. Bank specialization has been standardized. Standard errors are clustered at the bank-industry level. ***, ** and * denote p<0.01, p<0.05, and p<0.1, respectively.

	(1) New Loan	(2) ΔLn(Credit)	(3) $\frac{\Delta \text{Credit}}{\text{Assets}}$
Panel A: baseline specification – upper decile of specialization			
Specialization (top decile)	2.22***	0.86**	0.18**
	(0.71)	(0.42)	(0.08)
Z×Specialization (top decile)	-4.14**	-2.59*	-0.57*
	(1.63)	(1.39)	(0.33)
Observations	614,320	614,320	614,320
R-squared	0.47	0.45	0.46
Panel B: baseline specification – relative specialization			
Specialization (#borrowers)	2.07***	0.85***	0.14***
	(0.46)	(0.24)	(0.05)
Z×Specialization (#borrowers)	-1.12***	-0.79***	-0.30***
	(0.24)	(0.21)	(0.09)
Observations	614,320	614,320	614,320
R-squared	0.47	0.45	0.46
Panel C: baseline specification – NACE 1-digit level			
Specialization (NACE - 1 digit)	1.45***	0.62***	0.11***
	(0.39)	(0.20)	(0.04)
Z×Specialization (NACE - 1 digit)	-1.77***	-1.11***	-0.40***
	(0.45)	(0.32)	(0.11)
Observations	614,320	614,320	614,320
R-squared	0.47	0.45	0.46
Panel D: baseline specification – excluding utilities and real estate			
Specialization (excluding utilities)	2.17***	0.62***	0.14***
	(0.41)	(0.23)	(0.04)
Z×Specialization (excluding utilities)	-1.37***	-0.69***	-0.31***
	(0.29)	(0.24)	(0.10)
Observations	557,621	557,621	557,621
R-squared	0.47	0.45	0.46

Appendix G.4. Robustness of the baseline results: bank health and crisis periods

Table G.4: Robustness: bank health and crisis periods

This table shows the effect of bank specialization on the credit growth of healthy firms and zombies. The dependent variables are a dummy variable that equals 1 if the outstanding credit amount increases and 0 otherwise (Column 1), the logarithmic difference between the outstanding credit amount in year *t* and year *t-1* (Column 2), and absolute change in the outstanding credit amount scaled to the borrower's total assets (Column 3). The independent variables are bank specialization, the interaction between the bank specialization and a dummy indicator for zombie firms, the interactions between a dummy indicator for zombie firms and bank-health variables, and the interactions between bank specialization, a dummy indicator for zombie firms, and dummy indicators for time periods. Bank-health variables include bank total assets, common capital ratio, liquidity ratio, and return on equity. We include two dummy indicators for time periods. The first one captures the crises episodes and equals 1 for years between 2008 and 2013 and 0 otherwise. The second one captures the post-crisis period and equals 1 for years between 2014 and 2018 and 0 otherwise. The sample includes yearly bank-firm level data between 2004 and 2018. The sample includes firms borrowing from more than one bank. We control for firm demand and bank-specific effects using firm-year and bank-year fixed effects, respectively. Bank specialization and bank-health variables have been standardized. Standard errors are clustered at the bank-industry level. ***, ** and * denote p<0.01, p<0.05, and p<0.1, respectively.

	(1) New Loan	(2) ΔLn(Credit)	(3) $\frac{\Delta \text{Credit}}{\text{Assets}}$
Specialization	2.44***	0.81**	0.14**
	(0.54)	(0.36)	(0.07)
Z×Specialization	-1.34**	-1.87***	-0.54***
	(0.53)	(0.45)	(0.08)
Bank variables			
Z×Ln(Assets)	-1.36***	-1.40***	-0.16**
	(0.42)	(0.36)	(0.07)
Z×Capital Ratio	0.07	0.00	0.03
	(0.41)	(0.33)	(0.07)
Z×Liquidity Ratio	0.88**	0.34	0.10*
	(0.36)	(0.29)	(0.06)
Z×ROE	-0.40	0.45*	0.08
	(0.36)	(0.27)	(0.06)
Time blocks			
Specialization×$\text{Years}_{2008-2013}$	-0.76	0.47	0.02
	(0.71)	(0.54)	(0.09)
Specialization×$\text{Years}_{2014-2018}$	-0.22	-1.00**	-0.07
	(0.92)	(0.43)	(0.11)
Z×Specialization×$\text{Years}_{2008-2013}$	-0.89	0.93	0.24*
	(0.67)	(0.66)	(0.14)
Z×Specialization×$\text{Years}_{2014-2018}$	-1.71	0.57	0.11
	(1.10)	(0.84)	(0.20)
Observations	611,151	611,151	611,151
R-squared	0.47	0.45	0.46
N. of clusters	1768	1768	1768
Firm×Year FE	Yes	Yes	Yes
Bank×Year FE	Yes	Yes	Yes

Appendix G.5. Robustness of the baseline results: double clustering of standard errors

Table G.5: Average effect of bank specialization on zombie lending

This table shows the effect of bank specialization on the credit growth of healthy firms and zombies. The dependent variables are a dummy variable that equals 1 if the outstanding credit amount increases and 0 otherwise (Column 1), the logarithmic difference between the outstanding credit amount in year *t* and year *t-1* (Column 2), and absolute change in the outstanding credit amount scaled to the borrower's total assets (Column 3). The independent variables are bank specialization and the interaction between bank specialization and a dummy indicator for zombie firms. The sample includes yearly bank-firm level data between 2004 and 2018. The sample includes firms borrowing from more than one bank. We control for firm demand and bank-specific effects using firm-year and bank-year fixed effects, respectively. Bank specialization has been standardized. Standard errors are double-clustered at the bank and industry level. ***, ** and * denote p<0.01, p<0.05, and p<0.1, respectively.

	(1) New Loan	(2) ΔLn(Credit)	(3) $\frac{\Delta \text{Credit}}{\text{Assets}}$
Specialization	2.01***	0.51**	0.11**
	(0.59)	(0.25)	(0.05)
Z×Specialization	-1.53***	-0.85***	-0.34***
	(0.34)	(0.18)	(0.05)
Observations	614,320	614,320	614,320
R-squared	0.47	0.45	0.46
N. of industries	77	77	77
N. of banks	54	54	54
Firm×Year FE	Yes	Yes	Yes
Bank×Year FE	Yes	Yes	Yes

Appendix G.6. Robustness of the baseline results: subsidized zombie borrowers

Table G.6: Average effect of bank specialization on zombie lending: (non-)subsidized zombie borrowers

This table shows the effect of bank specialization on the credit growth of healthy firms, non-subsidized zombies, and subsidized zombies. The dependent variables are a dummy variable that equals 1 if the outstanding credit amount increases and 0 otherwise (Column 1), the logarithmic difference between the outstanding credit amount in year *t* and year *t-1* (Column 2), and absolute change in the outstanding credit amount scaled to the borrower's total assets (Column 3). The independent variables are bank specialization and the interactions between bank specialization and two dummy indicators. First, an indicator for non-subsidized zombies, which equals 1 if a firm is identified as a zombie to our definition and if its cost of financial debt exceeds the median cost of financial debt paid by zombie firms, and 0 otherwise. Second, an indicator for subsidized zombie firms, which equals 1 if a firm is identified as a zombie according to our definition and if its cost of financial debt is below the median cost of financial debt paid by zombie firms, 0 otherwise. The sample includes yearly bank-firm level data between 2004 and 2018. The sample includes firms borrowing from more than one bank. We control for firm demand and bank-specific effects using firm-year and bank-year fixed effects, respectively. Bank specialization has been standardized. Standard errors are clustered at the bank-industry level. ***, ** and * denote p<0.01, p<0.05, and p<0.1, respectively.

	(1) New Loan	(2) ΔLn(Credit)	(3) $\frac{\Delta \text{Credit}}{\text{Assets}}$
Specialization	1.96***	0.52**	0.12***
	(0.39)	(0.21)	(0.04)
Z=1 & Z^{Subs}=0×Specialization	-1.20***	-0.87**	-0.36***
	(0.44)	(0.43)	(0.11)
Z=1 & Z^{Subs}=1×Specialization	-1.91***	-0.91**	-0.32***
	(0.58)	(0.40)	(0.10)
Observations	592,163	592,163	592,163
R-squared	0.47	0.45	0.46
N. of clusters	1761	1761	1761
Firm×Year FE	Yes	Yes	Yes
Bank×Year FE	Yes	Yes	Yes

Appendix G.7. Robustness of the baseline results: zombies defined in the spirit of Acharya et al. (2019)

Table G.7: Average effect of bank specialization on zombie lending: alternative zombie definition

This table shows the effect of bank specialization on the credit growth of healthy firms and zombies. The dependent variables are a dummy variable that equals 1 if the outstanding credit amount increases and 0 otherwise (Column 1), the logarithmic difference between the outstanding credit amount in year *t* and year *t-1* (Column 2), and absolute change in the outstanding credit amount scaled to the borrower's total assets (Column 3). The independent variables are bank specialization and the interaction between bank specialization and a dummy indicator for zombie firms. Zombie firms are identified following the approach of Acharya et al. (2019). In particular, zombies are low-quality firms (BB-rated or worse, ICR below 3.5) that receive subsidized credit. The latter implies that they pay an interest rate below the rate paid by the best firms (AA-rated or better). The sample includes yearly bank-firm level data between 2004 and 2018. The sample includes firms borrowing from more than one bank. We control for firm demand and bank-specific effects using firm-year and bank-year fixed effects, respectively. Bank specialization has been standardized. Standard errors are clustered at the bank-industry level. ***, ** and * denote p<0.01, p<0.05, and p<0.1, respectively.

	(1) New Loan	(2) ΔLn(Credit)	(3) $\frac{\Delta \text{Credit}}{\text{Assets}}$
Specialization	2.14***	0.59**	0.12***
	(0.42)	(0.23)	(0.04)
$Z^{\text{Acharya}}\times$Specialization	-0.60***	-0.36	-0.05
	(0.23)	(0.22)	(0.05)
Observations	614,320	614,320	614,320
R-squared	0.47	0.45	0.46
N. of clusters	1774	1774	1774
Firm×Year FE	Yes	Yes	Yes
Bank×Year FE	Yes	Yes	Yes