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Norbert Ernst, Michael Sigmund

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www.oenb.at
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Norbert Ernst[1], Michael Sigmund[1]

Abstract

We test the hypotheses that zombie firms are less productive and have lower employment growth and lower gross investment ratios than non-zombie firms in the same industry sector and that they are a source of contagion for the latter. Ever since Caballero et al. (2008), it has been taken for granted that zombie firms cause contagion in non-zombie firms that ultimately leads to a misallocation of resources. Based on a yearly sample of around 8,000 firms that are observed between 2008 and 2018, we estimate the total factor productivity with the most common methods for the Cobb-Douglas and the translog production function that go beyond the Solow residual approach with fixed elasticities. We use four zombie firm definitions based on subsidized loans and the interest coverage ratio. As expected, we find that non-zombie firms are more productive, have a higher log employment growth and a higher gross investment ratio. However, we do not find any economically significant zombie firm contagion effects in non-zombie firms.

Keywords: production function; total factor productivity; zombie firms
JEL: D24, E22, C23

Email addresses: `norbert.ernst@oenb.at` (Norbert Ernst), `michael.sigmund@oenb.at` (Michael Sigmund)
[1]Oesterreichische Nationalbank (OeNB), Otto-Wagner-Platz 3, A-1090 Vienna, Austria. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Eurosystem or the OeNB.

Non Technical Summary

Ever since Hoshi (2006); Caballero et al. (2008) have drawn the attention on zombie lending in Japan between 1990 and 2003, many papers have analyzed consequences of zombie firms on total factor productivity, employment growth, capital stock growth and bank solvency among others. The zombie lending debate has been intensified since the global financial crisis of 2007–2008 hit major economies in the world. In competitive markets poorly performing firms should be forced out of market. However, in the real world, the existence of zombie firms has been well documented in the literature. For banks it seems to be less costly to continuously supply weak firms with credit than the sunk costs of insolvency proceedings.

In the literature two zombie firm effects have been documented, namely direct zombie effects and zombie contagion effects. Direct zombie effects imply that zombie firms are less productive, have lower log employment growth and have lower gross investment ratio than non-zombie firms (Adalet McGowan et al., 2018). Second, in industry sectors with a high share of zombie firms also the total factor productivity, of non-zombie firms is reduced and the productivity gap between non-zombie and zombie firms widens (Caballero et al., 2008; Adalet McGowan et al., 2018). These zombie contagion effects also reduce the gross investment ratio and the log employment growth of non-zombie firms. Based on a high-quality data set of around 8,000 Austrian firm which are observed for the period from 2008 to 2018 we test for these two zombie firm effects.

We use four definitions to identify zombie firms that are applied to firms that are older than 10 years. The first zombie definition, which is commonly used in the economic literature, rests upon the interest coverage ratio, which measures the earnings of a firm in relation to its interest expenses. The second definition defines zombies as firms who pay a preferential interest rate and have a probability of default above 1%. The third definition combines the preferred interest rate criterion with the interest coverage ratio criterion. Therefore, according to this definition firms are classified as zombies who pay a preferential interest rate, exhibit an interest coverage ratio below 1 for two consecutive years and are older than 10 years. Fourth, we also incorporate the simulated interest coverage ratio definition as introduced by Beer et al. (2021).

After estimating the total factor productivity with the most commonly used estimation methods for the Cobb-Douglas and translog production functions, we follow Caballero et al. (2008) and regress the total factor productivity on the dummy "non-zombie firm", the "asset share of zombie firms" in a sector, the interaction term "non-zombie firm times asset share zombie firms" and on the industry sector. The variable "non-zombie firm times asset share zombie firms" should capture the contagion effects of the zombie share in a sector on the total factor productivity of non-zombie firms.

In line with Adalet McGowan et al. (2018) but in contrast to Caballero et al. (2008), we find that zombie firms are less productive than non-zombie firms, have a significantly lower log employment growth and also a much lower gross investment ratio. However, in contrast to Caballero et al. (2008) and Adalet McGowan et al. (2018), we do not find any significant zombie contagion effects on the total factor productivity, the log employment growth and the gross investment ratio of non-zombie firms, especially when we account for firm fixed effects instead of sectoral fixed effects.

1. Introduction

Ever since Hoshi (2006) and Caballero et al. (2008) have drawn the attention on zombie lending in Japan between 1990 and 2004, many papers have analyzed the consequences of zombie firms on total factor productivity, employment growth, the gross investment ratio and bank solvency among others. The zombie lending debate has been intensified since the global financial crisis of 2007–2008 hit major economies in the world. In competitive markets poorly performing firms should be forced out of market. However, in a real world scenario, the existence of zombie firms has been well documented in the literature (Banerjee and Hofmann, 2018). For banks it could be less costly to continuously supply weak firms with credit than the sunk costs of insolvency proceedings.

Banerjee and Hofmann (2018) based on Worldscope data found that the rise of zombie firms has been driven by firms staying in the zombie state for longer, rather than recovering or exiting through bankruptcy. In particular, the probability of a zombie remaining a zombie in the following year rose from 60% in the late 1980s to 85% in 2016.

From an economic policy perspective, it is of high importance to understand the causes and also the consequences of an increasing share of zombie firms in an economy. One more recent strand of literature argues that banks supply credit to zombies and therefore do not supply enough credit to non-zombie firms. This literature also documents that weakly capitalized banks tend to engage in zombie lending to avoid the sunk costs of insolvency proceedings caused by provisioning and write-offs (Storz et al., 2017; Acharya et al., 2019; Anderson et al., 2019; Schivardi et al., 2021).

Another strand of the literature assumes that capital and labor are misallocated to zombies and tries to quantify the effects on total factor productivity, employment growth and gross investment ratio (Hallak et al., 2018; Huang et al., 2021; Acharya et al., 2019; Shen and Chen, 2017).

Caballero et al. (2008) estimate so called zombie contagion effects. For a dataset of listed Japanese firms during Japanese lost decade (Hayashi and Prescott, 2002) in the 1990s, Caballero et al. (2008) find that a high share of zombie firms in an industry sector leads to a reduction of total factor productivity for all firms in this sector. Moreover, they find that the coefficient of the interaction term of the non-zombie dummy times the asset share of zombie firms in an industry sector is significantly positive which implies that the productivity gap between zombie and non-zombie firms widens, especially if there is large asset share of zombie firms. Caballero et al. (2008) also provide empirical evidence that a high share of zombie firms negatively effects the log employment growth of non-zombie firms. The same holds true for the gross investment ratio. All three effects combined lead to a misallocation of resources in industry sectors with a high share of zombie firms.

However, Caballero et al. (2008) also find that the coefficient of the dummy variable non-zombie firm is not statistically significant, which means that non-zombie firms are not necessarily more productive and have a higher log employment growth than zombie firms without taking the asset share of zombie firms and the interaction term into account.[2] We call this direct zombie firm effect. Adalet McGowan et al. (2018) largely repeat the estimations of Caballero et al. (2008) with a larger

[2] Similar results were found by Hallak et al. (2018); Collijs and De Busscher (2020).

and different dataset for nine European countries but find a statistically and economically significant coefficient of the dummy variable non-zombie firm which implies a productivity gap between zombie and non-zombie firms, as expected by standard economic theory. Similar productivity gaps are estimated by Carreira et al. (2021) and Huang et al. (2021). Adalet McGowan et al. (2018) also find direct zombie effects for the log employment growth and the gross investment ratio.

There are at least four explanations for these conflicting results. First, the literature has developed different zombie definitions. Caballero et al. (2008) classify firms as zombies that have received some kind of subsidized credit. However, more recent literature on zombies including Adalet McGowan et al. (2018); Banerjee and Hofmann (2018); Andrews and Petroulakis (2019) apply a different method centered around the interest coverage ratio (ICR) which sets the operating income of a firm in relation to its interest expenses.

Second, neither Caballero et al. (2008) nor Adalet McGowan et al. (2018) use the most common methods to estimate total factor productivity (TFP). Caballero et al. (2008) approximate TFP based on the residuals obtained from a Cobb-Douglas production function with fixed parameters for labor and capital inputs. Adalet McGowan et al. (2018) apply more advanced techniques such as Solow residuals, OLS-based residuals and the technique introduced by Wooldridge (2009). However, there are more advanced estimation procedures suggested in the literature for panel data to deal with the endogeneity issues related to the unobserved firm-specific productivity in the Cobb-Douglas production function approach (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015; Blundell et al., 2000).

Third, whereas Caballero et al. (2008) draw their conclusion on a Japanese dataset of up to 2,500 listed firms on the Tokyo Stock Exchange observed between 1990 and 2004, Adalet McGowan et al. (2018) use a harmonised cross-country dataset, where the underlying firm level data are sourced from ORBIS provided by Bureau Van Dijk for the period 2003–2013 which therefore includes the global financial crisis of 2007–2008.[3]

Fourth, while Adalet McGowan et al. (2018) do not include the asset share of zombie firms in a sector as an explanatory variable in their empirical specifications, this important variable is included in Caballero et al. (2008). This omitted variable could alter the results of Adalet McGowan et al. (2018) and make them difficult to compare with the results in Caballero et al. (2008).

Our research questions are the following. First, are there direct zombie effects on total factor productivity, log employment growth and the gross investment ratio and are these effects economically significant? Second, can we find any significant zombie contagion effects? Which effects are more important? Third, do these effects dependent on the zombie definition we use? Fourth, are these effects caused by the total factor productivity estimation method?

Our contribution to the literature is the following: First, we use a newly combined dataset from the Austrian central bank that is a middle ground between the large but incomplete ORBIS dataset and

[3]Their dataset covers nine countries – Belgium, Finland, France, Italy, Korea, Slovenia, Spain, Sweden and the United Kingdom – for 2003-2013. To estimate the TFP depending on the regression specifications between 7.9 Mio and 10.1 Mio observations are included.

the Japanese dataset on listed companies. Our dataset represents a subset of the Austrian corporate sector, which includes larger as well as smaller firms. Since every annual statement in our dataset receives quality checks based on a four-eyes-principle, a very high data quality can be expected.[4] Second, we estimate TFP with different estimation methods and production functions suggested in the literature and compare their goodness of fits.[5] Third, the quality of our dataset allows us to calculate four zombie firm definitions based on subsidized loans and the interest coverage ratio. Fourth, we provide an answer to the question if and by how much non-zombie firms are more productive, have a higher log employment growth and a higher gross investment ratio than zombie firms. Fifth, we test the hypothesis that zombie firms cause contagion in non-zombie firms by widening the TFP gap, by reducing their log employment growth and by reducing their gross investment ratio.

We find direct zombie effects that are statistically and economically significant. Non-zombie firms are between 2% to 7% more productive than non-zombie firms. Non-zombie firms have a higher log employment growth by around 1.6 to 6.1 percentage points depending on the zombie firm definition. They also have a higher gross investment ratio by around 18% to 22%. Most importantly, we do not find any significant zombie contagion effects on the TFP, on log employment growth and on the gross investment ratio of non-zombie firms. In particular a high share of zombie assets in an industry sector does not lead to an increase in the TFP gap between non-zombie and zombie firms. Also a high share of zombie assets in an industry sector does not lead to a lower log employment growth in non-zombie firms. Next, a high share of zombie assets in an industry sector does not lead to a gross investment ratio in non-zombie firms. Finally, as a methodological remark the simple fixed effects estimator for the TFP unsurprisingly outperforms the Solow residual based approach used by Caballero et al. (2008); Adalet McGowan et al. (2018) and surprisingly the most recent estimation methods based on different control function approaches (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Wooldridge, 2009; Ackerberg et al., 2015) for our dataset.

The remainder of the paper is structured as follows. In Section 2, we describe our newly combined firm dataset and our zombie definitions. In Section 3, we discuss two commonly used production functions and a variety of ways to estimate them with our panel dataset. In Section 4, we present and compare our TFP estimation results. In Section 5, we quantify the loss of TFP of zombie firms as well as the loss of efficiency and potential zombie contagion effects in non-zombie firms. In Section 6, we estimate zombie and zombie contagion effects in log employment growth. In Section 7, we use the gross investment ratio as our dependent variable. In Section 8, we discuss our results and outline future research.

2. Data

For our empirical research, we employ a dataset similar to Beer et al. (2021). This dataset consists of a collection of annual financial statements of non-financial corporations located in Austria

[4]The annual financial statements are recorded by one employee and checked by a second.

[5]We do not only estimate TFP but also estimate the technical efficiency (TE) (Battese and Coelli, 1992) of each firm based on the stochastic frontier analysis (SFA) (Aigner et al., 1977; Meeusen and van Den Broeck, 1977).

compiled by the Oesterreichische Nationalbank (OeNB) for the purposes of Inhouse Credit Assessment (ICAS) ratings. These ratings are used to assess the eligibility of credit claims pledged by the banks to the OeNB for monetary policy operations. Since only credit claims to firms with a sufficiently high creditworthiness are accepted by the OeNB for this purpose, it is likely that more stable companies are overrepresented in our sample. Still, credit claims of a large part of the firms in the sample are not eligible for monetary policy operations.

An essential amount of these financial statements is drawn from the Austrian public commercial register ("Firmenbuch"). However, the granularity of the financial statements from the commercial register is quite heterogeneous, since reporting requirements are much lighter for smaller firms. Therefore, the OeNB additionally collects more granular financial statements provided by banks and the firms themselves.

We exclude firm-year observations which financial statements are not sufficiently granular to calculate the indicators for our analysis. This concerns mainly small firms which therefore are likely to be underrepresented in our sample. Furthermore, we only consider firms of whom at least three financial statements are available for the period under investigation. Additionally, we only include non-financial corporations (i.e., sector 11) according to the European System of Accounts. Based on the Statistical Classification of Economic Activities in the European Community (NACE) and considering the distinct scope of their economic activity, we omit holding companies (NACE-group 64.2) and head offices (NACE-group 70.1). Finally, financial statements that fail basic data quality checks are excluded from the sample. Thus, an unbalanced panel containing 45,224 firm-years for the years 2008 through 2018 is available for our analysis.

Table 1: Summary statistics of included variables

	Min	1st Qu.	Median	Mean	3rd Qu.	Max	Data.Cov
Production function: Dependent Variable							
Log(total revenue)	0.69	8.35	9.65	9.63	10.94	16.13	100.00
Cobb-Douglas production function: Explanatory Variables							
Log(labor costs)	0.00	6.80	7.97	7.94	9.18	14.51	99.65
Log(capital)	0.00	6.77	8.26	8.17	9.64	16.98	99.75
Log(material costs)	0.00	7.37	9.02	8.84	10.42	16.15	95.98
Translog production function: Additional Explanatory Variables							
Log(labor costs)ˆ2	0.00	46.27	63.59	66.39	84.21	210.57	99.65
log(capital)ˆ2	0.00	45.86	68.18	71.92	92.85	288.30	99.75
Log(material costs)ˆ2	0.00	54.32	81.30	83.10	108.64	260.75	95.98
log(labor) x log(capital)	0.00	45.78	63.64	66.96	85.03	234.03	99.40
log(labor) x log(material costs)	0.00	51.15	71.85	73.94	94.73	211.11	95.84
log(capital) x log(material costs)	0.00	50.41	70.10	74.28	94.97	234.18	95.79
Zombie effects: Additional Dependent Variables							
Number of Employees	1.00	20.00	59.00	252.14	192.00	30146.00	100.00
Log employment growth	-7.22	-0.02	0.00	0.02	0.06	6.28	81.52
Gross investment ratio	0.00	6.39	17.03	26.65	36.60	171.17	96.28
Zombie Definitions							
ICR definition	0.00	0.00	0.00	0.10	0.00	1.00	66.55
ICR definition (simulated)	0.00	0.00	0.00	0.13	0.00	1.00	66.55
PIR-PD definition	0.00	0.00	0.00	0.05	0.00	1.00	84.90
PIR-ICR definition	0.00	0.00	0.00	0.03	0.00	1.00	66.42

Data sources: OeNB. Austrian Commercial Register.
The table shows the minimum (Min.), first quantile (1st Qu.), the median (Median), mean (Mean), third quantile (3rd Qu.), maximum (Max) and the data coverage (Data Cov.) for the variables used in this paper. Data Cov. refers to the percentage of available observations if the data was a balanced panel.
We only include firms that at least report three times in the period 2008–2018. This leaves us with 45,224 observations between 2008 and 2018.
Log(total revenue) is the logarithm of total revenue. Log(labor costs) is the logarithm of labor costs. Log(capital) is the logarithm of the sum of fixed and intangible assets. Log(material costs) is the logarithm of material costs.
Number of employees is the number of employees a firm reports. Log employment growth is defines as $log(employment_t) - log(employment_{t-1})$. The gross investment ratio is defined as investments divided by the sum of intangible assets and fixed assets.
Our zombie definitions are based on Beer et al. (2021). See Section 2.2 for more details.

2.1. Firm Level Data

For the estimation of the TFP, we use labor, capital, and intermediate inputs (materials) as input factors to explain the output of a firm. The necessary data for this analysis is taken from the balance sheet and the profit and loss statement of the firms' financial statement in the corresponding year. Output in this context is defined as the firm's total revenue. Staff expenses represent labor input and material cost represent the intermediate input. Thus, output as well as the labor and intermediate input are taken from the profit and loss statement. Capital is defined as the sum of tangible and intangible assets and is taken from the firms' balance sheet. Capital input is therefore a stock size and not only includes the machinery and buildings which is used during the production process but also immaterial assets such as licenses. The gross investment ratio is defined as investments divided by the sum of intangible assets and fixed assets. Log employment growth is calculated by the difference of log employment at time t and log employment at time $t-1$ for each firm i.

2.2. Zombie Definitions

The term zombie firm labels poorly performing firms, which, instead of exiting the market, continue to operate instead. The economic literature offers a wide range of indicators to identify these firms (Caballero et al., 2008; Adalet McGowan et al., 2018; Banerjee and Hofmann, 2018). For the purpose of this paper, we build upon the work of Beer et al. (2021) that operationalize the four zombie definitions most commonly used in the literature. All four definitions relate to the firms' interest expense but focus on different aspects of them.

The first zombie definition, which is commonly used in the economic literature (Adalet McGowan et al., 2018; Banerjee and Hofmann, 2018; Andrews and Petroulakis, 2019), rests upon the interest coverage ratio (ICR), which measures the earnings of a firm (EBIT) in relation to its interest expenses (R). In this context, firm i is defined as a zombie in year t if the ICR is below one for two consecutive years and the firm is older than 10 years – i.e., the following conditions are fulfilled:

$$ICR_{i,t} = \frac{EBIT_{i,t}}{R_{i,t}} < 1 \, , \tag{1a}$$

$$ICR_{i,t-1} = \frac{EBIT_{i,t-1}}{R_{i,t-1}} < 1 \, , \tag{1b}$$

$$age_{i,t} > 10 \, . \tag{1c}$$

The next two zombie definitions classify a firm as a zombie that pays a preferential interest rate on its outstanding debt (PIR) and combines this feature with either the firm's credit rating or its ICR. The interest rate ($r_{i,t}$) that a firm pays on its outstanding debt is defined as ratio between its interest expenses and its debt.

$$r_{i,t} = \frac{R_{i,t}}{debt_{i,t}} \, . \tag{2}$$

A firm is said to pay a preferential interest rate if the interest rate $r_{i,t}$ is below a benchmark interest rate r^*_t.

$$r_{i,t} < r^*_t \, . \tag{3}$$

The benchmark interest rate (r^*_t) is defined as the median interest rate of all firms in our sample, that have a one-year probability of default (PD) below 0.1%. These firms qualify for the Credit Quality Steps (CQS) 1 and 2 on the harmonized rating scale of the Eurosystem.[6]

[6]The Eurosystem considers a probability of default over a one-year horizon of up to 0.10% as equivalent to a credit assessment of credit quality step 2 on the Eurosystemâs harmonised rating scale, subject to regular review. See https://www.ecb.europa.eu/paym/coll/risk/ecaf/html/index.en.html for more details.

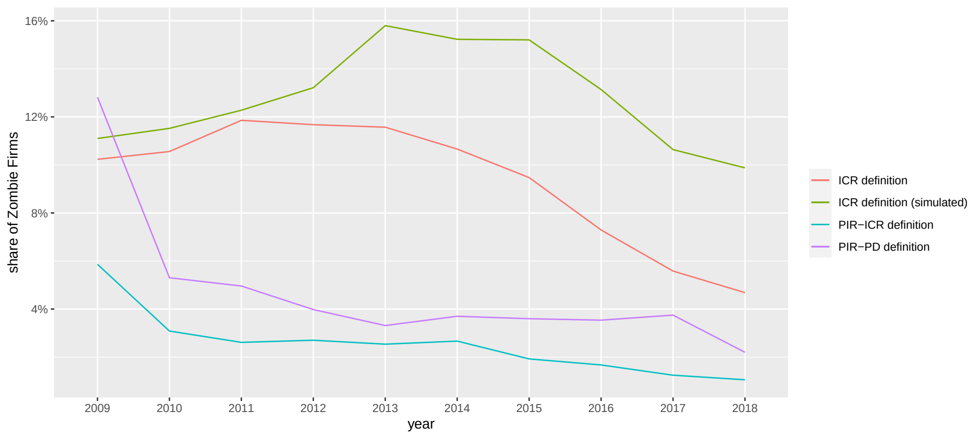
$$r_t^* = weighted\ median\left(\frac{R_{j,t}}{debt_{j,t}}\right). \tag{4}$$

The second definition (PIR-PD) defines zombies as firms who pay a preferential interest rate and have a PD above 1%. To harmonize the PIR-PD with the ICR definition only firms older than 10 years are classified as zombies.

The third definition (PIR-ICR) combines the PIR-criterion with the ICR-criterion and again with the age of the firm. Therefore, according to the PIR-ICR definition those firms are classified as zombies who pay a preferential interest rate, exhibit an ICR below 1 for two consecutive years and are older than 10 years.

In addition to these three zombie definitions, we also incorporate the simulated ICR-definition as introduced by Beer et al. (2021). This definition aims to account for the effect of falling interest rates, which we observe in our data set, and classifies those firms as zombies which would have been zombies according to the ICR-definition under the assumption of constant policy interest rates. For the precise construction of this zombie definition, we refer to Beer et al. (2021).

Figure 1: Share of Zombie Firms (2009-2018)



Source: Authors' calculations. Share of zombie firms in all non-financial corporates.

3. Estimating Total Factor Productivity

In this section, we first describe two commonly used production functions, namely the Cobb-Douglas (CD) production function and the translog production function. Next, in Section 3.2 we describe how these production functions can be estimated with panel data, highlight a few problems of standard methods and provide an overview on solutions suggested in the literature. We do not only use standard production function estimation techniques but also give a brief overview on SFA. Our considerations in Section 3.1 and in Section 3.2 are summarized in Table 2.

Table 2: Production Functions and Estimation Methods

TFP Estimation Method	Cobb-Douglas PF	Translog PF
Fixed effects model	*yes*	*yes*
Solow residual model	*yes*	*no*
Olley and Pakes (1996)	*yes*	*no*
Levinsohn and Petrin (2003)	*yes*	*no*
Ackerberg et al. (2015)	*yes*	*no*
Wooldridge (2009)	*yes*	*no*
Blundell and Bond (1998)	*yes*	*no*
SFA: Error Component (Battese and Coelli, 1992)	*yes*	*no*
SFA: Distributional Free Approach (Cornwell et al., 1990)	*yes*	*no*
SFA: True Fixed Effects (Greene, 2005)	*yes*	*no*

In Section 3.3, we explain our empirical approach to identify direct zombie effects and zombie contagion effects on the TFP, the log employment growth and the gross investment ratio. Our first empircal model is based on Caballero et al. (2008). In our second specification, we include firm-specific effects instead of industry sector fixed effects.

3.1. Production Function Theories

Production functions are an important concept in economic theory. Many theories and empirical specifications have been developed over the last centuries. From the beginning, empirical data played an important role in the formulation of production functions. Consequently, we are interested in production function theories that allow a parametric or semi-parametric estimation.

According to Mishra (2007), it is believed that the first algebraic formulation of output as a function of inputs is due to Wicksteed (1894). Humphrey (1997) even provides some evidence that Johann von Thuenen first formulated it in the 1840s. In any case, the first well known production function was introduced in Cobb and Douglas (1928):

$$P = bL^k * C^{1-k}. \tag{5}$$

P is the total production, b is considered to be independent of the capital input (C) and the labor input (L). b is therefore a catch-all for all forces where quantitative data are not available.[7] Although considering the same framework, Solow (1956) not only relabels b to $A(t)$ but also assigns a different meaning, namely technological change.

[7] According to Humphrey (1997), Paul Douglas, on a sabbatical at Amherst, asked mathematics professor Charles W. Cobb to suggest an equation describing the relationship among the time series on manufacturing output, labor input, and capital input that Douglas had assembled for the period 1889–1922, and this led to their joint paper.

$$Y = A(t)K^{\beta_k}L^{\beta_l} \,. \tag{6}$$

Although the Cobb-Douglas PF is an interesting starting point for estimating the total factor productivity, there are a few (implicit) restrictions. First, although it is possible to include more input variables, the elasticity of substitution is always one between any two inputs. Furthermore, all inputs are complements in production, i.e., the marginal productivity of any input j increases with the amount of any other input k.

Since we work with a panel dataset, we introduce the subscript i in the Cobb-Douglas production function:

$$Y_{i,t} = A_i K_{i,t}^{\beta_k} L_{i,t}^{\beta_l} \,, \tag{7}$$

where $Y_{i,t}$ is representing the physical output of the company i in period t; $A_{i,t}$ is representing the neutral level of efficiency for the company i. $K_{i,t}$ is representing capital input parameter for the company i in period t. $L_{i,t}$ is representing labour input parameter for the company i in period t and $M_{i,t}$ is representing materials input parameter for the company i in period t.

During the research on more flexible productions functions, many functional forms have been suggested such as the constant elasticity of substitution (CES) production function (Arrow et al., 1961), which arose as a utility function in consumer theory:

$$Y_{i,t} = (\beta_K K_{i,t}^{-\rho} + \beta_L L_{i,t}^{-\rho})^{-\frac{1}{\rho}} \,. \tag{8}$$

There is close relationship with the Cobb-Douglas specification. It can be shown that the CES PF and the CB PF are identical if $\rho = 0$.[8]

Another even more flexible functional form is the transcendental logarithmic function (Christensen et al., 1973) written in its original form:

$$Y_{i,t} = \alpha_i \prod_{j=1}^{n} X_{j,i,t}^{\beta_j} \prod_{j=1}^{n} X_{j,i,t}^{1/2\left(\sum_{k=1}^{n} \beta_{j,k} ln(X_{k,i,t})\right)} \,, \tag{9}$$

where X refers to input factors such as capital K or labor L, i refers to the individual firm, j and k are subscripts for the n different input factors and t refers to time. α_i refers to the efficiency parameter and β_j and $\beta_{j,k}$ are the unknown parameters of the input variables.

[8] If $\rho = 0$, then the PF is linear and the inputs are perfect substitutes. If $\rho = -\infty$, then we get the Leontief production function (Mishra, 2007) with perfect complements.

A more familiar way to write Eq. (9) is by taking the natural logarithm on both sides:

$$ln(Y_{i,t}) = ln(\alpha_i) + \sum_{j=1}^{n} \beta_j ln(X_{j,i,t}) + \frac{1}{2} \sum_{j=1}^{n} \sum_{k=1}^{n} \beta_{j,k} ln(X_{j,i,t}) ln(X_{k,i,t}) \,. \tag{10}$$

This specification is known as the translog PF. According to Boisvert (1982), there are three ways to interpret Eq. (10): (1) an exact production function, (2) a second order Taylor approximation to a general but unknown production function or (3) a second order approximation to a CES production function. It is also straightforward to show that if all $\beta_{j,k}$'s are zero, which can be tested empirically, then Eq. (9) is equivalent to a Cobb-Douglas PF.

It has been suggested by Berger and Humphrey (1997) based on the work of Gallant (1981) to augment the translog function above into a Fourier Flexible From.[9] Especially in the bank cost efficiency literature this augmentation has been used extensively (Altunbaş and Chakravarty, 2001; Rossi et al., 2004).

$$\begin{aligned} ln(Y_{i,t}) \quad = \quad & ln(\alpha_i) + \sum_{j=1}^{n} \beta_j ln(X_{j,i,t}) + \tfrac{1}{2} \sum_{j=1}^{n} \sum_{k=1}^{n} \beta_{j,k} ln(X_{j,i,t}) ln(X_{k,i,t}) + \sum_{j=1}^{n} \Big(\phi_n \cos(Z_{j,i,t}) + \omega_n \sin(Z_{j,i,t})\Big) + \\ & \sum_{j=1}^{n} \sum_{q=1}^{n} \Big(\phi_{nq} \cos(Z_{j,i,t} + Z_{q,i,t}) + \sin(Z_{j,i,t} + Z_{q,i,t})\Big) + \\ & \sum_{j=1}^{n} \Big(\phi_n \cos(Z_{j,i,t} + Z_{j,i,t} + Z_{j,i,t}) + \omega_n \sin(Z_{j,i,t} + Z_{j,i,t} + Z_{j,i,t})\Big) \,. \end{aligned} \tag{11}$$

The variables $Z_{j,i,t}$ for $j = 1, .., n$ are the transformed $ln(X_{j,i,t})$ again for $j = 1, .., n$ onto the interval $[0, 2\pi]$.

3.2. Estimating Production Functions

For the estimation of the Cobb-Douglas PF, we could take the logarithm of Eq. (6) after adding materials ($m_{i,t}$) as a further input factor:

$$y_{i,t} = \beta_0 + \beta_k k_{i,t} + \beta_l l_{i,t} + \beta_m m_{i,t} + \mathrm{TD}_t + \nu_{i,t} \,, \tag{12}$$

where

[9] According to Berger and Humphrey (1997), the Fourier Flexible From is a global approximation because all "cos" and "sin" terms are mutually orthogonal over the interval $[0, 2\pi]$, so that each additional term can make the approximating function closer to the true path of the data wherever it is most needed.

$$ln(A_{i,t}) = \beta_0 + \nu_{i,t} + \mathrm{TD}_t \ . \tag{13}$$

In this specification, we also add time dummies (TD_t).

However, Olley and Pakes (1996) claim that estimating Eq. (12) might be subject to an endogeneity problem. Based on a multiperiod optimization model they show that if a firm observes its productivity index ($\omega_{i,t}$) and then makes an investment decision which changes its capital according to

$$K_{i,t+1} = (1 - \delta)K_{i,t} + I_{i,t} \ , \tag{14}$$

then the covariances of $\nu_{i,t}$ with $k_{i,t}$ (and with $ł_{i,t}$ and $m_{i,t}$) are not zero. For example, firms with a higher $\nu_{i,t}$ might want to use more inputs. A common idea would be to separate $\nu_{i,t}$ into:

$$\nu_{i,t} = \omega_{i,t} + \epsilon_{i,t} \ . \tag{15}$$

In the relevant literature, a lot of different methods have been suggested to account for this endogeneity problem. In the next paragraphs, we discuss a few of them and compare the estimation results in Section 4. Unfortunately, most of them are centered around the Cobb-Douglas PF and do not make a comparison with the translog PF in Eq. (9) or with the SFA (Kumbhakar et al., 2020).

The first common solution to the endogeneity problem is to apply a fixed effects model. Instead of Eq. (12), we write

$$y_{i,t} = \alpha_i + \beta_k k_{i,t} + \beta_l l_{i,t} + \beta_m m_{i,t} + \mathrm{TD}_t + \epsilon_{i,t} \ , \tag{16}$$

and make the somewhat strong assumption that $\omega_{i,t} = \omega_i = \alpha_i$.

In the Solow residual model (Solow, 1957) with fixed effects we not only make the above mentioned assumption about $\omega_{i,t}$ but also impose that $\beta_k + \beta_l + \beta_m = 1$. This assumption imposes constant returns to scale. We do not entirely follow Caballero et al. (2008) by setting $\beta_k = 1/3$, $\beta_l = 2/3$ and $\beta_m = 0$.

The second solution to the endogeneity problem that we implement is suggested in Olley and Pakes (1996). They basically make four assumptions and then assume that there exist an inverse image ($f^{-1}(\cdot)$) of an investment function $i_{i,t} = f(k_{i,t}, \omega_{i,t})$ that depends on capital ($k_{i,t}$) and $\omega_{i,t}$.[10] Under these assumptions, $\omega_{i,t} = f^{-1}(i_{i,t}, k_{i,t})$. Econometrically, we arrive at

[10] The first assumption is about the information set of the firm at time t ($\Omega_{i,t}$) such that $\mathbf{E}[\omega_{i,t+1}|\Omega_{i,t}] = \omega_{i,t}$. Second, the labor input is $l_{i,t}$ is chosen by firm i after observing $\omega_{i,t}$. Third, the labor input at time t has no dynamic implications (i.e. there are no labor adjustment costs like firing or hiring costs.) Fourth, the capital accumulation process follows with: $K_{i,t} = \delta K_{i,t-1} + I_{i,t-1}$. Thus, the capital at time t depends on investment in period $t-1$.

$$y_{i,t} = \alpha_i + \beta_k k_{i,t} + \beta_l l_{i,t} + \beta_m m_{i,t} + \text{TD}_t + f^{-1}(k_{i,t}, m_{i,t}, i_{i,t}) + \epsilon_{i,t} \ , \tag{17}$$

if we further assume that $\omega_{i,t}$ only influences the investment equation and $\frac{\partial f(k_{i,t},\omega_{i,t})}{\partial \omega_{i,t}} > 0$. Olley and Pakes (1996) suggest to use a polynomial in $k_{i,t}$, $m_{i,t}$, $i_{i,t}$ to approximate $f^{-1}(\cdot)$. To estimate all parameters in Eq. (17), a two-stage procedure is applied by Olley and Pakes (1996). Based on Wooldridge (2009), Rovigatti (2017a); Rovigatti and Mollisi (2018a) provide three closely related alternative methods to estimate Eq. (17) by GMM where the first and second stage of Olley and Pakes (1996) are estimated jointly.

The method of Levinsohn and Petrin (2003) is in principle very similar to Olley and Pakes (1996) but instead of $i_{i,t} = f(k_{i,t}, \omega_{i,t})$, which is often not available in datasets, they suggest to search for an alternative to $i_{i,t}$ to learn about $\omega_{i,t}$. Levinsohn and Petrin (2003) suggest to use some sort of intermediate inputs such as materials, fuel or electricity: $m_{i,t} = f(k_{i,t}, \omega_{i,t})$.

Finally, Ackerberg et al. (2015) question the assumption that $l_{i,t}$ does not depend on $\omega_{i,t}$. If it was the case, then $l_{i,t} = h(k_{i,t}, \omega_{i,t}) = h(k_{i,t}, f^{-1}(k_{i,t}, m_{i,t}))$ but in this case $l_{i,t}$ is a deterministic function of $k_{i,t}$ and $m_{i,t}$. Going a step further, there would be no enough variation to identify β_l in Eq. (17). Thus, the Ackerberg et al. (2015) procedure results in

$$y_{i,t} = \alpha_i + \beta_k k_{i,t} + \beta_l l_{i,t} + \beta_m m_{i,t} + \text{TD}_t + f^{-1}(k_{i,t}, m_{i,t}, l_{i,t}) + \epsilon_{i,t} \ , \tag{18}$$

Thus, in the first stage neither β_k nor $l_{i,t}$ can be identified, but suitable moment conditions can be derived to identify both parameters in the second stage.

Another approach to account for the endogeneity problem can be borrowed from the dynamic panel model literature. The basic idea is to treat all input variables as predetermined and instrument them by its own past values after removing the fixed effects by the first difference transformation (or the forward orthogonal transformation). This first difference GMM estimator was introduced by Holtz-Eakin et al. (1988) and popularized by Arellano and Bond (1991). We start with

$$y_{i,t} = \alpha_i + \beta_k k_{i,t} + \beta_l l_{i,t} + \beta_m m_{i,t} + \text{TD}_t + \omega_{i,t} + \epsilon_{i,t} \ , \tag{19}$$

and first take the first difference transformation (or the forward orthogonal transformation) to remove the fixed effect:

$$\Delta^* y_{i,t} = \beta_k \Delta^* k_{i,t} + \beta_l \Delta^* l_{i,t} + \beta_m \Delta^* m_{i,t} + \Delta^* \text{TD}_t + \Delta^* \omega_{i,t} + \Delta^* \epsilon_{i,t} \ , \tag{20}$$

In dynamic panel models it is usually standard to include the lagged dependent variable as well. The first difference GMM moment conditions exploit the following moment conditions:

$$\mathbb{E}[\Delta^{*}\epsilon_{i,t}\mathbf{x}_{i,j}^{\intercal}] = \mathbf{0} \quad j \in \{1, \ldots, T-1\} \text{ and } t \in \mathbb{T}_{\Delta^{*}}, \tag{21}$$

where $\mathbf{x}_{i,j}^{\intercal} = [k_{i,j}, l_{i,j}, m_{i,j}]$ is the vector of input variables and $\mathbb{T}_{\Delta^{*}}$ denotes the set of indexes t for which the chosen transformation exists. In this GMM-style estimtor, we need to make the assumption that the productivity shock follows a linear model such as $\omega_{i,t} = \rho\omega_{i,t-1} + \zeta_{i,t}$. To derive Eq. (20), we make the simplifying assumption that $\rho = 1$ to avoid ρ-first differencing or double differencing. Since Blundell and Bond (1998) argue that the system GMM estimator performs better than the first difference GMM estimator because the additional instruments remain good predictors for the endogenous variable in this model even when the series is very persistent, we add these additional moment conditions.

$$\mathbb{E}[(\epsilon_{i,t} + \alpha_i)(\mathbf{x}_{i,t} - \mathbf{x}_{i,t-1})^{\intercal}] \quad = \quad \mathbf{0} \quad t \in \{2, 3, \ldots, T\}\,. \tag{22}$$

We use SFA introduced by Aigner et al. (1977); Meeusen and van Den Broeck (1977) as our final method to estimate TFP. The background of SFA is axiomatic, based on different measures of efficiency and therefore very similar to data envelopment analysis but it is still parametric. As a consequence it can be compared to the previous regression based approach, but also offers the possibility to interpret the results in the lights of Farrell output efficiency (Farrell, 1957) and by its inverse the Shephard output efficiency (Shepard, 1970). The standard SFA models has the following form:

$$\begin{aligned} Y_{i,t} &= f(k_{i,t}, l_{i,t}, m_{i,t})e^{v_{i,t}}e^{-u_{i,t}} \\ v_{i,t} &\sim \mathcal{N}(0, \sigma_v^2) \\ u_{i,t} &\sim \mathcal{N}_{+}(0, \sigma_u^2), \end{aligned} \tag{23}$$

where $u_{i,t} > 0$ is the so called inefficiency term which is half-normally distributed. The idea that one firm j at each point t in time produces most efficiently and for all other firms do not (i.e., $u_{i,t} > 0$ for $i \neq j$) is well known in deterministic frontier models. $v_{i,t}$ is the standard error term and follows a normal distribution. There are many different suggestions in the literature to estimate SFA model with panel data, we opt for the "true" fixed effects estimation by Greene (2005) and the error component specification of Battese and Coelli (1992).[11]

After taking logarithms of Eq. (23) and if it is possible to estimate $\hat{u}_{i,t}$, then firm-specific technical efficiency ($TE_{i,t}$) can be defined as

[11]Both methods have their advantages and disadvantages. If potential correlations between the error term and the explanatory variables was a concern the "true" fixed effects estimation would be preferred. However, this method is computationally burdensome and the results might still suffer from the incidental parameter bias (Neyman and Scott, 1948).

$$TE_{i,t} = \frac{f(k_{i,t}, l_{i,t}, m_{i,t})e^{-u_{i,t}}}{f(k_{i,t}, l_{i,t}, m_{i,t})}. \tag{24}$$

To strength the robustness of our SFA results, we also estimated the so-called distributional free stochastic frontier approach (DFA).[12] The DFA approach describes the average deviation of each firm from the best average-practise frontier in each time period without the distributional assumptions on $v_{i,t}$ and $u_{i,t}$ in Eq. (23). The starting point for the DFA approach already in logs is the following (Cornwell et al., 1990):

$$y_{i,t} = \alpha_{i,t} + x_{i,t}^{\intercal}\beta + v_{i,t}, \tag{25}$$

where $\alpha_{i,t} = \alpha - u_{i,t}$. Cornwell et al. (1990) assume $\alpha_{i,t} = w_{i,t}^{\intercal}\delta_i$ and that $w_{i,t} = 1$ as in the "classical" fixed effect model. Next, we estimate

$$y_{i,t} = \delta_i + x_{i,t}^{\intercal}\beta + v_{i,t}, \tag{26}$$

after demeaning the data (within transformation) and obtain the fitted residuals. Then δ_i can be estimated by regressing for panel unit i from Eq. (26) on $w_{i,t}$. The frontier intercept α_t and the time varying unit-specific level of inefficiency $u_{i,t}$ for panel unit i at time t is then given by:

$$\begin{aligned} \hat{\alpha}_t &= \max_j\{\hat{\alpha}_{j,t}\} \\ \hat{u}_{i,t} &= \hat{\alpha}_t - \hat{\alpha}_{i,t}\ . \end{aligned} \tag{27}$$

3.3. Total Factor Productivity: Direct Zombie Effects and Zombie Contagion Effects

We estimate the direct zombie effects and the zombie contagion effects on TFP in the same specification as in Caballero et al. (2008):

$$y_{i,t} = \alpha + \beta^{\intercal} Ind_{i,j,t} + \lambda_t + \delta_1 nonz_{i,t} + \delta_2 \cdot ShareZ_{i,j,t} + \delta_3(ShareZ_{i,j,t} \times nonz_{i,t}) + \epsilon_{i,t}\ . \tag{28}$$

$y_{i,t}$ can be one of the three dependent variables. In Section 5, $y_{i,t}$ represents one of the different TFP estimations based on the models presented in Section 3.2 and estimated in Section 4. In Section 6, $y_{i,t}$ is the log employment growth. In Section 7, $y_{i,t}$ is the gross investment ratio. α is the intercept. It is important to note that Eq. (28) is not a fixed effects model. λ_t is a common time-trend and $Ind_{i,j,t}$ represents a set of j industry dummies. $\epsilon_{i,t}$ is the error term.

The dummy variable $nonz_{i,t}$ takes the value 1 if firm i is classified as a non-zombie at time t

[12] An overview on this method can be found in Berger and Humphrey (1997).

and 0 otherwise. Therefore δ_1 measures the average difference of the TFP, the log employment or the gross investment ratio of non-zombie and zombie firms. We call this the direct zombie effect. Being a zombie therefore could directly effect a firm's performance measured by our three dependent variables.

$ShareZ_{i,j,t}$ is the percentage of firms' assets in sector j that are classified as zombies in which firm i operates at time t. Therefore δ_2 measures the influence of the asset share of zombie firms on TFP, log employment growth or the gross investment ratio. $ShareZ_{i,j,t} \times nonz_{i,t}$ is the interaction term of the asset share of zombie firms in sector j and the non-zombie status of firm i. According to Caballero et al. (2008), δ_3 captures the contagion effects of the zombie share on the non-zombie firms in the same sector. We define the sum of δ_2 and δ_3 as zombie contagion effects.

Since we have panel data at our disposal, we can improve on Eq. (28) by addressing a potential time-invariant omitted variable bias by including fixed effects for each firm.

$$y_{i,t} = \alpha_i + \lambda_t + \delta_1 nonz_{i,t} + \delta_2 \cdot ShareZ_{i,j,t} + \delta_3(ShareZ_{i,j,t} \times nonz_{i,t}) + \epsilon_{i,t} \,, \tag{29}$$

where α_i is a firm specific fixed effect. The other variables are defined as above. Importantly, we drop the sector specific dummies as they would only be identified if a firm changed its industry and would then capture this effect.

4. Results Production Functions

In this section, we report the results for all TFP estimation methods presented in Section 3.2. We split our TFP estimation results in three subsections. In Section 4.1, we report all results for the Cobb-Douglas PF. The results of the translog PF estimations are reported in Section 4.2. In Section 4.3, we report the results of our SFA estimations.

4.1. Results – Cobb-Douglas Production Function

In Table 3, we present the Cobb-Douglas PF estimation results for all different models discussed in Section 3.2. These results can be compared to Beveren (2012) who archives remarkable similar results (see Table 3 in Beveren, 2012). In Beveren (2012), higher coefficients for the material costs are reported which are likely to be caused by the fact that firm-level data on the Belgian food and beverages industry are used.

In accordance with Beveren (2012), we also find that the models "Olley-Pakes" and "WRDG" that are based on control function approach (see Eq. (17)) using investment data to learn about the unobserved productivity shock $\omega_{i,t}$ perform unsurprisingly relatively poorly and even show a negative coefficient for log(capital). This phenomena has already been documented in the literature (Klette and Griliches, 1996; Felipe and Adams, 2005) and Ackerberg et al. (2015); Levinsohn and Petrin (2003) offer alternative methods based on the same ideas.

Interestingly, the "Fixed Effects" and the "System-GMM" models show relatively credible results for the log(capital) coefficient which might lead to the conclusion that a firm's productivity shock could be constant over a short period of time, i.e., $\omega_{i,t} = \omega_t = \alpha_i$ in Eq. (16). This assumption might be a legit shortcut to address the endogeneity problem. Also based on the RMSE (reported in last row of Table 3), we conclude that the "Fixed Effects" and the "System-GMM models" outperform the other models by a large margin.

Table 3: Cobb-Douglas PF Estimations with time dummies

	Fixed Effects	Olley Pakes	ACF	LP	WRDG	Solow	System-GMM
Intercept							1.6530^{***}
							(0.1266)
Log(labor costs)	0.2450^{***}	0.2859^{***}	0.4319^{***}	0.3162^{***}	0.2623^{***}	0.4377^{***}	0.2459^{***}
	(0.0041)	(0.0077)	(0.0625)	(0.0078)	(0.0029)	(0.0036)	(0.0214)
Log(material costs)	0.3878^{***}	0.5126^{***}	0.3116^{***}	0.1908^{***}	0.4870^{***}	0.4252^{***}	0.4175^{***}
	(0.0028)	(0.0072)	(0.0530)	(0.0144)	(0.0038)	(0.0029)	(0.0239)
log(capital)	0.0639^{***}	-0.0035	0.0484^{**}	0.0366^{**}	-0.0626^{***}	0.1371^{***}	0.0669^{***}
	(0.0027)	(0.0081)	(0.0154)	(0.0131)	(0.0097)	(0.0027)	(0.0112)
Log(total revenue) (-1)							0.1912^{***}
							(0.0461)
TD 2009		0.0102	-0.0310^{***}	-0.0055	2.5613^{***}	0.0035	
		(0.0076)	(0.0066)	(0.0060)	(0.2387)	(0.0037)	
TD 2010		0.0052	-0.0117	0.0154^{*}	2.3831^{***}	0.0185^{***}	0.0249^{***}
		(0.0091)	(0.0073)	(0.0074)	(0.2207)	(0.0035)	(0.0066)
TD 2011		0.0006	-0.0033	0.0041	2.4184^{***}	0.0170^{***}	0.0357^{***}
		(0.0091)	(0.0061)	(0.0080)	(0.2232)	(0.0036)	(0.0077)
TD 2012		0.0008	-0.0110	-0.0050	2.4218^{***}	0.0077^{*}	0.0181^{**}
		(0.0087)	(0.0064)	(0.0087)	(0.2246)	(0.0036)	(0.0068)
TD 2013		-0.0066	-0.0190^{*}	-0.0114	2.4158^{***}	-0.0004	0.0043
		(0.0087)	(0.0075)	(0.0088)	(0.2253)	(0.0038)	(0.0070)
TD 2014		-0.0000	-0.0304^{***}	-0.0160	2.4245^{***}	-0.0053	0.0026
		(0.0107)	(0.0075)	(0.0096)	(0.2262)	(0.0040)	(0.0072)
TD 2015		0.0143	-0.0264^{***}	-0.0079	2.4292^{***}	-0.0059	0.0051
		(0.0110)	(0.0074)	(0.0093)	(0.2260)	(0.0041)	(0.0078)
TD 2016		0.0129	-0.0165^{*}	0.0048	2.4358^{***}	0.0045	0.0118
		(0.0108)	(0.0084)	(0.0087)	(0.2251)	(0.0043)	(0.0083)
TD 2017		0.0321^{*}	-0.0073	0.0091	2.4384^{***}	0.0080	0.0212^{*}
		(0.0138)	(0.0075)	(0.0090)	(0.2249)	(0.0049)	(0.0088)
TD 2018		-0.0180^{*}		0.0157	2.4517^{***}	0.0061	0.0322^{***}
		(0.0091)		(0.0092)	(0.2252)	(0.0057)	(0.0095)
TD 2008						0.0351^{***}	
						(0.0038)	
Within R-Squared	0.5656						
Between R-Squared	0.9194						
Overall R-Squared	0.9254					0.6071	
Nof Obs	40, 174	40, 174	40, 174	40, 174	38, 964	40, 174	23, 692
Nof Groups	7, 466	7, 466	7, 466	7, 466	7, 444	7, 466	6, 830
Avg. Obs. per Group	5.38	5.380	5.38	5.38	5.23	5.23	3.50
Min Obs. per Group	1	1	1	1	1	1	1
Max Obs. per Group	11	11	11	11	11	11	9
Hansen test of overid: statistics:							39.49
nof para:							7
p-value:							0.00
RMSE	0.03	0.22	0.11	0.14	*NA*	0.04	0.03

Source: OeNB. Authors' calculations.
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. We use cluster robust standard errors with clustering at the bank level in the Fixed effects and the Solow model. We use Windmeijer corrected robust standard errors (Windmeijer, 2005; Sigmund and Ferstl, 2021) at the bank level in the System-GMM model.
This table show the TFP estimations for the Cobb-Douglas PF with time dummies for the fixed effects model, the Olley-Pakes model (Olley and Pakes, 1996), the ACF model (Ackerberg et al., 2015), the LP model (Levinsohn and Petrin, 2003), the WRDG model (IV Wooldridge method), the Solow residual method and the System-GMM (Blundell and Bond, 1998).
The fixed effects model is estimated by Croissant and Millo (2008). The Olley Pakes, the ACF, the LP and the WRDG models are estimated with Rovigatti (2017b); Rovigatti and Mollisi (2018b). The Solow residual model is estimated with Croissant and Millo (2008). The System-GMM model is estimated with Sigmund and Ferstl (2021).
The dependent variable is the log(total revenue). The explanatory variables are log(labor costs), log(capital), log(material costs) and time dummies. In the System-GMM model, we add the lag of log(total revenue) as an additional explanatory variable.
RMSE refers to root mean squared error and gives a goodness of fit measure that can be used to compare these different models.

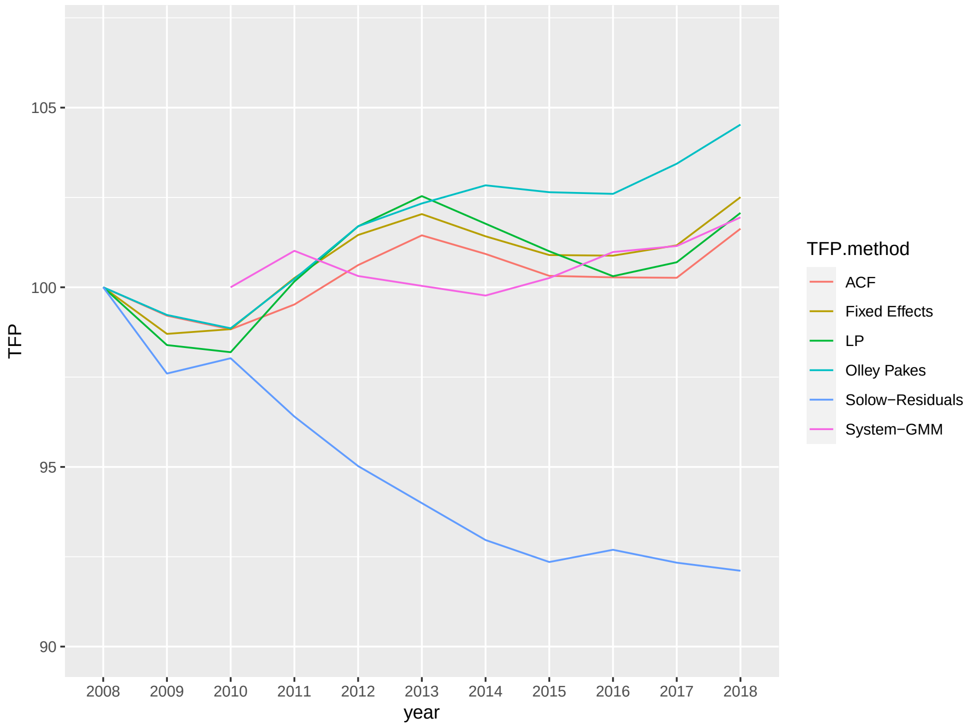
Based on these estimations results, we are able to calculate the TFP for each model which is similar to Eq. (13) but adjusted to the specific estimations method.[13] Most importantly, we improve on

[13]We summarize these results in Figure A.3 and Figure A.4.

the TFP measures in Caballero et al. (2008); Adalet McGowan et al. (2018) by applying the most common Cobb-Douglas productivity estimation techniques. Whereas Caballero et al. (2008) use fixed coefficients for log(labor) with 2/3 and log(capital) with 1/3, we estimate these coefficients and also include log(material costs) in the Cobb-Douglas production function. Adalet McGowan et al. (2018) only use OLS residuals, the WRDG and W-GMM methods which show rather implausible results, especially for the log(capital) coefficient, since they are based on the Olley and Pakes (1996) approach. We do not consider OLS residuals at all, since it would imply that $\omega_{i,t} = \omega_i = \omega$. Hence, all firms would receive the same productivity shock thereby completely ignoring the panel structure of our data.

For our time period 2008–2018, the estimated TFPs of Austrian non-financial firms follow a similar pattern. In Figure 2, we see that most estimated TFPs drop after the global financial crisis of 2007–2008 and rise again in the years afterwards. After the peak in 2013 the TFPs decline until 2017 before they increases sharply. The TFP based on the Solow residuals follows a different pattern, most likely caused by the imposed parameter restrictions which seem to be implausible. Without considering the Solow residuals TFP, at the end of our observation period in 2018, the other TFPs lie about 1.3% to 5.0% above the starting point in 2008.

Figure 2: Estimated average TFP developments for Austrian non-financial firms



Source: Authors' calculations. Based on the firm-specific TFP estimations in Table 3, we calculate the average TFP for each time period. We normalize the average TFP for each estimation to 100 in 2008.

4.2. Results – Translog Production Function

The methods by Olley and Pakes (1996); Levinsohn and Petrin (2003); Wooldridge (2009); Ackerberg et al. (2015) are not designed for the translog PF specification. The quadratic and interaction terms in Eq. (10) already are similar to the variables used in Olley and Pakes (1996); Levinsohn and Petrin (2003); Wooldridge (2009); Ackerberg et al. (2015) to proxy the inverse investment function.

We present our translog PF estimation results in Table 4. Our results are largely in line with the literature (Corbo and Meller, 1979; Kim, 1992; Tzouvelekas, 2000; Pablo-Romero and Gómez-Calero, 2013).

The translog Fixed Effects model in Table 4 shows a slight improvement to the Cobb-Douglas Fixed Effects model in Table 3 based on the RMSE. Many of the quadratic and the interaction terms show significant coefficients. This points to relatively complex input factor dynamics and firm size effects.

Additionally, the fixed effects translog model estimation ("Fixed Effects: Fourier Flexible Form") with the Fourier Flexible Form (see Eq. (11)) does not improve the model fit dramatically.

Table 4: Translog TFP Estimations with time dummies

	Fixed Effects Translog Model	Fixed Effects Fourier Flexible Model
Intercept	2.1472***	2.0262***
	(0.1122)	(0.2539)
Log(labor costs)	0.2298***	0.4434***
	(0.0127)	(0.1038)
log(capital)	0.1685***	0.1459***
	(0.0087)	(0.0128)
Log(material costs)	0.3183***	0.2304***
	(0.0087)	(0.0121)
Log(labor costs)^2	0.0491***	0.0354***
	(0.0009)	(0.0078)
log(capital)^2	0.0119***	0.0123***
	(0.0006)	(0.0008)
Log(material costs)^2	0.0517***	0.0552***
	(0.0006)	(0.0007)
log(labor) x log(capital)	−0.0087***	−0.0101***
	(0.0011)	(0.0013)
log(labor) x log(material costs)	−0.0670***	−0.0678***
	(0.0012)	(0.0014)
log(capital) x log(material costs)	−0.0257***	−0.0233***
	(0.0008)	(0.0009)
cos(Log(labor costs))		0.3359**
sin(Log(labor costs))		0.0549
cos(2xLog(labor costs))		0.0053
sin(2xLog(labor costs))		−0.0091
cos(2xlog(capital))		−0.1027***
sin(2xlog(capital))		0.0181
cos(2xlog(material costs))		−0.1480***
sin(2xlog(material costs))		−0.0194*
cos(log(labor costs)+log(capital))		−0.0421***
sin(log(labor costs)+log(capital))		0.0636***
cos(log(labor costs)+log(material costs))		0.1730***
sin(log(labor costs)+log(material costs))		0.0913***
cos(log(material costs)+log(capital))		0.1324***
sin(log(material costs)+log(capital))		0.0649***
cos(3xLog(labor costs))		−0.0031
sin(3xLog(labor costs))		0.0005
cos(3xlog(capital))		−0.0101*
sin(3xlog(capital))		0.0328***
cos(3xlog(material costs))		0.0220***
sin(3xlog(material costs))		−0.0298***
Firm fixed effects	*yes*	*yes*
Time fixed effects	*yes*	*yes*
Within R-Squared	0.6540	0.6611
Between R-Squared	0.9649	0.9667
Overall R-Squared	0.9659	0.9674
Nof Obs	40, 174	40, 174
Nof Groups	7, 466	7, 466
Avg/Min/Max Obs. per Group	5.38/1/11	5.38/1/11
RMSE	0.0265	0.0260

Source: OeNB. Authors' calculations.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. We use cluster robust standard errors with clustering at the bank level.
The dependent variable is the log(total revenue). The explanatory variables are log(labor costs), log(capital), log(material costs), various transformations and interaction terms.
The various transformations and interaction terms for the Fixed Effects Translog Model are explained in Eq. (10). The various transformations and interaction terms for the Fixed Effects Fourier Flexible Model are explained in Eq. (11).

4.3. Results – Stochastic Frontier Analysis

In this section, we present our results for the SFA method to estimate the TFP based on Eq. (23). The results are very much in line with the Fixed Effects Model in Table 3. The additional information is the mean efficiency of all firms in the sample. This mean efficiency is based on the TE defined in Eq. (24). Thus, the average firm in our data sample reaches an efficiency level of 27% to 49% with respect to the most efficient firm in the sample in each period.

Table 5: Cobb-Douglas SFA Estimations

	Error Component Model	DFA Fixed Effects Model	True Fixed Effects Model
Intercept	4.1893***		3.8282***
	(0.0232)		(0.5777)
Log(labor costs)	0.3503***	0.2739***	0.3868***
	(0.0027)	(0.0040)	(0.0513)
log(capital)	0.0791***	0.0673***	0.0697
	(0.0017)	(0.0027)	(0.0371)
Log(material costs)	0.3922***	0.3700***	0.3990***
	(0.0014)	(0.0026)	(0.0161)
sigmaSq	0.4061***		0.4687***
	(0.0074)		(0.1205)
gamma	0.8882***		0.9025***
	(0.0018)		(0.0127)
mu	1.2012***		1.3008
	(0.0201)		(0.8526)
Time fixed Effects	*Yes*	*Yes*	*Yes*
Mean Efficiency	27%	49%	28%
Nof Obs	48,301	48,301	48,301
Nof Groups	12,231	12,231	12,231
Avg. Obs. per Group	3.95	3.95	3.95
Min Obs. per Group	1	1	1
Max Obs. per Group	11	11	11

Source: OeNB. Authors' calculations.
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.
The dependent variable is the log(total revenue). The explanatory variables are log(labor costs), log(capital), log(material costs) and time dummies.
The Error Component Model is estimated by Battese and Coelli (1992).
The DFA Fixed Effects Model follows Cornwell et al. (1990).
The True Fixed Effects Model is estimated in accordance with Greene (2005).

5. The Total Factor Productivity and Zombie Firms

In this section, we present the results for direct zombie effects and zombie contagion effects on the TFP. In Section 5.1, we present four tables with different zombie definitions based on Eq. (28) (Caballero et al., 2008). In Section 5.2, we show the estimations results for the fixed effects specification defined in Eq. (29). We find strong empirical evidence for direct zombie effects, i.e., that non-zombie firms are more productive than zombie firms but limited evidence on zombie contagion effects. If we control for firm-specific fixed effects, we do not find any significant zombie contagion effects.

The calculation of the median percentage increase of the TFP for non-zombie firms is given by:

$$\Delta(\text{non-zombie TFP}) = \frac{median(TFP) + \delta_1 + (\delta_2 + \delta_3) * \text{median}(ShareZ_{i,j,t})}{median(TFP)} - 1\,, \tag{30}$$

The median(TFP) is calculated based on the estimated TFPs by the methods in Table 3. The coefficients δ_1, δ_2 and δ_3 are the coefficients in Eq. (28) and Eq. (29). The median($ShareZ_{i,j,t}$) is the median of the variable "Asset share zombie" based on one of the four zombie definitions.

5.1. *Zombie Effects: Evidence on a Sectoral Level*

In this section, we present the estimation results based on the main specification in Caballero et al. (2008) but for eight TFP estimations and four zombie definitions. The main results hold across all specifications: zombie firms are less productive than non-zombie firms but we only find limited empirical evidence for zombie contagion effects which are economically insignificant.

In Table 6, we show the estimation results for the ICR zombie definition in Eq. (1) for the eight different TFP estimations in Table 3. The results are similar across the models FE I, OP I, ACF I, LP I, WRDG I, Solow I and System-GMM I. The coefficient of Non-zombie (ICR) is positive and statistically significant. This means that non-zombie firms are significantly more productive than zombie firms. This is in line with the results in Adalet McGowan et al. (2018); Huang et al. (2021) but in contrast to Caballero et al. (2008) who do not find significant direct zombie effects on TFP. The coefficient of "Asset share zombie (ICR)" is statistically significant and positive but economically insignificant compared to the coefficient of "Non-zombie (ICR)". Thus, a high share of zombie assets in a sector increases the TFP. This result is also in contrast to Caballero et al. (2008). They estimate a statistically significant negative effect. "Asset share zombie (ICR)" or a similar variable is not included in Table 1 in Adalet McGowan et al. (2018).

The main variable in Caballero et al. (2008) is "Non-zombie x Asset share zombie (ICR)" which measures the contagion effect of zombie firms in the TFP of non-zombie firms. Caballero et al. (2008); Adalet McGowan et al. (2018) estimate a statistically and economically significant positive effects which means that the TFP gap between non-zombie and zombie firms widens. On the contrary, we find a statistically significant but economically small negative coefficient.

Table 6: Zombie Effects on TFP: Sectoral Evidence with the ICR Zombie Definition

	FE 1A	OP 1A	ACF 1A	LP 1A	WRDG 1A	Solow 1A	System-GMM 1A
Intercept	3.2840***	2.4924***	2.5438***	4.5112***	0.6280***	0.9460***	1.3265***
	(0.0414)	(0.0330)	(0.0362)	(0.0606)	(0.0404)	(0.0289)	(0.0249)
Non-zombie (ICR)	0.1621***	0.1241***	0.1848***	0.2409***	0.1435***	0.1245***	0.1172***
	(0.0362)	(0.0286)	(0.0315)	(0.0538)	(0.0351)	(0.0242)	(0.0223)
Asset share zombie (ICR)	0.0110***	0.0084***	0.0100***	0.0170***	0.0122***	0.0033	0.0076***
	(0.0041)	(0.0029)	(0.0034)	(0.0061)	(0.0038)	(0.0024)	(0.0026)
Non-zombie x Asset share zombie (ICR)	−0.0092**	−0.0063**	−0.0078**	−0.0161**	−0.0106***	0.0002	−0.0058**
	(0.0043)	(0.0030)	(0.0035)	(0.0063)	(0.0039)	(0.0025)	(0.0027)
Sectoral fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Time fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.0487	0.0984	0.1008	0.1029	0.0892	0.1248	0.0787
Number of obs.	26,741	26,745	26745	26,745	26,402	26,745	19,810
Number of groups	6,275	6,276	6,276	6,276	6,245	6,276	5,707
Average. Obs. group	4.26	4.26	4.26	4.26	4.22	4.26	3.47
Min. Obs. group	1	1	1	1	1	1	1
Max. Obs. Group	10	10	10	10	10	10	9
TFP %-increase non-zombie	2.07%	2.32%	3.20%	2.00%	5.81%	7.40%	7.74%

Source: OeNB. Authors' calculations.
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. We use cluster robust standard errors with clustering at the bank level.
We estimate Eq. (28) based on the estimations TFPs in Table 3, as the dependent variables. The explanatory variables are defined based on the "ICR zombie definition".
Non-zombie (ICR) is a dummy variable that takes the value of 1 if a firm i is a zombie at time t according to the interest coverage ratio (ICR) explained in Eq. (1).
Asset share zombie (ICR) is the share of assets at time t in industry sector j that are currently zombies.
Non-zombie x Asset share zombie (ICR) is an interaction term of the dummy variable Non-zombie (ICR) times Asset share zombie (ICR).
As in Caballero et al. (2008), the two-digit NACE industry classifications are used to generate the sectoral fixed effects.
TFP %-increase non-zombie is based on Eq. (30) and reports by how many percent on average non-zombie firms are more productive than zombie firms.

In Table 7 with the the ICR definition (simulated) zombie definition , we obtain similar results as in Table 6. The main results still hold true. Non-zombie firms are more productive than zombie firms as indicated by the positive coefficient of “Non-zombie (ICR simulated)”. The coefficient of “Asset share zombie (ICR simulated)” is also positive but again economically insignificant. Finally, the negative coefficient of “Non-zombie x Asset share zombie (ICR simulated)” shows that the TFP productivity gap does not widen between zombie and non-zombie firms.

Table 7: Zombie Effects on TFP: Sectoral Evidence with the simulated ICR Zombie Definition

	FE 2A	OP 2A	ACF 2A	LP 2A	WRDG 2A	Solow 2A	System-GMM 2A
Intercept	3.2805***	2.4939***	2.5438***	4.5223***	0.6417***	0.9250***	1.3241***
	(0.0424)	(0.0350)	(0.0375)	(0.0611)	(0.0420)	(0.0300)	(0.0267)
Non-zombie (ICR simulated)	0.1412***	0.0982***	0.1538***	0.2026***	0.1079***	0.1134***	0.0921***
	(0.0380)	(0.0309)	(0.0329)	(0.0545)	(0.0372)	(0.0244)	(0.0240)
Asset share zombie (ICR simulated)	0.0097***	0.0075***	0.0092***	0.0143***	0.0098***	0.0044**	0.0060***
	(0.0033)	(0.0026)	(0.0028)	(0.0048)	(0.0032)	(0.0019)	(0.0021)
Non-zombie x Asset share zombie (ICR simulated)	−0.0072**	−0.0046*	−0.0059**	−0.0124**	−0.0075**	−0.0000	−0.0032
	(0.0035)	(0.0027)	(0.0029)	(0.0051)	(0.0033)	(0.0020)	(0.0022)
Sectoral fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Time fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.0484	0.0980	0.1002	0.1024	0.0888	0.1253	0.0786
Number of obs.	26,741	26,745	26,745	26,745	26,402	26,745	19,810
Number of groups	5,170	6,276	6,276	6,276	6,245	6,276	5,707
Average. Obs. group	3.88	4.26	4.26	4.26	4.23	4.26	3.47
Min. Obs. group	1	1	1	1	1	1	1
Max. Obs. Group	10	10	10	10	10	10	9
TFP %-increase non-zombie	1.74%	1.74%	3.08%	1.67%	3.56%	6.05%	3.83%

Source: OeNB. Authors’ calculations.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. We use cluster robust standard errors with clustering at the bank level.
We estimate Eq. (28) based on the estimations TFPs in Table 3, as the dependent variables. The explanatory variables are defined based on the “ICR simulated zombie definition”.
Non-zombie (ICR simulated) is a dummy variable that takes the value of 1 if a firm i is a zombie at time t according to the interest coverage ratio (ICR simulated) explained in Section 2.2.
Asset share zombie (ICR simulated) is the share of assets at time t in industry sector j that are currently zombies.
Non-zombie x Asset share zombie (ICR simulated) is an interaction term of the dummy variable Non-zombie (ICR simulated) times Asset share zombie (ICR simulated).
As in Caballero et al. (2008), the two-digit NACE industry classifications are used to generate the sectoral fixed effects.
TFP %-increase non-zombie is based on Eq. (30) and reports by how many percent on average non-zombie firms are more productive than zombie firms.

Overall in Table 8, we again find similar results to the previous tables but the statistical significance of the coefficients “Asset share zombie (PIR-PD)” and “Non-zombie x Asset share zombie (PIR-PD)” is lower.

Table 8: Zombie Effects on TFP: Sectoral Evidence with the PIR-PD Zombie Definition

	FE 3A	OP 3A	ACF 3A	LP 3A	WRDG 3A	Solow 3A	System-GMM 3A
Intercept	3.3807***	2.4814***	2.6595***	4.6654***	3.1568***	1.1237***	1.2743***
	(0.0359)	(0.0278)	(0.0314)	(0.0519)	(0.0336)	(0.0251)	(0.0316)
Non-zombie (PIR-PD)	0.1383***	0.2001***	0.1314***	0.1717***	0.2499***	0.0341	0.1956***
	(0.0281)	(0.0229)	(0.0268)	(0.0394)	(0.0254)	(0.0227)	(0.0285)
Asset share zombie (PIR-PD)	0.0030	0.0117***	0.0072	0.0022	0.0119**	0.0045	0.0568***
	(0.0054)	(0.0043)	(0.0055)	(0.0076)	(0.0049)	(0.0049)	(0.0128)
Non-zombie x Asset share zombie (PIR-PD)	−0.0048	−0.0134***	−0.0091	−0.0057	−0.0152***	−0.0042	−0.0579***
	(0.0057)	(0.0044)	(0.0058)	(0.0079)	(0.0050)	(0.0050)	(0.0132)
Sectoral fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Time fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.0478	0.0969	0.0975	0.1004	0.6122	0.1206	0.0788
Number of obs.	34,170	34,175	34,175	34,175	33,363	34,175	20,122
Number of groups	5,338	6,606	6,606	6,606	6,572	6,606	5,826
Average. Obs. group	4.80	5.17	5.17	5.17	5.08	5.17	3.45
Min. Obs. group	1	1	1	1	1	1	1
Max. Obs. Group	11	11	11	11	11	11	9
TFP %-increase non-zombie	2.50%	2.89%	2.99%	2.04%	5.52%	7.91%	12.10%

Source: OeNB. Authors’ calculations.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. We use cluster robust standard errors with clustering at the bank level.
We estimate Eq. (28) based on the estimations TFPs in Table 3, as the dependent variables. The explanatory variables are defined based on the “PIR-PD definition”.
Non-zombie (PIR-PD) is a dummy variable that takes the value of 1 if a firm i is a zombie at time t according to the interest coverage ratio (PIR-PD) explained in Section 2.2.
Asset share zombie (PIR-PD) is the share of assets at time t in industry sector j that are currently zombies.
Non-zombie x Asset share zombie (PIR-PD) is an interaction term of the dummy variable Non-zombie (PIR-PD) times Asset share zombie (PIR-PD).
As in Caballero et al. (2008), the two-digit NACE industry classifications are used to generate the sectoral fixed effects.
TFP %-increase non-zombie is based on Eq. (30) and reports by how many percent on average non-zombie firms are more productive than zombie firms.

In Table 9, we estimate the highest direct zombie effects on TFP. Non-zombie firms are on average 3% to 9% more productive than zombie firms. The zombie contagion effects are also larger than in the previous tables but the coefficients of "Asset share zombie (PIR-ICR)" and "Non-zombie x Asset share zombie (PIR-ICR)" have opposite signs, a similar absolute value and therefore cancel each other out.

Table 9: Zombie Effects on TFP: Sectoral Evidence with the PIR-ICR Zombie Definition

	FE 4A	OP 4A	ACF 4A	LP 4A	WRDG 4A	Solow 4A	System-GMM 4A
Intercept	3.2998***	2.4712***	2.5634***	4.5641***	0.6264***	0.9471***	1.2711***
	(0.0506)	(0.0404)	(0.0467)	(0.0724)	(0.0473)	(0.0410)	(0.0374)
Non-zombie (PIR-ICR)	0.1314***	0.1556***	0.1614***	0.1389**	0.1445***	0.1539***	0.1928***
	(0.0431)	(0.0359)	(0.0419)	(0.0609)	(0.0405)	(0.0390)	(0.0357)
Asset share zombie (PIR-ICR)	0.0343***	0.0263***	0.0314***	0.0498***	0.0311***	0.0149**	0.0536***
	(0.0082)	(0.0064)	(0.0074)	(0.0122)	(0.0081)	(0.0068)	(0.0121)
Non-zombie x Asset share zombie (PIR-ICR)	−0.0286***	−0.0225***	−0.0259***	−0.0419***	−0.0270***	−0.0109	−0.0470***
	(0.0084)	(0.0065)	(0.0075)	(0.0124)	(0.0083)	(0.0068)	(0.0122)
Sectoral fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Time fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.0478	0.0979	0.0984	0.1018	0.0892	0.1216	0.0776
Number of obs.	26,694	26,698	26,698	26,698	26,355	26,698	19,773
Number of groups	5,168	6,271	6,271	6,271	,6240	6,271	5,697
Average. Obs. group	3.87	4.26	4.26	4.26	4.22	4.26	3.47
Min. Obs. group	1	1	1	1	1	1	1
Max. Obs. Group	10	10	10	10	10	10	9
TFP %-increase non-zombie	2.78%	3.22%	3.83%	2.47%	6.31%	9.32%	7.44%

Source: OeNB. Authors' calculations.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. We use cluster robust standard errors with clustering at the bank level.
We estimate Eq. (28) based on the estimations TFPs in Table 3, as the dependent variables. The explanatory variables are defined based on the "PIR-ICR definition".
Non-zombie (PIR-ICR) is a dummy variable that takes the value of 1 if a firm i is a zombie at time t according to the interest coverage ratio (PIR-ICR) explained in Section 2.2.
Asset share zombie (PIR-ICR) is the share of assets at time t in industry sector j that are currently zombies.
Non-zombie x Asset share zombie (PIR-ICR) is an interaction term of the dummy variable Non-zombie (PIR-ICR) times Asset share zombie (PIR-ICR).
As in Caballero et al. (2008), the two-digit NACE industry classifications are used to generate the sectoral fixed effects.
TFP %-increase non-zombie is based on Eq. (30) and reports by how many percent on average non-zombie firms are more productive than zombie firms.

Next, we use our results to determine which zombies (based on our four definitions) are the least productive. Firms that are classified as zombies by the "PIR-ICR definition", closely followed by the "PIR-PD definition" are less productive than zombies classified by the "ICR definition" and the "ICR definition (simulated)". This outcome confirms what economic intuition would suggest. Those firms who cannot cover their interest expenses with their earnings, although they pay a preferential interest rate, are the least productive zombie firms (PIR-ICR definition). Firms who are only identified as zombies according to the interest coverage ratio when simulating constant policy interest rates, turn out to be the most productive zombie firms (simulated ICR definition). Further, the combination of the PIR-criterion with the credit rating of firm (PIR-PD definition) seems to be better suited than only considering the interest coverage ratio (ICR definition) to identify weak and unproductive firms.

With these results and robustness checks, we give a relatively precise answer whether zombie firms are less productive than non-zombie firms. Zombie firms are on average between 1.7% and 9.3% less productive than non-zombie firms. While Caballero et al. (2008) findings would suggest that non-zombie firms are not significantly more productive than zombie firms (without incorporating the share of zombie firms in the sector), Adalet McGowan et al. (2018) estimate a coefficient of 0.52 in Table 1 which would be an increase of at least 9.1% in TFP (without considering the interaction term with share of zombie firms in the sector) which would further increase the TFP gap between non-zombie and zombie firms. Our results clearly show that zombie firms are less productive but not by an extremely large proportion. This finding is robust across zombie definitions and estimation methods.

5.2. Zombie Effects: Fixed Effects Estimation Results

In this section, we estimate Eq. (29) to address a potential omitted variable bias by including fixed effects for each firm. The main result that non-zombie firms are more productive than zombie firms from Section 5.1 is robust to the inclusion of firm fixed effects.

However, the significance of the coefficients for "Asset share zombie" and "Non-zombie x Asset share zombie" vanishes. In other words, controlling for firm-specific time constant unobserved heterogeneity removes any zombie contagion effects. We are not surprised by these results. Most contagion models are based on links between different firms such as loans and deposits on the interbank market (Eisenberg and Noe, 2001; Elsinger et al., 2006), any form of business relationship (Halinen et al., 1999; Villena et al., 2011) or common trend on the stock market (Ehrmann et al., 2011; Akhtaruzzaman et al., 2021). The fact that firms are in the same industry sector does not imply that these firms have any sources of contagion.

Table 10: Zombie Effects on TFP: Two-way FE Estimation with the ICR Zombie Definition

	FE 1B	OP 1B	ACF 1B	LP 1B	WRDG 1B	Solow 1B	System-GMM 1B
Non-zombie (ICR)	0.0686***	0.0556***	0.0752***	0.0927***	0.0611***	0.0575***	0.0647***
	(0.0135)	(0.0139)	(0.0143)	(0.0149)	(0.0142)	(0.0144)	(0.0149)
Asset share zombie (ICR)	0.0017	0.0011	0.0020	0.0033**	0.0018	0.0005	0.0047***
	(0.0013)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0015)	(0.0015)
Non-zombie x Asset share zombie (ICR)	−0.0001	0.0005	−0.0002	−0.0017	−0.0003	0.0013	−0.0033**
	(0.0013)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0015)	(0.0015)
Firm fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Time fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.0062	0.0044	0.0068	0.0075	0.0046	0.0055	0.0035
Number of obs.	26,741	26,745	26,745	26,745	26,402	26,745	19,810
Number of groups	6,275	6,276	6,276	6,276	6,245	6,276	5,707
Average. Obs. group	4.2615	4.2615	4.2615	4.2615	4.2277	4.2615	3.4712
Min. Obs. group	1	1	1	1	1	1	1
Max. Obs. Group	10	10	10	10	10	10	9
TFP %-increase non-zombie	0.0207	0.0232	0.0320	0.0200	0.0581	0.0740	0.0774

Source: OeNB. Authors' calculations.
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. We use cluster robust standard errors with clustering at the bank level.
We estimate Eq. (29) based on the estimations TFPs in Table 3, as the dependent variables. The explanatory variables are defined based on the "ICR zombie definition".
Non-zombie (ICR) is a dummy variable that takes the value of 1 if a firm i is a zombie at time t according to the interest coverage ratio (ICR) explained in Eq. (1).
Asset share zombie (ICR) is the share of assets at time t in industry sector j that are currently zombies.
Non-zombie x Asset share zombie (ICR) is an interaction term of the dummy variable Non-zombie (ICR) times Asset share zombie (ICR).
The TFP %-increase non-zombie is based on Eq. (30) and reports by how many percent on average non-zombie firms are more productive than zombie firms.

Table 11: Zombie Effects on TFP: Two-way FE Estimation with the ICR (simulated) Zombie Definition

	FE 2B	OP 2B	ACF 2B	LP 2B	WRDG 2B	Solow 2B	System-GMM 2B
Non-zombie (ICR simulated)	0.0557***	0.0421***	0.0642***	0.0748***	0.0416***	0.0551***	0.0354***
	(0.0136)	(0.0146)	(0.0138)	(0.0144)	(0.0141)	(0.0141)	(0.0134)
Asset share zombie (ICR simulated)	0.0011	0.0006	0.0021	0.0022*	0.0006	0.0018	0.0016
	(0.0012)	(0.0014)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0012)
Non-zombie x Asset share zombie (ICR simulated)	0.0002	0.0008	−0.0003	−0.0007	0.0007	0.0002	0.0000
	(0.0013)	(0.0014)	(0.0013)	(0.0013)	(0.0013)	(0.0014)	(0.0012)
Firm fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Time fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.0053	0.0038	0.0062	0.0063	0.0038	0.0053	0.0032
Number of obs.	26,741	26,745	26,745	26,745	26,402	26,745	19,810
Number of groups	6,275	6,276	6,276	6,276	6,245	6,276	5,707
Average. Obs. group	4.2615	4.2615	4.2615	4.2615	4.2277	4.2615	3.4712
Min. Obs. group	1	1	1	1	1	1	1
Max. Obs. Group	10	10	10	10	10	10	9
TFP %-increase non-zombie	0.0174	0.0174	0.0308	0.0167	0.0356	0.0605	0.0383

Source: OeNB. Authors' calculations.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. We use cluster robust standard errors with clustering at the bank level.
We estimate Eq. (29) based on the estimations TFPs in Table 3, as the dependent variables. The explanatory variables are defined based on the "ICR simulated zombie definition".
Non-zombie (ICR simulated) is a dummy variable that takes the value of 1 if a firm i is a zombie at time t according to the interest coverage ratio (ICR simulated) explained in Section 2.2.
Asset share zombie (ICR simulated) is the share of assets at time t in industry sector j that are currently zombies.
Non-zombie x Asset share zombie (ICR simulated) is an interaction term of the dummy variable Non-zombie (ICR simulated) times Asset share zombie (ICR simulated).
The TFP %-increase non-zombie is based on Eq. (30) and reports by how many percent on average non-zombie firms are more productive than zombie firms.

Table 12: Zombie Effects on TFP: Two-way FE Estimation with PIR-PD Zombie definition

	FE 3B	OP 3B	ACF 3B	LP 3B	WRDG 3B	Solow 3B	System-GMM 3B
Non-zombie (PIR-PD)	0.0978***	0.0888***	0.0932***	0.1067***	0.0841***	0.0851***	0.1603***
	(0.0145)	(0.0141)	(0.0145)	(0.0163)	(0.0133)	(0.0141)	(0.0332)
Asset share zombie (PIR-PD)	−0.0003	−0.0009	0.0001	0.0009	−0.0014	−0.0009	0.0208**
	(0.0027)	(0.0024)	(0.0028)	(0.0033)	(0.0024)	(0.0026)	(0.0094)
Non-zombie x Asset share zombie (PIR-PD)	−0.0018	−0.0027	−0.0013	−0.0015	−0.0019	−0.0007	−0.0219**
	(0.0026)	(0.0024)	(0.0027)	(0.0032)	(0.0023)	(0.0025)	(0.0097)
Firm fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Time fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.0073	0.0055	0.0063	0.0074	0.0053	0.0051	0.0121
Number of obs.	34,170	34,175	34,175	34,175	33,363	34,175	20,122
Number of groups	6,605	6,606	6,606	6,606	6,572	6,606	5,826
Average. Obs. group	5.1734	5.1733	5.1733	5.1733	5.0765	5.1733	3.4538
Min. Obs. group	1	1	1	1	1	1	1
Max. Obs. Group	11	11	11	11	11	11	9
TFP %-increase non-zombie	0.0250	0.0289	0.0299	0.0204	0.0552	0.0791	0.1210

Source: OeNB. Authors' calculations.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. We use cluster robust standard errors with clustering at the bank level.
We estimate Eq. (29) based on the estimations TFPs in Table 3, as the dependent variables. The explanatory variables are defined based on the "PIR-PD definition".
Non-zombie (PIR-PD) is a dummy variable that takes the value of 1 if a firm i is a zombie at time t according to the interest coverage ratio (PIR-PD) explained in Section 2.2.
Asset share zombie (PIR-PD) is the share of assets at time t in industry sector j that are currently zombies.
Non-zombie x Asset share zombie (PIR-PD) is an interaction term of the dummy variable Non-zombie (PIR-PD) times Asset share zombie (PIR-PD).
The TFP %-increase non-zombie is based on Eq. (30) and reports by how many percent on average non-zombie firms are more productive than zombie firms.

Table 13: Zombie Effects on TFP: Two-way FE Estimation with PIR-ICR definition

	FE 4B	OP 4B	ACF 4B	LP 4B	WRDG 4B	Solow 4B	System-GMM 4B
Non-zombie (PIR-ICR)	0.1045^{***}	0.0906^{***}	0.1076^{***}	0.1259^{***}	0.0860^{***}	0.0918^{***}	0.1006^{***}
	(0.0216)	(0.0209)	(0.0210)	(0.0244)	(0.0182)	(0.0189)	(0.0319)
Asset share zombie (PIR-ICR)	0.0036	0.0023	0.0048	0.0066^{*}	0.0023	0.0025	0.0080
	(0.0031)	(0.0031)	(0.0033)	(0.0035)	(0.0031)	(0.0031)	(0.0053)
Non-zombie x Asset share zombie (PIR-ICR)	−0.0026	−0.0017	−0.0030	−0.0049	−0.0016	−0.0009	−0.0066
	(0.0032)	(0.0031)	(0.0033)	(0.0035)	(0.0031)	(0.0031)	(0.0053)
Firm fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Time fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.0043	0.0030	0.0045	0.0054	0.0029	0.0034	0.0034
Number of obs.	26,694	26,698	26,698	26,698	26,355	26,698	19,773
Number of groups	6,270	6,271	6,271	6,271	6,240	6,271	5,697
Average. Obs. group	4.2574	4.2574	4.2574	4.2574	4.2236	4.2574	3.4708
Min. Obs. group	1	1	1	1	1	1	1
Max. Obs. Group	10	10	10	10	10	10	9
TFP %-increase non-zombie	0.0278	0.0322	0.0383	0.0247	0.0631	0.0932	0.0744

Source: OeNB. Authors' calculations.
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. We use cluster robust standard errors with clustering at the bank level.
We estimate Eq. (29) based on the estimations TFPs in Table 3, as the dependent variables. The explanatory variables are defined based on the "PIR-ICR definition".
Non-zombie (PIR-ICR) is a dummy variable that takes the value of 1 if a firm i is a zombie at time t according to the interest coverage ratio (PIR-ICR) explained in Section 2.2.
Asset share zombie (PIR-ICR) is the share of assets at time t in industry sector j that are currently zombies.
Non-zombie x Asset share zombie (PIR-ICR) is an interaction term of the dummy variable Non-zombie (PIR-ICR) times Asset share zombie (PIR-ICR).
The TFP %-increase non-zombie is based on Eq. (30) and reports by how many percent on average non-zombie firms are more productive than zombie firms.

In Appendix C in Table C.21, we estimate the fixed effects model from Eq. (29) with the "Non-zombie" dummy as the only explanatory variable but only for the TFP estimation by the fixed effects model for all four zombie definitions. We obtain the same results for the TFP %-increase non-zombie as for the corresponding models, "FE 1B", "FE 2B", "FE 3B" and "FE 4B" in the previous tables. Hence, we can rule out that the "Asset share zombie" or the "Non-zombie x Asset share zombie" are confounders or colliders (Cunningham, 2021; Cinelli et al., 2020) that change the coefficient of the "Non-zombie" dummy and as a result the TFP %-increase non-zombie.

5.3. Stochastic Frontier Analysis: Mean Efficiency of Zombie Firms

Our second criterion to measure the influence of zombie firms on TFP is $TE_{i,t}$ defined in Eq. (24). In Table 14, we present our results on TE. Zombie firms are only around $1-3$pp less efficient than non-zombie firms. The large difference in mean efficiency between the DFA-FE models and the other two models can be attributed to the distributional assumptions on the error terms ($v_{i,t}$ and $u_{i,t}$) in Eq. (23).

Table 14: Mean Technical Efficiency: Zombie vs. Non-Zombie

	Non-zombie	Zombie
SFA-EC: ICR definition	0.25	0.23
SFA-EC: ICR definition (simulated)	0.25	0.23
SFA-EC: PIR-PD definition	0.24	0.22
SFA-EC: PIR-ICR definition	0.25	0.23
DFA-FE: ICR definition	0.49	0.48
DFA-FE: ICR definition (simulated)	0.49	0.49
DFA-FE: PIR-PD definition	0.48	0.45
DFA-FE: PIR-ICR definition	0.49	0.48
SFA-True-FE: ICR definition	0.25	0.24
SFA-True-FE: ICR definition (simulated)	0.25	0.24
SFA-True-FE: PIR-PD definition	0.25	0.23
SFA-True-FE: PIR-ICR definition	0.25	0.24

Source: OeNB. Own calculations.
SFA-EC refers to the SFA error component model which is estimated in Table 5 in column "Error Component Model".
DFA-EC refers to the DFA model which is estimated in Table 5 in column "DFA Fixed Effects Model".
SFA-True-FE refers to the true fixed effects model which is estimated in Table 5 in column "True Fixed Effects Model".
ICR definition, ICR definition (simulated), PIR-PD definition and PIR-ICR definition refer to the four zombie definitions given in Section 2.2.

6. Zombie Effects: Log Employment Growth

In this section, we present our results on the direct zombie effects and zombie contagion on the log employment growth.[14] We present our results with sectoral dummies in Table 15 and with firm-specific fixed effects in Table 16.

We calculate the mean percentage point increase in log employment growth of non-zombie firms in the following way.

$$\Delta(\log(\mathrm{E})) = \delta_1 + (\delta_2 + \delta_3) * \mathrm{mean}(ShareZ_{i,j,t}) \;, \tag{31}$$

The coefficients δ_1, δ_2 and δ_3 are the coefficients in Eq. (28) and Eq. (29). The mean($ShareZ_{i,j,t}$) is the mean of the variable "Asset share zombie" based on one of the four zombie definitions.

In all models, we only find direct zombie effects. In Table 15, the Δ log(E) pp-increase non-zombie is between 1.61pp and 6.1pp. If we further compare the intercept with the relevant non-zombie dummy (e.g., Non-zombie (ICR) in the first column), then we see that zombie firms have on aver-

[14] We obtain similar results when we use the labor productivity and the log growth rate of labor costs as the dependent variable.

age a slightly negative log employment growth on average. Hence, non-zombie firms have a much higher growth rate of log employment than zombie firms which is in line with standard economic theory. The coefficients of "Asset share zombie" and "Non-zombie x Asset share zombie" are neither statistically nor economically significant. In three out of four model the coefficient "Non-zombie x Asset share zombie" is even positive indicating that a high asset share of zombie firms even increases the log employment growth of non-zombie firms in the same industry sector.

The negative intercepts in three out of four models in Table 15 imply that on average the log employment growth in zombie firms is negative.

Table 15: Zombie Effects on Employment Growth: Sectoral Evidence with the ICR Zombie Definition

	Δ log(E) ICR	Δ log(E) ICR (simulated)	Δ log(E) PIR-PD	Δ log(E) PIR-ICR
Intercept	-0.0378^{**}	-0.0265^{*}	0.0004	-0.0581^{***}
	(0.0157)	(0.0136)	(0.0172)	(0.0210)
Non-zombie (ICR)	0.0400^{***}			
	(0.0143)			
Asset share zombie (ICR)	−0.0002			
	(0.0018)			
Non-zombie x Asset share zombie (ICR)	0.0005			
	(0.0018)			
Non-zombie (ICR simulated)		0.0331^{***}		
		(0.0110)		
Asset share zombie (ICR simulated)		−0.0004		
		(0.0011)		
Non-zombie x Asset share zombie (ICR simulated)		0.0005		
		(0.0011)		
Non-zombie (PIR-PD)			0.0159	
			(0.0127)	
Asset share zombie (PIR-PD)			−0.0007	
			(0.0020)	
Non-zombie x Asset share zombie (PIR-PD)			0.0008	
			(0.0021)	
Non-zombie (PIR-ICR)				0.0588^{***}
				(0.0205)
Asset share zombie (PIR-ICR)				0.0029
				(0.0034)
Non-zombie x Asset share zombie (PIR-ICR)				−0.0020
				(0.0035)
Sectoral fixed effects	*yes*	*yes*	*yes*	*yes*
Time fixed effects	*yes*	*yes*	*yes*	*yes*
R-squared	0.0059	0.0057	0.0040	0.0045
Number of obs.	27,109	27,109	28,629	27,062
Number of groups	6,414	6,414	6,593	6,408
Average. Obs. group	4.23	4.23	4.34	4.22
Min. Obs. group	1	1	1	1
Max. Obs. Group	10	10	10	10
Δ log(E) pp-increase non-zombie	4.25*pp*	3.38*pp*	1.61*pp*	6.10*pp*

Source: OeNB. Authors' calculations.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Standard errors for the estimated model coefficients are obtained by using a cluster robust variance matrix estimator.
The dependent variable is all models is the growth rate of log employment.
In model "Δ log(E) ICR" the explanatory variables are defined based in the "ICR zombie definition".
In model "Δ log(E) ICR (simulated)" the explanatory variables are defined based in the "ICR zombie (simulated) definition".
In model "Δ log(E) PIR-PD" the explanatory variables are defined based in the "PIR-PD zombie definition".
In model "Δ log(E) PIR-ICR" the explanatory variables are defined based in the "PIR-ICR zombie definition".
Non-zombie is a dummy variable that takes the value of 1 if a firm i is a zombie at time t according to one of the four zombie definition in Section 2.2.
Asset share zombie is the share of assets at time t in industry sector j that are currently zombies.
Non-zombie x Asset share zombie is an interaction term of the dummy variable Non-zombie times Asset share zombie.
Δ log(E) pp-increase non-zombie is the percentage point increase in the log employment growth of non-zombie firms compared to zombie firms. In all models, the major driver of this difference in the coefficient of "Non-zombie".
Δ log(E) pp-increase non-zombie = Non-zombie dummy + Asset share zombie + Non-zombie x Asset share zombie.

In Table 16, we largely confirm the findings from Table 15. Again, we only find direct zombie effects that are slightly smaller than previously. The Δ log(E) pp-increase non-zombie ranges now between −0.04pp and 4.62pp.

Table 16: Zombie Effects on Employment Growth: Two-way FE Estimations with the ICR Zombie Definition

	FE Δ log(E) ICR	FE Δ log(E) ICR (simulated)	FE Δ log(E) PIR-PD	FE Δ log(E) PIR-ICR
Non-zombie (ICR)	0.0204			
	(0.0153)			
Asset share zombie (ICR)	0.0008			
	(0.0016)			
Non-zombie x Asset share zombie (ICR)	−0.0004			
	(0.0016)			
Non-zombie (ICR simulated)		0.0050		
		(0.0147)		
Asset share zombie (ICR simulated)		−0.0008		
		(0.0013)		
Non-zombie x Asset share zombie (ICR simulated)		0.0009		
		(0.0013)		
Non-zombie (PIR-PD)			−0.0054	
			(0.0177)	
Asset share zombie (PIR-PD)			0.0014	
			(0.0027)	
Non-zombie x Asset share zombie (PIR-PD)			0.0010	
			(0.0028)	
Non-zombie (PIR-ICR)				0.0445^{*}
				(0.0262)
Asset share zombie (PIR-ICR)				0.0039
				(0.0038)
Non-zombie x Asset share zombie (PIR-ICR)				−0.0030
				(0.0039)
Firm fixed effects	*yes*	*yes*	*yes*	*yes*
Time fixed effects	*yes*	*yes*	*yes*	*yes*
R-squared	0.0003	0.0002	0.0001	0.0005
Number of obs.	27,109	27,109	28,629	27,062
Number of groups	6,414	6,414	6,593	6,408
Average. Obs. group	4.2265	4.2265	4.3423	4.2232
Min. Obs. group	1	1	1	1
Max. Obs. Group	10	10	10	10
Δ log(E) pp-increase non-zombie	2.32*pp*	0.57*pp*	−0.04*pp*	4.62*pp*

Source: OeNB. Authors' calculations.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Standard errors for the estimated model coefficients are obtained by using a cluster robust variance matrix estimator.
The dependent variable is all models is the growth rate of log employment.
In model "FE Δ log(E) ICR" the explanatory variables are defined based in the "ICR zombie definition".
In model "FE Δ log(E) ICR (simulated)" the explanatory variables are defined based in the "ICR zombie (simulated) definition".
In model "FE Δ log(E) PIR-PD" the explanatory variables are defined based in the "PIR-PD zombie definition".
In model "FE Δ log(E) PIR-ICR" the explanatory variables are defined based in the "PIR-ICR zombie definition".
Non-zombie is a dummy variable that takes the value of 1 if a firm i is a zombie at time t according to one of the four zombie definition in Section 2.2.
Asset share zombie is the share of assets at time t in industry sector j that are currently zombies.
Non-zombie x Asset share zombie is an interaction term of the dummy variable Non-zombie times Asset share zombie.
Δ log(E) pp-increase non-zombie is the percentage point increase in the log employment growth of non-zombie firms compared to zombie firms. In all models, the major driver of this difference in the coefficient of "Non-zombie".
Δ log(E) pp-increase non-zombie = Non-zombie dummy + Asset share zombie + Non-zombie x Asset share zombie.

In Appendix C in Table C.22, we estimate the fixed effects model from Eq. (29) with the "Non-zombie" dummy as the only explanatory variable. We obtain the same results for the Δ log(E) pp-increase non-zombie as for the corresponding models, "FE Δ log(E) ICR", "FE Δ log(E) ICR (simulated)", "FE Δ log(E) PIR-PD" and "FE Δ log(E) PIR-ICR" in the previous table. Hence, we can rule out that the "Asset share zombie" or the "Non-zombie x Asset share zombie" are confounders or colliders (Cunningham, 2021; Cinelli et al., 2020) that change the coefficient of the "Non-zombie" dummy and as a result the Δ log(E) pp-increase non-zombie.

7. Zombie Effects: Gross Investment Ratio

In this section, we present our results on the direct zombie effects and zombie contagion effects on the gross investment ratio. We present our results with sectoral dummies in Table 17 and with firm-specific fixed effects in Table 18.

The calculation of the median percentage increase of the gross investment ratio for non-zombie firms is given by:

$$\Delta(\text{non-zombie I/K}) = \frac{median(I/K) + \delta_1 + (\delta_2 + \delta_3) * \text{median}(ShareZ_{i,j,t})}{median(I/K)} - 1\,, \tag{32}$$

The median(I/K) is calculated based on the gross investment ratio. The coefficients δ_1, δ_2 and δ_3 are the coefficients in Eq. (28) and Eq. (29). The median($ShareZ_{i,j,t}$) is the median of the variable "Asset share zombie" based on one of the four zombie definitions.

In all models, we find strong direct zombie effects on the gross investment ratio. The coefficients for the non-zombie dummies for all zombie definitions are statistically significant. For all zombie definitions but the "PIR-PD zombie definition" the effects are positive. This means that non-zombie firms have a higher gross investment ratio than zombie firms. The opposite results are obtained for two specification with the "PID-PD" zombie definition which imlies that firms that pay a preferred interest rate given their credit rating investment more. Also this finding is therefore reasonable. In our opinion the "PIR-PD zombie definition" might not be best suited to classify zombies.

In Table 17, we estimate statistically significant zombie contagion effects. Again for three out of four zombie definition, the coefficients for "Asset share zombie" are positive. This means that a higher asset share of zombie firms increases the gross investment ratio of all firms. On the other hand, the coefficients for "Non-zombie x Asset share zombie" are negative. These are zombie contagion effects that have the same sign as in Caballero et al. (2008); Adalet McGowan et al. (2018).

However, if we compare them with the sizes of the "Non-zombie" dummy across all models, they are economically negligible. In our results the "Non-zombie" dummies increases the gross investment ratio by 2.8% to 6.2%. Our coefficients of 'Asset share zombies" are between 0.26% and 0.44%. Our coefficients for "Non-zombie x Asset share zombie" are of similar magnitude but negative. This is in sharp contrast to Caballero et al. (2008). Their coefficient of the non-zombie dummy is around 2% whereas their coefficient of "Asset share zombie" is around −14% and their coefficient for "Non-zombie x Asset share zombie" is around −9%.

Comparing our results to Adalet McGowan et al. (2018) is difficult because they did not include the variable "Asset share zombie" in their specification, but only "Non-zombie" dummy and the interaction term "Non-zombie x Asset share zombie". However their coefficient of the "Non-zombie" dummy is around 7.4% which is close to our results.[15]

[15]We estimate all our models without the variable "Asset share zombie" and obtain almost identical results to the presented results. Direct zombie effects still dominate.

Table 17: Zombie Effects on the Gross Investment Ratio: Sectoral Evidence

	I/K ICR	I/K ICR (simulated)	I/K PIR-PD	I/K PIR-ICR
Intercept	26.0321***	25.3062***	40.3848***	27.3867***
	(1.8364)	(1.8125)	(1.5105)	(1.9508)
Non-zombie (ICR)	4.7884***			
	(1.4003)			
Asset share zombie (ICR)	0.3006*			
	(0.1565)			
Non-zombie x Asset share zombie (ICR)	−0.3023*			
	(0.1596)			
Non-zombie (ICR simulated)		6.2094***		
		(1.3514)		
Asset share zombie (ICR simulated)		0.2609**		
		(0.1161)		
Non-zombie x Asset share zombie (ICR simulated)		−0.2953**		
		(0.1194)		
Non-zombie (PIR-PD)			−5.8261***	
			(1.1313)	
Asset share zombie (PIR-PD)			−0.8381***	
			(0.2238)	
Non-zombie x Asset share zombie (PIR-PD)			0.8749***	
			(0.2293)	
Non-zombie (PIR-ICR)				2.8378*
				(1.6287)
Asset share zombie (PIR-ICR)				0.4383
				(0.2815)
Non-zombie x Asset share zombie (PIR-ICR)				−0.3635
				(0.2872)
R-squared	0.04	0.04	0.04	0.04
Number of obs.	26,605	26,605	33,820	26,559
Number of groups	6,383	6,383	6,732	6,374
Average. Obs. group	4.17	4.17	5.02	4.17
Min. Obs. group	1	1	1	1
Max. Obs. Group	10.	10	11	10
Gross investment ratio: Non-Zombie Increase (in %)	17.92	22.16	−21.58	11.26

Source: OeNB. Authors' calculations.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Standard errors for the estimated model coefficients are obtained by using a cluster robust variance matrix estimator.
The dependent variable is all models is the gross investment ratio.
In model "I/K ICR" the explanatory variables are defined based in the "ICR zombie definition".
In model "I/K ICR (simulated)" the explanatory variables are defined based in the "ICR zombie (simulated) definition".
In model "I/K PIR-PD" the explanatory variables are defined based in the "PIR-PD zombie definition".
In model "I/K PIR-ICR" the explanatory variables are defined based in the "PIR-ICR zombie definition".
Non-zombie is a dummy variable that takes the value of 1 if a firm i is a zombie at time t according to one of the four zombie definition in Section 2.2. Asset share zombie is the share of assets at time t in industry sector j that are currently zombies. Non-zombie x Asset share zombie is an interaction term of the dummy variable Non-zombie times Asset share zombie.
Gross investment ratio: Non-Zombie Increase (in %) is the percentage increase in the gross investment ratio of non-zombie firms outlined in Eq. (32).

Table 18: Zombie Effects on the Gross Investment Ratio: Two-way FE Estimations

	FE I/K ICR	FE I/K ICR (simulated)	FE I/K PIR-PD	FE I/K PIR-ICR
Non-zombie (ICR)	4.1487^{***}			
	(1.2453)			
Asset share zombie (ICR)	0.1479			
	(0.1184)			
Non-zombie x Asset share zombie (ICR)	−0.1926			
	(0.1212)			
Non-zombie (ICR simulated)		5.0822^{***}		
		(1.1816)		
Asset share zombie (ICR simulated)		0.1315		
		(0.0878)		
Non-zombie x Asset share zombie (ICR simulated)		-0.2095^{**}		
		(0.0895)		
Non-zombie (PIR-PD)			-3.8465^{***}	
			(1.0670)	
Asset share zombie (PIR-PD)			−0.2536	
			(0.1927)	
Non-zombie x Asset share zombie (PIR-PD)			0.3508^{*}	
			(0.1959)	
Non-zombie (PIR-ICR)				0.9725
				(1.4075)
Asset share zombie (PIR-ICR)				−0.2368
				(0.2494)
Non-zombie x Asset share zombie (PIR-ICR)				0.2237
				(0.2515)
R-squared	0.0009	0.0015	0.0007	0.0002
Number of obs.	26,605	26,605	33,820	26,559
Number of groups	6,383	6,383	6,732	6,374
Average. Obs. group	4.1681	4.1681	5.0238	4.1668
Min. Obs. group	1	1	1	1
Max. Obs. Group	10	10	11	10
Gross investment ratio: Non-Zombie Increase (in %)	14.3799	16.4084	−13.6943	3.5433

Source: OeNB. Authors' calculations.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Standard errors for the estimated model coefficients are obtained by using a cluster robust variance matrix estimator.
The dependent variable is all models is the gross investment ratio.
In model "FE I/K ICR" the explanatory variables are defined based in the "ICR zombie definition".
In model "FE I/K ICR (simulated)" the explanatory variables are defined based in the "ICR zombie (simulated) definition".
In model "FE I/K PIR-PD" the explanatory variables are defined based in the "PIR-PD zombie definition".
In model "FE I/K PIR-ICR" the explanatory variables are defined based in the "PIR-ICR zombie definition".
Non-zombie is a dummy variable that takes the value of 1 if a firm i is a zombie at time t according to one of the four zombie definition in Section 2.2. Asset share zombie is the share of assets at time t in industry sector j that are currently zombies. Non-zombie x Asset share zombie is an interaction term of the dummy variable Non-zombie times Asset share zombie.
Gross investment ratio: Non-Zombie Increase (in %) is the percentage increase in the gross investment ratio of non-zombie firms outlined in Eq. (32).

In Appendix C in Table C.23, we estimate the fixed effects model from Eq. (29) with the "Non-zombie" dummy as the only explanatory variable. We obtain the same results for the "Gross investment ratio: Non-Zombie Increase (in %)" as for the corresponding models, "FE I/K ICR", "FE I/K ICR (simulated)", "FE I/K PIR-PD" and "FE I/K PIR-ICR" in the previous table. Hence, we can rule out that the "Asset share zombie" or the "Non-zombie x Asset share zombie" are confounders or colliders (Cunningham, 2021; Cinelli et al., 2020) that change the coefficient of the "Non-zombie" dummy and as a result the "Gross investment ratio: Non-Zombie Increase (in %)".

8. Conclusion

In this paper, we answered the questions whether non-zombie firms have a higher TFP, a higher log employment growth and a higher gross investment ratio than zombie firms with a high-quality dataset of around 8,000 Austrian firms observed between 2008 and 2018. We calculated TFP productivity applying the most common production function estimation techniques and also define zombie firms with the four methods suggested in the literature.

Our results across all models suggest that non-zombie firms are by 2.0% to 9% more productive than non-zombie firms.[16] In contrast to (Caballero et al., 2008), we find that non-zombie firms are more productive independent of the share of zombie firms in the sector but not by more than 9% as suggested by the results of Adalet McGowan et al. (2018). Our results are more in line with Huang et al. (2021). Most importantly, in contrast to the literature we do not find any negative and economically significant zombie contagion effects on the TFP of non-zombie firms.

There are several reasons for these discrepancies to Caballero et al. (2008). First, our dataset does not include only listed firms from an economy that was in a permanent recession such as Japan during the 1990s which is also known as Japanese lost decade (Hayashi and Prescott, 2002). Moreover there could be some unaccounted common trends (e.g., on the Japanese the stock market) that could drive the zombie contagion results. In particular, only including listed firms could introduce a form of collider bias by sample selection. This bias is also known as "collider stratification bias". Both, the non-zombie dummy and TFP (as well as log employment growth and gross investment ratio) should influence the stock market price of a listed firm. Therefore, by selecting only listed firms, Caballero et al. (2008) implicitly condition on the stock market performance which is a collider for TFP and the non-zombie dummy variable (Cunningham, 2021; Cinelli et al., 2020). As a result, the estimated coefficients could be biased, i.e., the coefficient of the "non-zombie dummy" should be positive in the TFP estimation instead of being close to 0 and insignificant and the coefficients for "Asset share zombie" and "Non-zombie x Asset share zombie" should be insignificant which is the case for our dataset which does not only include listed firms.

Second, we estimate the TFP with the standard techniques suggested by the most recent literature (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015; Blundell et al., 2000) which all outperform our Solow residual approach even without fixing the coefficients for capital and labor. Third, there are more precise ways to model contagion between firms than being in the same industry sector (e.g., Eisenberg and Noe (2001) model credit links on the interbank market). It is more than likely that many firms in the same industry (based on the 2-digit NACE code) are not linked to each other by any common factors. Our results also show that non-zombie firms are more productive than zombie firms which is not the case in Caballero et al. (2008). This result is robust across many different zombie firm definitions and should be expected from standard economic theories. Adalet McGowan et al. (2018) estimate similar results on the direct zombie effects than ours.

Our results further suggest that non-zombie firms have statistically and economically significantly higher log employment growth than zombie firms. The employment growth of non-zombie firms is around 4-6 percentage points higher than in zombie firms which is in line with Adalet McGowan et al. (2018). Our results show that on average the log employment growth in zombie firms is negative. Again, we find no zombie contagion effects. This is in contrast to Caballero et al. (2008) who find that non-zombie and zombie firms have the same log employment growth, which is close to 0 as expected in Japan during the lost decade in the 1990s. However, they find very strong zombie contagion effects. The reasons for this discrepancy are mostly described in the previous paragraph. Only only listed firms in Japanese economy in the 1990s are not a representative sample

[16] In Table 8, we found a reduction of 12% with the system-GMM estimator which we consider an outlier.

of firms for most other advanced economies.

Next, our results suggest that non-zombie firms have a statistically and economically significantly higher gross investment ratio in six out of eight specifications.[17] The percentage increase in the gross investment ratio is around 11%–22% for non-zombie firms. In contrast to Caballero et al. (2008), who find extremely large effects, we only find economically small zombie contagion effects.

Putting all our results on the performance of zombie firms together, we see the following picture: Zombie firms are less productive, have a negative log employment growth and have a much lower gross investment ratio, which is in line with Adalet McGowan et al. (2018). Connecting these results with Beer et al. (2021), who find that the zombie status of a firm is not permanent and that there is a large probability of being revived to a non-zombie, zombie firms might not be as problematic as ordinarily assumed. In the life cycle of a firm there are different phases, such as growth, maturity and age. During some phases there might be negative aspects such as stagnation or even reaching the zombie status. Banks are not Samaritans pouring credit into a "bottomless" firm. If the situation of a firm is hopeless and it is not too-big-to-fail then there is a legally clearly defined settlement process which banks will go.

Comparing all Cobb-Douglas production function estimations in Table 3, we first note that "Olley Pakes" and "WRDG" show a negative coefficient for log(capital). This phenomena has already been documented by Klette and Griliches (1996); Felipe and Adams (2005). As suggested by Ackerberg et al. (2015), also in our setting, the "ACF" and the "LP" models clearly outperform these two models. Among the remaining models, the "Fixed Effects" and the "System-GMM" models perform best based on the RMSE. In both models, we make the strong assumption that the productivity shock is constant over time. Thus, selecting between the "Fixed Effects" model and the "ACF" model boils down to accepting a strong assumption on the nature of the productivity shock which might be acceptable if you observe firms over a short period of time or to correcting a potential endogeneity issue by applying a control function approach based on an inverse investment function. Surprisingly, neither the translog PF nor the translog PF with the Fourier Flexible Form in Table 4 have a much smaller RMSE than fixed effects and the system GMM estimations in Table 3.

From a macroeconomic perspective, for most of the estimation methods the TFP follows a similar pattern for our observation period 2008–2019. After a drop in 2009, the TFP increases and peaks in 2013/2014. In the years that follow, the TFP falls until 2017 before it, again, increases sharply. Irrespective of the empirical method, in 2018, which marks the end of our observation period, the TFP lies about 1.3% to 5.0% above the starting point of 2008.

For further research, we would also suggest using our results and combine it with the number of zombie firms from Beer et al. (2021) or other similar papers that quantify the share of zombie firms in a country/region to make projections of the aggregate loss in terms of output on the

[17]The opposite results are obtained for two specification with the "PID-PD" zombie definition which means that firms that pay a preferred interest rate given their credit rating investment more. Also this finding makes sense.

macroeconomic level.

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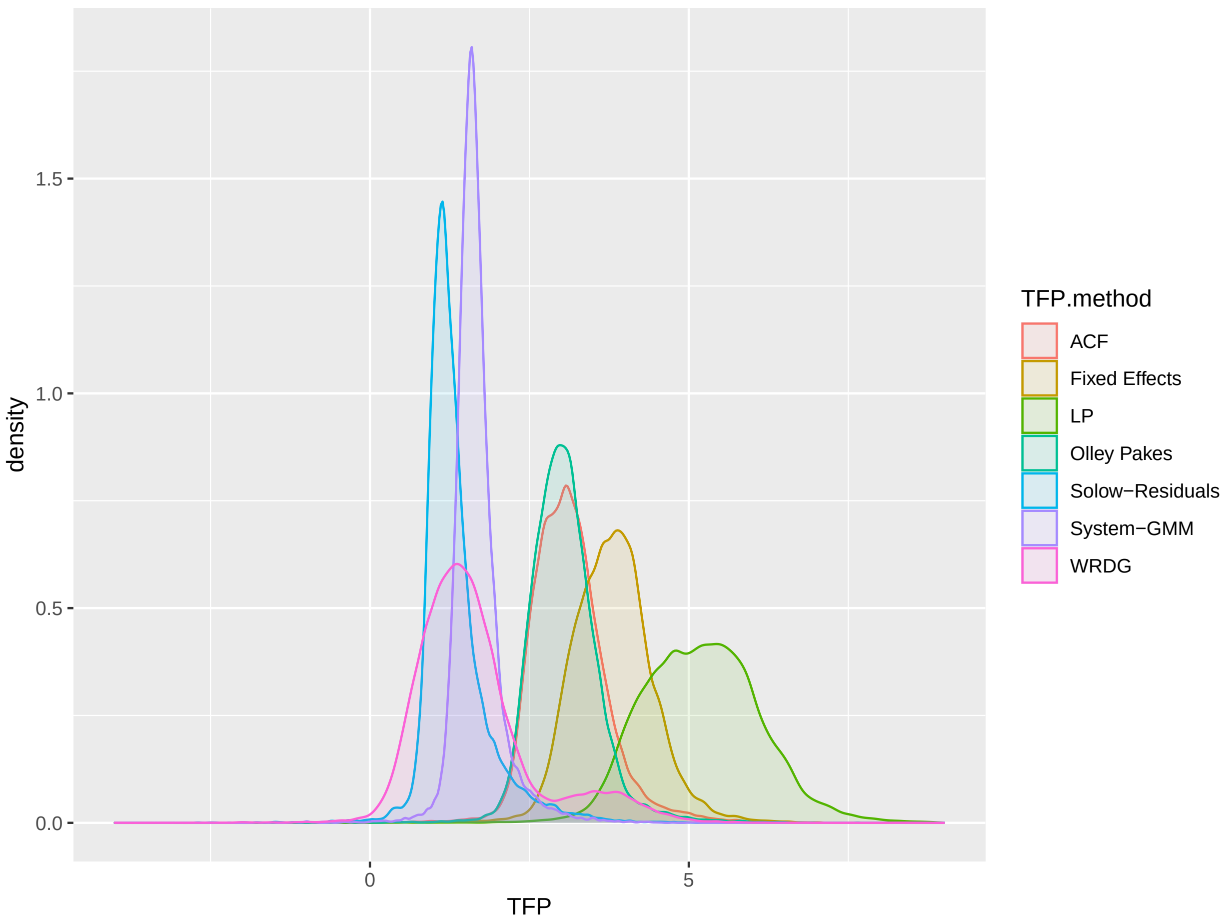
Appendix A. Total Factor Productivity: Density Plots

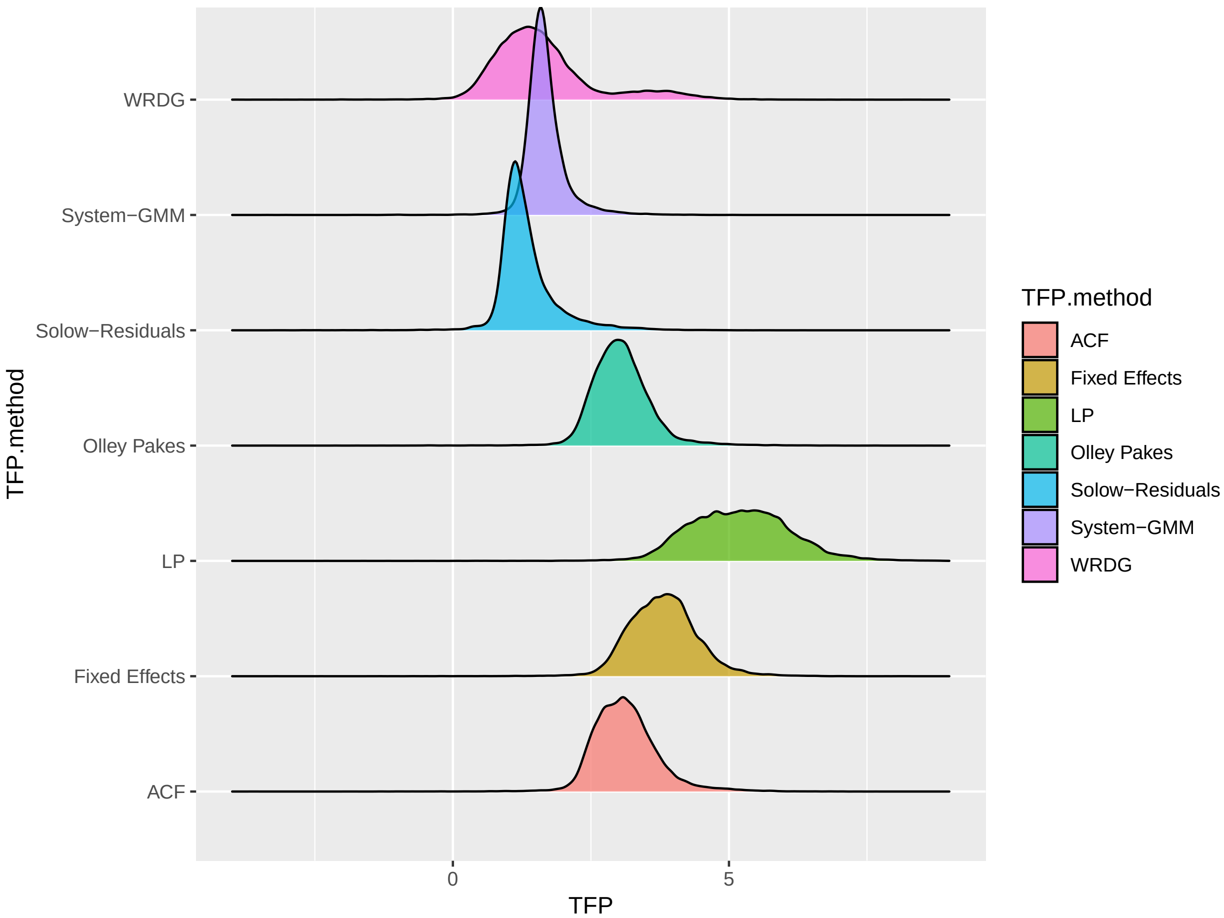
Based on the estimation results presented in section 4.1, we calculated the TFP for each firm-year available and for each model. Figures A.3 and A.4 display the density distribution of the firms TFP according to each model.

Figure A.3: TFP (density) of Austrian non-financial firms



Source: Authors' calculations.

Figure A.4: TFP (density) of Austrian non-financial firms



Source: Authors' calculations.

Appendix B. Zombie Effects: Evidence on a Sectoral Level with the Translog TFP

In this section, we check the robustness of our results in Table 6, Table 7, Table 8 and Table 9 by regressing the same four zombie definitions on TFP calculated by the translog models in Table 4.

Table B.19: Zombie Effects: Sectoral evidence with the ICR and the simulated ICR Zombie Definition

	FE Translog I	FE with Fourier Flexible Form I	FE Translog II	FE with Fourier Flexible Form II
Non-zombie (ICR)	0.0411	0.0396		
	(0.0230)	(0.0228)		
Share zombie (ICR)	−0.0037	−0.0035		
	(0.0027)	(0.0027)		
Non-zombie x Share zombie (ICR)	0.0021	0.0022		
	(0.0028)	(0.0028)		
Non-zombie (ICR simulated)			0.0255	0.0326
			(0.0247)	(0.0245)
Share zombie (ICR simulated)			−0.0046	−0.0030
			(0.0028)	(0.0027)
Non-zombie x Share zombie (ICR simulated)			0.0024	0.0016
			(0.0027)	(0.0026)
Sectoral fixed effects	*yes*	*yes*	*yes*	*yes*
Time fixed effects	*yes*	*yes*	*yes*	*yes*
R-squared	0.0111	0.0120	0.0109	0.0116
Number of obs.	26741	26741	26741	26741
Number of groups	6275	6275	6275	6275
Average. Obs. group	4.2615	4.2615	4.2615	4.2615
Min. Obs. group	1	1	1	1
Max. Obs. Group	10	10	10	10
TFP %-increase non-zombie	0.0215	0.0210	0.0183	0.0177

Source: Authors' calculations.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Standard errors for the estimated model coefficients are obtained by using a cluster robust variance matrix estimator.
We estimate Eq. (**??**) with TFP, based on the estimations in Table 4, as the dependent variable. The explanatory variable is the zombie dummy "ICR definition".
TFP %-increase non-zombie: Refers to the reduction in the median TFP in percent based on Eq. (30).
We estimate Eq. (**??**) with TFP, based on the estimations in Table 4, as the dependent variable. The explanatory variable is the zombie dummy "ICR definition (simulated)".
TFP %-increase non-zombie: Refers to the reduction in the median TFP in percent based on Eq. (30).

Table B.20: Zombie Effects: Sectoral evidence with the PIR-PD and the PIR-ICR Zombie Definition

	FE Translog III	FE with Fourier Flexible Form III	FE Translog IV	FE with Fourier Flexible Form IV
Non-zombie (PIR-PD)	0.1078***	0.1047***		
	(0.0167)	(0.0162)		
Share zombie (PIR-PD)	0.0024	0.0024		
	(0.0017)	(0.0017)		
Non-zombie x Share zombie (PIR-PD)	−0.0041*	−0.0039*		
	(0.0016)	(0.0016)		
Non-zombie (PIR-ICR)			0.1269***	0.1201***
			(0.0344)	(0.0343)
Share zombie (PIR-ICR)			0.0073	0.0071
			(0.0106)	(0.0105)
Non-zombie x Share zombie (PIR-ICR)			−0.0136	−0.0116
			(0.0103)	(0.0103)
Sectoral fixed effects	*yes*	*yes*	*yes*	*yes*
Time fixed effects	*yes*	*yes*	*yes*	*yes*
R-squared	0.0111	0.0120	0.0117	0.0124
Number of obs.	26741	26741	26694	26694
Number of groups	6275	6275	6270	6270
Average. Obs. group	4.2615	4.2615	4.2574	4.2574
Min. Obs. group	1	1	1	1
Max. Obs. Group	10	10	10	10
TFP %-increase non-zombie	0.0302	0.0291	0.0349	0.0336

Source: Authors' calculations.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Standard errors for the estimated model coefficients are obtained by using a cluster robust variance matrix estimator.
We estimate Eq. (**??**) with TFP, based on the estimations in Table 4, as the dependent variable. The explanatory variable is the zombie dummy "PIR-PD definition".
TFP %-increase non-zombie: Refers to the reduction in the median TFP in percent based on Eq. (30).
We estimate Eq. (**??**) with TFP, based on the estimations in Table 4, as the dependent variable. The explanatory variable is the zombie dummy "PIR-ICR definition".
TFP %-increase non-zombie: Refers to the reduction in the median TFP in percent based on Eq. (30).

Appendix C. Robustness Checks: Confounder and Collider Bias

In this section, we estimate some TFP models, log employment growth models and gross investment ratio models with only the "Non-zombie dummy" as an explanatory variable. We check if the explanatory variables "Asset share zombie" and "Non-zombie x Asset share zombie" would change our main results that mostly direct zombie effects dominate. The results for TFP are shown in Table C.21. We present the results for the log employment growth in Table C.22 and for the gross investment ratio in Table C.23.

Table C.21: Direct Zombie Effects on TFP: Two-way FE Models with the ICR Zombie Definition

	FE Non zombie ICR	FE Non zombie ICR (simulated)	FE Non zombie PIR-PD	FE Non zombie PIR-ICR
Non-zombie (ICR)	0.0671^{***}			
	(0.0087)			
Non-zombie (ICR simulated)		0.0570^{***}		
		(0.0082)		
Non-zombie (PIR-PD)			0.0920^{***}	
			(0.0091)	
Non-zombie (PIR-ICR)				0.0958^{***}
				(0.0176)
R-squared	0.0052	0.0046	0.0071	0.0041
Number of obs.	26741.0000	26741.0000	34170.0000	26694.0000
Number of groups	6275.0000	6275.0000	6605.0000	6270.0000
Average. Obs. group	4.2615	4.2615	5.1734	4.2574
Min. Obs. group	1.0000	1.0000	1.0000	1.0000
Max. Obs. Group	10.0000	10.0000	11.0000	10.0000
TFP Median % Reduction Zombie	0.0177	0.0150	0.0242	0.0252

Source: OeNB. Authors' calculations.
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. We use cluster robust standard errors with clustering at the bank level.
We estimate Eq. (29) based on the estimations TFPs in column 1 in Table 3, as the dependent variable. The explanatory variable is defined based on the "ICR zombie definition".
Non-zombie (ICR) is a dummy variable that takes the value of 1 if a firm i is a zombie at time t according to the interest coverage ratio (ICR) explained in Eq. (1).
The TFP %-increase non-zombie is based on Eq. (30) but with Non-zombie (ICR) as the only explanatory variable and reports by how many percent on average non-zombie firms are more productive than zombie firms.

Table C.22: Direct Zombie Effects on Employment Growth: FE Models

	Delta log(E) ICR	*Delta* log(E) ICR (simulated)	*Delta* log(E) PIR-PD	*Delta* log(E) PIR-ICR
Non-zombie (ICR)	0.0183^{**}			
	(0.0091)			
Non-zombie (ICR simulated)		0.0131^{*}		
		(0.0078)		
Non-zombie (PIR-PD)			−0.0023	
			(0.0104)	
Non-zombie (PIR-ICR)				0.0338^{*}
				(0.0185)
R-squared	0.0003	0.0002	0.0000	0.0004
Number of obs.	26,065	26,065	27,500	26,020
Number of groups	6,159	6,159	6,321	6,153
Average. Obs. group	4.2320	4.2320	4.3506	4.2288
Min. Obs. group	1	1	1	1
Max. Obs. Group	10	10	10	10
Delta log(E) pp-increase non-zombie	0.0183	0.0131	−0.0023	0.0338

Source: OeNB. Authors' calculations.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Standard errors for the estimated model coefficients are obtained by using a cluster robust variance matrix estimator.
The dependent variable is all models is the growth rate of log employment.
In model "FE Δ log(E) ICR" the explanatory variables are defined based in the "ICR zombie definition".
In model "FE Δ log(E) ICR (simulated)" the explanatory variables are defined based in the "ICR zombie (simulated) definition".
In model "FE Δ log(E) PIR-PD" the explanatory variables are defined based in the "PIR-PD zombie definition".
In model "FE Δ log(E) PIR-ICR" the explanatory variables are defined based in the "PIR-ICR zombie definition".
Non-zombie is a dummy variable that takes the value of 1 if a firm i is a zombie at time t according to one of the four zombie definition in Section 2.2.
Δ log(E) pp-increase non-zombie is the percentage point increase in the log employment growth of non-zombie firms compared to zombie firms.

Table C.23: Direct Zombie Effects on the Gross Investment Ratio: FE estimations

	I/K ICR	I/K ICR (simulated)	I/K PIR-PD	I/K PIR-ICR
Non-zombie (ICR)	2.8542***			
	(0.7956)			
Non-zombie (ICR simulated)		2.9026***		
		(0.6928)		
Non-zombie (PIR-PD)			−2.7800***	
			(0.7950)	
Non-zombie (PIR-ICR)				1.7848
				(1.2203)
R-squared	0.0009	0.0011	0.0006	0.0001
Number of obs.	25943.0000	25943.0000	33051.0000	25900.0000
Number of groups	6206.0000	6206.0000	6543.0000	6201.0000
Average. Obs. group	4.1803	4.1803	5.0514	4.1767
Min. Obs. group	1.0000	1.0000	1.0000	1.0000
Max. Obs. Group	10.0000	10.0000	11.0000	10.0000
Investment ratio: Non-Zombie Increase (in %)	17.9690	23.3014	−21.8632	10.6491

Source: OeNB. Authors' calculations.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Standard errors for the estimated model coefficients are obtained by using a cluster robust variance matrix estimator.
The dependent variable is all models is the gross investment ratio.
In model "FE I/K ICR" the explanatory variables are defined based in the "ICR zombie definition".
In model "FE I/K ICR (simulated)" the explanatory variables are defined based in the "ICR zombie (simulated) definition".
In model "FE I/K PIR-PD" the explanatory variables are defined based in the "PIR-PD zombie definition".
In model "FE I/K PIR-ICR" the explanatory variables are defined based in the "PIR-ICR zombie definition".
Non-zombie is a dummy variable that takes the value of 1 if a firm i is a zombie at time t according to one of the four zombie definition in Section 2.2.
Gross investment ratio: Non-Zombie Increase (in %) is the percentage increase in the gross investment ratio of non-zombie firms outlined in Eq. (32).

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