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Abstract

Spanish aggregate productivity was negatively correlated with the business cycle from 2000 to 2014, but this correlation later turned positive between 2015 and 2019. In this paper, we ask if this change is related to financial restrictions and firm creation and destruction in Spain. Using firm- level administrative data, we reach the following conclusions. First, during the 2000–07 expansion, low-productivity firms with access to financial resources were able to continue operating; in turn, this led to a crowding-out of financial resources, and forced high-productivity but financially vulnerable firms to close. We find that on average exiting firms were significantly larger and more productive than entering firms, a situation that entailed productivity losses in this period. Second, following the tightening of credit conditions after 2008, we find a more efficient selection at both exit and entry margins: exiting firms were less productive than entering firms. Both findings help explain, at least in part, the change in the productivity-GDP correlation. Finally, in a counterfactual exercise we quantify the effects of type-I selection errors, i.e., the closure of productive but financially vulnerable firms: had market selection not presented type-I errors, relative total factor productivity at the exit margin would have been 3% to 6.5% higher, while gains in relative labor productivity would have ranged between 27% and 46%.

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1 Introduction

During the preparatory period for joining the Euro, 1995–99, and also between 2000 and 2007, southern European economies witnessed a fall in real interest rates, an unprecedented easing of bank lending conditions and a huge expansion in output. These conditions, which occurred under the boom, crowded out productive firms and limited their opportunities, leading to considerable capital misallocation (Gopinath et al. (2017), Cette et al. (2016), García-Santana et al. (2020)). After the start of the recession in 2008, interest rates rose sharply and credit conditions strengthened. The rise in firm deaths under recessions, together with the fall in firm births, can be viewed as a cleansing opportunity for more efficient market selection at the exit margin.[1]

In this paper, focusing on Spain, we report a negative correlation between labor productivity and the business cycle for 2000–19. However, this correlation turned positive after 2015. We examine whether this change is attributable, at least in part, to firm-level entry and exit and the financial conditions of firms over the business cycle. To this end, we use firm-level administrative data from non-financial firms from the Bank of Spain's database (*CBI, Central de Balances Integrados*). Information on plants or establishments is unavailable at the administrative CBI base. We complement this analysis with aggregate data from the databases of the Spanish National Institute of Statistics (INE), Eurostat and EU KLEMS. Eventually, we reach the following results.

The Spanish aggregate series for the period 2000-19 show that the stock of firms is pro-cyclical and a leading indicator of the business cycle. While firm births are weakly procyclical, there is no clear evidence of (counter)cyclicality in firm deaths. Furthermore, firm entries positively lead the business cycle while firm exits positively lag behind them. Employment and hours worked are also pro-cyclical. Moreover, employment in larger firms has a positive correlation with the business cycle, but in the smallest firms there is no such correlation. These results are analogous to those found by Tian (2018) for US firms using aggregate time series.

Using Spanish firm-level data for the same period, we find, *first*, that entering firms were 43% smaller than exiting firms in 2000–07. After 2008, exiting and entering firms display similar relative sizes, on average 40% smaller than incumbent businesses. Moreover, the size of exiting businesses, relative to incumbent firms, fell after the recession in 2008. These features help explain the low correlation of employment in exiting and entering firms with the business cycle documented for aggregate data. *Second*, regarding firm-level total factor productivity (TFP), following Caves et al. (1982), during the expansion of 2000–07, exiting and entering firms displayed similar TFP levels. For the recession of 2008–14 and the recovery of 2015–19, the TFP of entrants was 28%-34% higher than that of closing businesses. A

[1] Several articles have endogenized TFP as a function of financial frictions in dynamic models and have discussed how capital misallocation can arise from credit constraints: Midrigan and Xu (2014), Moll (2014) and Buera and Moll (2015)).

similar change occurred in firm-level average labor productivity (gross value added, GVA, per hour worked): exiting firms were 18.75% more productive than entrants during the boom of 2000–2007, but 38-45% less productive during the 2008–14 and 2015–19 periods. We argue that these changes produced a stronger cleansing effect after the 2008 recession, spanning the period until 2019, which can account for the increase in aggregate productivity (Caballero and Hammour (1994), Osotimehin and Pappadà (2016)).

While previous papers have analyzed these patterns at the plant level (see Lee and Mukoyama (2015) for the US.), here we focus on the financial restrictions faced by an individual firm in making the choice to continue operating or to close. Some examples to illustrate the importance of firm-level heterogeneity for explaining the performance of aggregate productivity in Spain include Gopinath et al. (2017), Almunia et al. (2018), García-Santana et al. (2020) and González et al. (2023). Indeed, a firm may decide to open or close a plant for reasons others than its financial situation, such as technology adoption. To this end, we construct two financial condition indices that gather information from firms' financial statements (see Musso and Schiavo (2008) and Ferrando and Ruggieri (2018)). We show that these indices accrue information about a firm's financial health, affecting its ability to raise the financial resources necessary to operate, and that it correlates with other features: that is, the better a firm's financial health, the larger its size and its TFP and the greater its age.

These indices are exploited in three directions:

1. Using the Kolmogorov-Smirnov test, we examine the 1^{st} order stochastic dominance of the distribution of the financial index and the TFP index for continuing, exiting and entering firms. We find overwhelming evidence that the financial health and TFP of continuing firms are better than those of entering and exiting firms. Since 2008, we document an improvement in both financial conditions and TFP of entering firms relative to exiting firms, corroborating the results reported above for size and productivity.

2. In a regression analysis, we study the effect of financial conditions on firm survival. Controlling for other factors such as firm size, age and productivity, we estimate a hazard function and find consistent evidence that the probability of exiting increases with financial distress. Importantly, the role of financial conditions increases over time: the exit probability was twice as sensitive to a firm's financial conditions in the recovery phase of 2015–19 than in the earlier expansion of 2000–07.

3. Finally, we quantify the effect on productivity of misselection at the exit margin. To this end, we scrutinize exiting firms whose financial index score was *above* an arbitrarily high threshold, and conjecture that these firms should have stayed open. This subset of exiting firms would correspond to a type-I selection error. Interestingly, we note that the set of firms presenting a type-I

error rose sharply in 2006, while the proportion of type-II errors remained steady throughout the 2000–19 period within the range of 1% to 3%. In a counterfactual analysis, we recalculate the size and productivity of exiting and entering firms relative to continuing firms, conjecturing that firms that closed due to type-I errors had remained open. The counterfactual exercises reveal that this type of credit friction (type-I error) alters the productivity-enhancing effect of booms and recessions. In terms of productivity, had market selection been devoid of type-I errors, a 3%-6.5% increase in TFP would have been gained from exiting firms relative to continuing firms. The bulk of the adjustment, in the absence of type-I errors, would have occurred under the expansions of 2000–07 and 2015–19, rather than during the recession of 2008–14.

In summary, our findings suggest that low productivity firms with access to financial resources were able to continue operating, due to the favorable bank lending conditions during the period 2000–07. This crowded out financial resources, since highly productive but financially vulnerable firms were forced to exit the market, mostly during the boom period of 2000–07. The hardening of credit conditions throughout the recession of 2008–14 led to a more efficient selection at both the exit and the entry margins, according to the 1^{st} order dominance tests. Finally, during the recovery phase of 2015–19, the productivity and financial conditions of entering firms still 1^{st} order dominated that of exiting firms, a circumstance that helps explain the change in the correlation between productivity and the business cycle.

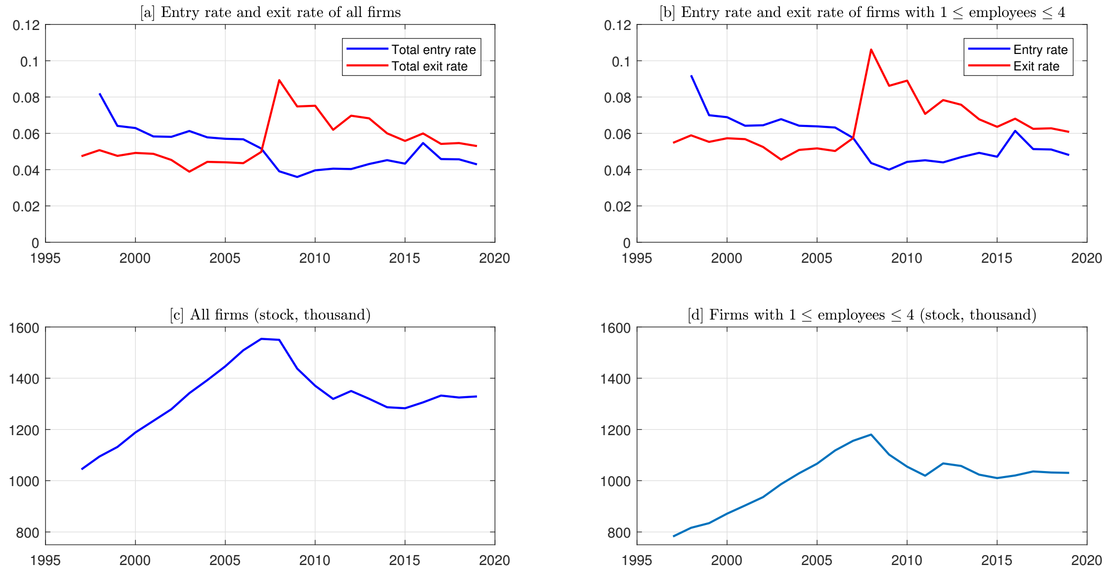
The paper is structured as follows. Section 2 presents a business cycle analysis using aggregate time series. Section 3 describes the firm-level data set (Subsection 3.1), shows how productivity is measured (Subsection 3.2), and reports the estimates of size and productivity for exiting and entering firms over sectors and cycles relative to continuing firms (Subsection 3.3). Section 4 estimates the financial indices (Subsection 4.1) and uses them for the exercises listed above: to test for first order stochastic dominance in the distribution of TFP and financial indices across firms (Subsection 4.2); to identify selection errors (Subsection 4.3); to estimate firms' hazard rates (Subsection 4.4); and in a counterfactual exercise (Subsection 4.5). Finally, Section 5 summarizes and presents several conclusions.

2 Business Cycle Analysis

This section studies the cyclical properties of aggregate Spanish series. We collect quarterly data from the INE (*Instituto Nacional de Estadística*) for GDP (2015 prices), employment, and hours worked per worker for 1995:1–2019:4, and use yearly series of GDP, firms (stock, entering and exiting firms) and employment from Eurostat, *Business demography by size class* for the same period.

Figures 1.a and b present the firm entry and exit rates in Spain on a yearly basis, calculated as the number of entering and exiting firms respectively relative to the stock of firms. The entry rate of firms was higher than the exit rate until 2007; however, since 1996 it had been declining, and after 2008 it hovered around 4% (Figure 1.a), mainly due to a fall in the entry of small firms (i.e., with four or fewer employees), which account for three-quarters of the total (Figure 1.d). By contrast, the exit rate of firms lingered around 4.6% until 2006, peaked at 8.9% in 2008 and declined afterward (Figure 1.a). Finally, the entry and the exit rates were higher for small firms (Figure 1.b). This changing pattern of firm births and deaths is reflected in the stock of small firms, shown in Figure 1 (c and d). The stock of firms grew until 2007, reaching a figure of 1.55 million, and collapsed afterward. However, from 2010–2019, the stock of firms remained relatively stable, presenting only a slight fall of 0.39%.

Figure 1: **Entry, exit, and stock of firms, 1996–2019.**



Notes: Own calculations based on Eurostat data.

Figure 2.a presents GDP, GDP per hour worked, and their respective HP-trends on a quarterly basis from 2000:1 to 2019:4. Both variables are logged and normalized to zero for the initial period. Spanish GDP rose annually by 2.1% from 2000 to 2019. Between 2000 and 2007 it grew by 3.6%; from 2008 to 2014 it fell (-0.95% growth), but recovered strongly after 2015 (2.8%), as illustrated by the upward trend. It is worth noting that, despite the high pace of growth, the GDP per hour worked declined by 8% between 2001 and 2005 (Figure 2.a); the implied HP cycles (Figure 2.b) confirm the counter-cyclical behavior of this variable. The annual GDP growth rate leads the business cycle (Figure 2.c): for example, for 2008-2014, it was also below 2.1%, highlighted by the red dots in Figure 2.c.

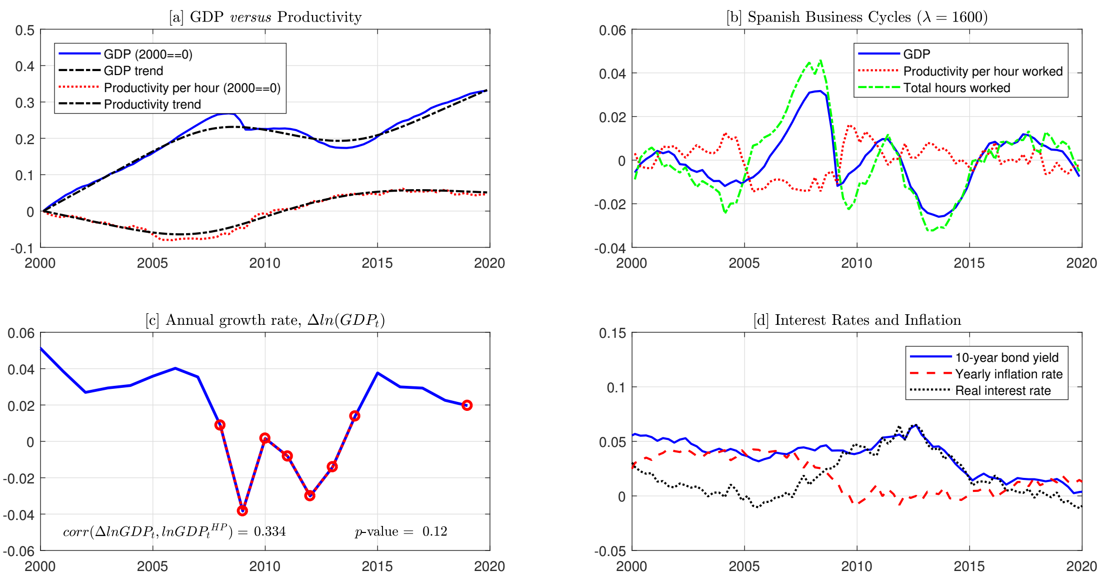
Finally, Figure 2.d presents series of interest rates and the inflation rate.[2] Financial costs fell dramatically during the convergence process prior to joining the European Monetary Union (EMU), between

[2] For the nominal interest rate, we use the annual 10-year bond yield of Spanish bonds from BD SICE, (code 867320q). The real interest rate is the nominal rate minus the yearly inflation rate, estimated using the GDP implicit deflator from INE.

1993 and 1998, particularly for countries with high starting levels of long-term interest rates and low productivity growth, such as Italy, Portugal and Spain. Differentiated sovereign risk disappeared, and during the first years of the EMU (1999–2005) this led to further decreases in the real long-term interest rate for countries with persistently high inflation; in Spain, for example, it reached negative values in 2005 (Figure 2.d). Fiscal imbalances in a number of countries, combined with the return to differentiated sovereign risk, triggered the EMU sovereign debt crises between 2010 and 2013. Both nominal and real long-term interest rates increased sharply in Spain, creating a risk premium for enterprises relative to France and Germany. The positive correlation between interest rates and productivity growth has been highlighted, among others, by Gopinath et al. (2017) and Cette et al. (2016).

Financial costs dramatically declined during the convergence process for joining the European Monetary Union (EMU) 1993–1998, particularly for countries with high starting levels of long-term interest rates and low productivity growth, such as Italy, Portugal and Spain. Differentiated sovereign risk disappeared and during the first years of the EMU (1999–2005), this translated into further decreases in the real long-term interest rate for countries with persistent high inflation, reaching in the case of Spain negative values in 2005 (Figure 2.d). Fiscal imbalances in a number of countries combined with the return to differentiated sovereign risk originated the EMU sovereign debet crises 2010–2013. Both nominal and real long-term interest rates increased sharply in Spain, translating into risk premium for enterprises relative to France and Germany. The positive correlation between interest rates and productivity growth have been highlighted, among others, by and Gopinath et al. (2017), Cette et al. (2016).

Figure 2: **Business cycles in Spain, 2000:1–2019:4.**



Notes: Data come from the INE. In 2.b, all variables have been logged, seasonally adjusted and detrended using the HP filter ($\lambda = 1600$). In Figure 2.c, red points indicate years where GDP growth was below the sample average growth (2.1%). In Figure 2.d, the inflation rate has been calculated through the GDP implicit deflator.

Figure 2 suggests the existence of three phases in recent Spanish business cycles: *i.* a long expansion from the second half of the 1990s through 2007; *ii.* a recession from 2008 to 2014; and i*iii.* a recovery phase from 2015 onward.

Table 1 introduces the correlogram 2000–19 for the following quarterly series: GDP, employment, hours, and aggregate productivity (GDP per worker and GDP per hour worked).[3] On the basis of Table 1, we reach the following findings. First, business cycles in Spain are very persistent given the one-lag autocorrelation of 0.94. Second, employment and hours worked are highly pro-cyclical ($corr = 0.93$), and more volatile than GDP ($S.D. = 0.018 > 0.013$). Third, interestingly, both measures of productivity, GDP per worker and GDP per hour worked, are negatively correlated with GDP ($corr = -0.35, -0.45$), and lead the business cycle; thus, aggregate productivity tends to rise during recessions and fall during booms. This kind of counter-cyclical behavior is anomalous among OECD countries. This asymmetrical behavior of GDP and productivity is seen in Figure 2.b; productivity was initially below its trend level during the years of expansion between 2000 and 2007 and began to rise after 2008.[4]

Table 1: **Business cycles properties, 2000:1-2019:4**

	$S.D.$	Correlations: $corr(GDP_t, x_{t+j})$				
Variable x_t		$j=-2$	$j=-1$	$j=0$	$j=1$	$j=2$
GDP	0.013	0.807	0.939	1.000	0.939	0.807
p-value		0.000	0.000	0.000	0.000	0.000
Employment	0.016	0.797	0.894	0.930	0.880	0.761
p-value		0.000	0.000	0.000	0.000	0.000
Total hours	0.018	0.793	0.891	0.928	0.879	0.760
p-value		0.000	0.000	0.000	0.000	0.000
GDP per worker	0.006	-0.404	-0.385	-0.347	-0.344	-0.306
p-value		0.000	0.000	0.002	0.002	0.006
GDP per hour	0.007	-0.474	-0.478	-0.454	-0.445	-0.394
p-value		0.000	0.000	0.000	0.000	0.000

Notes: Our own calculations from INE quarterly data. This Table presents standard deviations, $S.D.$, and correlations of GDP with listed variables, $corr(GDP_t, x_{t+j})$ for $j \in \{-2, -1, 0, 1, 2\}$. All variables have been logged and detrended using the Hodrick-Prescott filter with $\lambda = 1600$.

To complement the findings viewed in Table 1, Table 2 presents (absolute and relative) standard deviations, $(S.D.)$, and the current correlations of GDP with listed variables for the periods 2000–07, 2008–14, and 2015–19. The moderation in volatility after the recession of 2015–19, both in absolute and in relative terms is worth noting. Relative to GDP, volatility declined for all listed variables in 2015–19 compared to 2000–07 and 2008–14. Compared with the first period, 2000–07, the standard deviations of employment and hours worked declined by a factor ranging from 3.5 to 3.9. Looking at the last three columns of Table 2, boosted by the change in volatility, the contemporaneous output-productivity correlations increased after the recession, turning from negative (-0.564 and -0.616) to positive (0.619 and 0.467). Thus, the cyclical pattern of productivity changed from counter-cyclical to pro-cyclical after the recession. Employment and hours worked maintained a positive correlation over the different sub-sample

[3] Series have been logged, deseasonalized and detrended using the HP filter ($\lambda = 1600$)

[4] Dossche et al. (2023) provide evidence of a trade-off between employment volatility and cyclicality of labor productivity among OECD countries for 1984–2019. They also find a negative correlation between (HP) cyclical components of GDP and labor productivity for US and Spain.

periods. Note that this change is the reverse of the ones observed by Fernald and Wang (2016) and Galí and Van Rens (2021), among others, for the US after the mid-1980s: a rising volatility of employment paired with a counter-cyclical productivity. This change has been associated with lower employment protection and lower labor market regulation (Galí and Van Rens (2021), Dossche et al. (2023)).

Table 2: **The declining volatility of employment and the rising GDP–productivity correlation**

	Absolute S.D.			GDP-Relative S.D.			Correlations: $corr(GDP_t, x_t)$		
Variable x_t	2000-07	2008-14	2015-19	2000-07	2008-14	2015-19	2000–07	2008–14	2015–19
GDP	0.011	0.017	0.005	1.000	1.000	1.000	1.000	1.000	1.000
p-value	—	—	—	—	—	—	0.000	0.000	0.000
Employment	0.017	0.020	0.004	1.492	1.149	0.786	0.927	0.951	0.764
p-value	—	—	—	—	—	—	0.000	0.000	0.000
Total hours	0.018	0.021	0.005	1.595	1.239	0.930	0.925	0.951	0.696
p-value	—	—	—	—	—	—	0.000	0.000	0.001
GDP per worker	0.008	0.006	0.003	0.678	0.366	0.646	-0.564	-0.256	0.619
p-value	—	—	—	—	—	—	0.001	0.189	0.004
GDP per hour	0.009	0.007	0.004	0.771	0.423	0.755	-0.616	-0.420	0.467
p-value	—	—	—	—	—	—	0.000	0.026	0.038

Notes: Our own calculations from INE quarterly data. This Table presents standard deviations, *S.D.*, and contemporaneous correlations of GDP with listed variables, $corr(GDP_t, x_t)$. All variables have been logged and detrended using the Hodrick-Prescott filter with $\lambda = 1600$.

In this regard, as noted by Boldrin et al. (2010) and Bentolila et al. (2012), among others, Spain represents a special case. The labor market reforms of 1984 and 1994 overprotected tenured contracts workers, whereas temporary workers were underprotected. The cost of firing tenured workers were high, especially in the case of litigation; in contrast, temporary workers could be fired cheaply, which provided a high degree of flexibility for firms to adjust their labor input needs, and helps explain the volatility of employment in Table 1. As a result, the rate of temporary workers rose after these reforms, boosting a negative correlation between output and productivity from the mid-1990s, in contrast to the experience of other advanced economies. As a result, the rate of temporary workers rose after these reforms, boosting a negative correlation between output and productivity from the mid 1990's, in contrast to the experience of other advanced economies.[5]

Table 3 presents the correlogram for GDP and firms (stock, entering, and exiting) and employment on a yearly basis.[6] The stock of firms is pro-cyclical, especially for firms with five or more employees ($corr = 0.79$). Standard deviations increase with firm size. Importantly, employment is also pro-cyclical ($corr = 0.88$), although in smaller firms (the majority) it is acyclical ($corr = 0.07$). The correlation of employment with the business cycle increases with firm size.

For exiting firms, the findings in Table 3 are ambiguous and non-intuitive. For instance, contemporaneous correlations (i.e. for $j = 0$) are unexpectedly positive and non significant. The lagged correlations are negative (-0.27 and -0.41), although statistically non-significant: an increase (fall) in firm deaths *weakly* anticipates a GDP fall (rise). Both exiting firms and their employment positively lag the cycle

[5] Boldrin et al. (2010) have noted that this is a relatively new occurrence in Spanish business cycles, as the correlations were positive during the 1960s and had turned negative by the end of the 1970s. Standard RBC models cannot reproduce these cyclical regularities for Spain.

[6] Yearly series have been logged and detrended using the HP filter, $\lambda = 6.25$.

Table 3: **Firm dynamics (aggregate series)**

		Stock				Exiting firms				Entering firms		
		$corr(GDP_t, x_{t+j})$				$corr(GDP_t, x_{t+j})$				$corr(GDP_t, x_{t+j})$		
Variable x_t:	S.D.	$j=-1$	$j=0$	$j=1$	S.D.	$j=-1$	$j=0$	$j=1$	S.D.	$j=-1$	$j=0$	$j=1$
GDP	0,012	0,50	1,00	0,50	0,012	0,50	1,00	0,50	0,012	0,50	1,00	0,50
p-value		0,02	0,00	0,02		0,02	0,00	0,02		0,02	0,00	0,02
Firms	0.017	0.23	0.49	0.41	0.103	-0.27	0.24	0.52	0.071	0.35	0.12	-0.30
p-value		0.29	0.02	0.06		0.23	0.27	0.01		0.12	0.59	0.19
Firms 1-4 Empl.	0.018	0.05	0.28	0.34	0.109	-0.27	0.24	0.49	0.074	0.30	0.10	-0.27
p-value		0.83	0.20	0.12		0.22	0.27	0.02		0.18	0.65	0.23
Firms 5-9 Empl.	0.022	0.45	0.79	0.48	0.088	-0.23	0.21	0.59	0.069	0.51	0.19	-0.38
p-value		0.04	0.00	0.02		0.31	0.35	0.00		0.02	0.39	0.09
Firms over 10 Empl.	0.029	0.68	0.79	0.28	0.095	-0.10	0.04	0.62	0.077	0.61	0.23	-0.40
p-value		0.00	0.00	0.21		0.67	0.86	0.00		0.00	0.30	0.07
Employment	0.012	0.49	0.88	0.47	0.104	-0.41	0.08	0.61	0.069	0.54	0.16	-0.40
p-value		0.10	0.00	0.12		0.16	0.79	0.03		0.01	0.46	0.08
Empl. of firms with 1-4 workers	0.017	-0.25	0.07	0.37	0.126	-0.37	0.17	0.50	0.072	0.36	0.08	-0.34
p-value		0.43	0.82	0.23		0.21	0.56	0.08		0.11	0.72	0.14
Empl. of firms with 5-9 workers	0.024	0.15	0.61	0.56	0.095	-0.46	0.00	0.62	0.069	0.49	0.22	-0.35
p-value		0.64	0.03	0.06		0.11	1.00	0.02		0.02	0.32	0.12
Empl. of firms with ≥ 10 workers	0.015	0.62	0.86	0.29	0.115	-0.32	-0.19	0.58	0.093	0.62	0.17	-0.39
p-value		0.03	0.00	0.36		0.29	0.52	0.04		0.00	0.45	0.08

Notes: Our own calculations from Eurostat yearly data, *Business demography by size class*. This table presents standard deviations, *S.D.*, and correlations of GDP with listed variables, $corr(GDP_t, x_{t+j})$, for $j \in \{-1, 0, 1\}$. Series are expressed in a yearly basis, and have been logged and detrended using the Hodrick-Prescott filter with $\lambda = 6.25$.

(0.52*** and 0.61***): a GDP rise leads to rise of firm deaths. In turn, entering firms and job creation lead the cycle by one year (0.35 and 0.54): an increase (fall) in firm births anticipates a GDP rise (fall). Moreover, contemporaneous correlations between entering firms are positive, as expected, but only weakly significant. Thus, entering firms, particularly those with five or more workers, are key indicators of Spanish GDP. These patterns of exit/entry dynamics compare with those found by Tian (2018) for US firms and those found by Koellinger and Roy Thurik (2012) for a panel of 22 OECD countries.

The analysis so far reveals the following findings:

Fact 1: (*i*) Aggregate productivity was counter-cyclical throughout the boom and the recession, and it turned pro-cyclical during the recovery phase; (*ii*) The variability of employment and hours worked, relative to output, has smoothed after the recession; (*iii*) The stock of firms is pro-cyclical: exiting firms positively lag the business cycle and entering firms positively lead it. (*iv*) Exiting firms present an ambiguous cyclical behavior.

In the following sections, we study the properties of firm size and productivity using micro-level data and explore the connections with these preliminary results.

3 Firm productivity over sectors

3.1 Data description

We next combine sector-aggregate data and firm-level administrative data for 2000-2019. Sector level data come from the EU KLEMS productivity database: the GVA, gross output, intermediate inputs, aggregate capital, implicit deflators, hours worked per worker, and the average sector depreciation rate of capital. All EU KLEMS variables are provided at 2-digit sector level on a yearly basis. The base year of implicit deflators is 2015.

We also use administrative data of firms from the CBI database (*Central de Balances Integrados*) from the *Laboratorio de Datos del Banco de España* (BELab (2024)) at the Bank of Spain. The CBI data set contains detailed information from accounting balance sheets for 2.6 million non-financial firms from 1995 to the present. Financial and Insurance Activities (sector K) and Public administration (sector O) are not available at the CBI. As recommended by Almunia et al. (2018) and García-Santana et al. (2020), we use data after 2000, when firms were legally required to present accounting books in electronic format through the website of Mercantile Registers. The data set also includes information regarding the sector of activity at four-digit level, the year of the firm's legal birth, and employment measured in full time equivalent (FTE) units.[7] Information on plants or establishments is unavailable at the CBI base.

First, we select firms with at least one FTE worker. Then, we discard observations for which the financial statements are labeled as low-quality in the CBI database (code `calidad`). We also exclude those cases with missing or negative book values of assets or gross output (Kalemli-Ozcan et al. (2024), Almunia et al. (2018)).

The final selection spans 7,806,819 observations for 1,253,947 firms over the period 2000–2019.[8] Table 4 compares firm distribution by size in 2019, from the INE census and from our CBI selection. This INE distribution includes S.L. (Limited Responsibility Societies, usually small businesses) and S.A. (normally, but not necessarily, larger and corporate societies), and other legal forms. These two legal forms (S.L. and S.A.) account for 98.5% of all legal operating societies.[9] On the basis of Table 4, according to the INE census, the bulk of Spanish businesses (83.8%: $= 71.87 + 11.91$), are small firms with up to nine employees in 2019 (this distribution is comparable with those of other years of the sample). Larger firms with more than 100 employees account for 1.30% of the total. This distribution, however, contrasts with that from our CBI data set selection. Firms with up to four employees are underreported in our CBI selection relative to the INE census: 71.97% versus 58.56% respectively. This mis-representation of the small firms is due to our selection criterion based on the quality of records, which mostly affects smaller firms. Notwithstanding, truncated on firms with more than 10 employees (see third and sixth columns in Table 4, (%, ≥ 10)) the two distributions compare well. In order to overcome the likely selection bias, in the following Sections, we propose a *bootstrapping* algorithm (further details are given in Subsection 3.2).

Finally, for each year t, firms are classified into three categories based on their activity, namely as con-

[7] See section 4.1. at the 2024 CBI questionnaire made to the firms.

[8] From 2000 to 2020, we primarily collect 18.6 million observations (financial statements) for 2,297,239 firms: 13.6 million correspond to observations for Limited Responsibility Societies (*Sociedades Limitadas*, S.L.) and 1.3 million to *Sociedades Anónimas*, S.A. There are some other legal forms account for a minor fraction (0.5%) of firms in Spain: *Comanditas*, *Soc. Garantía Recíproca*, *Cooperativas*, etc.

[9] A descriptive overview of S.A. and S.L. societies in Spain is presented in sub-section A.1 of Appendix A

Table 4: **CBI selection versus INE census, 2019**

Employees n:	INE census Firms (#)	Share (%)	(%, $n \geq 10$)	CBI selection Firms (#)	Share (%)	(%, $n \geq 10$)
$1 \leq n \leq 4$	557976	71.87		266122	58.56	
$5 \leq n \leq 9$	92453	11.91		89818	19.77	
$10 \leq n \leq 19$	66951	8.58	52.9	51625	11.36	52.4
$20 \leq n \leq 49$	38845	5.00	30.8	31172	6.86	31.7
$50 \leq n \leq 99$	10431	1.34	8.3	8379	1.84	8.5
$100 \leq n$	10111	1.30	8.0	7307	1.61	7.4
Total	776407	100	100	454423	100	100

Notes: This table compares the distributions of firm size obtained from the CBI data set selection with that of the INE census for 2019. This census contains information for all Spanish firms *Empresas por estrato de asalariados (antigua estratificación) y condición jurídica*. INE census includes Limited Responsibility Societies (*Sociedades Limitadas*, S.L.) and Corporate Societies (*Sociedades Anónimas*, S.A.). Self-employed persons are not included.

tinuing, exiting, and entering. Continuing firms $\mathcal{C}_t$ are those employing at least one worker in the current year t, in the previous year $t-1$ and in the following year $t+1$. Exiting firms $\mathcal{X}_{t+1}$ are those with at least one worker in t but none in $t+1$. Entering firms $\mathcal{N}_t$ are the ones that employ at least one worker in the current year t and are less than two years old.[10] Age is calculated as the difference between the current year and the year of the firm's legal constitution or birth. Moreover, we identify firms which participated in a merger or were acquired by another firm using code `cab` in the database, and classify them accordingly.[11]

3.2 Measures of firm productivity

Using the CBI data set, we estimate two productivity measures at the firm level: average output per hour worked, LP_{jst}, and total factor productivity, TFP_{jst}. Sub-indices indicate the firm j, the sector of activity s, and the year t.

Let y_{jst} denote the quantity of output produced by firm j in sector s and year t, estimated as the book value of gross output divided by the EU KLEMS implicit deflator, p^y_{st}, and let m_{jt} denote intermediate inputs estimated using the nominal cost of intermediate inputs (C^m_{jst}) divided by the EU KLEMS implicit deflator p^m_{st}: $m_{jst} = C^m_{jst}/p^m_{st}$. The nominal gross value added, GVA, of firm j:

$$p^{GVA}_{st} GVA_{jst} = p^y_{st} y_{jst} - C^m_{jst} = p^y_{st} y_{jst} - p^m_{st} m_{jst}. \tag{1}$$

GVA_{jst} is expressed in GDP terms using the implicit GDP deflator, p^{GDP}_t (base year 2015).

For labor input l_{jst}, we use the number of full time equivalent (FTE) employees, n_{jst}, from the CBI base times the EU KLEMS hours per worker, $h_{s,t}$ (2-digit classification): $l_{jst} = n_{jst} \cdot h_{st}$. Then, the average

[10] We impose this flexibility to identify entering firms for two reasons. First, most starting firms have no employment. Second, Table 3 shows that entering firms lead the business cycle by one year, especially those with five or more employees. In Spain, firms can start operating before they are officially registered.

[11] This is a problem shared in this type of data sets (see Bellone et al. (2008) and Musso and Schiavo (2008) for France). A merger can result either in the disappearance of the ID numbers of both firms and in the creation of a new one, or the disappearance of one of the ID and the persistence of the other. An acquisition results in the disappearance of the ID of the acquired unit and persistence of the ID of the acquiring firm.

labor productivity is estimated according to:

$$LP_{jst} = \frac{p_{st}^{GVA}}{p_t^{GDP}} \times \frac{GVA_{jst}}{l_{jst}}. \tag{2}$$

Note that while gross output y_{jst} is expressed in units produced in sector s, average labor productivity LP_{jst} is given in terms of GDP.

Capital k_{jst} is estimated using the book value of total assets divided by the EU KLEMS sector capital deflator p_{st}^k (García-Santana et al., 2020). The cost of the capital input usage is calculated as capital k_{jst} times the rental price of capital: $R_{st}k_{jst}$,. The rental price R_{st} is estimated according to the following expression:

$$R_{st} = p_{st}^I \frac{i_t - E_t(\pi_{t+1}) + \delta_{st}^k}{1 - \tau_t^k},$$

where p_{st}^I is the EU KLEMS nominal price of investment and $E_t(\pi_{t+1})$ the expected growth rate for p_{st}^I (*i.e.*, capital gain, using a three-year moving average). δ_{st}^k denotes the EU KLEMS average depreciation rate of capital in sector s. Finally, i_t is the nominal interest rate, using the Spanish government 10-year bond yield as an alternative asset, represented in Figure 2.d. τ_t^k denotes the effective capital income tax rate from Boscá et al. (2005), updated up to 2022, who follow the methodology proposed by Mendoza et al. (1994).

A *sector-adjusted* measure of TFP at firm level is estimated using the *multilateral productivity index* proposed by Caves (1998):

$$\begin{aligned}
\ln(TFP_{jst}^{sa}) = \ln(y_{jst}) - \overline{\ln(Y_{st})} + \sum_{\tau=2}^{t}(\overline{\ln(Y_{s\tau})} - \overline{\ln(Y_{s\tau-1})}) \\
-0.5 \times \sum_{z\in\{l,k,m\}} (\theta_{jst}^z + \overline{\theta_{st}^z})(\ln(z_{jst}) - \overline{\ln(z_{st})}) \\
-0.5 \times \sum_{\tau=2}^{t} \sum_{z\in\{l,k,m\}} (\overline{\theta_{s,z,\tau}} + \overline{\theta_{s,z,\tau-1}})(\overline{\ln(z_{s,\tau})} - \overline{\ln(z_{s,\tau-1})}),
\end{aligned} \tag{3}$$

for $z \in \{l, k, m\}$. In the above, overlined variables represent values averaged in sector s. Cost shares are denoted by θ_{jst}^z. Both the labor cost and intermediate input cost are directly provided by the balance sheets in the CBI database, C_{jst}^l and C_{jst}^m, respectively. The output elasticities are estimated through the cost shares:

$$\begin{aligned}
\theta_{jst}^l &= \frac{C_{jst}^l}{C_{jst}^l + C_{jst}^m + R_{st}k_{jst}}, \\
\theta_{jst}^m &= \frac{C_{jst}^m}{C_{jst}^l + C_{jst}^m + R_{st}k_{jst}},
\end{aligned}$$

and $\theta^k_{jst} = 1 - \theta^m_{jst} - \theta^l_{jst}$. Hence, the individual TFP index estimated from expression (3) denotes the (detrended) percentage deviation from the geometric average efficiency in sector s and year t.

Next, in order to correct for a selection bias due to the miss-representation of smaller firms (Table 4), we use the following *bootstrapped* correction:

1. *First*, we impose a sample selection of firms governed according to the INE census. For example, as of 2019 we assume that the firm size weights are those reported in Table 4, $\{\omega^{INE}_{2019,i}\}_i = \{71.9, 11.9, 8.6, 5.0, 1.3, 1.3\} \times \frac{1}{100}$, with i denoting firm size range. For the remaining years, weights are borrowed from *INE*. Then, for each year t, we pick a random sample of firms from our CBI selection, which meets the INE weights $\{\omega^{INE}_{t,i}\}_i$. We calculate sample moments from this random sample.

2. *Second*, the first step is repeated 5000 times, and moments are averaged over these 5000 realizations.

A summary of descriptive moments for employment, productivity and age is reported in Table 5. In the upper panel, the first two columns display the firm size distribution shown in Table 4. The following columns (upper panel) present conditional bootstrapped moments for employment, productivity, and firm age. As of 2019, most Spanish firms (92.36%) had fewer than 20 employees, accounting for 42.63% of employment. In addition, the largest firms (100 workers or above) represented 1.3% of the total and employed a disproportionate number of workers (26.87%). Average productivity per hour worked (LP_{jst}, equation (2)) is expressed in 2015 euros. Productivity was 26.37 euros per hour worked for the smallest firms, reached its lowest point for firms with between five and nine employees (21.74 euros), and increased for larger firms. The individual TFP index increased with firm size: the largest firms (100 employees or more) were 13% greater than more productivity than the smallest firms (1-4 employees). Average age, expressed in years, also increases with firm size: small firms had an average of 14-15 years, while firms with more than 100 employees had an average of 25 years.

The lower panel in Table 5 reports bootstrapped averages and tests for differences in means between 2007 and 2019 for listed variables: size, productivity and age. Firms are now classified as continuing, exiting, and entering: $(\mathcal{C}, \mathcal{X}, \mathcal{N})$. First, the size of continuing firms has decreased in 2019 relative to 2007, the average number of employees falling from 9.1 to 8.1. For exiting and entering firms, there were no significant changes in size. The p-value associated with the t-test of the mean difference in size between 2007 and 2019 was 0.00 for continuing firms, and 0.41 and 1.00 respectively for exiting and entering firms. Second, in 2019 relative to 2007, both continuing and entering firms presented slight TFP gains, while the productivity of exiting firms relative to continuing firms was much lower, which implies a larger cleansing effect: $\frac{0.705}{0.928} = 0.760 > \frac{0.746}{1.027} = 0.726$. The average productivity of continuing and exiting firms did not change significantly. However, average productivity has increased

Table 5: **Descriptive statistics, 2007 and 2019**

(Bootstrapped, 2019)	Firms (INE)		Labor (CBI)		Productivity		
Employees:	Share (%)	Cum. (%)	Share (%)	Cum. (%)	*LP*	*TFP*	Age
$1-4$	71.87	71.87	17.69	17.69	26.37	1.001	13.9
$5-9$	11.91	83.78	10.22	27.91	21.74	1.056	15.4
$10-19$	8.58	92.36	14.71	42.63	22.35	1.063	17.6
$20-49$	5.00	97.36	18.93	61.56	24.61	1.071	20.5
$50-99$	1.34	98.70	11.57	73.13	29.15	1.086	23.2
≤ 100	1.30	100	26.87	100	33.15	1.130	25.4

(Bootstrapped Averages)	Continuing $\mathcal{C}$			Exiting $\mathcal{X}$			Entering $\mathcal{N}$		
Variable:	2007	2019	$p-$value	2007	2019	$p-$value	2007	2019	$p-$value
Size (employees)	9.1	8.1	0.000	5.5	4.5	0.409	4.3	4.3	1.000
TFP (index)	0.928	1.027	0.000	0.705	0.746	0.000	0.850	0.928	0.000
Avg. Prod. (Euros 2015)	26.0	26.0	0.894	21.1	13.9	0.280	15.1	17.5	0.000
Age (years)	10.5	15.5	0.000	8.2	13.0	0.000	—	—	—

Notes: The upper panel of this table uses the distributions of firm size from the INE census for 2019, which contains employment information for all Spanish firms *Empresas por estrato de asalariados (antigua estratificación) y condición jurídica*. The weights are those reported in Table 4. These INE-census weights are used to bootstrap the CBI selection and to compute the distribution for employment, productivity (*LP* and *TFP*) and age (years). The lower panel compares the bootstrapped distributions obtained from the CBI data set selection for 2007 and 2019, using the weights from the INE census.

for entering firms. Finally, the average age of continuing and exiting firms was five years higher in 2019 relative to 2007.

In the following subsection, we examine whether these conclusions are not driven by the choice of two particular years, 2007 and 2019.

3.3 Relative size and relative productivity

Table 6 presents the average values for relative size and relative productivity. As in Table 5, the sample has been bootstrapped. The sample is split into three periods: the expansion of 2000–2007, the recession of 2008–2014, and the recovery phase of 2015–2019. For each year, the relative size of an exiting (entering) firm is defined as its size divided by the average size of continuing firms in the same four-digit sector. Relative productivity is calculated analogously. The p-values associated with the t-tests of the mean differences in size and productivity between exiting and entering firms are also reported for each period. The upper sub-panel in Table 6 presents the results aggregated over sectors (weighted by the GVA-shares, given in Table A.3). The lower panels disaggregate the exercise for ten 1-digit sectors.[12] This exercise is analogous to the one described by Lee and Mukoyama (2015) for US plants, but we focus on individual firms rather than on plants, since our aim is to establish how financial conditions determine firms' choices whether to continue operating or to close. Notwithstanding, as we show in Sections 4.4 and 4.5, these results are robust when we construct a sub-sample of small firms with less than 10 FTE workers, likely consisting in single plant businesses and, moreover, when we control for the legal form of the firm.

[12] A complete list of sectors at 2-digit level can be found in Table A.2 in Appendix A. The primary sectors comprise: (A) *Agriculture, forestry and fishing* and (B) *Mining and quarrying*. The secondary sectors comprise: (C) *Manufacturing*, (D) *Electricity, Gas, Steam*, and (E) *Water Supply, Sewerage, Waste Management*. Sectors (K) *Financial and insurance activities* are not included in the CBI database. We also exclude sectors O-P-Q, *Public administration, defense, education, human health and social work activities*, sectors R-S, *Arts, entertainment, recreation; other services and service activities, etc.*, and sector U *Activities of extraterritorial organizations and bodies*.

On the basis of Table 6, the following conclusions can be drawn. First, during the boom period of 2000–07, entering firms were smaller than exiting firms, with average sizes of 0.54 *versus* 0.95. Differences in size were statistically significant at the aggregate level and in manufacturing sectors (sectors C–E). For the remaining sectors, differences in relative size were weakly significant. In the manufacturing sectors (C–E), exiting firms were 15% larger than continuing firms. The relative size of exiting firms fell after 2008. Between 2008 and 2014, exiting and entering firms had similar relative size, that is, they were on average 40% smaller than continuing firms (1-0.6). The relative size of exiting firms fell after the 2008 recession, but remained similar in entering firms over the business cycle. This evidence contrasts with that reported by Lee and Mukoyama (2015) for US industry plants, who found that entering plants were 25% larger in recessions than in booms, while the relative size of exiting plants was similar across recessions and booms. For Spanish firms (not plants) we find the opposite pattern.

Table 6: **Relative size and productivity**

	2000-2007			2008-2014			2015-2019		
All sectors	Exiting	Entering	p-value	Exiting	Entering	p-value	Exiting	Entering	p-value
Size	0.95	0.54	0.068	0.55	0.59	0.337	0.63	0.59	0.366
TFP	0.86	0.88	0.135	0.77	1.03	0.000	0.74	0.95	0.009
Avg. Prod.	0.76	0.64	0.153	0.42	0.76	0.004	0.48	0.77	0.190
A-B. Primary sectors	Exiting	Entering	p-value	Exiting	Entering	p-value	Exiting	Entering	p-value
Size	0.81	0.49	0.413	0.48	0.68	0.244	0.54	0.56	0.089
TFP	0.85	0.88	0.467	0.81	1.05	0.016	0.75	0.95	0.009
Avg. Prod.	0.70	0.66	0.395	0.45	0.79	0.321	0.23	0.78	0.075
C-E Manuf. Energy. Water	Exiting	Entering	p-value	Exiting	Entering	p-value	Exiting	Entering	p-value
Size	1.15	0.54	0.066	0.51	0.53	0.353	0.51	0.57	0.446
TFP	0.87	0.88	0.238	0.76	1.03	0.000	0.72	0.94	0.000
Avg. Prod.	0.80	0.64	0.167	0.34	0.76	0.007	0.36	0.78	0.297
F. Construction	Exiting	Entering	p-value	Exiting	Entering	p-value	Exiting	Entering	p-value
Size	0.85	0.55	0.138	0.74	0.54	0.322	0.74	0.75	0.371
TFP	0.85	0.88	0.272	0.76	1.02	0.000	0.74	0.94	0.000
Avg. Prod.	0.69	0.65	0.135	0.42	0.76	0.055	0.67	0.77	0.206
G. Trade. Repairs	Exiting	Entering	p-value	Exiting	Entering	p-value	Exiting	Entering	p-value
Size	0.90	0.59	0.310	0.52	0.58	0.419	0.72	0.57	0.498
TFP	0.85	0.89	0.247	0.77	1.04	0.000	0.74	0.95	0.000
Avg. Prod.	0.79	0.69	0.120	0.39	0.76	0.045	0.37	0.78	0.075
H. Transp. and Storage	Exiting	Entering	p-value	Exiting	Entering	p-value	Exiting	Entering	p-value
Size	1.02	0.56	0.291	0.48	1.08	0.276	0.64	0.54	0.469
TFP	0.93	0.87	0.419	0.77	1.05	0.000	0.76	0.94	0.000
Avg. Prod.	0.86	0.62	0.213	0.41	0.74	0.095	0.60	0.77	0.337
I. Accom. and Food Serv.	Exiting	Entering	p-value	Exiting	Entering	p-value	Exiting	Entering	p-value
Size	0.88	0.50	0.130	0.51	0.50	0.423	0.54	0.75	0.483
TFP	0.86	0.88	0.455	0.78	1.03	0.000	0.75	0.95	0.000
Avg. Prod.	0.81	0.65	0.395	0.53	0.74	0.203	0.62	0.78	0.412
J. Inform. and Comm.	Exiting	Entering	p-value	Exiting	Entering	p-value	Exiting	Entering	p-value
Size	0.79	0.46	0.104	0.49	0.72	0.401	0.49	0.63	0.249
TFP	0.85	0.87	0.299	0.77	1.04	0.000	0.77	0.95	0.000
Avg. Prod.	0.69	0.63	0.235	0.42	0.73	0.015	0.53	0.81	0.096
L. Real Estate	Exiting	Entering	p-value	Exiting	Entering	p-value	Exiting	Entering	p-value
Size	0.96	0.56	0.277	0.56	0.51	0.530	0.63	0.53	0.361
TFP	0.85	0.89	0.387	0.76	1.03	0.000	0.74	0.95	0.000
Avg. Prod.	0.75	0.62	0.160	0.48	0.76	0.131	0.61	0.75	0.363
M. Prof. Sci. and Tech. Serv.	Exiting	Entering	p-value	Exiting	Entering	p-value	Exiting	Entering	p-value
Size	1.03	0.63	0.306	0.54	0.63	0.368	0.89	0.50	0.325
TFP	0.85	0.88	0.141	0.79	1.04	0.000	0.75	0.94	0.000
Avg. Prod.	0.76	0.63	0.122	0.50	0.76	0.244	0.52	0.75	0.164
N. Adm. and Support Serv.	Exiting	Entering	p-value	Exiting	Entering	p-value	Exiting	Entering	p-value
Size	0.63	0.48	0.289	0.72	0.53	0.352	0.68	0.54	0.312
TFP	0.84	0.88	0.428	0.79	1.03	0.013	0.74	0.96	0.000
Avg. Prod.	0.68	0.63	0.286	0.31	0.73	0.050	0.45	0.78	0.006

Notes: For each period and sector, the p-values represent the t-tests for the mean differences in size, TFP, and labor productivity LP between exiting ($\mathcal{X}$) and entering firms ($\mathcal{N}$). In the upper panel, mean values have been aggregated using the GVA shares given in Table A.3 in Appendix A.

Second, for 2000–2007, TFP losses from exits were cushioned by TFP improvements from entrants, (0.86/0.88). In terms of average labor productivity, exiting firms were 18.75% more productive than entrants (0.76/0.64). However, these differences were only weakly significant. Since the entry rate was higher than the exit rate during this period (see Figure 1), the net entry effect was negative. This finding may help explain the counter-cyclical behavior of productivity per hour worked during the boom, as shown in Figure 2.

The recession and the recovery phases revealed a change in the pattern of productivity. Relative to incumbent firms, the TFP of entering firms is around 34% higher than that of exiting firms (1.03/0.77). In terms of average labor productivity, the difference is even larger (0.76/0.42). Again, this finding contrasts with that reported by Lee and Mukoyama (2015), who observed that the relative productivity of entering (plants) was always 10-20% higher than that of exiting plants over the cycle. Concerning Spain, Table 6 shows that, after the recession, the cleansing effect of exiting firms strengthened (Osotimehin and Pappadà, 2016), paired with the incoming of more productive new firms. The TFP of entering firms was 3% higher than in continuing firms in 2008–2014 (1.03), and 5% lower between 2015–2019 (0.95) homogenously for most sectors. These two facts would entail an upsurge in TFP due to the net entry effect following the recession, which accords with the description given in Figure 2. This result also contrasts with those presented by Foster et al. (2016) for the US after the 2008 recession; those authors concluded that the strength of reallocation fell rather than rose and that cleansing mechanism was less productivity-enhancing than in prior recessions.

The above findings indicate a change in size and productivity of exiting and entering firms after 2008:

Fact 2: (*i*) Relative to continuing firms, exiting firms were larger and more productive than entering firms; due to the turnover, this entailed size and productivity losses during the GDP boom between 2000 and 2007. (*ii*) After 2008, exiting firms were less productive while entering firms were more productive than incumbent firms, leading to gains in productivity through the *net entry* margin.

Using the decomposition proposed by Foster et al. (2001), González et al. (2023) recently showed that the fall in aggregate TFP 2003–12 can be explained, for the most part, by the within term, i.e., the term due to incumbent firms (see their Table 2, p. 560). The net entry effect had a negative impact on TFP growth throughout the entire period. By contrast, we found a change in the *net entry* effect on productivity, from negative to positive, after 2008. In the next section we look into this issue in greater depth, using an index of financial conditions and several tests of 1^{st}-order stochastic dominance.

4 The role of financial conditions

In this section, we examine the role of financial conditions at the operating, exit, and entry margins. To do so, following Musso and Schiavo (2008) we first construct an index of firms' financial conditions that includes a variety of features from their financial statements. Using tests of first-order stochastic dominance, we show that this index helps to explain the turnover in the financial situation and productivity following the start of the recession in 2008. Moreover, we conjecture two indicators of market (mis)-selection: i) the share of exiting firms that should have continued operating, and ii) the share of low- productivity continuing firms that should have closed. In a regression analysis, we incorporate this index to estimate whether the exit probability is affected by its financial health. Finally, we propose a counterfactual exercise to measure productivity losses due to market selection.

4.1 Measures of financial conditions

Following Musso and Schiavo (2008), we estimate two indexes of financial health from a rich variety of factors that may affect firms' ability to obtain financial resources and, as a result, may affect their capacity to operate.[13] These indicators are built upon seven variables from the firms' balance sheets: (i) *Cash flow*: earnings before interests, taxes, depreciation and amortization (EBITDA); (ii) *Liquidity*: current assets relative to current liabilities; (iii) *Solvency*: own funds relative to total liabilities; (iv) *Repaying ability*: non-current liabilities relative to cash-flow; (v) *Trade credit*: current liabilities over *total* assets; (vi) *Size*: total assets; and (vii) *Profitability*: gross value added at current market prices relative to total (nominal) assets.

For each firm and year, we calculate the quintiles for each variable $\in \{1,2,3,4,5\}$ relative to the four-digit sector average. For each item, this means that a firm in the lowest quintile has a score of 1, and a firm in the highest quintile has a score of 5. Finally, we calculate the two indices to proxy the financial conditions faced by each firm. The first index, *score A*, is the sum of the seven score values, such that for each firm and year, *score A* ranges between 7 and 35 (29 positions). The second index, *score B*, is the number of times a firm scores in the lowest quintile, ranging between 0 and 7 (eight positions). In both cases, scores are scaled in a common range from 0 to 10.[14] Note that while a firm's financial *health* improves with a larger *score A*, it decreases with a larger *score B*. The higher the *score A*, the better the firm's financial health; in contrast, the higher the *score B*, the higher the firm's financial constraints, since it is more likely to be located more often in the lowest quintile.

Table 7 reports basic moments for *scores A* and *B* and some basic correlations for the three sub-periods. Again, firms are divided into continuing, exiting, and entering. First, by construction, both scores were negatively correlated, around -0.8 over the three periods (i.e., they provide similar information regarding a firm's financial situation). Second, continuing firms were, on average, financially healthier than exiting and entering firms over all periods and for both scores. For 2000–2007, the average *score A* was higher for exiting firms than for entering firms $(5.08 > 4.87)$. The financial condition of entering businesses improved after the 2008 recession and beyond, and worsened for exiting firms.

[13] A similar exercise for several European countries, including Spain, can be seen in Ferrando and Ruggieri (2018).

[14] For firm j, *score A* is scaled according to $10 \times \frac{A^j - 7}{35-7}$. The score B is modified analogously.

The remaining rows of Table 7 report the correlations of these indices with selected variables. The better a firm's financial health, the higher its TFP. The correlation with labor productivity (not logged) is low. However, both indices perform better for older firms and larger continuing firms.

Table 7: **Descriptive Statistics for Scores A and B**

	2000–2007			2008–2014			2015–2019		
	Cont. $\mathcal{C}$	Exiting $\mathcal{X}$	Entering $\mathcal{N}$	Cont. $\mathcal{C}$	Exiting $\mathcal{X}$	Entering $\mathcal{N}$	Cont. $\mathcal{C}$	Exiting $\mathcal{X}$	Entering $\mathcal{N}$
$corr(A, B)$	-0.78	-0.85	-0.79	-0.77	-0.81	-0.74	-0.78	-0.83	-0.76
Mean Score A	5.88	5.08	4.87	5.83	4.85	5.15	5.80	4.72	5.08
S.D. Score A	1.27	1.42	1.16	1.26	1.26	1.08	1.25	1.29	1.14
Mean Score B	2.21	3.68	3.57	2.19	3.84	2.71	2.30	4.28	2.97
S.D. Score B	2.01	2.45	2.17	1.97	2.26	1.94	1.98	2.29	2.06
$corr(A, \ln(n))$	0.42	0.33	0.16	0.38	0.07	0.16	0.40	0.08	0.15
$corr(A, \ln(TFP))$	0.36	0.40	0.11	0.28	0.26	0.37	0.28	0.27	0.39
$corr(A, LP)$	0.08	0.10	0.05	0.03	0.06	0.13	0.02	0.01	0.16
$corr(A, Age)$	0.29	0.27	0.05	0.21	0.12	0.02	0.20	0.16	0.03
$corr(B, \ln(n))$	-0.32	-0.27	-0.12	-0.26	0.00	-0.10	-0.30	-0.03	-0.09
$corr(B, \ln(TFP))$	-0.39	-0.44	-0.13	-0.35	-0.32	-0.38	-0.35	-0.34	-0.37
$corr(B, LP)$	-0.06	-0.09	-0.04	-0.02	-0.05	-0.08	-0.01	-0.01	-0.11
$corr(B, Age)$	-0.20	-0.20	-0.04	-0.12	-0.06	0.02	-0.11	-0.11	0.00
No. Obs.	2319945	44318	97279	2927391	63488	80067	2154280	28672	70021

Notes: Our own calculations using administrative data from the CBI data base.

4.2 Stochastic dominance

Next, we work on the concept of 1^{st}-order stochastic dominance and examine differences in the *cumulative* distribution of score A between continuing, exiting and entering firms. Let $F^g(z)$ denote the *cumulative* distribution function of the score A corresponding to the set g of firms, $g \in \{\mathcal{C}, \mathcal{X}, \mathcal{N}\}$. Then, the first-order stochastic dominance of F^g relative to $F^{g'}$ (for $g \neq g'$) is defined by the following condition: $F^g(z) - F^{g'}(z) \leq 0$ uniformly for $z \in \mathbb{R}$, with strict inequality for some z. This gives rise to the following two hypotheses for *score* A:

1. *Hypothesis* $\mathbb{H}1$: If differences in market selection at the *exit (entry) margin* are due to financial conditions, the distribution of score A of continuing firms should first order dominate that of exiting (entering) firms: $F^{\mathcal{C}} \leq F^{\mathcal{X}}$ ($F^{\mathcal{C}} \leq F^{\mathcal{N}}$).

2. *Hypothesis* $\mathbb{H}2$: If differences in firm turnover are due to financial conditions, the distributions of scores A of entering and exiting firms should differ: $F^{\mathcal{X}} \neq F^{\mathcal{N}}$.

We test these hypotheses through the one-sided and the two-sided two-sample Kolmogorov-Smirnov tests. In all cases, the null hypothesis assumes $H_0 : F^g(z) = F^{g'}(z)$ for all z, that is, no stochastic dominance or equal distribution. The alternative hypothesis, for the one-sided test, implies that F^g 1^{st} order stochastically dominates $F^{g'}$, $H_1 : F^g(z) \leq F^{g'}(z)$; for the two-sided test, the alternative is $H_1 : F^g(z) \neq F^{g'}(z)$. The null hypothesis is rejected whenever the p-value lies below the 5% confidence threshold.

Table 8 reports the asymptotic p-values for the Kolmogorov-Smirnov test. To ensure sample independence, we test the hypothesis for each year separately. The first two columns (a)-(b) in Table 8 indicate that, for all years, the distribution in *score* A of continuing firms 1^{st}-order stochastically dominates those

Table 8: **Score A, Kolmogorov-Smirnov Test**

	(a)	(b)	(c)	(d)	(e)
	One-sided:	**One-sided:**	**One-sided:**	**One-sided:**	**Two-sided:**
$H_1:$	$F^{\mathcal{C}} \leq F^{\mathcal{X}}$	$F^{\mathcal{C}} \leq F^{\mathcal{N}}$	$F^{\mathcal{X}} \leq F^{\mathcal{N}}$	$F^{\mathcal{N}} \leq F^{\mathcal{X}}$	$F^{\mathcal{X}} \neq F^{\mathcal{N}}$
2000	0.000	0.000	0.003	0.930	0.006
2001	0.000	0.000	0.007	0.010	0.014
2002	0.000	0.000	0.000	1.000	0.000
2003	0.000	0.000	0.000	0.745	0.000
2004	0.000	0.000	0.000	0.151	0.000
2005	0.000	0.000	0.000	0.962	0.000
2006	0.000	0.000	0.000	1.000	0.000
2007	0.000	0.000	0.572	0.000	0.000
2008	0.000	0.000	0.001	0.000	0.000
2009	0.000	0.000	0.927	0.000	0.000
2010	0.000	0.000	0.415	0.000	0.000
2011	0.000	0.000	0.745	0.000	0.000
2012	0.000	0.000	0.589	0.000	0.000
2013	0.000	0.000	0.834	0.000	0.000
2014	0.000	0.000	0.679	0.000	0.000
2015	0.000	0.000	0.575	0.000	0.000
2016	0.000	0.000	0.944	0.000	0.000
2017	0.000	0.000	0.970	0.000	0.000
2018	0.000	0.000	0.883	0.000	0.000
2019	0.000	0.000	1.000	0.000	0.000

Notes: Figures in this table represent, for each year, the asymptotic p-values for the two-sample Kolmogorov-Smirnov hypothesis test for A. In all cases, the null hypothesis assumes that $F^g(z) = F^{g'}(z)$ for all z, i.e., no stochastic dominance. The alternative implies $F^g(z) \leq F^{g'}(z)$, i.e. F^g 1^{st} order stochastically dominates $F^{g'}$, for $g, g' \in \{\mathcal{C}, \mathcal{X}, \mathcal{N}\}$.

of both exiting and entering firms (i.e., the null hypotheses $\mathbb{H}1$ is rejected). Hence, the financial conditions matter for business selection at both the exit and the entry margins. Importantly, the third and fourth columns (c)-(d) in Table 8 indicate that *score A* for exiting firms 1^{st}-order stochastically dominates that of entering firms for the years preceding the Great recession, 2000-06 (the null hypotheses $\mathbb{H}1$ cannot be rejected for these years). In turn, as of 2009 and onward, the tests conclude that the financial conditions of entering firms 1^{st}-order dominate that of exiting firms. The tests are somewhat inconclusive for 2001 and 2008. Finally, the last column (e) concludes that the null hypothesis $\mathbb{H}2$ of equal distribution between entering and exiting firms is rejected for all years.

Fact 3: (i) Table 8 presents overwhelming evidence of stochastic dominance of *score A* for continuing firms over exiting and entering firms. This implies that financial condition matters at both exit and entry margins (Hypotheses $\mathbb{H}1$). (ii) Before the recession, the financial score of exiting firms 1^{st}-order stochastically dominates that of entering firms. After 2009 and onward, there is evidence of an improvement in the financial conditions of entering firms relative to exiting firms, which compares the description given in Table 7. The financial conditions of these two sets, $\mathcal{X}$ and $\mathcal{N}$, have been otherwise unequally distributed (Hypotheses $\mathbb{H}2$).

Analogously, we formulate the following hypothesis for the TFP distribution:

1. *Hypothesis* $\mathbb{H}3$: If differences in market selection at the *exit (entry) margin* are due to productivity, the distribution of TFP of continuing firms should 1^{st}-order dominate that of exiting (entering) firms: $F^{\mathcal{C}} \leq F^{\mathcal{X}}$ ($F^{\mathcal{C}} \leq F^{\mathcal{N}}$).

2. *Hypothesis* $\mathbb{H}4$: If differences in firms turnover are due to productivity, the distributions of TFP of entering and exiting firms should differ: $F^{\mathcal{X}} \neq F^{\mathcal{N}}$.

These hypotheses are tested through the one-sided and the two-sided two-sample Kolmogorov-Smirnov tests. Table 9 presents the asymptotic p-values for the Kolmogorov-Smirnov test for the TFP distribution. The first two columns (a)-(b) in Table 9 indicate that, for all years, the distribution in TFP of continuing firms first-order stochastically dominates those of exiting and entering firms. Hence, TFP matters for business selection at both the exit and the entry margins (the null hypothesis $\mathbb{H}3$ is rejected). Importantly, the third and fourth columns (c)-(d) in Table 9 indicate that TFP for entering firms first-order stochastically dominates that of exiting firms after the Great recession, 2007-19. Finally, the last column (e) concludes that the null hypothesis of equal distribution between entering and exiting firms is rejected for all years (the null $\mathbb{H}4$ is rejected).

Fact 4: (i) Table 9 concludes a TFP stochastic dominance of continuing firms relative to exiting and entering firms (hypothesis $\mathbb{H}3$). (ii) Before 2007, the distributions of exiting and entering firms differ, according to both the one-sided and the two-sided tests. After 2007 and onward, results clearly indicate higher levels of productivity for entering firms than for exiting firms, which reinforces the results reported in Table 6.

Table 9: TFP, **Kolmogorov-Smirnov Test**

	(a)	(b)	(c)	(d)	(e)
	One-sided:	**One-sided:**	**One-sided:**	**One-sided:**	**Two-sided:**
$H_1:$	$F^{\mathcal{C}} \leq F^{\mathcal{X}}$	$F^{\mathcal{C}} \leq F^{\mathcal{N}}$	$F^{\mathcal{X}} \leq F^{\mathcal{N}}$	$F^{\mathcal{N}} \leq F^{\mathcal{X}}$	$F^{\mathcal{X}} \neq F^{\mathcal{N}}$
2000	0.000	0.000	0.0075	0.000	0.000
2001	0.000	0.000	0.0468	0.000	0.000
2002	0.000	0.000	0.0000	0.000	0.000
2003	0.000	0.000	0.0000	0.000	0.000
2004	0.000	0.000	0.0000	0.000	0.000
2005	0.000	0.000	0.0000	0.000	0.000
2006	0.000	0.000	0.0000	0.000	0.000
2007	0.000	0.000	0.9876	0.000	0.000
2008	0.000	0.000	0.9833	0.000	0.000
2009	0.000	0.000	0.9982	0.000	0.000
2010	0.000	0.000	0.9956	0.000	0.000
2011	0.000	0.000	0.9997	0.000	0.000
2012	0.000	0.000	0.9956	0.000	0.000
2013	0.000	0.000	1.0000	0.000	0.000
2014	0.000	0.000	0.5175	0.000	0.000
2015	0.000	0.000	0.9908	0.000	0.000
2016	0.000	0.000	0.8147	0.000	0.000
2017	0.000	0.000	0.8396	0.000	0.000
2018	0.000	0.000	0.4536	0.000	0.000
2019	0.000	0.000	0.8593	0.000	0.000

Notes: Figures in this table represent, for each year, the asymptotic p-values for the two-sample Kolmogorov-Smirnov hypothesis test for TFP. In all cases, the null hypothesis assumes that $F^g(z) = F^{g'}(z)$ for all z, i.e., no stochastic dominance. The alternative implies $F^g(z) \leq F^{g'}(z)$, i.e. F^g 1^{st} order stochastically dominates $F^{g'}$, for $g, g' \in \{\mathcal{C}, \mathcal{X}, \mathcal{N}\}$.

4.3 Misselection at the exit margin and credit misallocation

Score A is exploited to measure two probabilities. First, we examine the likelihood by which exiting firms display financial conditions in the upper range of values of score A. This approximates the fraction of exiting firms, enjoying *healthy* financial conditions, that should continue open. This measure is labeled as type-I error probability, Pr^I, as an indication of market selection failure at exit. Second, we estimate the likelihood that continuing firms face financial conditions grading in the lower range of index A, labeled as type-II error probability, Pr^{II}, as an indication of financial misallocation.[15] The probability of type-I error is estimated as the fraction of exiting firms with index $A^{\mathcal{X}}$ scoring *above* a given threshold z^u. Accordingly, Pr^{II} is estimated as the fraction of operating firms with index $A^{\mathcal{C}}$ *below* a given threshold z^ℓ:

$$Pr^I = \text{Pr}\left[A^{\mathcal{X}} \geq z^u\right] = 1 - F^{\mathcal{X}}(z^u), \quad (4)$$

$$Pr^{II} = \text{Pr}\left[A^{\mathcal{C}} \leq z^\ell\right] = F^{\mathcal{C}}(z^\ell). \quad (5)$$

We arbitrarily select $z^u \in \{7.1, 7.4, 7.7\}$ and $z^\ell \in \{2.6, 2.9, 3.1\}$. For all cases, Pr^I and Pr^{II} are calculated independently for each year, to preserve sample independence. Strictly speaking, the type-II error probability Pr^{II} should be calculated using the same threshold as that in Pr^I, z^u.

These fractions Pr^I and Pr^{II} are represented in Figures 3.a and 3.b, respectively. Figure 3.a shows that, for every threshold $z^u \in \{7.1, 7.4, 7.7\}$, the share of business closures with index A scoring above z^u increased from 2000 to 2006, alongside the fall in productivity per hour worked (Figure 1), and dramatically declined in 2007–08. The peak in 2006 occurs for every $z^u \in \{7.1, 7.4, 7.7\}$. This implies an increase in the misselection of firms at the exit margin for 2000–06, which was later corrected. Figure 3.c below indicates that these thresholds $z^u \in \{7.1, 7.4, 7.7\}$ account for at least the 80th percentile of score A of the continuing firms.

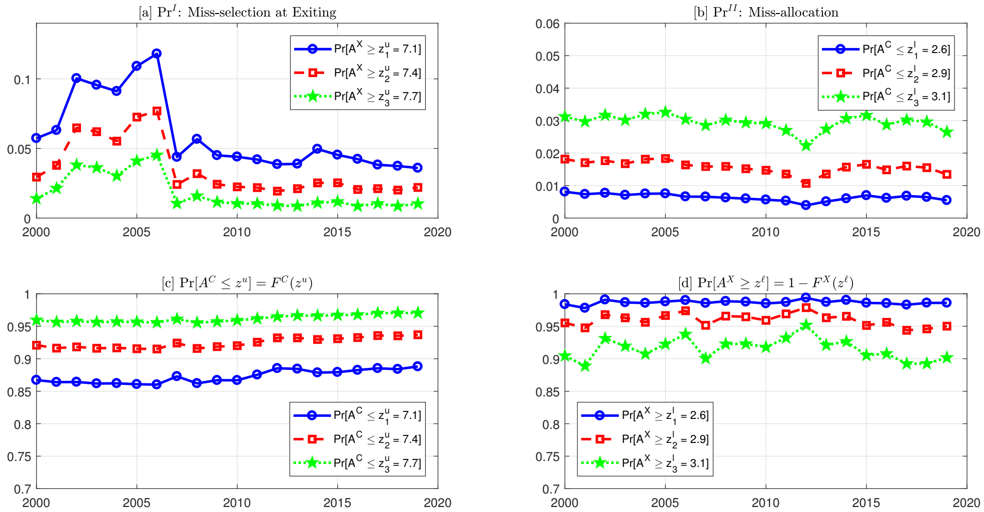
By contrast, in Figure 3.b the share of continuing firms with an index A scoring below z^ℓ, Pr^{II}, lingers between 0.8% and 3% for 2000–19, reaching a mild trough in 2012 for $z^\ell \in \{2.6, 2.9, 3.1\}$. Figure 3 [*d*] shows that the selected thresholds z^ℓ account between the 90th and the 99th percentile of score A of exiting firms X. During the boom of 2000–07, changes in the type-I probability were steeper than for type-II.

The share Pr^{II} can be linked to the issue of capital misallocation, as an explanation for the productivity slowdown in southern European countries. Under credit frictions and capital misallocation, continuing businesses that would typically close under competitive conditions survive, a circumstance that may bring down productivity and hinder opportunities for productive firms. Both Gopinath et al. (2017) and García-Santana et al. (2020) have shown that capital misallocation rose during the of 2000–07 expansion, paired with a fall in the real interest rate.

The research on the crowding-out effects of credit misallocation dates back to early studies of the zom-

[15] The type-II misallocation can crowd-out financial resources for productive but vulnerable firms, and cause a type-I misselection at the exit margin.

Figure 3: Selection errors, 2000–2019.



Source: CBI and own calculations.

bie firms during the stagnation Japanese in 1990s (see Peek and Rosengren (2005) and Caballero et al. (2008)). The experience of Japan indicates that the cost of zombie firms in terms of potential productivity losses at the exit margin was large in the 1990s. McGowan et al. (2018) provide evidence that the amount of resources sunk in the zombies rose after the Great Recession, and that a higher share of capital sunk in zombie firms tends to crowd out opportunities for healthy firms. This contrasts with the expected cleansing effect that should naturally occur in a recession (Caballero and Hammour (1994), Osotimehin and Pappadà (2016)), which would potentially provide opportunities for productive firms and a productivity-enhancing credit reallocation.

McGowan et al. (2018) estimate that Spain had the largest share of zombie firms across nine OECD countries during 2008–14, reaching the figure of 10% in 2013. In our context, the misallocation due to zombie firms is more likely to cause type-II errors than to type-I. In Figure 3, while $\Pr^{I}$ peaked in 2006, $\Pr^{II}$ has been hovering in the 1-3% range throughout the sample. Álvarez et al. (2023), using a tighter definition of zombie firms than McGowan et al. (2018), estimated a much lower zombie share for Spain, peaking at 2.1% in 2013. In turn, they estimate that the credit-to-zombie share peaked at 16.4% in the same year. Therefore, despite the low zombie share at the end of the recession, credit to zombie firms accounted for a non-negligible share of the total credit to non-financial firms. This suggests that these credit ever-greening practices by *soft* banks kept the zombie firms afloat, misallocating financial resources away from high productivity companies undergoing temporary financial distress. This helps explains, at least in part, the rise in capital misallocation found by Gopinath et al. (2017) and García-Santana et al. (2020). Indeed, as Álvarez et al. (2023) found, the probability of exiting the market was substantially lower for zombie firms than for other (non-zombie) distressed firms.[16]

Moreover, using Spanish monthly data for 2002:02–2008:12, Jiménez et al. (2012) found that higher short-term interest rates or lower GDP growth reduced the probability of a loan application being approved. The 2000–07 boom in Spain took place under historically low real interest rates and high GDP growth rates (see Figures 2.c and d), with loans highly concentrated in real estate services and construction, mostly granted by soft banks. After 2008, GDP growth declined, real interest rates rose and many soft (savings) banks disappeared. In this regard, for Spain, Akin et al. (2014) reported that credit standards applied to loans eased during the 2000–07 boom, with excessive risk-taking during this period, and tightened during the 2008–14 recession.[17]

Figures 4 and 5 respectively represent the $\Pr^I$ and $\Pr^{II}$ fractions disaggregated into ten sectors. Both figures indicate that the dynamics shown in Figure 3 are not driven by the sector composition; rather, the evolution of $\Pr^I$ in Figure 4 replicates the increase in Figure 3.a during the 2000–2007 boom. Likewise, the flat dynamic of $\Pr^{II}$ in Figure 5 is analogous to that in Figure 3.b.

Fact 5: The probability of type I error, i.e., closing a business when it should remain open, rose before the 2000–07 boom and then fell slightly after 2008. This suggests an increase in the misselection at the exit margin for 2000–07 and a correction afterwards. The probability of type II error, i.e., that the share of firms in financial difficulties that continued but should have closed ranged between 0.8% and 3% over the sample.

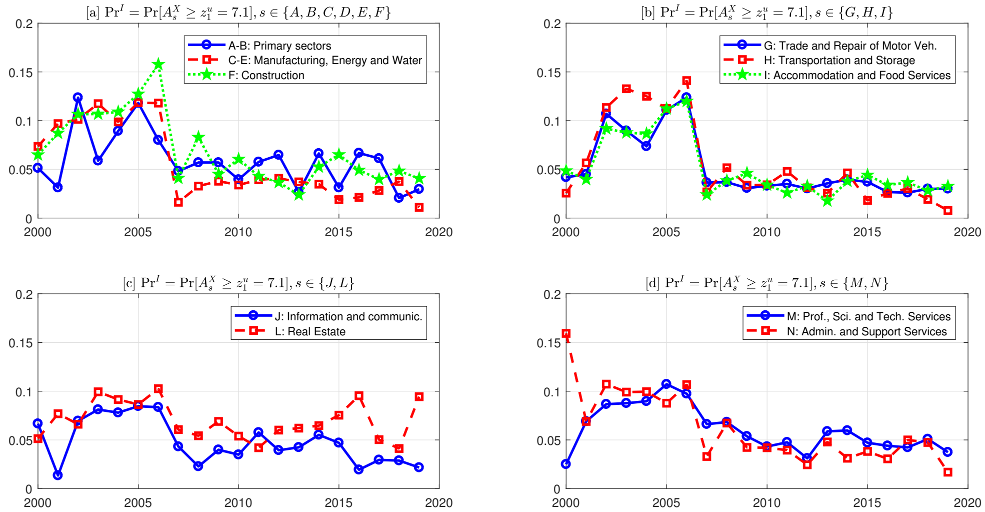
4.4 Firm's financial conditions and exit probability

Next, we study how financial conditions affect the likelihood of firm exit, using scores A and B. We define the hazard of a firm exiting the market using the proportional hazard function, which we assume to be common for all firms. Since we do not observe firms over their entire lifetimes, our data are right-censored, because we cannot infer the possible exit date beyond the study period of 2000–19. Similarly, although we know the birth date of firms after 2000, we do not have this information before that date. Thus, our data set is also left-censored. Moreover, the exit of a firm is a rare event (Figure 1). Therefore, the complementary log-logistic specification is the most appropriate to address these three issues. In this context, the firm $j = 1, ..., N$ enters the market at time t_0 and the hazard rate is given by the probability of exiting in the interval $\{t_\tau, t_{\tau+1}\}$ relative to the probability of surviving until τ. Thus, τ is a unit of time $\tau = 1, 2, 3, ..$ and the survival time is expressed in years. According to the

[16] They define financially distressed firms as firms under cash-flow insolvency, whereas zombie firms a re distressed firms that still receive new credit.

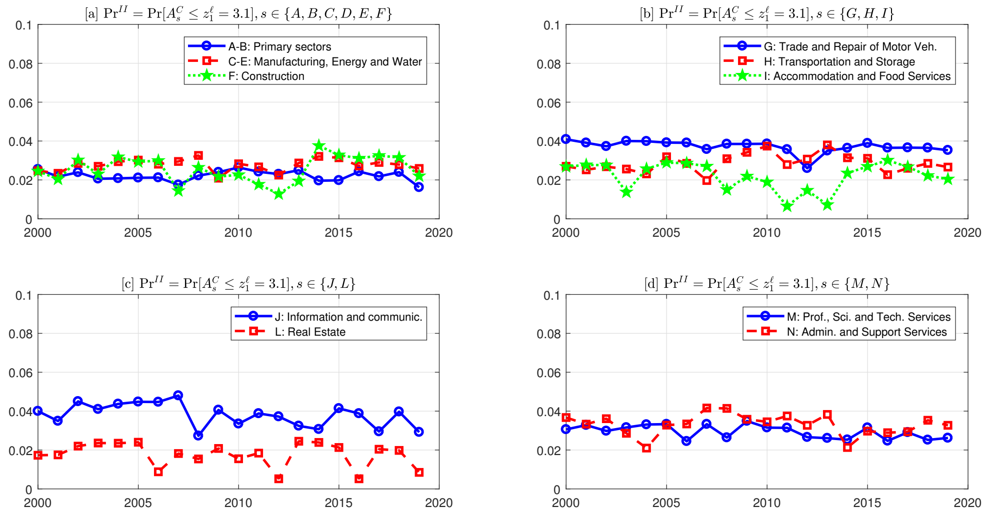
[17] The ECB Bank Lending Survey (BLS) for Spain reflects that the difference between the share of banks reporting a tightening of credit standards applied to loan approvals and the share of banks reporting an easing of these standards declined during the boom, and then rose after 2008. Moreover, the Great Recession was characterized by the disruption of the banks' ability to access market financing, the deterioration of their liquidity positions and the perception of higher risks, triggering altogether a significant tightening of credit standards and conditions for loans to enterprises.

Figure 4: Misselection at exit across sectors, 2000–19.



Source: CBI and own calculations.

Figure 5: Misallocation over sectors, 2000–2019.



Source: CBI and our own calculations.

proportional hazard theory, the hazard of exit for firm j is thus defined as a continuous proportional hazard function

$$\lambda(t, X_{j,t}) = \lambda_0(t) \exp\left(b_0 + b' X_{j,t}\right). \tag{6}$$

In the above, $\lambda_0(t)$ denotes the baseline hazard function, which is assumed to be common to all firms and independent of firm characteristics, and defines the pattern of duration dependence. The second term in (6), $\exp(b_0 + b' X_{jt})$, is firm-specific and includes all explanatory variables $X_{j,t}$ that may affect the hazard function. Applying the *clog-log* transformation, the complementary log-logistic discrete-time model is:[18]

$$\lambda(t_\tau \mid X_{jt}) = 1 - \exp\left[-\exp(b_0 + b' X_{jt} + \alpha_s)\right], \tag{7}$$

where $\alpha_s = \log\left(-\log(1 - \lambda_0(t_\tau))\right)$ is the complementary log-log transformation and captures the pattern of duration dependence. To specify the baseline hazard function $\lambda_0(t)$, we define a set of year and sector dummies captured by α_τ. The parameters of b describe the effect of explanatory variables on the hazard rate. A positive coefficient means that the hazard of firm exit increases with the explanatory variable or, in another words, that the probability of survival decreases with the explanatory variable.

Table 10 presents the estimated coefficients for the probability of firm exit according to expression (7). The dependent variable is binary and takes value one if the firm exits the market in year t, and zero otherwise. The following regressors are included: financial score (A or B), firm size (logged, number of employees), and TFP (logged). In all cases, we include an intercept, a dummy for firm age, a year dummy, and sector dummy at two-digit level. The first three columns, (a)-(c), use *Score A*, while columns (d)-(f) use *Score B*.

All coefficients have the expected sign and are statistically significant at the 1% level. The higher the *Score A*, the greater the ability to access financial resources and the lower the probability of exit. Table 10 column (a), for example, shows that a unit increase in *Score A* reduces the proportional hazard rate by 32.4% ($e^{-0.391} - 1 = -0.324$), *ceteris paribus*. Larger firms also face a lower hazard rate: $e^{-0.881} - 1 = -0.586$: a one percentage point increase in FTE employment brings down the hazard rate by 58.6%. A percentage increase in TFP by one unit reduces the hazard rate by 3.8% ($e^{-0.039} - 1 = -0.038$). The inclusion of TFP (column b) has little effect on the rest of coefficients. This finding corroborates those of other studies which have found that the productivity level helps predict business closure, even after controlling for factors such as size and age (see Bartoloni et al. (2021) for Italian firms, Bellone et al. (2008) and Musso and Schiavo (2008) for French firms, and Foster et al. (2001) and references therein).

In order to account for changes in type-I error Pr^I shown in Figure 3, in column (c) we impose that the *Score A* must interact with three time binary dummies of the business cycle phases (see Figure 1): $A \times D_{2000-07}$ for the boom, $A \times D_{2008-14}$ for the recession, and $A \times D_{2015-19}$ for the post-recession period. Consistent with the findings in Figure 3, the role of *Score A* (as a proxy of financial health) was moderate during the 2000–07 boom relative to the 2008–14 recession, and the 2015–19 recovery: $|-0.236| < |-0.425| < |-0.483|$. This result reflects that the selection at the exit margin worsened during 2000–07 due to credit misallocation, with an increase in the fraction of exiting businesses with healthy financial conditions (Pr^I).

[18] For additional details see Jenkins (2005); Bellone et al. (2008); Bartoloni et al. (2021).

Table 10: **Firm survival and financial health**

	Score A			Score B		
Variable	(*a*)	(*b*)	(*c*)	(*d*)	(*e*)	(*f*)
Financial *Score*	-0.379^{***}	-0.373^{***}	$---$	0.244^{***}	0.240^{***}	$---$
	(0.002)	(0.003)		(0.001)	(0.001)	
Employment (logged)	-0.881^{***}	-0.878^{***}	-0.883^{***}	-0.880^{***}	-0.878^{***}	-0.882^{***}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
TFP index (logged)		-0.039^{***}	-0.038^{***}		-0.037^{***}	-0.037^{***}
		(0.004)	(0.004)		(0.004)	(0.004)
$Score \times D_{2000-07}$	$---$	$---$	-0.236^{***}	$---$	$---$	0.174^{***}
			(0.004)			(0.002)
$Score \times D_{2008-14}$	$---$	$---$	-0.425^{***}	$---$	$---$	0.259^{***}
			(0.004)			(0.002)
$Score \times D_{2015-19}$	$---$	$---$	-0.483^{***}	$---$	$---$	0.304^{***}
			(0.005)			(0.003)
Age $= 0$ year	-1.292^{***}	-1.376^{***}	-1.350^{***}	-1.195^{***}	-1.245^{***}	-1.228^{***}
	(0.028)	(0.037)	(0.039)	(0.028)	(0.037)	(0.038)
Age $1-2$ years	0.095^{***}	0.103^{***}	0.115^{***}	0.145^{***}	0.153^{***}	0.163^{***}
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Age $3-4$ years	0.137^{***}	0.145^{***}	0.147^{***}	0.189^{***}	0.197^{***}	0.198^{***}
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Age $5-6$ years	0.105^{***}	0.112^{***}	0.107^{***}	0.154^{***}	0.161^{***}	0.158^{***}
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Age $7-8$ years	0.057^{***}	0.063^{***}	0.056^{***}	0.103^{***}	0.109^{***}	0.103^{***}
	(0.011)	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)
Age $9-10$ years	0.045^{***}	0.050^{***}	0.041^{***}	0.083^{***}	0.089^{***}	0.080^{***}
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Age $11-12$ years	-0.028^{**}	-0.025^{**}	-0.035^{***}	0.005	0.009	0.001
	(0.012)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
Age $13-15$ years	-0.042^{***}	-0.040^{**}	-0.051^{***}	-0.015	-0.012	-0.020
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Sector (2-digit) dummy	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Sample	7465201	7465201	7465201	7485453	7485453	7485453
*Non-zero outcomes	131699	131699	131699	133896	133896	133896
$Log-pseudolikelihood$	-583449.05	-582428.91	-581398.92	-585569.21	-584774.71	-583858.56
Wald Test $\chi^2_{d.f.}$	$1.15e+05^{***}$	$1.14e+05^{***}$	$1.15e+05^{***}$	$1.46e+05^{***}$	$1.47e+05^{***}$	$1.46e+05^{***}$

Notes: Estimation of the complementary log-log function with unobserved heterogeneity. All estimations include sector effects at 2 digit-level, age, and time effects. Standard errors are in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Firm age has a non-linear effect on the probability of closure (these coefficients are reported relative to firms older than 16 years). By construction, entering firms do not quit during the first operating year ($\approx -1.35^{***}$). For firms older than one year, the estimated coefficients increase, peaking at 3-4 years and decaying until age 10 years. Interestingly, the effect declines after age 11 (columns (a)-(b)), which suggests an age of business consolidation. These outcomes meet some estimates made by the INE for several years, where half of starting firms exit after four years of operating.[19] Our results are comparable to those of Bellone et al. (2008) for French industrial firms, who find a high degree of sensitiveness of firm survival to firm age. For their part, for US firms, Haltiwanger et al. (2013) after controlling for firm age found no systematic relation between firm growth and size.

When *Score B* is used, the results are similar to those for *Score A* (columns (a)-(c) *versus* (d)-(f)). Recall that *Score B* measures how often the company is in the lowest quintile of the seven items considered in this index, among them liquidity and solvency. As expected, the higher the *Score B*, the worse the financial situation of the firm and the higher the exit probability (column (d)). A one-unit decrease in *Score B* reduces the firm hazard rate by 27.6% ($e^{0.244} - 1 = 0.276$, column (d)). This figure falls slightly to 27.1% when TFP is added into the regression (column (e)). Analogously to column (c), in column (f), the effect of the financial conditions becomes steeper after 2008. Moreover, the effect of age, firm size,

[19] See *Indicadores de Demografía Empresarial.*, several years

and TFP level on the exit hazard rate is quite stable compared to those in columns (a) to (c).

As a robustness check exercise, we have re-estimated previous regressions in Table 10 for those firms with less than 10 workers. We conjecture that these small firms are likely single-plant businesses, and explore whether previous results are sensible to the size of the firm. Firms with 10 or fewer employees account for 85% of all firms in Spain (Table 5). The results are shown in Table 11. As compared with Table 10 in the paper, all estimates are similar, except that for the (logged full time equivalent) employment, where the coefficient shows a stronger elasticity: $|-1.13| > |-0.88|$. Now, a one percentage point increase in employment decreases the hazard rate by 67.7% rather than 58.6%, as a result from diminishing returns on labour.

Table 12 reports the results when we control for the legal form of the firm: S.L. (Limited Responsability Society), S.A. (*Sociedad Anónima*) and other forms (accounting for 0.5% of our sample, see Table 5). Again, relative to Table 10, the coefficients for TFP, the financial scores, and the firm age are similar. Importantly, the dummy for S.L. firms, which tend to be small size businesses, are positively correlated with the exit probability, relative to the S.A. and other legal forms. This implies that S.L. firms are smaller and more vulnerable than S.A. firms. In line with earlier findings in Table 11 above, when the legal form interact with employment and the period, the sensitiveness is higher in S.L. firms. S.A. and other legal forms present similar elasticities with respect to employment.

Fact 6: The regressions in Table 10 show that, in Spain, a firm's probability of exiting the market increases with its financial distress. The sensitiveness of a firm's exit probability to its financial condition rose substantially over the sample period. Firm size, productivity and age also help predict the probability of exit. The findings in Tables 11 and 12 show that the results are robust to the firm size and the legal form.

4.5 A counterfactual exercise

In Table 13, we impose that exiting firms with index A scores above $x^u = 7.1$ to continue operating during the year that they are observed to close. More formally, for each particular year t, this subset of exiting firms are reclassified from set $\mathcal{X}_t$ to the set of continuing firms $\mathcal{C}_t$. We impose two additional assumptions: first, the size distribution of incumbent firms $\mathcal{C}_t$ does not change after the reclassification; second, we assume that the reclassification has no effect on the economy sector composition. After bootstrapping, relative moments for size and productivity are computed and aggregated in much the same way as in Table 6. Thus, differences in size and productivity can only be due to the cancellation of the type-I errors.

The first two panels in Table 13 present the aggregate measures, for the untreated sample (as in Table

Table 11: **Firm survival and financial health for firms with less than 10 employees**

	Score A			Score B		
Variable	(a)	(b)	(c)	(d)	(e)	(f)
Financial *Score*	-0.378***	-0.371***	—	0.240***	0.236***	—
	(-147.57)	(-141.02)	—	(191.69)	(175.77)	—
Employment (logged)	-1.131***	-1.127***	-1.137***	-1.115***	-1.112***	-1.124***
	(-205.15)	(-203.15)	(-205.23)	(-205.98)	(-202.42)	(-205.01)
TFP index (logged)	—	-0.0383***	-0.0381***	—	-0.0370***	-0.0368***
	—	(-9.50)	(-9.63)	—	(-9.99)	(-9.92)
$Score \times D_{2000-07}$	—	—	-0.269***	—	—	0.183***
	—	—	(-60.13)	—	—	(81.13)
$Score \times D_{2008-14}$	—	—	-0.401***	—	—	0.246***
	—	—	(-110.11)	—	—	(133.65)
$Score \times D_{2015-19}$	—	—	-0.468***	—	—	0.297***
	—	—	(-75.75)	—	—	(100.60)
Age $= 0$ year	-1.285***	-1.370***	-1.344***	-1.186***	-1.242***	-1.224***
	(-44.41)	(-38.70)	(-36.74)	(-41.35)	(-34.54)	(-33.67)
Age $1-2$ years	0.117***	0.125***	0.143***	0.166***	0.174***	0.188***
	(10.99)	(11.74)	(13.38)	(15.79)	(16.43)	(17.76)
Age $3-4$ years	0.159***	0.168***	0.176***	0.209***	0.217***	0.223***
	(15.62)	(16.42)	(17.29)	(20.70)	(21.47)	(22.05)
Age $5-6$ years	0.127***	0.134***	0.138***	0.173***	0.180***	0.182***
	(12.04)	(12.71)	(13.11)	(16.66)	(17.30)	(17.47)
Age $7-8$ years	0.0750***	0.0812***	0.0823***	0.118***	0.124***	0.123***
	(6.85)	(7.40)	(7.51)	(10.88)	(11.41)	(11.29)
Age $9-10$ years	0.0670***	0.0720***	0.0711***	0.101***	0.106***	0.104***
	(5.92)	(6.36)	(6.28)	(9.04)	(9.44)	(9.27)
Age $11-12$ years	-0.0102	-0.00626	-0.00810	0.0202***	0.0238***	0.0216***
	(-0.85)	(-0.52)	(-0.67)	(1.70)	(2.00)	(1.81)
Age $13-15$ years	-0.0335***	-0.0306***	-0.0342***	-0.00765	-0.00505	-0.00819
	(-3.01)	(-2.75)	(-3.07)	(-0.69)	(-0.46)	(-0.74)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Sector (2-digit) dummy	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Sample	5842598	5842598	5842598	5861151	5861151	5861151
Non-zero outcomes	124991	124991	124991	127155	127155	127155
log-pseudolikelihood	-537318.6	-536369.4	-536645.8	-539843.7	-539106.6	-539648.8
Wald Test $\chi^2_{d.f.}$	123.802	123.336	122.119	150.535	150.794	147.252

Notes: Estimation of the complementary log-log function with unobserved heterogeneity. Figures into parenthesis are t-values. All estimations include sector effects at 2 digit-level, age, and time effects. Standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

6) and the treated sample. The bottom panel compares the two. If market selection at the exit margin had been absent of type-I errors, the cleansing effect would have been greater: it would have occurred mainly during the boom of 2000–07 and the recovery of 2015–19, rather than during the recession of 2008–14. For instance, relative to continuing firms, the firms shutting down in our counterfactual exercise would have been 42% smaller in size in 2000–07 (0.95/0.67). The potential gains in TFP would range from 3% to 6.5%, and on average labor productivity would range from 27% to 46%. As expected, removing the type-I errors has a negligible impact at the entry margin.

Fact 7: The counterfactual exercise suggests that type-I selection errors had potentially large effects on productivity through the cleansing effect. Under credit frictions, a portion of highly productive but financially vulnerable firms were forced to exit the market, mostly during the boom of 2000–07: had market selection been absent of type-I errors at the exit margin, the cleansing effect would have been amplified, relative TFP gains would have potentially been between 3% and 6.5% larger, and gains in relative labor productivity would range between 27% to 46%. The cleansing effect would have been greater during the 2000–07 boom and the 2015–19 recovery, rather than under the 2008–14 recession.

Table 12: **Firm survival and financial health by type of legal form**

Variable	Score A Coef.	Score A t-value	Score B Coef.	Score B t-value
TFP index (logged)	-0.0385***	(-10.41)	-0.0371***	(-10.72)
$Score \times D_{2000-07}$	-0.283***	(-65.22)	0.194***	(88.20)
$Score \times D_{2008-14}$	-0.412***	(-113.03)	0.252***	(136.90)
$Score \times D_{2015-19}$	-0.477***	(-75.64)	0.302***	(100.38)
$S.L. \times D_{2000-07}$	2.646***	(17.10)	2.479***	(16.25)
$S.L. \times D_{2008-14}$	3.011***	(16.15)	2.939***	(16.13)
$S.L. \times D_{2015-19}$	2.411***	(6.29)	2.270***	(6.04)
$S.L. \times \ln(n) \times D_{2000-07}$	-0.748***	(-85.09)	-0.734***	(-83.78)
$S.L. \times \ln(n) \times D_{2008-14}$	-1.069***	(-133.07)	-1.074***	(-138.41)
$S.L. \times \ln(n) \times D_{2015-19}$	-1.105***	(-79.98)	-1.093***	(-81.60)
$S.A. \times \ln(n) \times D_{2000-07}$	-0.390***	(-25.13)	-0.400***	(-26.27)
$S.A. \times \ln(n) \times D_{2008-14}$	-0.669***	(-31.91)	-0.695***	(-33.92)
$S.A. \times \ln(n) \times D_{2015-19}$	-0.780***	(-17.54)	-0.797***	(-18.28)
$Others \times \ln(n) \times D_{2000-07}$	-0.404***	(-23.24)	-0.411***	(-24.04)
$Others \times \ln(n) \times D_{2008-14}$	-0.714***	(-30.61)	-0.730***	(-31.99)
$Others \times \ln(n) \times D_{2015-19}$	-0.861***	(-18.00)	-0.867***	(-18.44)
Age $= 0$ year	-1.250***	(-30.81)	-1.141***	(-28.70)
Age $1-2$ years	0.214***	(19.66)	0.247***	(22.89)
Age $3-4$ years	0.239***	(23.28)	0.274***	(26.89)
Age $5-6$ years	0.196***	(18.51)	0.228***	(21.79)
Age $7-8$ years	0.141***	(12.90)	0.170***	(15.70)
Age $9-10$ years	0.122***	(10.80)	0.144***	(12.86)
Age $11-12$ years	0.0378***	(3.18)	0.0573***	(4.86)
Age $13-15$ years	0.0102	(0.93)	0.0262**	(2.40)
Year dummy	Yes		Yes	
Sector (2-digit) dummy	Yes		Yes	
Constant	Yes		Yes	
Sample	7465201		7485453	
Non-zero outcomes	131669		133898	
log-pseudolikelihood	-582797.1		-585703.6	
Wald Test $\chi^2_{d.f.}$	124070.289		154496.618	

Notes: Estimation of the complementary log-log function with unobserved heterogeneity. All estimations include sector effects at 2 digit-level, age effects, and time effects. Standard errors are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 13: **Keeping firms open otherwise exiting**

	2000-2007		2008-2014		2015-2019	
Untreated sample:	Exiting	Entering	Exiting	Entering	Exiting	Entering
Size	0.95	0.54	0.55	0.59	0.63	0.59
TFP	0.86	0.88	0.77	1.03	0.74	0.95
Avg. Prod.	0.76	0.64	0.42	0.76	0.48	0.77
Treated sample:	Exiting	Entering	Exiting	Entering	Exiting	Entering
Size	0.67	0.54	0.54	0.59	0.51	0.59
TFP	0.81	0.88	0.74	1.03	0.72	0.95
Avg. Prod.	0.57	0.64	0.33	0.75	0.33	0.77
Change (%):	Exiting	Entering	Exiting	Entering	Exiting	Entering
Size	42.3%	0.05%	3.1%	0.06%	23.0%	0.00%
TFP	6.5%	0.09%	3.8%	0.04%	3.1%	0.01%
Avg. Prod.	34.3%	0.07%	26.9%	0.25%	45.7%	0.14%

The potential effects on the entry margin are negligible.

5 Conclusion

In this paper, we document changes observed in labor productivity and firm dynamics over the business cycle from 2000 to 2019 in Spain. We have examined how these changes connect to misselection at the exit margin, credit misallocation, and firms financial conditions. Eventually, we reach the following conclusions. *First*, low productive firms with access to financial resources were able to continue operating, due to the soft bank lending conditions during the 2000–07 period. This crowded out financial resources, since highly productive but financially vulnerable firms were forced to exit the market, mostly during the boom of 2000–07. We found that exiting firms were larger and more productive than entering firms, which led to size and productivity losses alongside the GDP boom in 2000–07. *Second*, following the tightening of credit conditions after 2008, the 1^{st} order dominance tests suggest a more efficient selection at both the exit and the entry margins. From 2008 and onward, exiting firms had lower productivity and entering firms higher productivity, relative to incumbent firms, indicating productivity gains through the *net entry* margin. *Finally*, during the recovery phase of 2015–19, the productivity and financial conditions of entering firms still 1^{st} order dominate those of exiting firms, which helps to explain the change in the correlation between productivity and the business cycle.

The above analysis has interesting policy implications regarding the impact of the cleansing mechanism on productivity and employment. For instance, during the COVID-19 pandemic, keeping small firms open was a common policy objective implemented via direct subsidies, such as the *Paycheck Protection Program* (PPP) in the US or, in Spain, via indirect policies through labor market mechanism (*Expedientes de Regulación Temporal de Empleo*, ERTE). The rationale was to prevent the closure of valuable firms which, due to financial constraints, might otherwise have closed (Ulyssea et al. (2021)). An associated danger of these policies is that it may keep afloat inefficient firms that should have closed. The assessment is that these policies have not been very successful, and have allowed some inefficient firms to survive (see Kurmann et al. (2021) for U.S.).

However, after the credit collapse in 2008, fiscal policies were not designed to prevent the closure of firms. The recession of 2008–14, as a natural experiment, has allowed us to quantify the effect of cleansing mechanism and market misselection on aggregate productivity. In a follow-up extension of this paper, we propose a model of firm creation and destruction able both to address the study of business cycles and to accommodate different policies. Hence, the evaluation of these type of policies for Spain remains an open question.

A.1: **Descriptive Statistics for S.A. and S.L. firms**

CBI Database	**2007**	**2019**	**Growth**
No. of S.A. ($n \geq 0$)	84228 (9.6%)	55336 (5.6%)	-34.3%
No. of S.L. ($n \geq 0$)	796696 (90.4)	931835 (94.4%)	$+16.9\%$
Avg. No. of FTE employees S.A. ($n \geq 1$)	62.1	84.7	$\Delta n = +22.6$ empl.
Avg. No. of FTE employees S.L. ($n \geq 1$)	8.3	9.6	$\Delta n = +1.3$ empl.
$\Pr[n \geq 100 \mid S.A.] \times 100$	5.6	7.0	$\Delta \Pr = +1.4\%$
$\Pr[n \geq 100 \mid S.L.] \times 100$	2.1	1.7	$\Delta \Pr = -0.4\%$
Avg. Age (years) S.A. ($n \geq 1$)	20.7	31.7	$\Delta Age = +11$ years
Avg. Age (years) S.L. ($n \geq 1$)	8.7	13.6	$\Delta Age = +4.9$ years
$\Pr[Age \geq 10yrs. \mid S.A.] \times 100$	85.08	96.27	$\Delta \Pr = +11.2\%$
$\Pr[Age \geq 10yrs. \mid S.L.] \times 100$	34.47	56.23	$\Delta \Pr = +21.8\%$

A Appendix

A.1 Descriptive figures of legal forms

Table A.1 introduces descriptive moments for S.A. and S.L. firms from the CBI database for 2007 and 2019. As of 2007, the number of S.A. and S.L. were 64941 and 632047, respectively, accounting for 99.5% of all companies in every year (for more precision, see Bank of Spain (2023)). As of 2019 and relative to 2007, S.A. companies had decreased by -34%, while S.L. companies had increased by $+17\%$. The **modal** legal form of Spanish firms are S.L. societies, accounting for 94% of all firms in 2019.

Also in Table A.1, another difference points to a larger S.A.'s growth relative to S.L. firms. The average number of **FTE employees** in S.A.'s increased from 62.1 to 84.7, i.e. an average net increase of 22.6 FTE employees between 2007 and 2019. In S.L. firms this average barely moves from 8.3 to 9.6. Yet, while the share of S.A. firms employing over 100 FTE workers has raised by 1.4%, for S.L. businesses has decreased by -0.4%.

Both types of firms have become older on average, but the aging of S.A. businesses points to a bigger life expectancy relative to S.L. firms: in both periods, the average age of S.A. doubles that of S.L. firms. The age increase is 11 years versus 5 years for S.A. and S.L. firms, respectively. Accordingly, the share of S.A. firms older than 10 years has grown by 11.2%, accounting for 96.3% of S.A. firms. As for S.L. firms, this fraction has increased by 34.5% to 56.2% between 2007 and 2019.

A.2 List of sectors and sector shares

A.2: **List of sectors**

CNAE	Activity	NACE2	Sector
A	Primary	1	Crop and animal production, hunting and related service activities
A	Primary	2	Forestry and logging
A	Primary	3	Fishing and aquaculture
B	Primary	5	Mining of coal and lignite
B	Primary	6	Extraction of crude petroleum and natural gas
B	Primary	7	Mining of metal ores
B	Primary	8	Other mining and quarrying
B	Primary	9	Mining support service activities
C	Manufacturing	10	Manufacture of food products
C	Manufacturing	11	Manufacture of beverages
C	Manufacturing	12	Manufacture of tobacco products
C	Manufacturing	13	Manufacture of textiles
C	Manufacturing	14	Manufacture of wearing apparel
C	Manufacturing	15	Manufacture of leather and related products
C	Manufacturing	16	Manufacture of wood and of products of wood and cork, except furniture
C	Manufacturing	17	Manufacture of paper and paper products
C	Manufacturing	18	Printing and reproduction of recorded media
C	Manufacturing	20	Manufacture of chemicals and chemical products
C	Manufacturing	21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C	Manufacturing	22	Manufacture of rubber and plastic products
C	Manufacturing	23	Manufacture of other non-metallic mineral products
C	Manufacturing	24	Manufacture of basic metals
C	Manufacturing	25	Manufacture of fabricated metal products, except machinery and equipment
C	Manufacturing	26	Manufacture of computer, electronic and optical products
C	Manufacturing	27	Manufacture of electrical equipment
C	Manufacturing	28	Manufacture of machinery and equipment n.e.c.
C	Manufacturing	29	Manufacture of motor vehicles, trailers and semi-trailers
C	Manufacturing	30	Manufacture of other transport equipment
C	Manufacturing	31	Manufacture of furniture
C	Manufacturing	32	Other manufacturing
C	Manufacturing	33	Repair and installation of machinery and equipment
D	Manufacturing	35	Electricity, gas, steam and air conditioning supply
E	Manufacturing	37	Sewerage
E	Manufacturing	38	Waste collection, treatment and disposal activities; materials recovery
E	Manufacturing	39	Remediation activities and other waste management services
F	Construction	41	Construction of buildings
F	Construction	42	Civil engineering
F	Construction	43	Specialized construction activities
G	Trade	45	Wholesale and retail trade and repair of motor vehicles and motorcycles
G	Trade	46	Wholesale trade, except of motor vehicles and motorcycles
G	Trade	47	Retail trade, except of motor vehicles and motorcycles
H	Services	49	Land transport and transport via pipelines
H	Services	50	Water transport
H	Services	51	Air transport
H	Services	52	Warehousing and support activities for transportation
H	Services	53	Postal and courier activities
I	Services	55	Accommodation
I	Services	56	Food and beverage service activities
J	Services	58	Publishing activities
J	Services	59	Motion picture, video and television programme production, sound recording
J	Services	60	Programming and broadcasting activities
J	Services	61	Telecommunications
J	Services	62	Computer programming, consultancy and related activities
J	Services	63	Information service activities
L	Services	68	Real estate activities
M	Services	69	Legal and accounting activities
M	Services	70	Activities of head offices; management consultancy activities
M	Services	71	Architectural and engineering activities; technical testing and analysis
M	Services	72	Scientific research and development
M	Services	73	Advertising and market research
M	Services	74	Other professional, scientific and technical activities
M	Services	75	Veterinary activities
N	Services	77	Rental and leasing activities
N	Services	78	Employment activities
N	Services	79	Travel agency, tour operator reservation service and related activities
N	Services	80	Security and investigation activities
N	Services	81	Services to buildings and landscape activities
N	Services	82	Office administrative, office support and other business support activities

A.3: **Sector GVA-shares in Spain**

Sector:	2000-2007	2008-2014	2015-2019
A-B. Primary sectors	5.07	3.97	4.38
C-E Manuf., Energy. and Water	24.73	22.24	21.84
F. Construction	14.86	11.09	8.15
G. Trade. Repairs	15.50	16.75	17.55
H. Transp. and Storage	6.03	6.11	6.35
I. Accom. and Food Serv.	9.01	8.19	8.61
J. Inform. and Communications	5.82	5.42	5.07
L. Real Estate	10.02	15.60	16.06
M. Prof., Sci. and Tech. Serv.	4.93	5.87	6.42
N. Adm. and Support Serv.	4.03	4.77	5.56
Sum:	100	100	100

Note: This table reports the average sector shares using the EU KLEMS yearly series (February 2023) of Gross Value Added at current prices in Spain. Sectors K (*Financial and insurance activities*) and R through U (*Arts, entertainment, recreation; other services and service activities, etc.; Activities of extraterritorial organizations and bodies*) have been excluded. These shares are used to weight the average sector moments in Tables 6 and 13.

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