

Firm Dynamics and Productivity Growth in Spain*

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Abstract

This chapter examines the relationship between firm dynamics and aggregate productivity growth in Spain over 2000–2023, using firm-level data from the Central Balance Sheet Database of the Banco de España. It argues that Spain’s stagnation in total factor productivity reflects the interaction of two forces.

The first is cyclical. A credit boom generated capital deepening alongside misallocation. The crisis then depressed productivity through slow factor adjustment among older incumbents and a banking-crisis-driven credit contraction constraining younger firms, while the recovery was driven disproportionately by incumbents aged 21 and over. The second is secular: Spain experienced a persistent decline in firm dynamism, reflected in falling entry rates, declining job reallocation, and a marked aging of the firm population that predates and outlasts the crisis.

Their interaction helps explain the narrowness of the post-crisis recovery: as younger cohorts shrank, aggregate productivity became increasingly dependent on older incumbents rather than renewed by productive entry. The chapter finds no strengthening of the cleansing mechanism during the recession, and shows that age-related productivity growth differences flattened after the crisis, turning mildly negative for firms aged 6–20 during the recovery. This points to weaker life cycle dynamics underlying long-run productivity growth in Spain.

*The views expressed here are of the authors only, and not necessarily those of the Banco de España, ECB or the Eurosystem.

1 Introduction

Why did Spain's aggregate total factor productivity stagnate over 2000–2019, despite ongoing technological progress and innovation globally? This chapter argues that the answer lies in the evolution of the firm distribution. Aggregate productivity growth depends not only on technological improvements within incumbent firms, but also on the process of creative destruction: the reallocation of resources toward more productive uses through firm entry, firm exit, and the expansion of surviving firms ([Schumpeter, 1942](#); [Aghion and Howitt, 1992](#); [Caballero and Hammour, 1994](#)). We show that firm dynamics in Spain weakened along two dimensions over this period: one cyclical and one secular, and that their interaction helps explain both the depth and persistence of this stagnation.

The first dimension is cyclical. During the boom, a significant expansion of credit generated substantial capital deepening, raising labour productivity while also worsening allocation as resources flowed toward less productive uses ([Gopinath et al., 2017](#); [Garcia-Santana et al., 2020](#)). The crisis then pushed TFP down through two age-specific channels. Among older incumbents, capital adjusted only gradually as output collapsed, consistent with slow factor adjustment, depressing measured TFP through factor underutilisation. Younger firms, which tend to rely more on the extension of new external finance and have less collateral, were particularly exposed to the systemic credit contraction triggered by the banking crisis and appear to have operated at lower capital intensity than comparable pre-crisis cohorts. These patterns are consistent with the banking crisis limiting entry and young firm expansion during the downturn. Taken together, these cyclical forces left deep marks on TFP but are, at least in principle, reversible as conditions normalise.

The second dimension is secular, and more concerning because it appears structural. A growing literature documents declining business dynamism across advanced economies, reflected in lower entry, weaker job reallocation, and an aging firm population ([Decker et al., 2016, 2017](#); [Akcigit and Ates, 2021](#)). We show that Spain experienced a similarly broad-based decline that both predates and outlasts the crisis episode (see also [Villegas-Sanchez \(2025\)](#)). Entry rates fell after the boom and remained subdued. Gross job reallocation declined steadily across sectors throughout the period. The firm population also aged substantially, driven not only by fewer entrants but also by weak post-entry growth, as surviving younger firms struggled to move into older and larger parts of the distribution ([Haltiwanger et al., 2013](#); [Bartelsman et al., 2013](#); [Sterk et al., 2021](#)). We do not find evidence that this shift was accompanied by a marked rise in top-end concentration, suggesting broad distributional aging rather than a simple winner-takes-all pattern.

The interaction between these two forces is central to understanding Spain's productivity stagnation. As the firm population aged, the post-2014 recovery depended increasingly on the performance of older incumbents rather than being renewed by a strong flow of young, high-productivity entrants. Firms aged 21 and over were the main contributors to the recovery in

aggregate productivity, and by the end of the sample they were the only age group clearly above their initial productivity level. At the same time, the cleansing mechanism failed to strengthen during the recession: exiting firms remained less productive than continuing firms, but the productivity gap between the two did not widen in the way standard cleansing models would predict ([Foster et al., 2016](#)).

Our within-firm regressions further indicate that age-related productivity growth differences became markedly flatter after the crisis, and turned mildly negative for firms aged 6–20 during the 2014–2019 recovery, including in balanced samples that exclude selection effects. In the pre-crisis period, younger firms exhibited stronger within-firm productivity growth, consistent with standard life cycle dynamics in which productivity improvements are concentrated in early stages of the firm life cycle. For these gains to translate into aggregate productivity growth, however, young firms must scale successfully as they mature. The evidence in this chapter suggests that this transmission mechanism weakened after the crisis: not only did age-related productivity growth differentials diminish, but younger firms also accounted for a declining share of economic activity and exhibited limited expansion into middle-aged cohorts. Spain thus faces a double burden on future productivity growth: a diminished role for young firms in the firm distribution, and a weakening of the life cycle dynamics through which they scale into mature, high-productivity incumbents.

Our empirical analysis uses the Central Balance Sheet Database (*Central de Balances Integrada*, CBI) compiled by the Banco de España, which provides annual balance sheet and income statement information for incorporated Spanish firms over 2000–2023. The panel structure of the CBI allows us to follow firm cohorts over time, study firm life cycles, proxy entry and exit, and decompose aggregate productivity into within-firm and reallocation components using the [Olley and Pakes \(1996\)](#) framework. We benchmark the CBI against official INE statistics and show that it broadly tracks the size and age distribution of incorporated firms, while noting some overrepresentation of the oldest firms. The core productivity analysis focuses on 2000–2019 in order to avoid the confounding effects of the pandemic, and aggregate series are constructed using fixed sector weights to abstract from changes in industry composition over time. For robustness, the entry and exit patterns observed in the CBI are compared with independent evidence from DIRCE-based microdata.

The remainder of the chapter is structured as follows. Section [2](#) describes the CBI dataset and the measurement of TFP and labour productivity. Section [3](#) documents entry, exit, and the secular decline in firm dynamism. Section [4](#) analyses the relationship between firm dynamics and aggregate productivity across the three sub-periods. Section [5](#) concludes.

2 Data

2.1 The CBI Dataset

The empirical analysis in this chapter draws on the Central Balance Sheet Database (*Central de Balances Integrada*, hereafter CBI) compiled by Banco de España. The CBI contains annual balance sheet and income statement information for incorporated Spanish firms and is one of the main longitudinal firm-level data sources available for Spain. The sample used in this chapter spans 2000–2023, although the core productivity analysis focuses on the pre-pandemic period 2000–2019 in order to avoid the confounding effects of Covid-19 on firm dynamics and factor utilisation. Appendix A.1 provides further details on the data construction.

The database contains detailed information on firms’ revenues, intermediate inputs, capital stock, employment, and wage bill, which together allow the construction of firm-level measures of total factor productivity (TFP) and labour productivity. The panel dimension of the CBI is well suited to the study of firm dynamics: it allows us to follow cohorts of firms over their life cycle, proxy entry and exit based on first and last appearance in the panel, and decompose aggregate productivity trends into within-firm and reallocation components. Throughout the analysis, we restrict attention to incorporated firms, for which the CBI provides consistent coverage and for which comparable official benchmarks are available.¹ Appendix A.2 provides definitions of the variables used in the analysis.

2.2 Representativeness

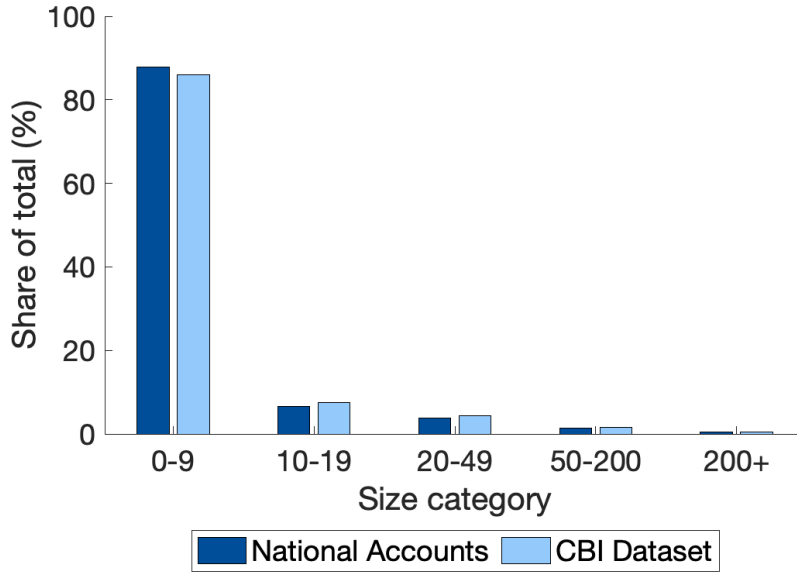
We start by documenting how well the CBI represents the population of Spanish incorporated firms. We benchmark the CBI against two official sources: the firm census published by the Spanish National Institute of Statistics (Instituto Nacional de Estadística, INE), drawn from the Central Business Register (*Directorio Central de Empresas*, DIRCE), and the second source is obtained from National Accounts.

Figure 1 compares the size distribution of firms in the CBI against the National Accounts benchmark, using employment bins. Both sources show that micro-firms with 0–9 employees account for roughly 85 per cent of the total number of incorporated firms, with the remaining shares distributed across the 10–19, 20–49, 50–200, and 200-plus size categories in broadly similar proportions. The CBI therefore closely mirrors the official size distribution, providing confidence that the database is representative along this dimension.

Benchmarking the age distribution is less straightforward because national accounts do not provide an age breakdown separately for incorporated and individual firms. To construct a

¹The analysis does not consider the role of self-employed (*autónomos*).

Figure 1: Size Distribution of Firms by Employment Bins



Note: The figure plots the average share of the number of firms in each employment size category relative to the total number of firms, both in the CBI dataset and in the official census reported by the Spanish National Institute of Statistics (INE), over the period 2000–2023. The sample is restricted to incorporated firms.

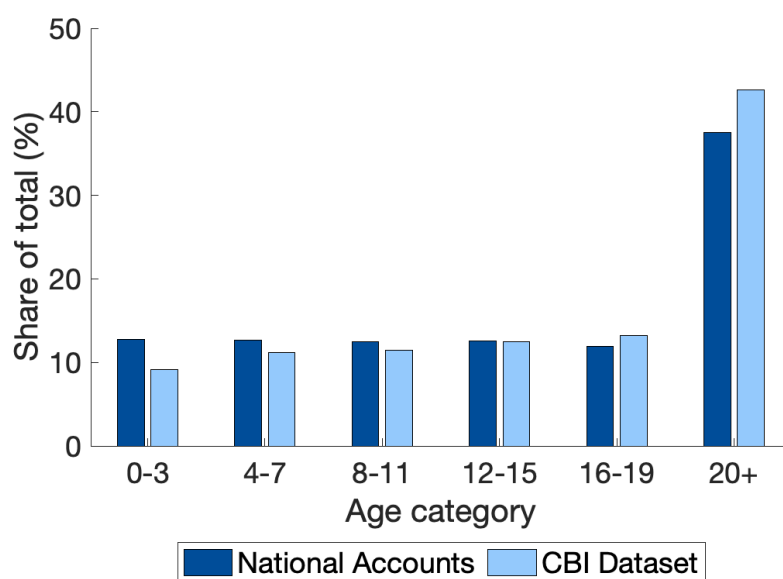
comparable benchmark, we restrict attention to firms with more than 10 employees, a threshold that excludes most individual firms and therefore selects a similar pool of firms in both the CBI and the INE census. Figure 2 reports the result. The CBI tracks the INE distribution reasonably well across most age categories, though it somewhat under-represents younger cohorts and over-represents oldest cohorts of firms. These small differences are probably due to the fact that INE still includes some individual firms, and that these are younger on average.

2.3 TFP Measurement

Firm-level TFP is estimated using the control-function approach of [Akerberg et al. \(2015\)](#), which builds on the methods of [Olley and Pakes \(1996\)](#) and [Levinsohn and Petrin \(2003\)](#) and addresses the simultaneity problem arising from the fact that firms observe their own productivity when choosing inputs. We estimate the production function separately by sector in order to allow production technologies to differ across industries. Firm-level TFP is then defined as the residual from the estimated production function and is expressed in logarithms throughout. Appendix [A.3](#) provides full details of the productivity estimation procedure.

All nominal variables are deflated using sector-specific price deflators so that productivity mea-

Figure 2: Age Distribution of Firms



Note: For firms with 10 or more employees.

Note: The figure plots the average share of the number of firms in each age category relative to the total number of firms, both in the CBI dataset and in the official census reported by INE. To ensure comparability, the sample is restricted to firms with more than 10 employees, which selects predominantly incorporated firms in both sources. Age categories are: 0–3, 4–7, 8–11, 12–15, 16–19, and 20 or more years since incorporation.

asures are expressed in real terms. Because the CBI does not observe firm-level quantities, the resulting TFP measure should be interpreted as a revenue-based productivity measure, as is standard in the literature using balance sheet data. This is important when interpreting changes over time, since firm-level prices and markups may also affect measured productivity.

Aggregate TFP series are constructed by taking sales-weighted averages of firm-level TFP within sectors, and then aggregating across sectors using fixed sector weights. The use of fixed sector weights is intentional: it abstracts from the contribution of between-sector reallocation to aggregate productivity, allowing us to focus on the within-sector dynamics that are the main subject of this chapter.² Labour productivity is measured as the ratio of revenues to the number of employees, and aggregate labour productivity is constructed analogously using employment weights.

²Garcia-Santana et al. (2020) document a small contribution of the between sector reallocation to aggregate productivity during the period 2000-2008.

3 Entry, Exit, and the Decline in Firm Dynamism

This section documents the evolution of firm dynamics in Spain over the period 2000–2019, focusing on the pre-pandemic years. Where relevant, we also report descriptive evidence extending beyond 2019 to illustrate longer-run changes in the firm distribution. We begin with entry and exit rates, before turning to broader measures of dynamism based on gross job reallocation and the age and size composition of aggregate employment. Together, these facts paint a consistent picture of a gradually aging firm population and a secular decline in the intensity of creative destruction.

3.1 Entry and Exit Rates

Figure 3 plots smoothed entry and exit rates for incorporated firms in the CBI over 2001–2019, where entry and exit are defined in Appendix A.2. Three broad phases emerge. During the boom years of 2000–2007, entry rates were high, averaging around 7–8 per cent per year, while exit rates were substantially lower, at around 3–4 per cent. This gap is consistent with a period of rapid expansion in the firm population, supported by strong demand and easy access to credit.³

From 2008 onwards, entry rates declined sharply in the wake of the financial crisis, falling to around 5 per cent by 2011–2012, while exit rates rose temporarily before stabilising. Over the subsequent period, entry and exit rates converged to broadly similar levels of approximately 5–6 per cent, consistent with a steady but smaller flow of firms entering and exiting each year. Changes in total population over this period were modest, suggesting that aggregate demographic trends are unlikely to account for the sustained decline in entry, although shifts in population composition may still play a role.

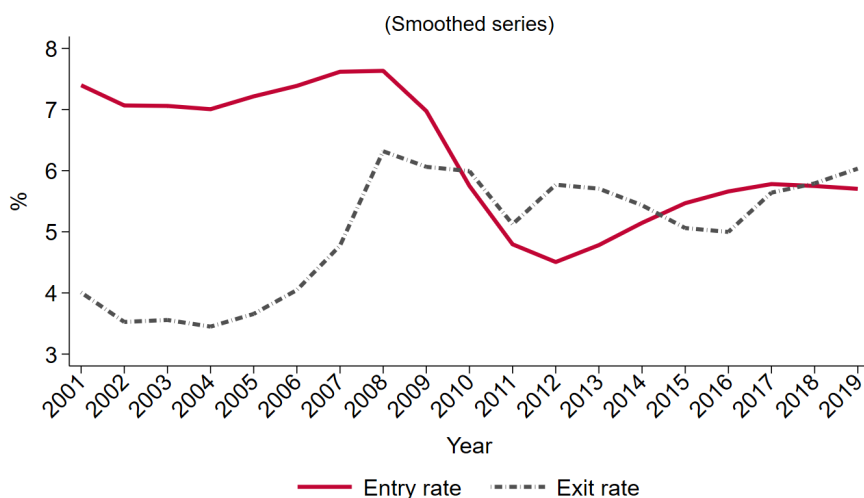
3.2 Gross Job Flows

Entry and exit rates capture only one margin of firm dynamism. A broader measure is provided by the gross job reallocation rate, defined as the sum of job creation and job destruction across all firms in a given year, normalised by total employment. This measure captures the intensity of labour reallocation across the entire firm distribution, including among continuing firms, and is therefore less sensitive to the specific definition of entry and exit used.

Figure 4 plots the aggregate job reallocation rate for incorporated firms in the CBI over the full sample period. The picture that emerges is striking: gross job reallocation declined continuously and substantially throughout the entire period, falling from around 21–22 per cent in

³Figure B.1 in the Appendix shows that the patterns are broadly consistent with those documented by [Albrizio et al. \(2026\)](#) using official information from the National Statistical Office.

Figure 3: Entry and Exit Rates over Time



Note: The figure plots smoothed annual entry and exit rates for incorporated firms in the CBI over the period 2001–2019. Entry rate is defined as the number of firms appearing in the CBI for the first time in a given year divided by the total number of firms. Exit rate is defined analogously for firms disappearing from the dataset.

2001 to approximately 16 per cent by 2019. Crucially, this decline is not confined to the crisis years but continues uninterrupted through the recovery period of 2014–2019, suggesting that it reflects a structural trend rather than a purely cyclical response to the recession.

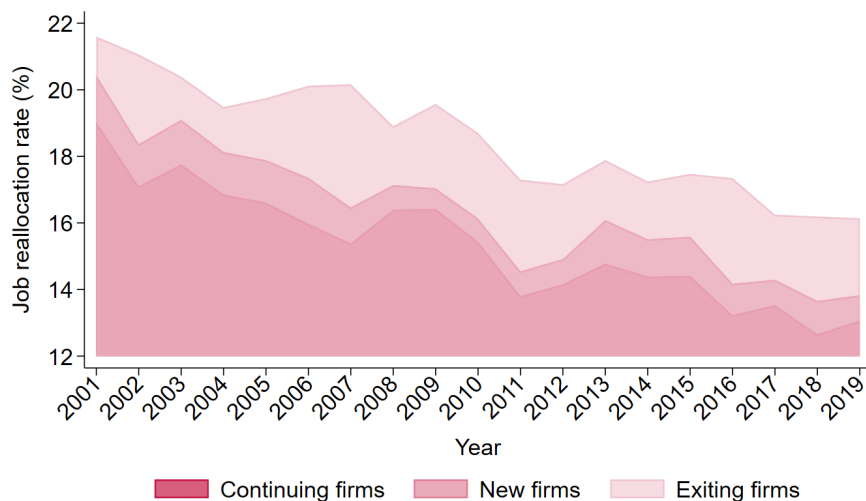
Figure 4: Gross Job Reallocation over Total Employment



Note: The figure plots the annual job reallocation rate, defined as the sum of gross job creation and gross job destruction normalised by total employment, for incorporated firms in the CBI over the period 2001–2019. The series is consistent with a decline in both job creation and job destruction over the sample period.

Figure 5 decomposes the job reallocation rate into its three components: job flows attributable to new entrants, exiting firms, and continuing firms respectively. The decomposition reveals that the secular decline in gross job reallocation is driven largely by a reduction in churning among continuing firms rather than by changes at the entry and exit margins. This points to an important mechanism: as the firm population ages and the share of older, more stable firms increases, the intensity of employment reallocation within the continuing firm population declines. The reduction in dynamism therefore reflects not only fewer new firms entering, but also weaker reallocation among incumbents. This margin is distinct from the productivity-credit alignment among surviving firms studied by [Guner et al. \(2026\)](#), which can improve even as aggregate employment churn declines.

Figure 5: Gross Job Reallocation: Decomposition by Firm Type



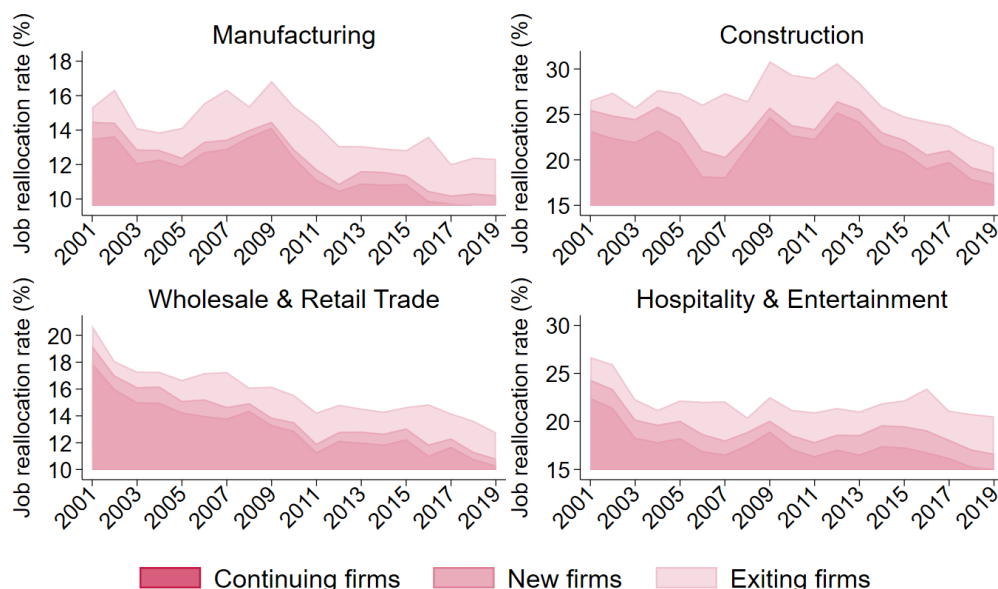
Note: The figure decomposes the annual job reallocation rate into contributions from new entrants, exiting firms, and continuing firms. The decline in gross job reallocation over the sample period is driven primarily by a reduction in churning among continuing firms, consistent with the increasing importance of older and more stable firms in the employment distribution.

3.3 Sectoral Consistency

One might worry that the aggregate decline in gross job reallocation is driven by compositional shifts in the sectoral mix of the Spanish economy, for instance, a contraction of construction, which is an inherently high-churn sector, in the aftermath of the housing bust. Figure 6 addresses this concern by plotting the decomposed job reallocation rate separately for four broad sectors: manufacturing, construction, wholesale and retail trade, and hospitality and entertainment. While the levels of the job reallocation rate differ substantially across sectors — construction exhibits notably higher churning than manufacturing, for instance — the downward trend over the 2010–2019 period is remarkably consistent across all four sectors. This cross-

sectoral uniformity rules out a purely compositional explanation and strengthens the case that the declining dynamism of Spanish firms reflects a structural, economy-wide phenomenon.

Figure 6: Gross Job Reallocation by Sector



Note: The figure plots the decomposed annual job reallocation rate separately for manufacturing, construction, wholesale and retail trade, and hospitality and entertainment. The decline in gross job reallocation over the 2010–2019 period is consistent across all four sectors, ruling out a purely compositional explanation.

3.4 The Aging of the Firm Population

The decline in entry rates and gross job reallocation documented above is mirrored in a marked shift in the distribution of employment across firms of different ages. Figure 7 plots the share of aggregate employment accounted for by firms in four age groups — 0–5, 6–10, 11–20, and 21 or more years since incorporation — over the full sample period, extending to 2023.

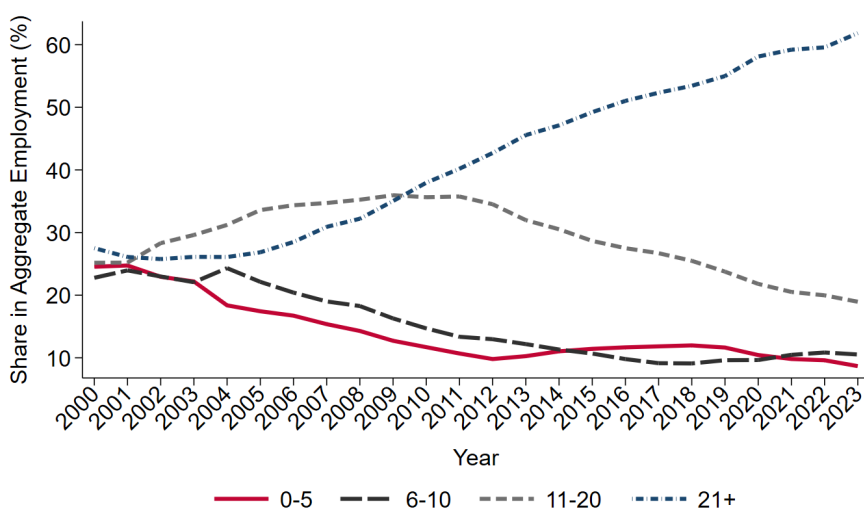
The figure reveals a striking pattern. The employment share of firms aged 21 and over rose from around 25 per cent in 2000 to over 60 per cent by 2023, an increase of more than 35 percentage points over two decades. This rise was mirrored by declines across all younger age groups. The share of the youngest firms (0–5 years) fell from around 23 per cent to approximately 10 per cent, reflecting both the decline in entry rates documented above and a reduction in the employment footprint of new entrants. The share of firms aged 6–10 followed a similar downward trajectory.

Perhaps the most informative pattern, however, concerns firms in the 11–20 year age group. This cohort also experienced a substantial decline in employment share over the period, despite having survived the critical early years of operation. This is likely due in part to the reduced

entry in the initial years of the sample, since a drop in entry in 2000-2010 would begin affecting this group from around 2011 (when firms born in 2000 turn 11 years old), and we indeed observe a decline in their employment share starting from around that time. It is also due in part to barriers to post-entry growth, whereby surviving younger firms do not scale up sufficiently to move into the upper tiers of the distribution.

The divergence between the trajectories of the 11–20 and 21-plus groups also helps link these compositional changes to the decline in job turnover documented in Section 3.2. Transitions across age cohorts are an important source of employment reallocation, and a weakening of this transition is consistent with the observed reduction in aggregate job reallocation.

Figure 7: Employment Share by Firm Age Group



Note: The figure plots the share of aggregate employment accounted for by firms in each age group — 0–5, 6–10, 11–20, and 21 or more years since incorporation — over the period 2000–2023.

Figure B.2 in the appendix, repeats the exercise using size classes rather than age classes, plotting the employment shares of firms with 0–9, 10–49, and 50 or more employees. The share of the largest firms (50-plus employees) rose over the period, broadly consistent with the aging of the firm population documented above, since older firms tend also to be larger. However, the trends are considerably less pronounced when firms are grouped by size than when grouped by age, suggesting that age rather than size is the more informative dimension along which to characterise the structural shift in the Spanish firm distribution.

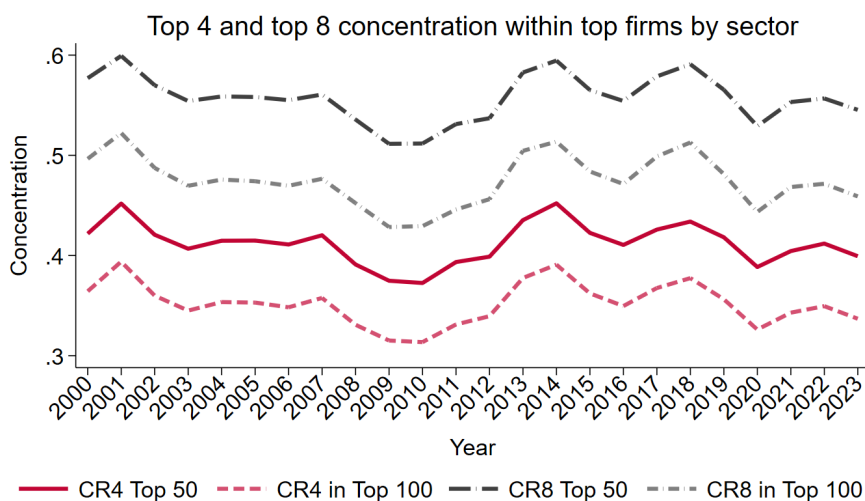
3.5 Concentration

The significant rise in the employment share of older firms raises a natural question: does it reflect an increase in market concentration, with a small number of dominant incumbents crowding out younger competitors? Figure 8 addresses this question by plotting standard con-

centration ratios, CR4 and CR8, defined as the combined employment share of the top 4 and top 8 firms respectively, computed within the top 50 and top 100 firms by sector.

Strikingly, none of these concentration measures displays a clear upward trend over the sample period. They fluctuate around relatively stable levels, rising somewhat during the crisis years before returning to pre-crisis values. This finding has an important implication: the increasing dominance of older firms in aggregate employment is not driven by a winner-takes-all dynamic in which a handful of superstar firms at the very top of the distribution are absorbing ever-larger shares of activity. Rather, it reflects a broad-based aging of the firm distribution, in which the entire cohort of long-established incumbents has expanded its collective footprint while the younger tiers of the distribution have shrunk.

Figure 8: Concentration Ratios by Sector



Note: The figure plots CR4 and CR8 concentration ratios — the combined employment share of the top 4 and top 8 firms — within the top 50 and top 100 firms by sector, over the period 2000–2023. None of the measures displays a clear upward trend, indicating that the rising dominance of older firms reflects broad distributional aging rather than increased concentration at the top.

Taken together, the evidence in this section establishes three facts that will structure the productivity analysis in Section 4. First, entry rates declined after the boom period and have remained subdued. Second, gross job reallocation fell continuously and across all sectors, driven by declining dynamism among continuing firms. Third, the firm population aged substantially, with older firms absorbing a growing share of aggregate employment while middle-aged firms failed to grow, and without any corresponding increase in top-end concentration. These patterns are consistent with a structural and economy-wide decline in the intensity of creative destruction in Spain.

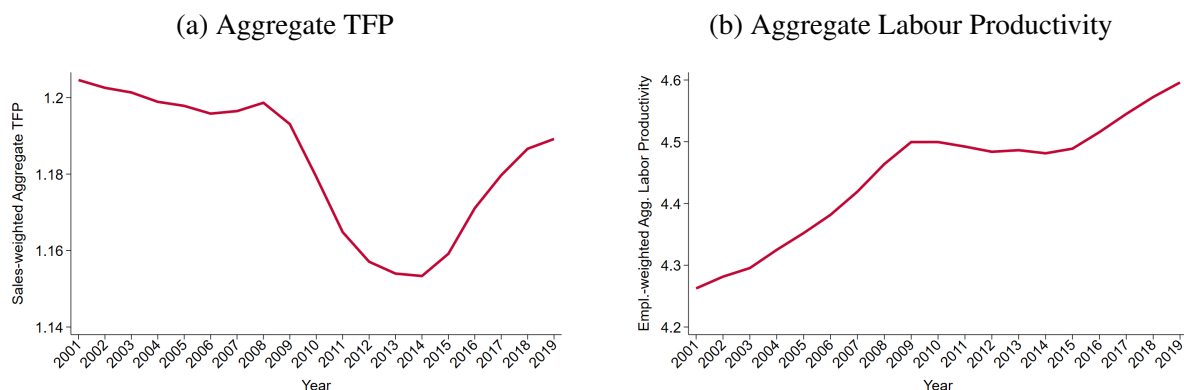
4 Firm Dynamics and Aggregate Productivity

The evidence in Section 3 established that Spain experienced a secular decline in firm dynamism over 2000–2019, characterised by fewer entrants and a shrinking employment share of young firms, an inability of middle-aged firms to grow, and a steady aging of the employment distribution. This section asks what these dynamics imply for aggregate productivity. We show that productivity dynamics over the period are best understood through the lens of three distinct sub-periods, each governed by a different combination of shocks and mechanisms, and that the interaction between cyclical forces and the secular aging of the firm population is central to understanding both the depth of the productivity contraction and the character of the subsequent recovery.

4.1 Three Sub-periods

Figure 9 plots aggregate TFP and labour productivity for incorporated Spanish firms over 2001–2019, constructed using fixed sector weights and smoothed to abstract from year-to-year fluctuations. The two series tell a related but distinct story, and together they point to three clearly delineated sub-periods.

Figure 9: Aggregate TFP and Labour Productivity over Time



Note: The left panel plots sales-weighted aggregate TFP and the right panel plots employment-weighted aggregate labour productivity, both constructed using fixed sector weights and smoothed. The sample covers incorporated firms in the CBI over the period 2001–2019.

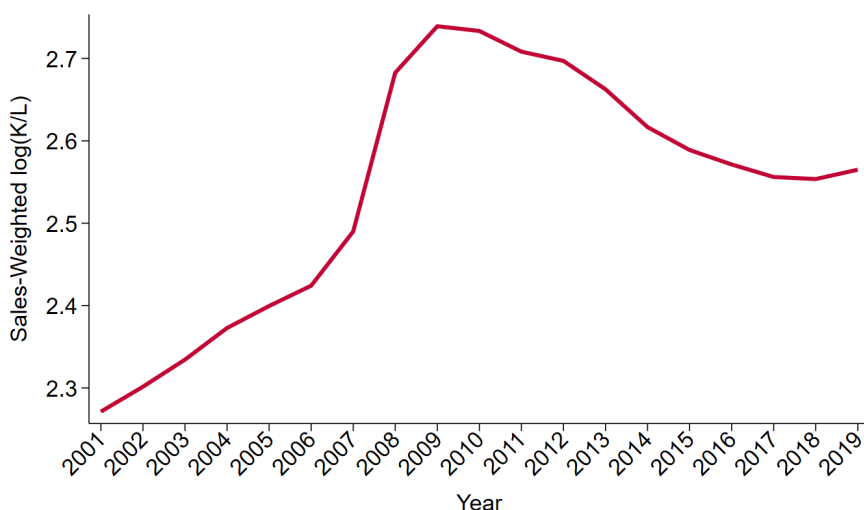
The first sub-period, 2000–2007, is characterised by a divergence between the two productivity measures: labour productivity rose consistently throughout the boom, while TFP declined. As we document in Section 4.2, this divergence is consistent with substantial capital deepening during the credit-fuelled expansion, which raised output per worker without generating true efficiency gains. The second sub-period, 2008–2013, saw a sharp and synchronised contraction in both TFP and labour productivity in the wake of the financial crisis and the sovereign debt shock. The third sub-period, 2014–2019, is one of partial recovery, with both measures rising,

though TFP had not recovered to its pre-crisis level by the end of the sample. As we document below, this recovery was driven disproportionately by older firms, with younger cohorts contributing little to aggregate productivity growth.

4.2 Capital Deepening and Misallocation (2000–2007)

The boom period of 2000–2007 was characterised by an extraordinary expansion of credit in Spain, underpinned by the low interest rates that accompanied euro area membership and by the rapid growth of the domestic banking sector. A large share of this credit flowed into capital investment, producing a sharp and sustained rise in the aggregate capital-labour ratio. Figure 10 plots the sector-weighted average log capital-labour for incorporated firms in the CBI. The ratio rose from approximately 2.3 in 2001 to a peak of around 2.75 in 2009–2010, an increase of nearly 20 per cent over less than a decade, before declining as the post-crisis adjustment took hold.

Figure 10: Aggregate Capital-Labour Ratio



Note: The figure plots the sector-weighted sales-weighted log capital-labour ratio for incorporated firms in the CBI over the period 2001–2019.

This capital deepening is the proximate explanation for the rise in labour productivity during the boom: more capital per worker mechanically raises output per worker, even in the absence of any improvement in productive efficiency. The simultaneous decline in TFP is consistent with inefficient allocation of this additional capital. Resources flowed toward firms that were not the most productive users of capital — a pattern consistent with the broader literature on misallocation ([Restuccia and Rogerson, 2008](#); [Hsieh and Klenow, 2009](#)), misallocation and financial constraints ([Buera and Shin, 2013](#); [Midrigan and Xu, 2014](#)) and the specific evidence on capital misallocation in Spain prior to the global financial crisis ([Gopinath et al., 2017](#); [Garcia-Santana et al., 2020](#)).

The boom therefore sowed the seeds of the subsequent TFP contraction by building up a stock of misallocated capital that was unwound during the crisis.

4.3 Factor Adjustment and Financial Frictions (2008–2013)

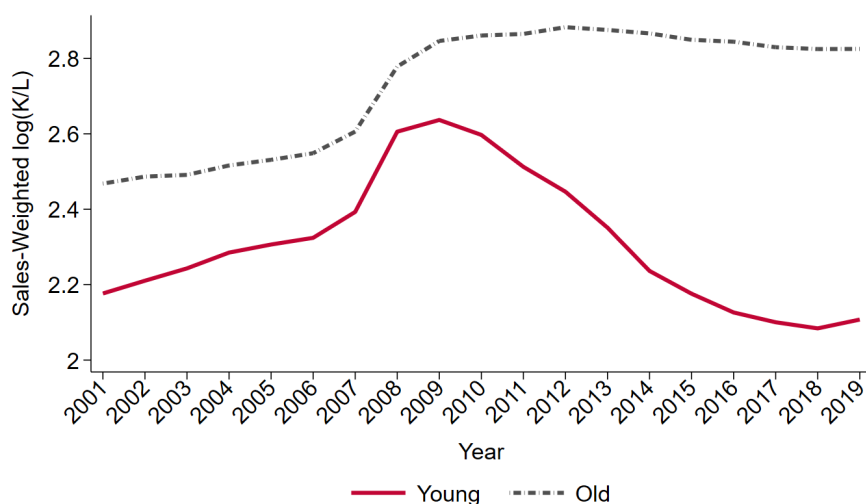
The crisis period of 2008–2013 drove aggregate TFP down sharply through two distinct channels that operated differently on old and young firms. Understanding this heterogeneity is essential for interpreting the productivity evidence and, as we show in Section 4.5, for understanding why the standard cleansing mechanism of creative destruction failed to operate.

The first channel operated through incumbent firms’ adjustment of inputs during the collapse in demand. The evidence points to sluggish adjustment of the incumbent capital stock and, more broadly, to factor underutilisation as output fell. Older firms entered the crisis with higher capital intensity and adjusted their capital-labour ratios only gradually, so the decline in activity translated into lower measured TFP.⁴ We therefore interpret the fall in incumbent productivity during the crisis as reflecting slow factor adjustment, especially along the capital margin. The second channel operates through the systemic banking crisis that unfolded in Spain from 2009. Domestic banks, heavily exposed to real estate, faced solvency concerns and underwent extensive recapitalisation and restructuring. Matched credit register evidence for Spain documents a strong and asymmetric bank lending channel over this period, with weaker banks curtailing credit supply substantially even after controlling for firm-level demand (Jiménez et al., 2012, 2020). Although this contraction affected firms of all ages, it was especially consequential for entry and young firm growth. Incumbents with established banking relationships and existing collateral could draw on relationship capital or benefit from lender forbearance, whereas the creation and early-stage financing of new firms depended more directly on the extension of new credit. This channel is consistent with the entry rate decline documented in Section 3.1 and, more directly, with the finding that new entrants during and after the crisis were capitalised at persistently lower levels than their pre-crisis counterparts (see Figure B.3). This interpretation is also consistent with broader evidence of corporate deleveraging in Spain following the global financial crisis, with corporate leverage ratios declining substantially from their pre-crisis peak (European Systemic Risk Board, 2023).

Figure 11 documents the divergence in capital-labour ratios between young and old firms within sectors over the sample period. Among old firms, the capital-labour ratio rose sharply during the crisis and remained elevated well into the recovery. This pattern is consistent with slow capital adjustment or capital underutilisation among older incumbents: capital was not being shed as quickly as output declined. Among young firms, by contrast, the capital-labour ratio peaked around 2009 and then fell sharply and persistently, reaching levels well below those of

⁴Appendix Figures B.4 and B.5 split the capital-labour ratio into tangible capital and labour components by firm age. The decomposition shows that old firms’ capital adjusted gradually during and after the crisis, while labour fell sharply through 2013 and only partially recovered.

Figure 11: Capital-Labour Ratio by Firm Age: Young versus Old



Note: The figure plots the sales-weighted log capital-labour ratio separately for young and old firms, computed within sectors, over the period 2001–2019. Young firms are defined as those aged 0–10 years and old firms as those aged 11 years and above.

old firms by the end of the sample. This decline is consistent with the banking crisis channel constraining young firms’ ability to maintain or expand their capital base. Entry rates stabilised at lower levels, as documented in Section 3.1, but the firms that did enter were capitalised at a lower level than their predecessors.

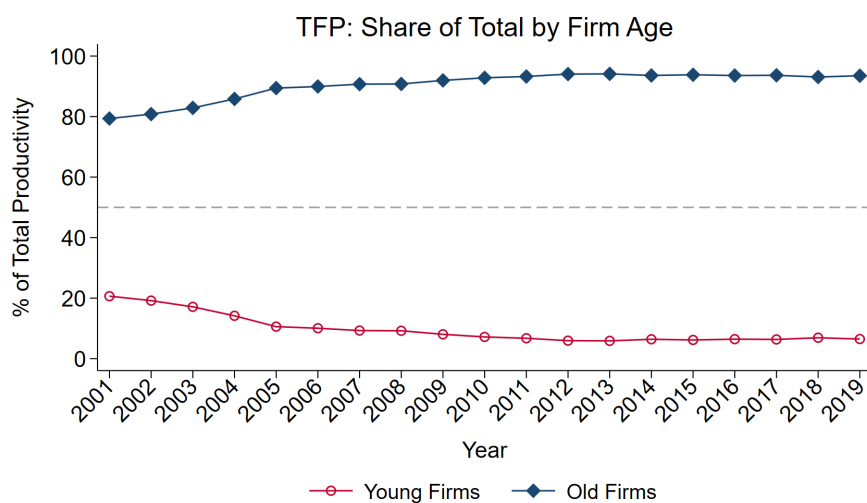
4.4 The Olley-Pakes Decomposition

To separate the within-firm and reallocation channels of aggregate productivity dynamics, we apply the Olley-Pakes decomposition (Olley and Pakes, 1996) separately for young and old firms. The Olley-Pakes decomposition expresses aggregate productivity as the sum of the unweighted mean of firm-level productivity and a covariance term between productivity and market share. A rising covariance term indicates that more productive firms are gaining market share; a falling term indicates worsening allocative efficiency. Full details of the implementation are provided in Appendix A.4.

Figure 12 plots the contribution of young and old firms to aggregate TFP. The share of old firms rose continuously over the sample period, mirroring the employment share trends documented in Section 3.4, while the share of young firms fell from around 20 per cent in 2001 to below 10 per cent by the end of the sample. This decline reflects primarily the shrinking share of young firms in the firm distribution rather than a deterioration in their average productivity, as shown in appendix Figure B.6.

Figure 13 plots the within component of the Olley-Pakes decomposition separately for young

Figure 12: TFP Shares by Firm Age

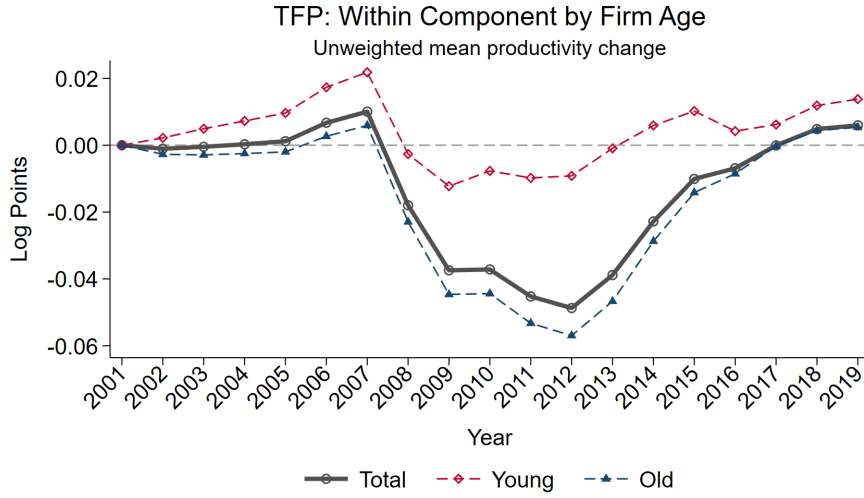


Note: The figure plots the share of aggregate TFP accounted for by young and old firms respectively over the period 2001–2019. Young firms are defined as those aged 10 years or below and old firms as those aged 11 years and above.

and old firms, expressed as log-point deviations from the 2001 value. The figure reveals a sharp asymmetry between the two groups. For old firms, the within component declined substantially during the crisis, falling by around 4–5 log points between 2008 and 2013, before partially recovering in the post-crisis period. This large decline in average firm-level productivity among old incumbents is consistent with the factor adjustment mechanism described above: as output fell faster than measured inputs, average productivity within the group of old continuing firms deteriorated.

For young firms, the picture is strikingly different: the within component shows no significant decline during the crisis and even rises somewhat during this period. This finding indicates that the average productivity of young continuing firms did not fall, if anything, the surviving young firms maintained or improved their individual efficiency. Summing up, we find several pieces of evidence consistent with the banking crisis and associated credit supply contraction limiting entry and young firm growth. First, the systemic credit contraction is likely to have been one of the barriers that strongly reduced firm entry. Second, Figure 11 shows that the capital-labour ratio declined for young firms in the period 2011–2019, and later, in Section 4.7, we show that this period coincides with relatively slower TFP growth for young and middle-aged firms relative to old incumbents. These patterns are consistent with the banking crisis constraining young firms’ ability to invest, adopt productivity-enhancing technologies, and scale.

Figure 13: Olley-Pakes Decomposition: Within Component by Firm Age



Note: The figure plots the within component of the Olley-Pakes decomposition — the unweighted mean of firm-level TFP — separately for young and old firms, expressed as log-point deviations from the 2001 value. The total within component is also shown.

4.5 No Cleansing Effect

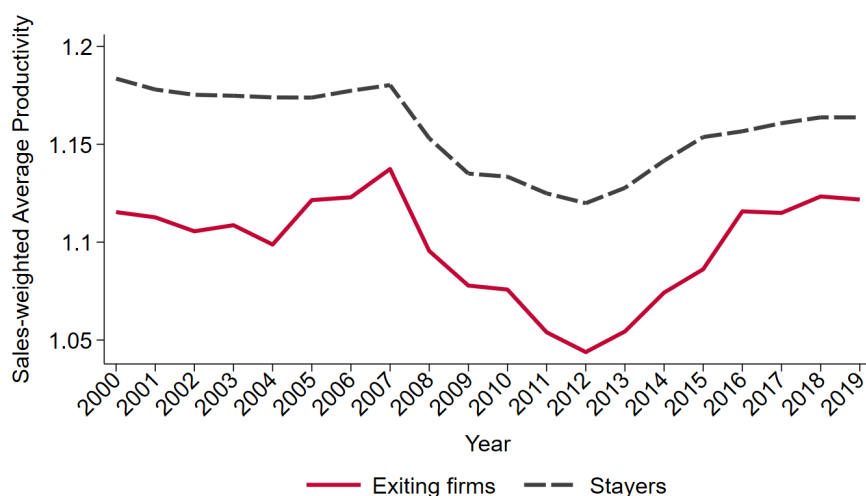
A central prediction of models of creative destruction is that recessions should act as a cleansing mechanism, accelerating the exit of low-productivity firms and thereby improving the average quality of the surviving firm population (Caballero and Hammour, 1994).

Figure 14 tests this prediction directly by plotting aggregate TFP separately for exiting and continuing firms over the sample period, using fixed sector weights.

The figure shows that exiting firms were consistently less productive than continuing firms, and this productivity gap widened during the crisis. This evidence is consistent with inefficient firms staying in operation because the minimum productivity to survive declined, consistently with a sullyng rather than cleansing effect. There is therefore no cleansing effect of the Great Recession in the Spanish firm distribution. This finding is consistent with the evidence documenting the absence of strong cleansing during the post-2008 recession in European countries (Bartelsman et al., 2019) and the documented increase in the so-called zombie firms (Banerjee and Hofmann, 2018; Albuquerque and Iyer, 2024).

The mechanism is straightforward: when banking distress and credit supply disruptions weaken the reallocation of resources from distressed firms toward more productive firms, the margin of exit is not determined by productivity alone. Low productivity incumbents may survive, while high potential young firms may be unable to enter, invest, or scale. The result is a recession in which destruction is not accompanied by strong productivity-enhancing reallocation — the opposite of the Schumpeterian ideal.

Figure 14: TFP of Exiting Firms versus Continuing Firms

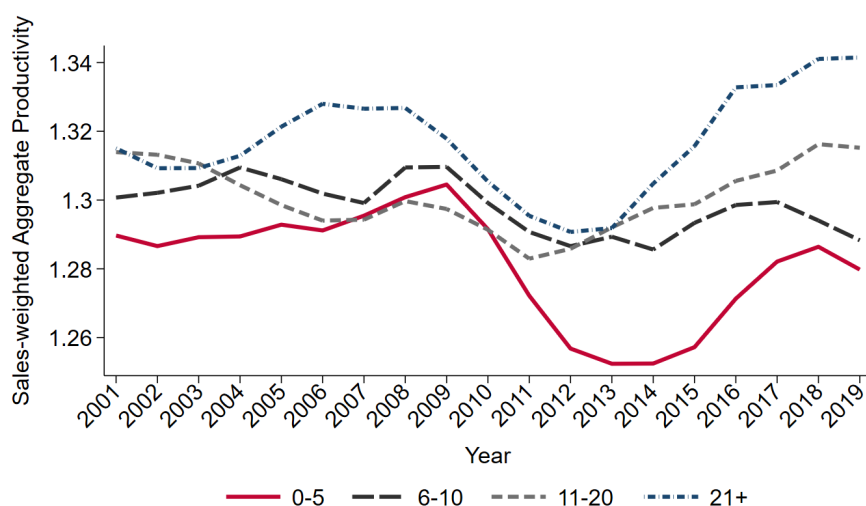


Note: The figure plots sales-weighted aggregate TFP separately for exiting firms and continuing firms (stayers), constructed using fixed sector weights, over the period 2000–2019.

4.6 The Recovery and the Dominance of Older Firms (2014–2019)

Figure 15 plots aggregate TFP by age group over the full sample period, using constant sector shares to abstract from the compositional shifts documented in Section 3. The figure confirms the three-period narrative established in Section 4.1 and reveals a striking heterogeneity in the recovery across age groups.

Figure 15: TFP Evolution by Age Group



Note: The figure plots sales-weighted aggregate TFP separately for four age groups — 0–5, 6–10, 11–20, and 21 or more years since incorporation — using constant sector shares to abstract from compositional shifts. The series are smoothed.

All age groups experienced a decline in TFP during the crisis, confirming that the shock was pervasive across the firm distribution. However, the recovery was highly uneven. Firms aged 21 and over were the only group to end the sample period more productive than they began it: their TFP rose steadily from its trough around 2013–2014 and exceeded its 2001 level by the end of the sample. Firms aged 11–20 partially recovered but remained below their pre-crisis levels. Firms in the youngest two age groups — 0–5 and 6–10 years — recovered less strongly and ended the sample period with TFP levels below or only marginally above their 2001 values. The recovery was therefore not a broad-based improvement in productive efficiency across the firm distribution but rather a highly concentrated phenomenon, driven almost entirely by the oldest incumbents.

This pattern has an important implication for the secular trends documented in Section 3. The dominance of older firms in driving the recovery is not independent of their increasing weight in the employment distribution: as younger cohorts shrank, the aggregate productivity index became ever more dependent on the performance of older firms. The two forces, cyclical recovery and secular aging, therefore reinforced each other, producing a recovery that was both narrower and more fragile than would have been the case had the firm distribution remained more dynamic. This reading is consistent with [Guner et al. \(2026\)](#) in this same volume, who document an improvement in the alignment between firm-level productivity and credit growth after 2013 but caution that this reflects intensive margin reallocation among surviving firms rather than a broad-based restoration of dynamism. Our finding that the recovery was driven almost entirely by incumbents aged 21 and over, with no corresponding strengthening of entry or of the exit-based cleansing mechanism, offers a complementary firm age perspective on the same underlying pattern: improved allocation among continuing firms coexisting with a firm population that grew steadily less dynamic at the extensive margin.

4.7 Within-firm Productivity Growth: Regression Evidence

The aggregate patterns documented above could, in principle, reflect compositional effects within age groups, for example, the exit of less productive firms raising average productivity within a cohort, rather than genuine improvements in firm-level efficiency. To isolate within-firm productivity growth, and to align the regression evidence with the three-period narrative used elsewhere in the chapter, we estimate the following regression:

$$\text{TFP}_{it} = \sum_a \sum_p \beta_{a,p} \cdot \mathbf{1}[\text{age}_{it} \in a] \times \text{trend}_t^p + \alpha_i + \gamma_{s(i)t} + \varepsilon_{it} \quad (1)$$

where TFP_{it} denotes log total factor productivity for firm i in year t , and $\mathbf{1}[\text{age}_{it} \in a]$ is an indicator for firm i belonging to age group a at time t . The variable trend_t^p is a linear time trend defined separately for each sub-period $p \in \{2000\text{--}2007; 2008\text{--}2013; 2014\text{--}2019\}$, cor-

Table 1: Productivity Growth within Firms: Full Sample

	2000–2007	2008–2013	2014–2019	2000–2007	2008–2013	2014–2019
0-5 $\times$ Trend	-0.0002 (0.0002)	-0.0118*** (0.0002)	0.0007*** (0.0001)	0.0028*** (0.0002)	0.0006*** (0.0001)	0.0003*** (0.0001)
6-10 $\times$ Trend	-0.0019*** (0.0001)	-0.0116*** (0.0001)	0.0001 (0.0001)	0.0009*** (0.0001)	0.0008*** (0.0001)	-0.0003*** (0.0001)
11-20 $\times$ Trend	-0.0025*** (0.0001)	-0.0117*** (0.0001)	0.0000 (0.0001)	-0.0001 (0.0001)	0.0006*** (0.0001)	-0.0004*** (0.0000)
21+ $\times$ Trend	-0.0026*** (0.0001)	-0.0120*** (0.0001)	0.0004*** (0.0001)			
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector $\times$ Year FE	–	–	–	Yes	Yes	Yes
Observations	2,505,807	2,034,510	1,993,009	2,505,715	2,034,403	1,992,919
R-squared	0.7739	0.7647	0.8059	0.7756	0.7672	0.8070

Notes: The table reports estimates of equation (1) on the full sample. The dependent variable is log TFP. The base group is the interaction of the 21-plus age class with the linear trend. All specifications include firm fixed effects. Columns (4) to (6) additionally include sector-year fixed effects. In columns without sector-year fixed effects, the 21-plus trend is reported explicitly; in columns with sector-year fixed effects, it is absorbed, and the younger-age coefficients are interpreted relative to that omitted group. Standard errors clustered at the firm level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

responding respectively to the boom, crisis, and recovery phases analysed in Section 4. The specification includes firm fixed effects, α_i , which absorb all time-invariant firm characteristics, and sector-year fixed effects, $\gamma_{s(i)t}$, which control for common shocks at the sector level. The omitted category is the oldest age group (21 years and above), so the coefficients $\beta_{a,p}$ capture the differential within-firm TFP growth trend of each younger age group relative to the oldest incumbents within each sub-period. Standard errors are clustered at the firm level.

Tables 1 and 2 report the results for the full sample and for a balanced subsample, respectively. The balanced sample restricts attention to firms that are observed continuously throughout each sub-period, thereby excluding the effects of entry, exit, and selective survival on the estimated trends and isolating within-firm productivity dynamics.

The full and balanced samples point to the same broad evolution of within-firm productivity growth over the three periods, although some coefficients are less precisely estimated in the balanced sample. We focus on columns (4) to (6), which include sector-year fixed effects and therefore compare firms of different ages within the same sector-year environment. These specifications identify the differential within-firm TFP trend of each younger age group relative to firms aged 21 and above.

In the boom period (2000–2007), the youngest firms exhibit faster within-firm TFP growth than firms aged 21 and above, while the advantage declines with age. In the full sample, a firm aged 0–5 gained roughly 0.3 percentage points more in productivity per year than an otherwise identical firm aged 21 or older; a firm aged 6–10 gained about 0.1 percentage points more per

Table 2: Productivity Growth within Firms: Balanced Sample

	2000–2007	2008–2013	2014–2019	2000–2007	2008–2013	2014–2019
0-5 × Trend	-0.0032*** (0.0003)	-0.0113*** (0.0002)	0.0012*** (0.0002)	0.0013*** (0.0003)	0.0001 (0.0002)	0.0005*** (0.0001)
6-10 × Trend	-0.0029*** (0.0001)	-0.0108*** (0.0002)	0.0005*** (0.0001)	0.0003 (0.0002)	0.0005*** (0.0001)	-0.0001* (0.0001)
11-20 × Trend	-0.0026*** (0.0001)	-0.0108*** (0.0001)	0.0003*** (0.0001)	-0.0002 (0.0001)	0.0004*** (0.0001)	-0.0003*** (0.0000)
21+ × Trend	-0.0024*** (0.0001)	-0.0109*** (0.0001)	0.0007*** (0.0001)			
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector x Year FE	–	–	–	Yes	Yes	Yes
Observations	803,936	955,458	995,274	803,768	955,320	995,166
R-squared	0.7911	0.7675	0.8135	0.7950	0.7717	0.8152

Notes: The table reports estimates of equation (1) on a balanced subsample of firms observed continuously throughout each sub-period. The dependent variable is log TFP. The base group is the interaction of the 21-plus age class with the linear trend. All specifications include firm fixed effects. Columns (4) to (6) additionally include sector-year fixed effects. In columns without sector-year fixed effects, the 21-plus trend is reported explicitly; in columns with sector-year fixed effects, it is absorbed, and the younger-age coefficients are interpreted relative to that omitted group. Standard errors clustered at the firm level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

year; firms aged 11–20 grew no faster than the oldest incumbents. By the end of the boom period, this implies a cumulative differential of roughly 2 percentage points for the youngest firms, depending on the normalization of the trend. This is a real but modest advantage, and not the kind of gap that would let young firms overtake incumbents quickly. This pattern is consistent with standard life cycle dynamics, in which young firms learn, expand, and adopt more efficient practices as they mature. The balanced sample shows the same ranking, though only the 0–5 coefficient is precisely estimated.

In the crisis period (2008–2013), the young firm advantage shrinks sharply. In the full sample, younger firms retain a small positive differential relative to firms aged 21 and above, of around 0.06–0.08 percentage points per year. This is only about one-quarter of the annual advantage held by the youngest firms during the boom. The balanced sample also shows positive differentials for firms aged 6–10 and 11–20, although the coefficient for firms aged 0–5 is small and not precisely estimated. Thus, the crisis compresses the pre-crisis life cycle gradient rather than simply preserving the earlier youngest-firm advantage. The ranking is no longer clearly monotonic by age: middle-aged firms grow at a similar or slightly faster relative pace than the youngest firms. This is consistent with the view, developed in Section 4.3, that the credit contraction disrupted the normal life cycle pattern of productivity growth, weakening the strong advantage previously enjoyed by young firms.

The recovery period (2014–2019) delivers the clearest reversal. The productivity advantage of younger firms does not simply flatten to zero: for firms aged 6–20, it turns negative. In the

full sample, firms aged 6–10 and 11–20 grow about 0.03–0.04 percentage points more slowly per year than firms aged 21 and above, while the youngest firms retain only a small positive differential of around 0.03 percentage points per year. The balanced sample confirms the same qualitative pattern, with a positive coefficient for firms aged 0–5 and negative coefficients for firms aged 6–20, especially for firms aged 11–20. This suggests that the post-2014 recovery was not led by the productivity growth of young and middle-aged firms. Instead, it is consistent with the aggregate evidence in Section 4.6 showing that firms aged 21 and over drove most of the recovery in TFP.

This shift has important implications for aggregate productivity. In the pre-crisis period, productivity growth was concentrated among younger firms, but for these gains to translate into aggregate outcomes, young firms needed to scale successfully as they matured. The regression evidence shows that this mechanism did not merely weaken uniformly after the crisis: the pre-crisis youngest-firm advantage was sharply compressed during the crisis period and then turned negative for firms aged 6–20 during the recovery, precisely the cohorts that Section 3.4 shows failed to expand their employment share over the same period. Only the very youngest firms retained any productivity growth advantage by the end of the sample, and even that advantage was smaller than the one enjoyed by young firms during the boom.

Together, these patterns point to a broader decline in the role of young and middle-aged firms as drivers of productivity growth. Aggregate productivity becomes less responsive to the entry and growth of young firms, reflecting both a reduced presence of young cohorts and (in the case of firms aged 6–20 during the recovery) a small but real productivity growth disadvantage relative to the oldest incumbents, rather than merely a disappeared advantage.

5 Conclusions

This chapter has documented the evolution of firm dynamics and aggregate productivity in Spain over 2000–2019 using firm-level data from the Central Balance Sheet Database of the Banco de España. The central finding is that Spain’s TFP stagnation reflects the interaction of two forces: large cyclical shocks that affected firms differently by age, and a secular decline in firm dynamism that weakened the process of creative destruction.

On the cyclical side, the boom of 2000–2007 was characterised by substantial capital deepening alongside a deterioration in allocative efficiency. The crisis of 2008–2013 then reduced TFP through mechanisms consistent with slow factor adjustment, particularly along the capital margin, among older firms, together with a banking-crisis-driven credit contraction that constrained entry and young firm financing. The subsequent recovery of 2014–2019 was uneven, driven disproportionately by firms aged 21 and over. Consistent with these credit market disruptions, we find no evidence of a strengthening of the cleansing mechanism during the recession: exiting firms were consistently less productive than continuing firms, but the productivity gap

between the two did not widen relative to pre-crisis levels.

On the secular side, entry rates declined after the boom and remained subdued, gross job reallocation fell steadily across all sectors, and the firm population aged substantially without a corresponding increase in top-end concentration. The regression evidence shows that before the crisis, productivity growth was concentrated among younger firms, with a clear life cycle gradient across age groups, whereas after the crisis these differences became markedly compressed and turned mildly negative for firms aged 6–20 during the recovery — a pattern that holds even in balanced samples that exclude the effects of entry and exit. Read alongside the credit reallocation evidence in [Guner et al. \(2026\)](#), this suggests two sides of the same post-crisis adjustment: allocative efficiency improved among the firms that survived and continued operating, while the pool of young firms entering, surviving, and scaling into that population continued to shrink.

Taken together, these results point to a breakdown in the transmission from firm-level productivity gains to aggregate outcomes. In the pre-crisis period, young firms contributed to productivity growth not only through faster within-firm improvements but also by scaling up as they matured. After the crisis, this mechanism weakened: younger firms accounted for a smaller share of economic activity and no longer exhibited systematically stronger productivity dynamics. Spain thus faces a double burden on future productivity growth: a diminished presence of young firms in the economy, and a weakening of the life cycle process through which early productivity gains are translated into the growth of mature, high-productivity incumbents.

These findings point to three broad policy priorities, while recognising that the analysis in this chapter is primarily descriptive and that identifying precise policy levers requires further causal work. First, improving young firms’ access to external finance, particularly in downturns, could help restore dynamism at the lower end of the age distribution. Second, reducing barriers to post-entry growth — whether regulatory, financial, or labour-market related — is at least as important as facilitating entry, since it is through the transition from young to mature firms that productivity gains translate into aggregate outcomes. Third, policies that facilitate orderly exit, including efficient insolvency procedures, can help restore the reallocation function of downturns without imposing unnecessary costs on viable firms facing temporary distress.

Two further questions raised by this chapter’s findings deserve more direct investigation and are worth flagging as directions for future work. The first concerns the mechanism behind the erosion, and partial reversal, of the young firm productivity growth advantage after the crisis. Candidate explanations include a rising cost of adopting new technologies that disproportionately burdens young, capital-constrained firms; barriers to entry in the high productivity sectors that historically absorbed young entrants; and a lengthening lag between the acquisition of intangible assets and their translation into measured productivity gains, particularly if young firms shifted toward intangible-intensive investment as external finance became scarcer. Distinguishing between these channels would require firm-level data on technology adoption, sectoral entry conditions, and the composition of intangible investment that lie beyond the scope of the

CBI. The second concerns the innovation consequences of the growing weight of older incumbents in the firm population. A body of work suggests that established firms tend to pursue incremental rather than radical innovation relative to younger entrants ([Akcigit and Kerr, 2018](#)); if this pattern holds in Spain, the secular aging of the firm distribution documented in Section 3 may imply not only slower productivity growth among incumbents themselves but also weaker innovation spillovers to the smaller and younger firms that have historically benefited from the diffusion of new technologies and practices. Assessing this channel would require patent, R&D, or innovation survey data linked to the firm age structure documented here.

Finally, several further open questions remain. A more direct test of the banking crisis channel would require firm-level data on leverage, debt maturity, and bank relationships, allowing an assessment of whether balance sheet heterogeneity mediated the age-specific responses to the crisis documented here. Comparative analyses across other European economies that experienced similar boom–bust cycles would help determine whether these patterns reflect Spain-specific institutional features or broader trends in European firm dynamics. Further work quantifying the contribution of frontier firms to aggregate TFP growth, and examining whether these firms are predominantly young or old, would provide a richer picture of the sources of productivity dynamics. Finally, allowing for age-varying factor prices or heterogeneous production technologies would offer a useful robustness check on the productivity results.

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Firm Dynamics and Productivity Growth in Spain

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Appendix

A Data Construction and Variable Definitions

A.1 Data Construction

Central de Balances Integrada (CBI). We clean the CBI data following [González and Sy \(2026\)](#), with detailed steps outlined below:

1. There are cases for which financial statements are missing for some firm-year observations. We maximize coverage by utilizing the fact that firms can have multiple records for a given year, based on the current and next year's filings. When the current year financial statement is not available, we use the following year's values to fill this gap. When both current and next year's filings are available, we prioritize the current year's values except for when the current filings are flagged as low quality records in the database. In such cases, we use the following year's values instead.
2. We keep firms with legal status of corporation or limited liability company. This is inferred from the Spanish tax identification number of firms (*CIF* in Spanish or *NIF* in English), which consists of a letter, representing the legal status, followed by eight digits unique to a firm. We treat observations that switch legal status as observations of the same firm.
3. When a firm has multiple records of its industry classification, we use the most frequent one.
4. When a firm reports different dates of incorporation across the years in which it appears in the database, we take the earliest year as the actual year when a firm starts its business.
5. We implement standard cleaning procedures on firm balance sheet information, following [Kalemli-Ozcan et al. \(2024\)](#). In particular, we drop observations with missing or negative values of assets and revenues. We also drop observations with negative values of tangible fixed assets, inputs, employees, and wage bill.
6. We follow [Almunia et al. \(2018\)](#) in excluding the following sectors: financial services, public administration and defense, education, health and social work, and membership activities (NACE codes K, O, P, Q, and S). We also drop observations without sector classification.
7. We drop observations flagged as low quality.
8. Variables constructed for subsequent analysis are winsorized at 1% on both tails.

Note that financial statement items in CBI are measured in thousands of euros.

Other Data. We use industry-specific capital deflators and value-added deflators taken from EU-KLEMS to deflate capital and other variables, respectively.

A.2 Variable Definitions

Aggregated sectors. For purposes of constructing summary plots, we aggregate the categories of the NACE 1-letter codes in [Table A.1](#):

Table A.1: Aggregated Industry Classification

NACE 1-letter	Description	Aggregated Classification
A	Agriculture, Forestry And Fishing	Primary sector
B	Mining And Quarrying	Primary sector
C	Manufacturing	Manufacturing
D	Electricity, Gas, Steam And Air Conditioning Supply	Utilities
E	Water Supply; Sewerage, Waste Management And Remediation Activities	Utilities
F	Construction	Construction
G	Wholesale And Retail Trade	Wholesale And Retail Trade
H	Transportation And Storage	Transportation And Storage
I	Accommodation And Food Service Activities	Hospitality & Entertainment
J	Information And Communication	Information And Communication
L	Real Estate Activities	Real Estate Activities
M	Professional, Scientific And Technical Activities	Professional & Admin. Services
N	Administrative And Support Service Activities	Professional & Admin. Services
R	Arts, Entertainment And Recreation	Hospitality & Entertainment

Variables from CBI. [Table A.2](#) summarizes the definitions of the variables used in the empirical analysis. The corresponding item codes in CBI are provided in parentheses.¹

Table A.2: Definition of Variables from CBI

Variable	Description/ Entry in CBI
Age	Number of years since firm incorporation (any – anyconst)
Assets	Assets (c200135)
Employees	Average number of employees of a firm in a year (c200084)
Sales (or revenues)	Output (c200075)
Capital	Tangible fixed assets (c200093)
Wage bill	Personnel costs (c200025)
Material costs	Inputs minus other operating costs (c200076 – c200012)
Value-added	Revenues minus material costs
log(K/L)	log(Capital/Employees)
Labour productivity	log(Revenues/Employees)
TFP	Derived from production function estimation (see Appendix A.3).

¹A user guide can be downloaded from <https://www.bde.es/wbe/en/para-ciudadano/servicios/belab/contenido/microdatos-disponibles/microdatos-empresas-individuales-cbi.html>.

Entrants, continuing firms, exiters. We classify firms into entrants, exiters, and continuers based on their observed presence in the CBI dataset. A firm is defined as an *entrant* in its incorporation year. Firm exit is inherently harder to pin down since firms may stop filing financial statements without actually shutting down, and some firms may drop out of the dataset for a couple of years before reappearing again. Our definition mitigates the latter measurement issue by treating a firm as an *exiter* only if its last observed year precedes 2019, or if its last observed year is 2019 and it does not reappear by 2023 (final year in our extended dataset). Firms that are neither entrants nor exiters in a given year are classified as *continuing firms*.

Thus, the *entry rate* is defined as the share of entrants relative to the total number of firms in a given year while the *exit rate* is defined as the share of exiters relative to the total number of firms in a given year.

Gross job reallocation rate. We construct a measure of (gross) job reallocation that decomposes total employment reshuffling into contributions from entrants, continuing firms, and exiting firms. For each year, we compute

1. absolute employment changes among continuing firms,
2. employment of firms entering in year t , and
3. employment of firms exiting in year t

The gross job reallocation in a given year is then obtained by summing these three components. This is equivalent to the sum of gross job creation and gross job destruction in the [Davis and Haltiwanger \(1990\)](#) framework. Dividing each component by total employment yields the corresponding reallocation rates for entrants, continuing firms, and exiters.

Concentration measures. To examine concentration among the largest firms within each sector-year, we compute concentration ratios based on the revenue distribution of the top 50 and top 100 firms. Firms are ranked by their revenues within each sector-year, and the subset of top 50 and top 100 firms with the largest revenues within a particular sector-year, is then identified. Within each of these groups, we compute the share of total revenue accounted for by the four and eight largest firms, yielding the $CR4$ and $CR8$ measures for the top 50 and top 100 firms in each sector-year. These sector-level concentration measures are then aggregated to the national level using the time-invariant sectoral value-added weights.

A.3 Production Function Estimation

To estimate firm-level TFP, we employ the control function approach of [Akerberg et al. \(2015\)](#), extended as in [De Loecker and Warzynski \(2012\)](#). We assume a Cobb-Douglas production function given by

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \varepsilon_{it} \quad (2)$$

where y_{it} denotes log revenues, k_{it} , l_{it} and m_{it} are log of capital, labour and materials respectively, ω_{it} is the time-varying firm-level productivity observed by the firm when choosing inputs and ε_{it} is measurement error. Because firms observe ω_{it} before choosing inputs, materials and labour are correlated with productivity, generating simultaneity bias.

To address this, we follow [Akerberg et al. \(2015\)](#) and impose a timing structure on input choices. Capital is predetermined and fixed at the beginning of period t . Labour is assumed to be chosen at $t - 1$, reflecting hiring and firing costs or contractual rigidities that make labour adjustment sluggish.² This is particularly important in the context of the Spanish labour market ([Fella et al., 2022](#)). Materials, by contrast, are assumed to be a fully flexible input that the firm chooses after observing ω_{it} . Under these assumptions, firms choose inputs using only the information available at the end of period $t - 1$, which we denote by $\mathbb{I}_{it-1}$.

We use materials as a proxy for productivity. Since materials are chosen after observing ω_{it} , materials demand can be written as

$$m_{it} = f(k_{it}, l_{it}, \omega_{it}) \quad (3)$$

where $f(\cdot)$ is invertible and strictly increasing in ω_{it} . [De Loecker and Warzynski \(2012\)](#) argue that this monotonicity property holds under a broad class of models with imperfect competition. This allows us to invert the materials demand function in [Equation 3](#) and express productivity as

$$\omega_{it} = f_t^{-1}(k_{it}, l_{it}, m_{it}) \quad (4)$$

Thus, we can estimate the production function following a two-step procedure.

1. *First stage.* Estimate an ordinary least squares (OLS) regression of y_{it} on k_{it} , l_{it} , m_{it} and $f_t^{-1} = \phi_t(k_{it}, l_{it}, m_{it})$.

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \phi_t(k_{it}, l_{it}, m_{it}) + \varepsilon_{it} \equiv \Phi_t(k_{it}, l_{it}, m_{it}) + \varepsilon_{it} \quad (5)$$

In practice, this is done by regressing y_{it} on higher order polynomials of k_{it} , l_{it} and m_{it} (including interactions), and obtaining the estimate $\widehat{\Phi}_t$.

To ensure consistency, we assume that the measurement error is not predictable from past information:

$$\mathbb{E}[\varepsilon_{it} | \mathbb{I}_{it-1}] = 0$$

Given a candidate parameter vector $(\beta_0, \beta_k, \beta_l, \beta_m)$, we can back out productivity as

$$\omega_{it}(\beta) = \widehat{\Phi}_t(k_{it}, l_{it}, m_{it}) - \beta_0 - \beta_k k_{it} - \beta_l l_{it} - \beta_m m_{it}$$

2. *Second stage.* Productivity is assumed to follow a first-order Markov process:

$$\omega_{it} = g(\omega_{it-1}) + \xi_{it}$$

where $g(\cdot)$ is approximated using a third-order polynomial and ξ_{it} is the innovation in

²[Akerberg et al. \(2015\)](#) treat predetermined labour as a special case within their general timing framework, which allows labour to be chosen either within the period or in advance.

productivity – the part that firms cannot predict when choosing inputs.

Using the estimated productivities, we estimate the function $g(\cdot)$ by regressing $\omega_{it}(\beta)$ on a polynomial in $\omega_{it-1}(\beta)$. This gives us a fitted value $\hat{g}(\omega_{it-1})$ and a residual

$$\xi_{it}(\beta) = \omega_{it}(\beta) - \hat{g}(\omega_{it-1})$$

Given the Markovian structure of productivity, productivity innovations ξ_{it} are not predictable based on past information, which yields the following moment condition:

$$\mathbb{E}[\xi_{it} | \mathbb{I}_{it-1}] = 0$$

This implies that only variables determined before period t productivity is realized can be used as instruments. Using

$$\mathbf{z}_{it} = [1 \ m_{it-1} \ l_{it} \ l_{it-1} \ k_{it}]'$$

the production-function parameters are identified through the GMM moment condition

$$\mathbb{E}[\xi_{it}(\beta_0, \beta_k, \beta_l, \beta_m) \times \mathbf{z}_{it}] = 0$$

Pre-estimation filters. We exclude sectors with fewer than 50 firm-year observations, to ensure sufficient within-industry variation for the estimation. We also drop implausible labour or materials shares, specifically negative shares, shares above one or shares of less than 5%.

A.4 Olley-Pakes Decomposition

We use the [Olley and Pakes \(1996\)](#) cross-sectional decomposition to separate aggregate productivity into an unweighted average component and a covariance (reallocation) component. Let ϕ_{it} denote a firm-level productivity measure (either labour productivity or TFP) and s_{it} its corresponding weights. Aggregate productivity in year t can be written as the share-weighted average of firm-level productivity

$$\Phi_t = \sum_i s_{it} \phi_{it} \tag{6}$$

where the shares $s_{it} \geq 0$ sum to 1. Following [Olley and Pakes \(1996\)](#), we decompose this into

$$\begin{aligned} \Phi_t &= \underbrace{\bar{\phi}_{it}}_{\text{unweighted mean (within-firm)}} + \underbrace{\sum_i (s_{it} - \bar{s}_t)(\phi_{it} - \bar{\phi}_t)}_{\text{covariance (across-firm) term}} \\ &= \bar{\phi}_{it} + \text{cov}(s_{it}, \phi_{it}) \end{aligned} \tag{7}$$

where $\bar{\phi}_{it}$ is the unweighted mean firm productivity and $\bar{s}_t$ is the average weight.

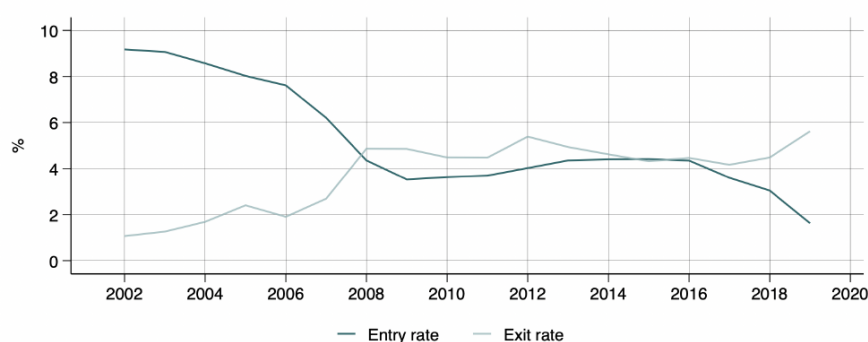
In the implementation, we compute for each year t the aggregate productivity, the unweighted mean firm productivity and obtain the across-firm (covariance) component as the difference between these two terms.

We construct this decomposition separately for labour productivity (using employment shares as weights) and TFP (using revenue shares as weights), and then normalize each component relative to its 2001 value to study the evolution of aggregate productivity, the within-firm component, and the reallocation (across-firm) component over time.

B Figures

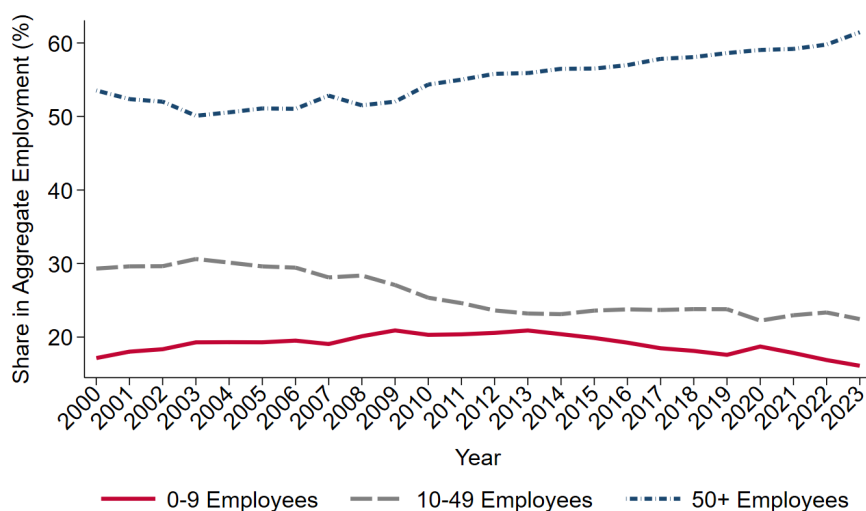
The patterns documented in the CBI are broadly corroborated by an independent source. Figure B.1 reproduces entry and exit rates from [Albrizio et al. \(2026\)](#), who construct firm-level entry and exit indicators using microdata from the DIRCE, the INE’s firm registry, which compiles information from administrative sources including tax records and social security data. The two sources tell a consistent story of declining entry rates from the early 2000s and a convergence of entry and exit rates in the post-crisis period, with the exception of 2019 where some divergence is apparent, possibly reflecting differences in the timing of firm registration and exit between the two datasets.

Figure B.1: Entry and Exit Rates over Time: Evidence from DIRCE



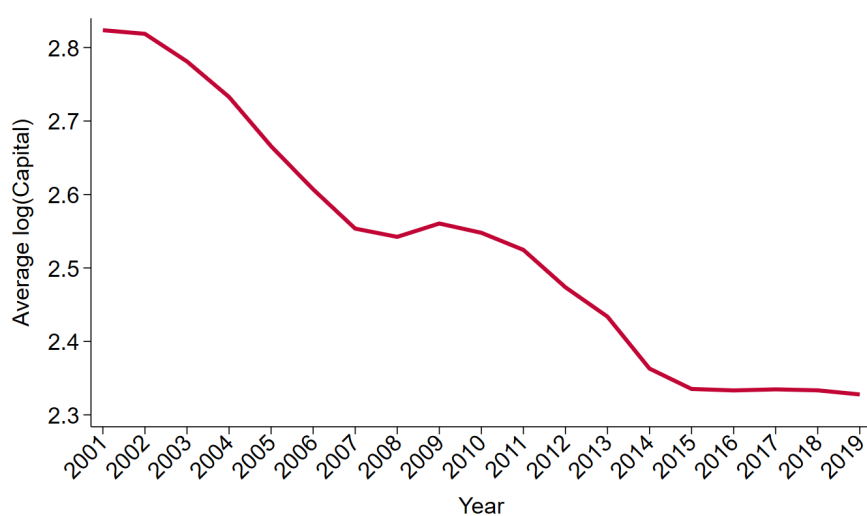
Note: The figure plots annual entry and exit rates using microdata from DIRCE, the INE’s firm registry. Source: [Albrizio et al. \(2026\)](#).

Figure B.2: Employment Share by Firm Size Class



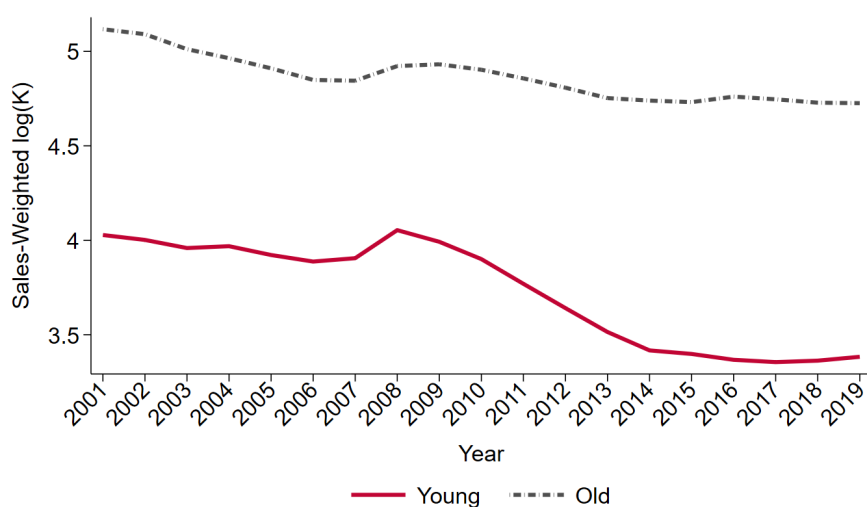
Note: The figure plots the share of aggregate employment accounted for by firms in each size class — 0–9, 10–49, and 50 or more employees — over the period 2000–2023. Trends are less pronounced than those observed for age groups.

Figure B.3: Average Capital of Entrants Over Time



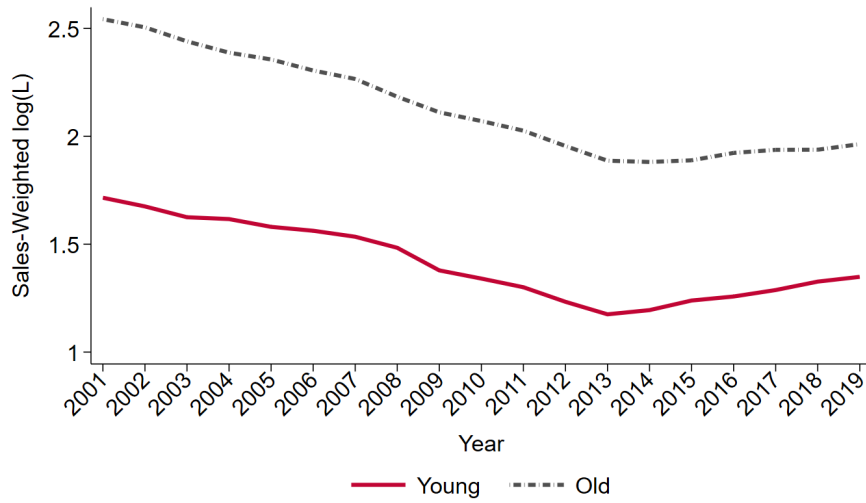
Note: The figure plots the average level of capital ($\log(K)$) over the period 2001–2019 for entrant firms.

Figure B.4: Capital by Firm Age: Young versus Old



Note: The figure plots the sector-weighted sales-weighted log capital separately for young and old firms over the period 2001–2019. Young firms are defined as those aged 0–10 years and old firms as those aged 11 years and above. Capital is measured using tangible fixed assets.

Figure B.5: Labour by Firm Age: Young versus Old

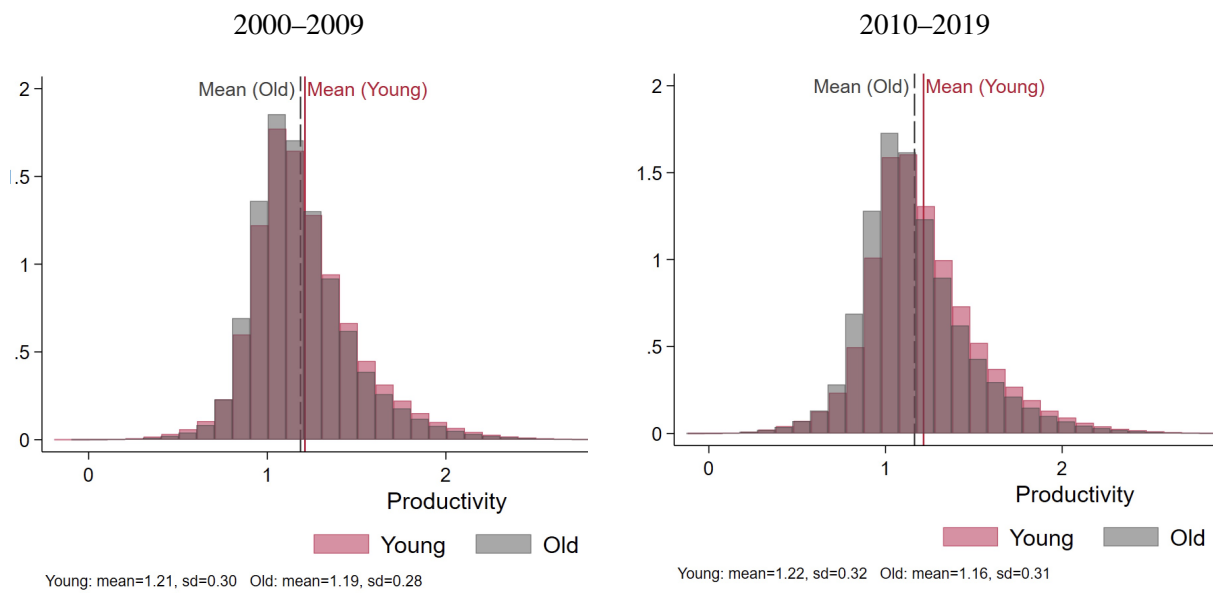


Note: The figure plots the sector-weighted sales-weighted log labour separately for young and old firms over the period 2001–2019. Young firms are defined as those aged 0–10 years and old firms as those aged 11 years and above.

B.1 Productivity Distribution

Figure B.6 plots the distribution of firm-level TFP separately for young and old firms in the two sub-periods 2000–2009 and 2010–2019. In the first sub-period, old firms were on average marginally more productive than young firms, with means of 1.19 and 1.21 respectively and similar dispersion across the two groups. In the second sub-period, this ranking reverses: young firms display a slightly higher mean productivity than old firms (1.22 versus 1.16). This reversal, however, should not be interpreted as an improvement in the productive efficiency of young firms. As the figure makes clear, the distributions of young firms are broadly stable across the two periods; it is the distribution of old firms that shifts leftward, compressing the gap from below. The relative improvement of young firms in the second period is therefore entirely attributable to the productivity decline of older incumbents documented in Section 4.4, consistent with the factor adjustment and crisis period mechanisms described in the text.

Figure B.6: Productivity Distribution: Young versus Old Firms



Note: The figure plots the distribution of firm-level TFP separately for young and old firms in the periods 2000–2009 (left panel) and 2010–2019 (right panel). Vertical lines denote group means. In the first period, young firms have mean TFP of 1.21 (s.d. 0.30) and old firms 1.19 (s.d. 0.28). In the second period, young firms have mean TFP of 1.22 (s.d. 0.32) and old firms 1.16 (s.d. 0.31). The sample covers incorporated firms in the CBI. Young firms are defined as those aged 10 years or below and old firms as those aged 11 years and above.