WESTMINSTER
BUSINESS SCHOOL

WORKING PAPER SERIES

2025/001

Firm productivity and exit during economic crisis: does market potential foster resilience?

Sabine D'Costa
Westminster Business School, University of Westminster

Adelheid Holl
Instituto de Politicas y Bienes Publicos, Consejo Superior de Investigaciones Cientificas (CSIC)

UNIVERSITY OF
VISION
STRATEGY
OPPORTUNITY
WESTMINSTER

Firm productivity and exit during economic crisis: does market potential foster resilience?*

Sabine D'Costa
University of Westminster
35 Marylebone Road, London NW1 5LS, United Kingdom.
s.dcosta@westminster.ac.uk

Adelheid Holl
CSIC - Consejo Superior de Investigaciones Científicas
Instituto de Políticas y Bienes Públicos, c. Albasanz 26-28, 28037 Madrid.
a.holl@csic.es

June 2025

Abstract: This paper examines the relationship between firm productivity, market potential, and firm exit over the economic cycle, focusing on the COVID-19 crisis. Using Spanish firm-level data (2011–2022), we analyse how market potential shapes the link between productivity and survival. Results show that while being closer to the industry productivity frontier increases survival, firms in high market potential areas were more likely to exit at higher productivity levels. However, this moderating effect of market potential was reduced during the COVID-19 pandemic, indicating that competitive dynamics were altered, most likely due to employment retention schemes and the nationwide implementation of lockdowns.

Keywords: firm exit, productivity, market potential, COVID-19.

* This project has received support from the 2023 British Academy/Leverhulme Small Research Grant SRG23\230005. We are also grateful to Patricia Franco Jiménez, Regional Minister of Economy, and Javier Rosell, Director General of Enterprises, from the Consejería de Economía, Empresas y Empleo of Castilla-La Mancha, Spain, for their time and the insightful discussion, to the participants of the impact workshop on "Firm productivity and exit during economic crisis: does the urban environment foster resilience?" (University of Westminster, May 2025) as well as seminar participants at the University of West Virginia and audiences at the Regional Studies Association Annual Conference (Porto, 2025), the Regional Science Association International – British and Irish Section (Bristol, 2024) and the Global Economic Policy Group annual workshop (London, 2025).

1. Introduction

Productivity is a key driver of economic growth and competitiveness, shaping firms' ability to innovate, create jobs, and compete in increasingly dynamic and challenging environments. It has become a cornerstone of policy discussions, as highlighted in the recent Draghi report (Draghi, 2024), which underscores its critical role in enhancing Europe's global competitiveness.

There is ample evidence that competition spurs productivity (Holmes and Schmitz, 2010). At the same time, competitive economies experience constant business turnover, with new firms emerging while others exit the market.[1] This process influences the reallocation of resources, potentially driving productivity improvements. Economic theory suggests that, in an efficient outcome, the least productive firms exit the market (Schumpeter, 1942). Empirical studies such as Aga and Francis (2017), Frazer (2005), and Soderbom *et al.* (2006) for developing countries, and Fariñas and Ruano (2005) for Spain, support this prediction.

While in normal times, more productive firms are more likely to survive, there is conflicting evidence on whether this holds true during economic crises (Carreira and Teixeira, 2016; Foster *et al.,* 2016). Moreover, crises tend to strike different locations with varying degrees of intensity and some areas tend to be more resilient than others. This spatial heterogeneity in crisis exposure but also in recovery can reinforce divergent growth trajectories over time, contributing to long-run uneven territorial growth patterns (Martin, 2012, 2021).

It is well known that businesses in larger markets tend to be more productive (Melitz and Ottaviano, 2008; Combes *et al.,* 2012; Duranton and Puga, 2020), little is still known about the uneven territorial dimension of the productivity-exit relationship and whether this is affected during times of crisis. In this paper, we investigate, for the first time, the relationship between firm location, productivity and exit over the economic cycle, including a major crisis. We place a particular focus on the role of market potential in shaping firm survival.

The analysis is conducted in the context of the recession brought about by the COVID-19 pandemic, when productivity levels declined across sectors due to widespread disruptions. Instead of using absolute productivity values, we adopt a measure of a firm's distance to the industry productivity frontier (or productivity gap), which proxies for competitiveness better than productivity levels. By focusing on relative firm performance, we are better able to account for sector heterogeneity and for the sector-specific severity the COVID-19 shock.

---

[1] Cefis *et al.* (2022) provide a recent review of the literature on firm exit.

We use data from Spain, a country characterised by large and growing regional economic disparities, which was severely impacted by the COVID-19 crisis. In particular, persistent geographic disparities in productivity have been widely documented (Sanromá and Ramos, 2007; Holl, 2012; Badunenko and Romero-Avila, 2014). Related to this paper, D'Costa *et al.* (2024) examined the relationship between productivity and exit of service sector firms across urban, suburban and rural areas in Spain during the 2010-2019 period, and find evidence for greater "cleansing" of less productive knowledge-intensive services firms in core urban locations compared to other areas. In this paper, we focus on locations with different levels of market potential, to include the effect of competition from other markets. We examine whether being located in an area with better market potential strengthens or weakens the positive relationship between productivity and business survival. We include the COVID-19 period, to assess whether during a crisis, firms nearer the productivity frontier and in areas with better market potential are more resilient. Finally, we study services and manufacturing firms and investigate whether these industries are affected differently.

Our results show that higher productivity enhances a firm's chances of survival. However, firms situated in areas with greater market potential are more likely to exit at higher productivity levels, likely due to intensified competition in these larger markets. This moderating effect of market potential on the relationship between productivity and firm survival, however, largely vanished during the COVID-19 pandemic, possibly as a result of government intervention and support measures. This has important implications for regional policy aimed to reduce spatial disparities.

This paper adds to the body of literature on firm exit and productivity by assessing how geographical factors influence firm dynamics in times of crisis, particularly in a context of strong regional economic inequalities.

2. Conceptual framework and relevant literature

Our paper relates to different strands of literature. First, in classical economic theory, firm exit is a central mechanism of "creative destruction" (Schumpeter, 1942), whereby less productive firms exit the market through a "cleansing" process reallocating resources such as labour and capital to more productive firms (Hopenhayn, 1992; Jovanovic, 1982; Schumpeter, 1942; Baldwin & Gu, 2006). This process is considered essential for aggregate productivity growth (Olley and Pakes, 1996; Frazer, 2005). During economic downturns, this cleansing effect could intensify, accelerating the productivity-enhancing reallocation of resources (Caballero & Hammour, 1994). Yet, evidence from past crises is mixed. For instance, Hallward-Driemeier and Rijkers (2013) find that exit was not directly related to productivity in Indonesia during the East-Asian crisis. Foster *et al.* (2016) find that the "cleansing" of unproductive manufacturing firms during the Great Recession in the U.S. was minimal. Similarly, in the UK, exit rates did not increase significantly during 2020 and 2021, possibly due to the mitigating effects of government support programs (Bloom *et al.,* 2025). This points to the role of context-specific factors—including geography and policy—in shaping the relationship between productivity and exit.

Second, the urban economics along with the international trade literature emphasize how market size and integration shape firm competition and survival. Competition is higher in larger and more integrated markets, affecting both firm survival and productivity (Melitz and Ottaviano, 2008). Tougher competition in larger markets tends to force out the least productive firms, facilitating the reallocation of resources toward more productive firms. Related to this, Behrens and Robert-Nicoud (2014) develop a monopolistic competition model where productivity and city size are complementary in firm profits. More productive firms benefit the most from city size and less productive firms suffer relatively more from the urban costs brought about by city size. This means that selection on productivity is stronger in larger cities and therefore the effect of productivity on the probability of firm exit should be greater in larger markets. In the aggregate, larger markets see higher exit rates and also higher productivity levels. Similarly, Combes et al. (2012) develop a model that explains productivity differences across more or less dense cities. This model combines firm selection, where selection on productivity is stronger in denser markets, with agglomeration economies, where cities increase productivity for all firms.

Empirical studies have demonstrated that businesses located in denser areas and larger markets tend to be more productive than those situated in areas with less economic activity (Ciccone and Hall, 1996; Combes *et al.,* 2012; Rosenthal and Strange, 2003; Sveikaukas, 1975). On the other hand, tougher competition on factor and product markets in denser areas may decrease survival rates and force the least productive firms to exit. Consequently, the empirical evidence is also mixed, although evidence that urbanization increases exit is more prevalent. Fritsch *et al.* (2006) and Neffke *et al.* (2012) provide evidence that larger, denser locations favour firm exit. Artz *et al.* (2020) show that, in the retail sector, both entry and exit rates are higher in US metropolitan areas than in rural areas. Chen *et al.* (2020) find that firm entry and exit are both higher in larger labour markets, using U.S. aggregate data. Renski (2008) finds significantly higher failure rates of entrants in the U.S. urban core areas, particularly so for advanced services and high-tech manufacturing. However, Basile *et al.* (2017) find no significant effect of density on the survival of Italian start-ups.

Of particular relevance to this paper, is the fact that the degree of competition depends not only on the size of the local market but also on access to other markets. More integrated markets with greater access to external markets provide greater opportunities for growth but at the same time expose businesses to more intense competition. In this sense, trade openness and integration into broader markets can act as additional engines of industrial restructuring, encouraging the exit of less productive firms.

Third, unlike the urban economics view, which emphasizes selection and market forces, evolutionary economic geography (EEG) stresses co-evolutionary dynamics between firms and places (Boschma and Martin, 2010). EEG stresses the uneven development path of space. Exit is not only viewed as a function of firm-level productivity trajectories and external competition, but also depends on the embeddedness of firms in their regional and local environments. Different agglomeration economies, such as industrial diversity - especially related variety that favours between-industry knowledge spillovers - play a key role in survival (Basile *et al.,* 2017; Boschma, 2005; Frenken *et al.,* 2007).

The literature suggests that creative destruction is more intense in larger markets or locations with greater market potential than in peripheral areas. During a recession, this reallocation should increase the productivity advantage of such areas, making both firms and regions with high market potential more resilient. However, the absence of an increase in the productivity advantage during a recession could indicate the presence of distortions (such as those brought about by government support policies to prevent firm exits). The prediction of accelerated reallocation in high-market potential areas during recessions aligns with empirical findings that during economic crises, urban areas tend to recover more quickly, while rural areas face greater difficulties in recovering from recessions (Holl, 2018). This could contribute to the widening of spatial disparities (Evenhuis *et al.*, 2021). In this sense, the policies implemented to mitigate the economic effects of COVID-19 may have affected firm exit rates in a geographically heterogeneous way.

3. Spain's Major Economic Challenge: Improving Productivity

Poor productivity performance is one of the key factors hindering Spain's long-term economic growth and competitiveness. Spain's productivity levels have consistently lagged behind the European Union (EU) average, and this gap has widened in recent decades (Pérez García *et al.,* 2024).

A persistent pattern of year-on-year decline in TFP has been documented since 1995 (García-Santana *et al.*, 2020). Figure 1 illustrates these efficiency losses over time with TFP estimates from the Productivity and Competitiveness Observatory in Spain[2], for the period 1995–2023. After the 2008 Global Financial Crisis, between 2013 and 2019, Spain experienced a modest recovery in TFP, with a cumulative increase of 1.2%, but did not recover to 1990s levels. During the COVID-19 pandemic, there was a sharp decline with a 5.1% drop in 2020, reflecting the sudden halt in economic activity and the inefficiencies introduced by the crisis. Following this drop, TFP showed signs of recovery with an upward trend, but it has yet to reach pre-2015 levels. Spain's persistent productivity problem is linked to misallocation (Díaz and Franjo, 2016; García-Santana et al, 2020).

Spain has historically struggled to foster entrepreneurship and competition, as structural inefficiencies, labour market rigidities, and financial constraints often prevent the most productive firms from growing while allowing low-productivity firms to survive. Additionally, Spain’s productivity challenges are also linked to its high proportion of small and medium-sized enterprises (SMEs) and the relative scarcity of large firms. This limits innovation, scalability, and global competitiveness, as SMEs often lack the resources needed to invest in advanced technologies to improve productivity.

During the COVID-19 pandemic, Spain implemented an ambitious job retention program to preserve employment, the Temporary Workforce Reduction Schemes (ERTEs). Introduced in March 2020, the program was extended several times until March 31, 2022. At the peak of the pandemic, in April 2020, nearly one in four jobs was supported by an ERTE (OECD, 2024; Díaz *et al.,* 2025). The program was unprecedented in scale, with approximately 4.4 million workers placed on ERTEs over its duration, at a total cost of around 20 billion euros.

Focusing on workers who did not participate in ERTE, Cabanillas-Jiménez and Galanakis (2024) show that both working hours and labour force participation reduced during the national lockdown of 2020. However, findings in Hijzen and Montenegro (2024) indicate that the ERTE program delayed the transition of workers from low-productivity to higher-productivity firms. Díaz *et al.* (2025) also show that ERTE slowed down worker reallocation and suggest that many of the jobs preserved may have been destroyed once ERTE support

[2] The Productivity and Competitiveness Observatory is a joint initiative of the BBVA Foundation and the Valencian Institute of Economic Research (IVIE).

ended, due to their low productivity. These findings are consistent with Giupponi and Landais (2023) for the case of Italy.

4. Data and Descriptives

Our panel dataset is constructed from the SABI database (*Sistema de Análisis de Balances Ibéricos*). This database, collected by INFORMA, contains information on nearly 3 million Spanish companies in manufacturing as well as services. SABI records detailed information on the balance sheets and other characteristics of the companies, including turnover, various costs, the number of employees, total assets, and if the firm experienced a merger or acquisition. Crucially, SABI provides the exact geographic coordinates of companies and their address. SABI is the only firm-level dataset for Spain that is available for our research purpose: administrative data offers only partial information on firms that cannot be combined to obtain such a rich set of variables over a large number of firms covering the entire country.[3]

Companies with multiple plants are excluded from the empirical analysis because SABI does not allow to observe plant-level variables and compute plant-level productivity. Consequently, our sample contains mostly small and medium sized firms. Additionally, we have excluded from the analysis companies that have changed location or have been affected by mergers and acquisitions. When cleaning the dataset, observations for companies without financial information as well as outliers in the top and bottom 0.5% in TFP were also removed. The resulting sample consists of an unbalanced panel of 726,177 companies and more than 2.7 million observations for the years 2011-2022.

Summary statistics are provided in Table 1. The average exit rate after data cleaning is 1%. This seemingly low exit rate is a common feature of analysis conducted with firm-level datasets from Spain.[4] Figure 2 shows the evolution of exit rates in the dataset. About 80% of observations are from services, including 19% in knowledge-intensive services (KIS) and

[3] The ESEE (Encuesta sobre Estrategias Empresariales) dataset has been used to analyse TFP in Spain, however this is a smaller survey that only includes a sample of manufacturing firms. The exact location of firms is not known, making it inappropriate for the analysis of TFP and exit at a micro-geographical level or the computation of firms' market potential.

[4] Esteve-Pérez *et al.* (2010) report annual exit rates ranging from 0.9% to 3.7% using data for manufacturing firms for 1990–2000 from the ESEE annual survey. Rotarescu (2023) reports firm exit rates ranging from 0.7% to 2% based on ORBIS data for 2001-2016. Lopez-Garcia and Puente (2006) obtain exit rates of about 2%, with manufacturing exit rates as low as 1.2% for firms with less than 200 employees and 0.6% for larger firms, using the Bank of Spain Firm Demography Database.

61% in less knowledge-intensive services (less KIS). Figure 3 shows the geo-localization of our sample firms which reflects well the spatial distribution of economic activity in Spain.

4.1. Productivity at the Firm Level

We estimate firm-level Total Factor Productivity (TFP) using the Levinsohn-Petrin method (Levinsohn & Petrin, 2003) and the Ackerberg, Caves, and Frazer (ACF) correction (Ackerberg *et al.,* 2015). Our TFP measure is based on value added data as SABI does not report physical output quantities.[5]

Based on the firm-level TFP estimates obtained, we calculate the industry-year Productivity Frontier (PF) as the average TFP of the 10 percent most productive firms in each 2-digit industry / year *(j, t)* group. We then calculate the Distance to the Productivity Frontier (DFR) for each firm, which is the difference between firm *i*'s TFP and *i*'s industry productivity frontier:

$$DFR_{i,t} = lnTFP_{i,t} - lnPF_{i,j,t}$$

The Distance to the Productivity Frontier represents the productivity gap between firm *i* and the most productive firms in the industry. In the context of the rise of "superstar firms" (Autor *et al.,* 2020), we are interested in capturing a firm's competitiveness relative to frontier firms in the same industry. Evidence from the US and the UK suggest that during the COVID-19 pandemic, a small minority of firms have driven productivity growth in many sectors while the vast majority has stagnated (De Loecker *et al,* 2022). This indicates a lack of "catching-up" among follower firms in each industry. The productivity gap with the top 10% achievers in a firm's industry is therefore a more relevant measure of a firm's competitiveness. Moreover, whilst Spanish TFP estimates are sensitive to the choice of deflators used for the production function variables, possibly due to different industry prices having evolved in different directions during the 2020-2022 period, the distance to the frontier measure is robust to the choice of deflators.[6]

[5] Hence, one of the limitations of our approach is that there can still be unaccounted pricing heterogeneity (Van Beveren, 2012).

[6] All input and output variables have been deflated when estimating TFP. We have considered two alternative sets of deflators. First, the World Bank GDP deflators for all variables, and second, World Bank GDP deflators for the material input variable and sector-specific deflators constructed by the FBBVA and IVIE for all other variables. A comparison of both approaches for deflating is shown in Appendix Figure 1 for our TFP measure and in Appendix Figure 2 for our DFR measure. While with the former option, the TFP estimates more accurately reflect the aggregate data on the evolution of TFP in Spain, our DFR measure is less influenced by the type of deflator used. Results reported here are based on our TFP estimates using the World Bank GDP deflators.

Values of DFR are mostly negative (only positive for frontier firms with TFP larger than the average of frontier firms' TFP), and DFR takes on increasingly negative values for firms more distant from their industry's productivity frontier. Figure 4 shows the spatial distribution of the Distance to the Productivity Frontier (*i.e.,* the productivity gap) in Spain in 2022, based on a spatial interpolation of the municipal average of firm DFR in municipalities with companies included in the sample. The map reflects a significant geographic disparity in distance to the productivity frontier, with higher values (in red and orange tones) concentrated in major urban and industrial areas, while lower levels (in dark green tones) dominate rural and inland areas. The regions closest to the productivity frontier are located in the Northeast and North of Spain, particularly in the Basque Country, Navarra, Catalonia, and the Valencian Community, where important industrial and technological clusters are found. High average productivity is also observed in Madrid and its metropolitan area.

Figure 5 shows the evolution of the distance to the productivity frontier for firms that remain in the market (*Survivors*) and those that are forced to close in any year during the period (*Exiters*) from 2011 to 2022. *Survivors* tend to be closer to their sector productivity frontier (*i.e.,* they are more competitive). During the analysis period, a slight narrowing of the gap with the productivity frontier is observed for the *Survivors* until the COVID-19 crisis, when they experience a sharp decline. However, these firms manage to recover from this shock. In contrast, *Exiters* start at a greater distance to the productivity frontier and gradually fall further behind.

4.2. Market Potential

Market potential measures the economic accessibility of a location based on demand in nearby areas. It is calculated as the sum of distance discounted populations of destination areas. The idea is that closer markets exert more influence due to lower transport costs, better accessibility, and more trading opportunities. Market potential reflects both own market size and the advantages of connectivity beyond the local municipality.

The market potential function has a long history in urban and regional economics (Harris, 1954). The market potential index, *mp*, is calculated as:

$$mp_j = pop_j + \sum_{k \in L_{573}} \frac{pop_k}{d_{jk}}$$

Specifically, mp_j for municipality j is its own population plus the sum of the populations of all other municipalities in the destination set L573, discounted by the distance to municipality j. The destination set L573 is defined as the 573 largest cities in mainland Spain and includes all cities with more than 10,000 inhabitants. This set covers more than 75% of the total population of mainland Spain. Note that the market potential index does not include destinations outside Spain and should hence be regarded as a domestic potential measure. d_{jk} is the distance between municipalities j and k, based on travel times along the shortest route using the Spanish road network (for more details, see Holl, 2012).[7] Figure 6 shows the resulting map of domestic market potential.

Note that our measure of market potential reflects the structural locational advantages firms face. To address potential endogeneity concerns—particularly the possibility that firm outcomes such as productivity or exit could influence contemporaneous measures of market potential—we rely on a lagged version of this variable, based on data for 2005, well prior to our period of analysis. Given that market potential and spatial economic structure tend to evolve gradually over time, especially in established regions, the 2005 measure serves as a stable proxy for long-run locational advantages. Moreover, in our estimations we standardize market potential relative to the sample mean, allowing for comparability across regions and interpretation as a firm's relative market potential. This supports the use of market potential as an exogenous baseline condition.

4.3. Productivity and Market Potential

Figure 7 plots average distance to the frontier over time in low versus high market potential municipalities. In all years, companies in locations with high domestic market potential (blue line) are on average closer to the productivity frontier than those in areas with low domestic market potential. Both groups appear to be relatively stable until around 2019-2020, when a significant divergence occurs. Companies in the top quartile of market potential (blue line) experience a sharp decline but then recover quickly. Companies in the bottom quartile of market potential (red line) also decline but do not recover as quickly.

The data suggest that the COVID-19 pandemic temporarily narrowed the productivity gap between companies in high and low market potential areas. However, companies in locations with high market potential adapted more quickly, possibly due to benefits related to

[7] Travel time is calculated as the travel time along the shortest path on the 2005 road network and is expressed in 30-minute units. For all destinations within a 30-minute travel time, the population of the destination is not discounted by distance when calculating market potential.

agglomeration economies, as well as better access to various resources, technology, or stronger networks. Companies in locations with low market potential faced more difficulties and higher barriers to recovery.

Figure 8 shows these patterns separately for *Survivors* and *Exiters*. The same patterns in Figure 7 are observed both for companies that survive throughout the analysis period and for those that exit during the period. In locations with higher market potential, both *Survivors* and *Exiters* tend to be closer to the productivity frontier.

5. Empirical strategy and Results

5.1. Empirical strategy

We model the determinants of firm exit using a complementary log-log (cloglog) model, particularly suitable when the probability of an event is very small (as in our case) or very large. The proportional hazard function is formulated as:

$$\mathrm{h}(j, X) = 1 - \exp\left[\exp\left(\beta' X + y_j\right)\right]$$

where $h(j, X)$ is the hazard in the interval between the start and end of year j after the entry date.

The parameters show the effects of the explanatory variables X on the hazard rate, and y captures the time-specific effects on the hazard.[8] X includes the distance to the productivity frontier (*DFR*), market potential (*mp*), and an interaction term of *DFR* x *mp* capturing whether the relationship between firm exit and DFR differs according to a firm's market potential. Furthermore, we include controls for the size of the company (employment) and its square, age and its square, exporter or importer status, foreign ownership status and dummy variables for years, two-digit sectors and firm birth cohorts. We also include various geographical controls (latitude, longitude, a terrain ruggedness index, and the municipality's altitude). The market potential variable is standardised to ease the interpretation of coefficients.

We report coefficients in exponentiated form. A coefficient greater than 1 indicates that the variable increases the probability of exit, whilst a coefficient less than 1 indicates the variable

[8] Though other estimators have been used such as Probit, this type of estimation assumes that observations are temporally independent. Moreover, Probit (and logit) models are symmetrical whereas cloglog is asymmetrical, assuming a response to covariates that increases sharply when the probability approaches 1. This fits data on the exit of firms better. Previous research using cloglog to model the probability of firm exit includes Bandick and Görg (2010) and Esteve-Pérez *et al.,* (2018).

reduces it. We therefore expect, according to theory, the coefficient on *DFR* to be less than one, and the coefficient on *mp* to be greater than 1. If firms in locations with high market potential face tougher competition that increases cleansing, then the coefficient on the interaction term should be greater than 1. We conduct this estimation separately for two periods, pre-COVID-19 and post-COVID-19, to capture any changes in cleansing in high market potential areas.

5.2. Main estimation results

Table 2 presents our estimation results for the entire sample of firms, pooling manufacturing and services. Column 1 reports estimates for the pre-COVID-19 period (2011–2019), while Column 2 presents results for the COVID-19 period (2020–2022). As expected, the findings show that more productive firms—those closer to the productivity frontier—were significantly more likely to survive throughout the entire period of analysis. On the other hand, the greater the distance from the productivity frontier, the higher the likelihood of exit. The estimates for both periods indicate that being a unit closer to the productivity frontier reduces the probability of exit for a firm located in a municipality with average market potential by about 46%.

Conversely, market potential is positively associated with higher exit probabilities, indicating that firms located in areas with greater market potential tend to face more intense competition, which reduces their chances of survival. Pre-pandemic, the hazard ratio is 1.403 for firms at the productivity frontier (*i.e.* frontier firms where DFR=0) which means for one standard deviation increase in market potential, the likelihood of exit increases by about 40%. This relationship remained stable even during the COVID-19 period, although the coefficient estimate is somewhat smaller indicating that during the pandemic exit rates were still higher in high market potential areas but less so than pre-pandemic. This suggests that the pandemic may have altered competitive dynamics, potentially due to social distancing being in effect everywhere, and to the mitigating effects of government support programs.

Importantly, our results highlight that the local economic environment shapes the relationship between firm productivity and survival, especially in the pre-COVID-19 period. The interaction term between market potential and distance to the productivity frontier is 1.094 and statistically significant at the 1 percent level.

This implies that, up to the onset of the pandemic, the protective effect of productivity against firm exit weakened in areas with higher market potential. In other words, even more productive firms face greater closure risk when located in larger markets. This is in line with the literature on competition and trade that argues that competition depends on the size of markets. Our results support the view that the more competitive the markets are, the less effective productivity is at protecting a firm from closure. However, during the COVID-19 period, the interaction between market potential and distance to the productivity frontier was no longer significant for the pooled sample of firms. This change compared to the pre-COVID-19 period suggests that the moderating effect of market potential on the relationship between productivity and exit probability was reduced during the COVID-19 pandemic, and confirms that the pandemic may have altered competitive dynamics.

5.3. Heterogeneity

Table 3 disaggregates the analysis by broad sectoral categories. We first distinguish between manufacturing (columns 1–2) and overall services (columns 3–4). Given the heterogeneity within services, we further separate knowledge-intensive services (*KIS*; columns 5–6), from less knowledge-intensive services (*LessKIS*; columns 7–8). These sectors differ not only in production characteristics but also in their dependence on local versus non-local markets, which may influence their sensitivity to market potential and competitive pressures.

Across all sectors, proximity to the productivity frontier consistently reduces the likelihood of firm exit, both before and after 2020. Similarly, higher market potential continues to be associated with increased exit probabilities across sectors. However, in manufacturing and KIS, the post-2020 coefficients for market potential are not statistically significant.

Table 2 had identified a moderating effect of market potential on the productivity-survival relationship in the pre-COVID-19 period. Table 3 shows that this is driven by the services sector, particularly less knowledge-intensive service firms. For manufacturing, the coefficient on the interaction term is not statistically significant and for knowledge-intensive services firms it is only significant at the 10% level.

During the COVID-19 period, however, the moderating effect of market potential largely disappeared as the coefficient on the interaction term is insignificant for all sectors. This could reflect the impact of government support measures such as the ERTE, which may have cushioned the effects of competition across locations. During this period, the effect of distance to the productivity frontier on exit is unaffected by a firm's market potential. For manufacturing and knowledge intensive service firms, only distance to the frontier has a significant effect on firm exit.

The above results are average effects. To ascertain whether distance to the productivity frontier operates on firm exit differently in high and low market potential areas, we use quartiles of market potential, specifically estimating the impact of DFR on exit for the quartile with the highest market potential versus the impact in all other quartiles, pre and post-2020.[9]

Table 4 shows the results. Looking at the coefficients on the interaction terms, we see that being closer to the productivity frontier reduces the likelihood of exit everywhere - both in top quartile market potential areas as well as in other areas - but with some interesting nuances. For manufacturing, in either period the coefficients are not statistically significantly different between the top quartile and the locations with less market potential, meaning that being closer to the productivity frontier reduces the probability of exit in the same way for firms in the top quartile of market potential areas as for firms elsewhere. In services however, in the pre-pandemic years, the protective effect of higher productivity was weaker in the top market potential areas. Being closer to the frontier by one unit is associated with a 32% lower probability of exit in the highest market potential quartile, compared to a 47% lower probability in other locations. The Wald Test of equality of coefficients confirms that the coefficients are significantly different across the two types of areas. In the post 2020- period the differences are generally no longer significant. Breaking down services shows that the same is true for less *KIS* firms but the coefficients are only different at the 10% level for *KIS* firms. In line with our previous results, for the pandemic period, the relationship between distance to the frontier and exit is not significantly different for top market potential quartile firms versus firms elsewhere, in any sector.

We now turn to the hazard ratios for the top quartile of market potential indicator. These reflect the effect of being in the top quartile of market potential for an average *frontier* firm, compared to being an average frontier firm with lower market access (the omitted category). For manufacturing, the hazard rate pre-pandemic is 1.307, which means that productivity frontier firms in the top quartile of market potential are about 30% more likely to exit than similar firms in lower quartiles, though this result is only statistically significant at the 10% level. For services, the hazard rate is even higher with 1.810 and significant at the 1 percent level, indicating that service frontier firms in high market potential areas are 81% more likely to exit than those in lower market potential areas. The differential market access effect for frontier firms holds for both *KIS* and less *KIS* firms.

[9] The summary statistics reported in Table A1 show that firms in the top quartile of market potential differ from firms located elsewhere. In particular, they are larger and more likely to be in services industries.

During the COVID-19 period, the hazard ratios generally decrease and lose statistical significance, indicating that post-2020, frontier firms were no more likely to exit in high market potential areas than in other areas. This suggests that the restrictions and protective measures adopted during the pandemic have facilitated the resilience of frontier firms everywhere and have weakened the competitive pressure particularly in high market potential areas that pre-pandemic had led to higher exit rates.

In further analysis reported in Table 5 we focus on younger manufacturing and service firms—those established after 2008.[10] Young firms are more vulnerable during economic crisis but also tend to benefit more from being in an urban local environment with better market potential. Results in columns (1) and (2) show that, for young manufacturing firms, being closer to the productivity frontier reduces the exit risk and this positive effect was stronger during the COVID-19 period. But our results also indicate that younger manufacturing firms at the productivity frontier that are located in high market potential areas experienced higher exit rates during the COVID-19 period. This suggests younger frontier manufacturing firms in high market potential areas were particularly vulnerable to the economic disruptions caused by the pandemic. ERTE measures might have been less effective in preventing closures among younger manufacturing firms compared to more established ones. This higher exit probability among younger manufacturing firms in high market potential areas may again reflect the intense competitive pressure in such regions.

Interestingly, we do not observe the same heightened exit rates among young service frontier firms located in high market potential areas during the COVID-19 period. This divergence in patterns between manufacturing and services frontier firms may reflect differences in sectoral dynamics, but also the nature of pandemic-related disruptions. Service frontier firms may be more agile and operate with greater flexibility for adjustments including the possibilities of teleworking and moving to online services. Especially young service frontier firms may have been born already more "digital".

For young services sector firms, we also observe again a positive and significant interaction term with market potential for the pre-COVID-19 years that vanished during the pandemic. This is again in line with our previous results that indicate that the protective effects of higher productivity were weaker in higher market potential areas before the pandemic.

[10] Summary statistics of this sample shown in Table A2 indicate that there are compositional differences between this sample and the full sample. Younger firms are on average smaller, less likely to engage in international trade and more likely to be in services industries.

In Table 6 we repeat the analysis for the younger cohort of firms focusing on the top quartile of market potential area effect. The results are again consistent with those using the continuous measure of market potential. In general, being closer to the productivity frontier protects against business closure in all areas. However, in the COVID-19 years, younger manufacturing frontier firms faced significantly higher exit probability in the top quartile market potential locations (column (2)). For service sector firms in the pre-COVID-19 years (column (3)), the moderating effect of market potential on the role of productivity for firm survival is also again confirmed. The coefficients of distance to the productivity frontier differ significantly between the top market potential areas and the rest and indicate that the protective effect of being closer to the productivity frontier was significantly lower in the top market potential locations.

5.4. Robustness checks

To assess the reliability of our main findings, we conducted a series of robustness checks to ensure that the results are not driven by specific sample choices or by the particular method used to measure productivity. In the main analysis, we distinguished between the pre- and post-2020 periods to examine whether the COVID-19 pandemic altered survival patterns across regions with varying levels of market potential.

One potential concern is that the pre-2020 period spans a longer timeframe (2011–2019) compared to the post-2020 period (2020–2022). To address this, we re-estimate our models by restricting the pre-2020 period to the three years preceding the pandemic (2017–2019), making it more comparable in length to the post-pandemic window. The results, reported in Table A3 of the Appendix, largely confirm our main findings. While the coefficients for market potential in the manufacturing and *KIS* sectors decrease slightly in magnitude and lose statistical significance, the estimates for the pooled services sector and the less knowledge-intensive services remain virtually unchanged.

In a second robustness check, we test whether our results are sensitive to the specific measure of productivity used. In the main analysis, total factor productivity (TFP) is used to compute the distance to the productivity frontier. In Table A4, we replicate the analysis using labour productivity as an alternative measure. The results remain robust and consistent, indicating that the key relationships are not driven by the specific choice of productivity metric.

Third, market potential is not only determined by access to population but also by access to economic opportunity and demand intensity of surrounding areas. To capture this, we test an alternative specification of market potential in which the population of municipalities is weighted by the GDP per capita of their respective provinces. This approach accounts for the fact that access to wealthier markets may offer greater economic opportunities than access to larger but poorer populations.[11] Our main results remain robust when using GDP per capita–weighted market potential, with the magnitude of the coefficients largely unchanged (Table A5). The only exception is the *KIS* sector, where market potential and its interaction with distance to the productivity frontier lose statistical significance.

Next, the map in Figure 6 shows strong disparities in market potential across Spanish municipalities, with particularly high market potential around Madrid and Barcelona. We therefore consider whether our main results of Table 3 may be driven by firms in the municipalities of Madrid and Barcelona. When removing these firms, the results, reported in Table A6 are almost identical to the main results using the full sample.

Finally, as an alternative to our preferred complementary log-log estimation, we provide the results from Probit estimations of the probability of exit in Table A7. The Probit results are qualitatively similar though somewhat smaller in magnitude compared to the main results.

8. Conclusions

In this paper we have examined the relationship between firm productivity, market potential, and firm survival across two periods: pre- and post-COVID-19. Our findings confirm that productivity increases survival, but they also show that firms located in high market potential areas face heightened exit probabilities most likely due to increased competition in larger market areas. Notably, the moderating effect of market potential on firm survival was diminished during the COVID-19 period. This may have been due to the spatially-blind government support measures and lower levels of spatial interaction in the economy in that period.

Our analysis further identifies different patterns between manufacturing and service sector firms. In manufacturing, the effect of productivity on firm survival did not significantly differ across areas with different market potential even in the pre-2020 period. However, young manufacturing firms at the productivity frontier and in high market potential areas were more vulnerable to closures during the pandemic, while younger frontier service firms exhibited more resilience, possibly due to their ability to quickly adapt to digital models.

[11] Municipality-level GDP per capita data are not available. As a result, we use province-level GDP per capita as a proxy for local economic conditions when weighting population.

Our research has significant policy implications. The findings suggest that younger firms, especially in manufacturing, may require more targeted support during crises. While support mechanisms like ERTE were effective for many firms in preventing closure, their impact was less pronounced for younger manufacturing firms in high market potential areas, indicating the need for policies tailored to their specific challenges.

In most countries business support strategies are designed and implemented mainly at the national level, but our results also highlight the importance of place-based policies, which are designed to address the unique characteristics and challenges of firms in different geographic areas.

Our study also relates to the problem of the trade-off between efficiency and territorial cohesion objectives in regional policy. Protective measures and support programs may avoid job losses but at the same time slow down the reallocation of resources toward more productive companies. If these dynamics vary by location – as our results show - then this may ultimately contribute to growing disparities in regional productivity growth and widen spatial disparities.

Our study of course is not without limitations. While we were able to work with a very rich firm level data set that has allowed us to geo-localize firms and relate them to a geographically detailed market potential measure, we might not fully capture all firm exits as SABI and similar datasets may suffer from delayed reporting and smaller firms may disappear without being recorded in those datasets. Business register data could provide more accurate information on firm exits. However, in Spain this type of dataset is only provided in aggregate form without the possibility to link to firm-level data. Moreover, while we use total factor productivity (TFP) and provide robustness checks with labour productivity to assess firm performance, further work could explore different approaches for the production function estimation. Our focus on the distance to the sector-specific productivity frontier does reduce the problem of measurement error in productivity and the sensitivity of results to the way productivity has been estimated and to the deflators used. Yet, issues for multi-product and multi-sector firms could still remain.

Furthermore, while we also control in our estimations for a wide number of firm-level and location specific factors, there could still be some unobserved factors which we are not able to control for in our estimations and that could be correlated with other regressors (such as managerial capacities and take-up of government support). Finally, further research could control for the sorting of firms into more dynamic areas.

References

Ackerberg, D. A., Caves, K., & Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, *83*(6), 2411-2451.

Aga, G. and Francis, D. (2017). As the market churns: productivity and firm exit in developing countries. *Small Business Economics*, 49(2), 379-403.

Artz, G. M., Eathington, L., Francois, J., Masinde, M., and Orazem, P. F. (2020). Churning in rural and urban retail markets. *Review of Regional Studies*, 50(1), 110-126.

Asturias, J., Hur, S., Kehoe, T. J., & Ruhl, K. J. (2023). Firm entry and exit and aggregate growth. *American Economic Journal: Macroeconomics*, 15(1), 48-105.

Autor, D., Dorn, D., Katz, L., Patterson, C., Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, 135(2), 645-709.

Badunenko, O., & Romero-Avila, D. (2014). Productivity growth across Spanish regions and industries: a production-frontier approach. *Regional Studies*, 48(7), 1242-1262.

Baldwin, J. R., & Gu, W. (2006). Plant turnover and productivity growth in Canadian manufacturing. *Industrial and Corporate Change*, 15(3), 417-465.

Bandick, R. and Görg, H. (2010). Foreign acquisition, plant survival, and employment growth. *Canadian Journal of Economics*, 43, 547–573.

Basile, R., Pittiglio, R., and Reganati, F. (2017). Do agglomeration externalities affect firm survival?. *Regional Studies*, 51(4), 548-562.

Behrens, K., & Robert-Nicoud, F. (2014). Survival of the fittest in cities: Urbanisation and inequality. *The Economic Journal*, 124(581), 1371-1400.

Boschma, R. (2005). Proximity and innovation: A critical assessment. *Regional Studies*, 39, 61–74.

Boschma, R. A., & Martin, R. L. (Eds.). (2010). The handbook of evolutionary economic geography. Edward Elgar Publishing.

Bloom, N., Bunn, P., Mizen, P., Smietanka, P., & Thwaites, G. (2025). The impact of COVID-19 on productivity. *Review of Economics and Statistics*, 107(1), 28-41.

Cabellaro, R., Hammour, M., 1994. The cleansing effects of recession. *American Economic Review* 84, 1350–1368

Carreira, C., & Teixeira, P. (2016). Entry and exit in severe recessions: lessons from the 2008–2013 Portuguese economic crisis. *Small Business Economics*, 46, 591-617.

Cefis, E., Bettinelli, C., Coad, A., & Marsili, O. (2022). Understanding firm exit: a systematic literature review. *Small Business Economics*, 59(2), 423-446.

Chen, Y., Ma, L., and Orazem, P. F. (2021). Churning in Urban and Rural Markets: Evidence from Firm Entry and Exit, 1999-2015. Mimeo.

Ciccone, A. and Hall, R. (1996) Productivity and the Density of Economic Activity. *American Economic Review,* 86, 54-70.

Combes, P.-P., Duranton, G., Gobillon, L., Puga, D. and Roux, S. (2012). The Productivity Advantages of Large Cities: Distinguishing Agglomeration from Firm Selection. *Econometrica,* 80, 2543-2594.

D'Costa, S., Holl, A., & Ribaudo, D. (2024). Service sector firm death and productivity in urban and rural locations. *Economics Letters*, 235, 111560.

De Loecker, J., Obermeier, T., Van Reenen, J. (2022). *'Firms and inequality'* London: Institute for Fiscal Studies.

Diaz, A., Dolado, J. J., Jáñez, Á., & Wellschmied, F. (2025). Labor reallocation effects of furlough schemes: Evidence from two recessions in Spain. *European Economic Review*, *171*, 104894.

Díaz, A and L Franjo (2016). Capital Goods, Measured TFP and Growth: The Case of Spain, *European Economic Review* 83(1): 19-39.

Draghi M. (2024) The Future of European Competitiveness. Available at: https://commission.europa.eu/topics/eu-competitiveness/draghi-report_en.

Duranton, G., & Puga, D. (2020). The economics of urban density. *Journal of economic perspectives*, *34*(3), 3-26.

Esteve-Pérez, S., Pieri, F., Rodriguez, D. (2018) Age and productivity as determinants of firm survival over the industry life cycle. *Industry and Innovation,* 25(2): 167-198.

Evenhuis, E., Lee, N., Martin, R., & Tyler, P. (2021). Rethinking the political economy of place: challenges of productivity and inclusion. *Cambridge Journal of Regions, Economy and Society*, 14(1), 3-24.

Fariñas, J.C. and S. Ruano 2005. Firm productivity, heterogeneity, sunk costs and market selection. *International Journal of Industrial Organization*, 3(7–8), 505-534.

Foster, L., Grim, C., & Haltiwanger, J. (2016). Reallocation in the great recession: cleansing or not?. *Journal of Labor Economics*, 34(S1), S293-S331.

Frazer, G. (2005). Which firms die? A look at manufacturing firm exit in Ghana. *Economic Development and cultural change*, 53(3), 585-617.

Frenken, K., Van Oort, F. G., and Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional Studies*, 41, 685–697.

Fritsch, M., Brixy, U., & Falck, O. (2006). The effect of industry, region, and time on new business survival–a multi-dimensional analysis. *Review of Industrial Organization*, *28*, 285-306.

Cabanillas-Jiménez, G., Galanakis, Y. (2024). The varying impact of COVID-19 in the Spanish Labor Market. *Empirica*, 51(4), 1075-1104.

García-Santana, M., Moral-Benito, E., Pijoan-Mas, J., & Ramos, R. (2020). Growing like Spain: 1995–2007. *International Economic Review*, 61(1), 383-416.

Giupponi, G., & Landais, C. (2023). Subsidizing labour hoarding in recessions: the employment and welfare effects of short-time work. *The Review of economic studies*, *90*(4), 1963-2005.

González, B., Moral-Benito, E., & Soler, I. (2023). Schumpeter meets Goldilocks: the scarring effects of firm destruction. *SERIEs*, 14(3), 555-577.

Görg, H., and Spaliara, M. E. (2014). Financial health, exports and firm survival: Evidence from UK and French firms. *Economica,* 81.323, 419-444.

Guariglia, A., Spaliara, M. E. and Tsoukas, S. (2016). To what extent does the interest burden affect firm survival? Evidence from a panel of UK firms during the recent financial crisis. *Oxford Bulletin of Economics and Statistics,* 78.4, 576-594.

Hallward-Driemeier, M., & Rijkers, B. (2013). Do crises catalyze creative destruction? Firm-level evidence from Indonesia. *Review of Economics and Statistics*, 95(5), 1788-1810.

Harris, C.D. (1954). The Market as a Factor in the Localization of Industry in the Uni-ted States. *Annals of the Association of American Geographers* 44, 315-348.

Hijzen, A., and Montenegro, M. (2024). An in-depth evaluation of ERTE.

Holl, A. (2012). Market potential and firm-level productivity in Spain. *Journal of Economic Geography*, 12(6), 1191-1215.

Holl, A. (2018). Local employment growth patterns and the Great Recession: The case of Spain. *Journal of Regional Science*, *58*(4), 837-863.

Holmes, T. J., & Schmitz Jr, J. A. (2010). Competition and productivity: a review of evidence. *Annu. Rev. Econ.*, *2*(1), 619-642.

Hopenhayn, H. (1992). Entry, Exit, and Firm Dynamics in Long-Run Equilibrium. *Econometrica,* 60, 1127–50.

Jose C. Fariñas and Sonia Ruano (2005). Firm productivity, heterogeneity, sunk costs and market selection. *International Journal of Industrial Organization*, 3(7–8), 505-534.

Jovanovic, B. (1982). Selection and the Evolution of Industry. *Econometrica,* 50(3), 649–70.

Levinsohn, J., and Petrin, A. (2003). Estimating Production Functions Using Inputs to Control for Unobservables. *Review of Economic Studies* 70, 317–41.

Martin, R. (2012). Regional economic resilience, hysteresis and recessionary shocks. *Journal of Economic Geography*, 12(1), 1-32.

Martin, R. (2021). Rebuilding the economy from the Covid crisis: time to rethink regional studies?. *Regional Studies, Regional Science*, 8(1), 143-161.

Martín-Marcos, A., & Jaumandreu, J. (2004). Entry, exit and productivity growth: Spanish manufacturing during the eighties. *Spanish Economic Review*, 6, 211-226.

Melitz, M. J., & Ottaviano, G. I. (2008). Market size, trade, and productivity. *The Review of Economic Studies*, *75*(1), 295-316.

Meriküll, J., & Paulus, A. (2024). Were jobs saved at the cost of productivity in the COVID-19 crisis? *European Economic Review*, *161*, 104618.

Muzi, S., Jolevski, F., Ueda, K., & Viganola, D. (2023). Productivity and firm exit during the COVID-19 crisis: Cross-country evidence. *Small Business Economics*, 60(4), 1719-1760.

Neffke, F. M., Henning, M., & Boschma, R. (2012). The impact of aging and technological relatedness on agglomeration externalities: a survival analysis. *Journal of Economic Geography*, 12(2), 485-517.

Olley, S., & Pakes, A. (1992). The dynamics of productivity in the telecommunications equipment industry. *Econometrica* 64(6):1263-97.

OECD (2024). Preparing ERTE for the Future: An Evaluation of Job Retention Support in Spain During the COVID-19 Pandemic, OECD Publishing, Paris, https://doi.org/10.1787/a70bf8ec-en.

Renski, H. (2008). New firm entry, survival, and growth in the United States: A comparison of urban, suburban, and rural areas. *Journal of the American Planning Association*, 75(1), 60-77.

Rosenthal, S. and Strange, W. (2003). Geography, Industrial Organization, and Agglomeration. *The Review of Economics and Statistics*, 85(2), 377-393.

Sanromá, E., & Ramos, R. (2007). Local human capital and productivity: an analysis for the Spanish regions. *Regional Studies*, 41(3), 349-359.

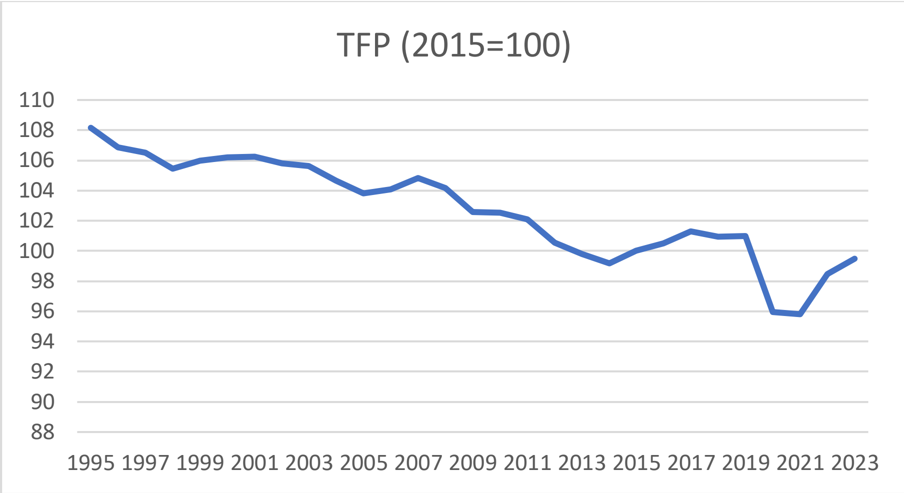
Schumpeter, J. A. (1942), Capitalism, Socialism and Democracy, Harvard University Press, Cambridge, MA.

Soderbom, M., Teal, F., and Harding, A. (2006). The determinants of survival among African manufacturing firms. *Economic Development and Cultural Change*, 54(3), 533–555.

Sveikauskas, L. (1975). The Productivity of Cities. *The Quarterly Journal of Economics*, 89(3), 393–413.

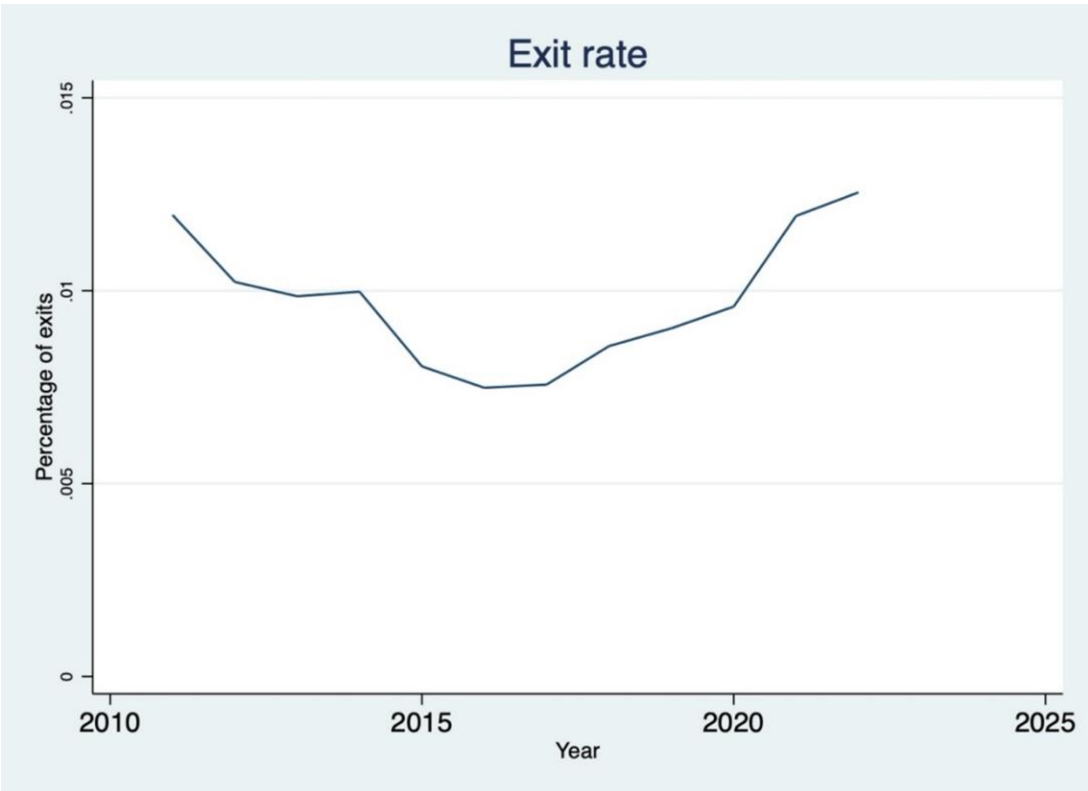
Van Beveren, I. (2012). Total factor productivity estimation: A practical review. *Journal of Economic Surveys*, 26(1), 98-128.

Figure 1. TFP evolution in Spain



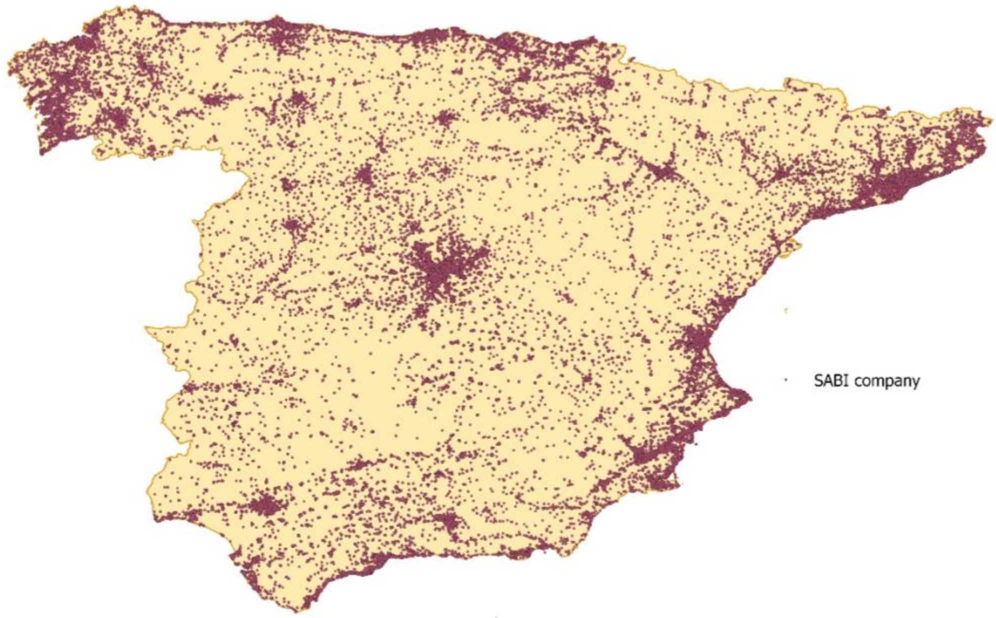
Own elaboration based on data from the Fundación BBVA-Ivie.

Figure 2. Exit rates, 2011-2022



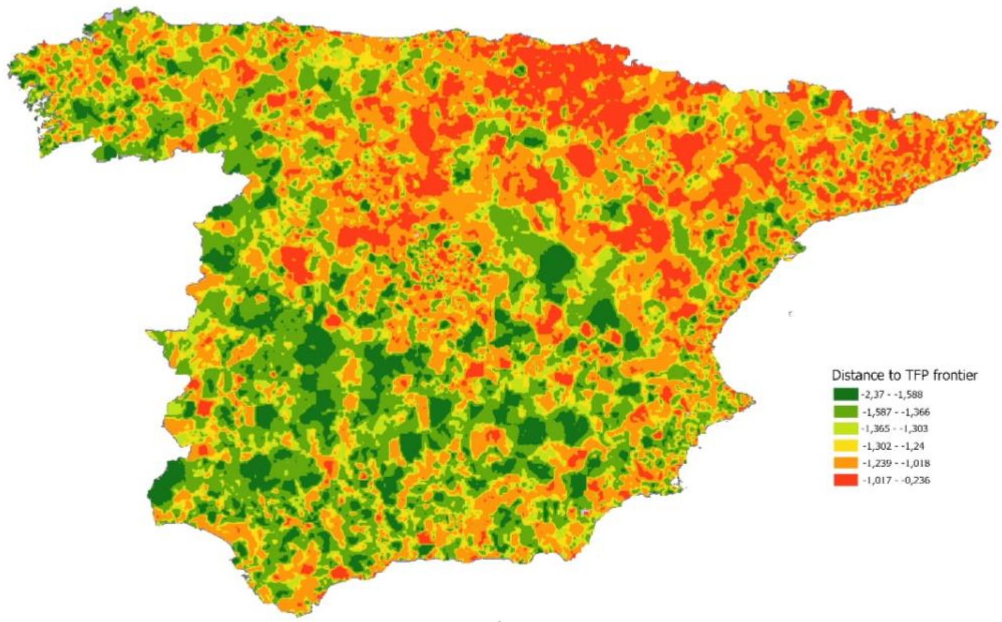
Own elaboration based on SABI data

Figure 3. Map of SABI firms



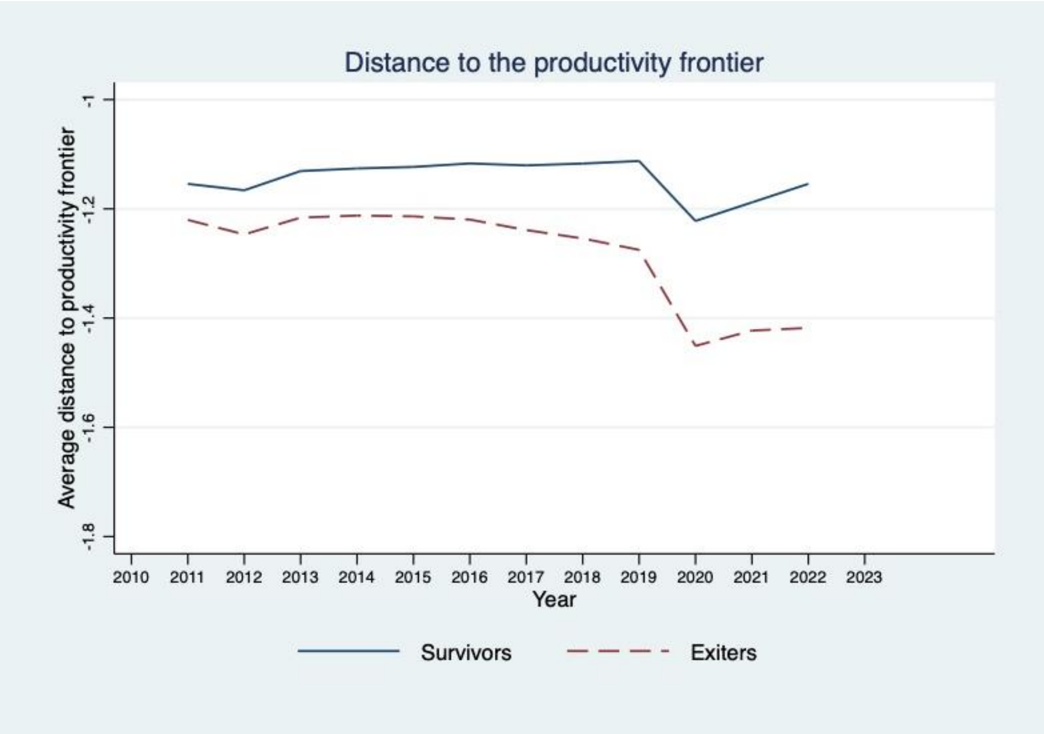
Own elaboration based on SABI data.

Figure 4. Distance to the productivity frontier (DFR) - 2022



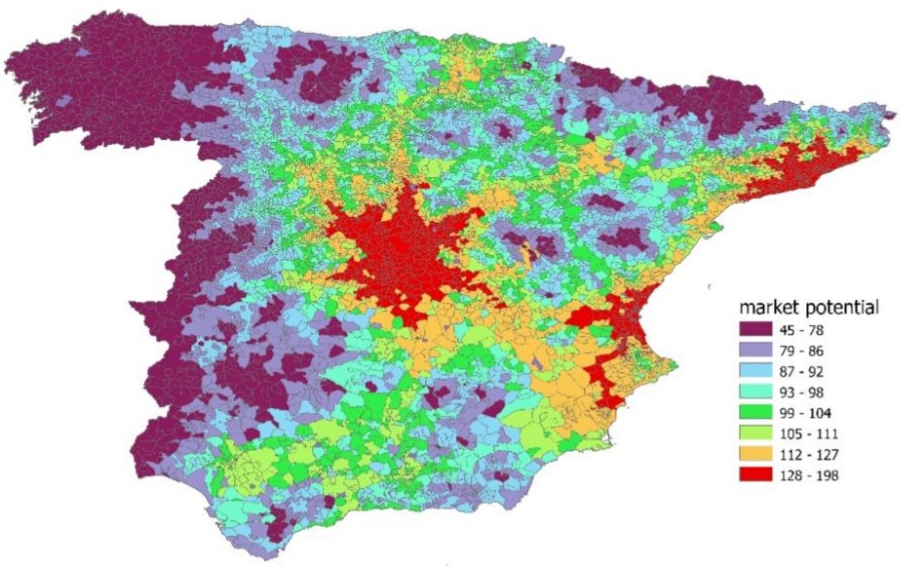
Own elaboration based on SABI data.

Figure 5. Distance to the productivity frontier: "*Survivors*" versus "*Exiters*"



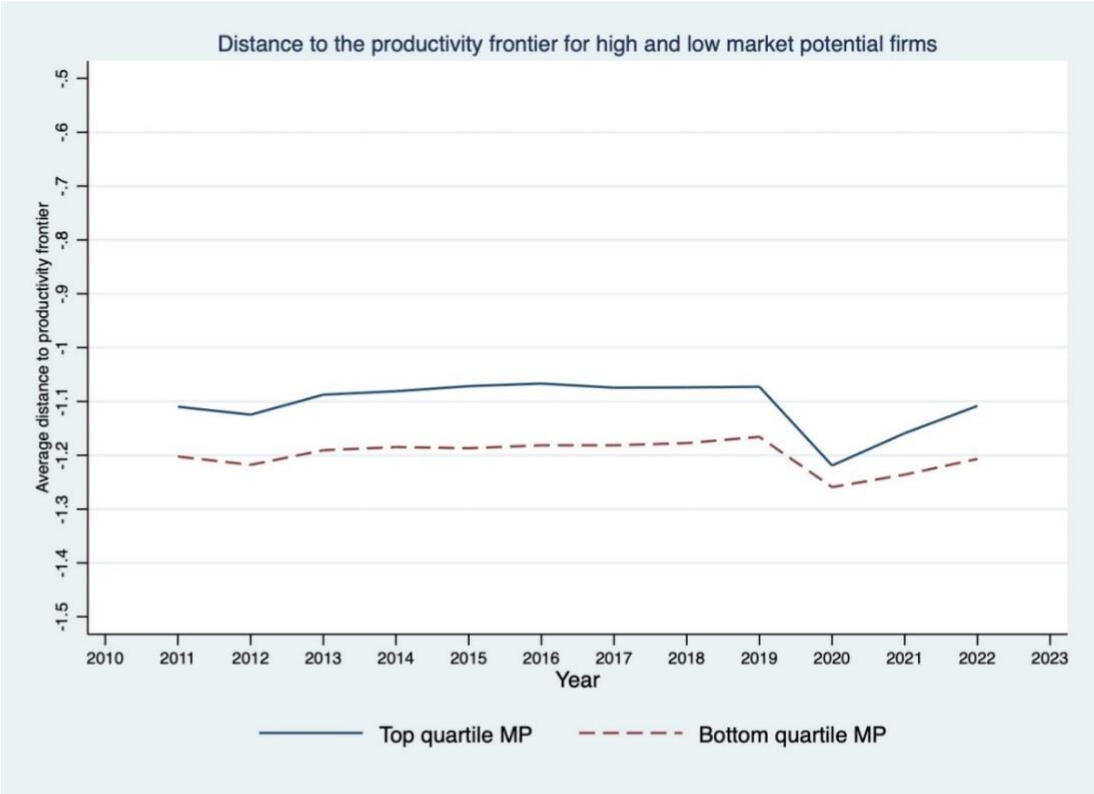
Own elaboration based on SABI data.

Figure 6. Domestic market potential



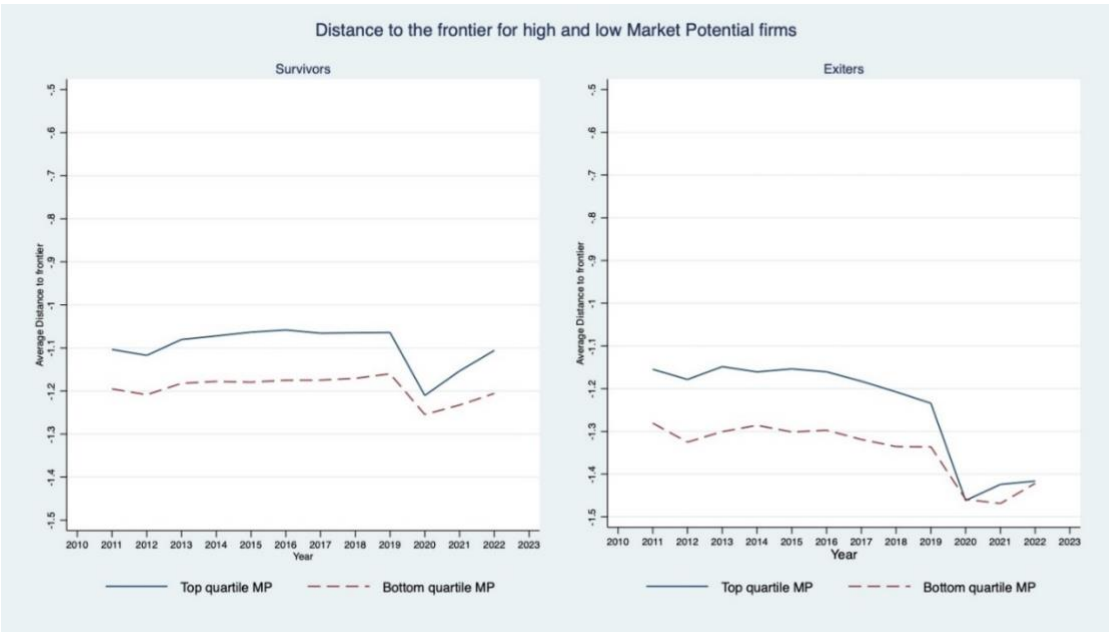
Own elaboration (national mean=100).

Figure 7. Distance to the productivity frontier in high and low market potential locations



Own elaboration.

Figure 8. Distance to the productivity frontier for firms in high and low market potential locations: '*Survivors*' versus '*Exiters*'



Own elaboration.

Table 1. Summary statistics

	Mean	Std. Dev.	Min	Max
Exit	0.010	0.098	0	1
Distance to the productivity frontier	-1.15	0.69	-7.32	4.00
Market Potential	127.18	38.44	45.06	197.81
Employment	11.14	74.12	1	26179
Employment squared	5617.69	737444.40	1	685340041
Age	16.66	10.21	2	160
Age squared	381.65	520.87	4	25600
Export/Import	0.10	0.30	0	1
Foreign ownership	0.02	0.12	0	1
Manufacturing	0.20	0.40	0	1
Services	0.79	0.40	0	1
Knowledge-intensive services	0.19	0.39	0	1
Less knowledge-intensive services	0.61	0.49	0	1

Note: Number of observations: 2725879.
Source: authors' own calculation based SABI data, except for market potential that is based on the Spanish 2005 road network and 2005 municipality population data.

Table 2. Estimation results (exit hazard ratios): pooled across sectors

Dependent variable = 1 if firm exits in year t	(1)	(2)
Exit hazard ratios	2011-2019	2020-2022
Ln distance to the frontier (t-1)	0.543***	0.539***
	(0.011)	(0.020)
Market potential (MP)	1.403***	1.252***
	(0.045)	(0.064)
Ln distance to the frontier (t-1) x MP	1.094***	0.989
	(0.020)	(0.029)
Observations	1.999.285	726.594

Robust s.e. eform in parentheses. *** p<0.01 ** p<0.05 * p<0.1
Controls: all estimations include year fixed effects, 2-digit sector fixed effects, cohort fixed effects, age and age squared, employment and employment squared, an exporter/importer dummy and a dummy for foreign ownership >10%. In addition, all estimations include geography controls: latitude, longitude, altitude, terrain ruggedness index.

Table 3. Estimation results (exit hazard ratios) by sectors

Dependent variable = 1 if firm exits in year t	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	MANUFACTURING		SERVICES		KIS		LESS KIS	
Exit hazard ratios	2011-2019	2020-2022	2011-2019	2020-2022	2011-2019	2020-2022	2011-2019	2020-2022
Ln distance to the frontier (t-1)	0.458***	0.423***	0.567***	0.567***	0.618***	0.751***	0.552***	0.531***
	(0.019)	(0.034)	(0.013)	(0.023)	(0.032)	(0.071)	(0.015)	(0.024)
Market potential (MP)	1.341***	1.163	1.406***	1.247***	1.260***	1.154	1.427***	1.237***
	(0.096)	(0.144)	(0.051)	(0.070)	(0.092)	(0.136)	(0.060)	(0.080)
Ln distance to the frontier (t-1) x MP	1.033	0.906	1.105***	1.001	1.079*	0.924	1.108***	1.008
	(0.041)	(0.062)	(0.023)	(0.032)	(0.045)	(0.064)	(0.027)	(0.037)
Observations	413,001	140,845	1,563,893	585,749	371,026	140,224	1,192,867	443,521

Robust s.e. eform in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Controls: all estimations include year fixed effects, 2-digit sector fixed effects, cohort fixed effects, age and age squared, employment and employment squared, an exporter/importer dummy and a dummy for foreign ownership >10%. In addition, all estimations include geography controls: latitude, longitude, altitude, terrain ruggedness index.

Table 4. Results by market potential quartile and sectors

Dependent variable = 1 if firm exits in year t	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	MANUFACTURING		SERVICES		KIS		LESS KIS	
Exit hazard ratios	2011-2019	2020-2022	2011-2019	2020-2022	2011-2019	2020-2022	2011-2019	2020-2022
Top quartile of market potential (MP)	1.307*	1.397	1.810***	1.275*	1.469**	1.069	1.880***	1.254
	(0.199)	(0.338)	(0.140)	(0.159)	(0.221)	(0.263)	(0.171)	(0.182)
Top quartile MP x ln distance to the frontier	0.452***	0.381***	0.680***	0.557***	0.700***	0.658***	0.672***	0.523***
	(0.038)	(0.045)	(0.031)	(0.035)	(0.056)	(0.078)	(0.037)	(0.038)
Rest of quartiles MP x ln distance to the frontier	0.461***	0.436***	0.533***	0.572***	0.596***	0.790**	0.516***	0.534***
	(0.022)	(0.040)	(0.014)	(0.028)	(0.036)	(0.093)	(0.015)	(0.029)
Observations	413,001	140,845	1,563,893	585,749	371,026	140,224	1,192,867	443,521
Wald Test of equality of coefficients: Prob > chi2	0.837	0.339	0.000	0.716	0.099	0.254	0.000	0.797

Robust s.e. eform in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Controls: all estimations include year fixed effects, 2-digit sector fixed effects, cohort fixed effects, age and age squared, employment and employment squared, an exporter/importer dummy and a dummy for foreign ownership >10%. In addition, all estimations include geography controls: latitude, longitude, altitude, terrain ruggedness index.

Table 5. Younger cohorts: firms born after 2008

Dependent variable = 1 if firm exits in year t	(1)	(2)	(3)	(4)
	MANUFACTURING		SERVICES	
Exit hazard ratios	2011-2019	2020-2022	2011-2019	2020-2022
Ln distance to the frontier	0.414***	0.305***	0.522***	0.519***
	(0.042)	(0.034)	(0.024)	(0.030)
Market potential (MP)	1.344	1.555**	1.319***	1.201**
	(0.268)	(0.322)	(0.091)	(0.102)
Ln distance to the frontier x MP	1.087	1.004	1.103**	0.969
	(0.119)	(0.097)	(0.043)	(0.044)
Observations	23,855	13,219	221,915	102,630

Robust s.e. eform in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Controls: all estimations include year fixed effects, 2-digit sector fixed effects, age and age squared, employment and employment squared, an exporter/importer dummy and a dummy for foreign ownership >10%. In addition, all estimations include geography controls: latitude, longitude, altitude, terrain ruggedness index.

Table 6. Younger cohorts: firms born after 2008 by market potential quartiles

Dependent variable = 1 if firm exits in year t	(1)	(2)	(3)	(4)
	MANUFACTURING		SERVICES	
Exit hazard ratios	2011-2019	2020-2022	2011-2019	2020-2022
Top quartile of market potential (MP)	1.865	2.044*	1.802***	1.043
	(0.861)	(0.806)	(0.284)	(0.197)
Top quartile MP x ln distance to the frontier	0.510**	0.285***	0.668***	0.466***
	(0.142)	(0.046)	(0.063)	(0.041)
Rest of quartiles MP x ln distance to the frontier	0.395***	0.314***	0.481***	0.543***
	(0.043)	(0.041)	(0.024)	(0.038)
Observations	53,137	38,397	329,662	239,744
Wald Test of equality of coefficients: Prob > chi2	0.392	0.613	0.001	0.158

Robust s.e. eform in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Controls: all estimations include year fixed effects, 2-digit sector fixed effects, age and age squared, employment and employment squared, an exporter/importer dummy and a dummy for foreign ownership >10%. In addition, all estimations include geography controls: latitude, longitude, altitude, terrain ruggedness index.

Appendix

Figure A1. TFP based on INE & FBBVA-IVIE sectoral deflators versus World Band GDP deflators

Figure A2. Distance to the productivity frontier based on INE & FBBVA-IVIE sectoral deflators versus World Band GDP deflators

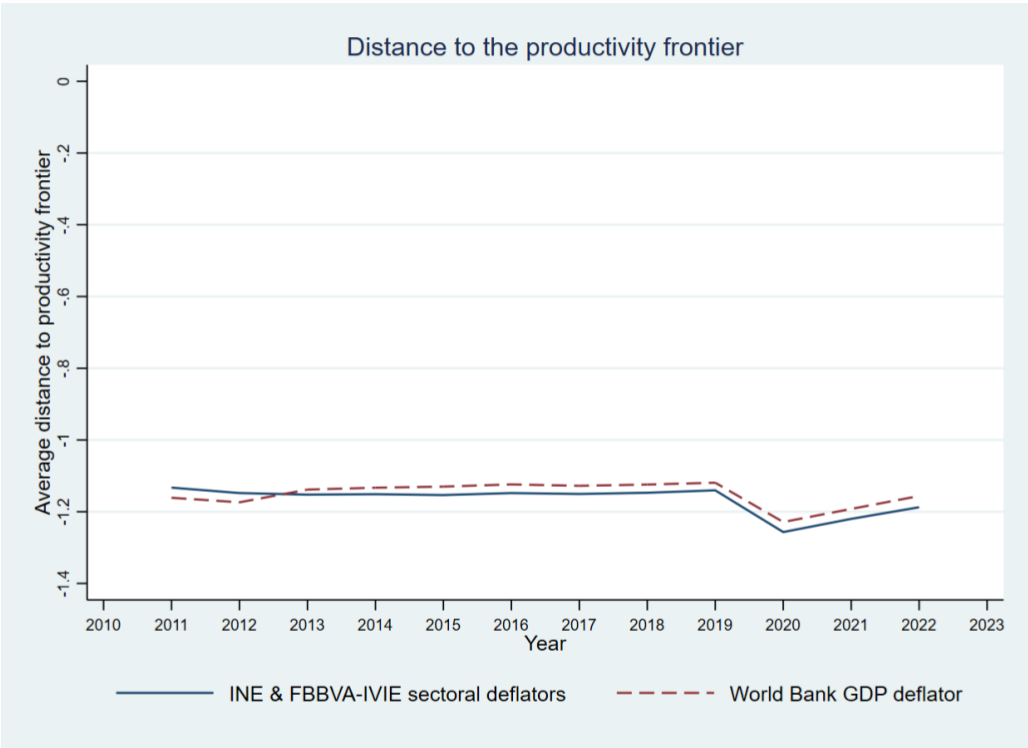


Table A1. Summary statistics, firms in the top quartile of market potential versus others

	Top quartile of market potential				Other quartiles of market potential			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Exit	0.01	0.111	0	1	0.01	0.093	0	1
Distance to the productivity frontier	-1.11	0.724	-7.17	4.00	-1.17	0.675	-7.32	3.58
Market Potential	182.54	17.464	158.79	197.81	108.84	22.698	45.06	158.78
Employment	14.88	124.913	1	26179	9.91	46.628	1	10064
Employment squared	15824.64	1433208	1	685000000	2272.40	220901.200	1	101000000
Age	16.78	10.758	2	160	16.62	10.019	2	151
Age squared	397.18	588.639	4	25600	376.50	496.290	4	22801
Export/Import	0.11	0.311	0	1	0.10	0.295	0	1
Foreign ownership	0.03	0.179	0	1	0.01	0.095	0	1
Manufacturing	0.15	0.355	0	1	0.22	0.414	0	1
Services	0.85	0.355	0	1	0.78	0.414	0	1
Knowledge-intensive services	0.27	0.445	0	1	0.17	0.371	0	1
Less knowledge-intensive services	0.58	0.494	0	1	0.62	0.487	0	1
N		698511				2006374		

Source: authors' own calculation based SABI data, except for market potential that is based on the Spanish 2005 road network and 2005 municipality population data.

Table A2. Summary statistics, firms born since 2008 only

	Mean	Std. Dev.	Min	Max
Exit	0.012	0.1087	0	1
Distance to the productivity frontier	-1.175	0.6968	-6.06	3.27
Market Potential	128.131	39.0688	45.06	197.81
Employment	7.870	34.4567	1	14946
Employment squared	1249.198	278984.4000	1	223000000
Age	6.177	2.8445	2	14
Age squared	46.252	41.1691	4	196
Export/Import	0.078	0.2682	0	1
Foreign ownership	0.014	0.1155	0	1
Manufacturing	0.142	0.3492	0	1
Services	0.858	0.3492	0	1
Knowledge-intensive services	0.221	0.4152	0	1
Less knowledge-intensive services	0.636	0.4810	0	1

Note: Number of observations: 660940.
Source: authors' own calculation based SABI data, except for market potential that is based on the Spanish 2005 road network and 2005 municipality population data.

Table A3. Restricting the pre-COVID-19 period to 2017-2019

Dependent variable = 1 if firm exits in year t	(1)	(2)	(3)	(4)
	MANUFACTURING	SERVICES	KIS	LESS KIS
Exit hazard ratios	2017-2019	2017-2019	2017-2019	2017-2019
Ln distance to the frontier (t-1)	0.371***	0.501***	0.539***	0.491***
	(0.039)	(0.022)	(0.057)	(0.024)
Market potential (MP)	1.197	1.367***	1.077	1.465***
	(0.189)	(0.087)	(0.140)	(0.106)
Ln distance to the frontier (t-1) x MP	0.936	1.073*	0.974	1.103**
	(0.087)	(0.039)	(0.073)	(0.047)
Observations	140,882	572,038	137,243	434,795

Robust s.e. eform in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Controls: all estimations include year fixed effects, 2-digit sector fixed effects, cohort fixed effects, age and age squared, employment and employment squared, an exporter/importer dummy and a dummy for foreign ownership >10%. In addition, all estimations include geography controls: latitude, longitude, altitude, terrain ruggedness index.

Table A4. Exit hazard ratios based on labour productivity instead of TFP for the distance to the productivity frontier

Dependent variable = 1 if firm exits in year t	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	MANUFACTURING		SERVICES		KIS		LESS KIS	
Exit hazard ratios	2011-2019	2020-2022	2011-2019	2020-2022	2011-2019	2020-2022	2011-2019	2020-2022
Ln distance to the frontier lp (t-1)	0.432***	0.457***	0.534***	0.572***	0.589***	0.695***	0.518***	0.541***
	(0.017)	(0.026)	(0.012)	(0.020)	(0.031)	(0.055)	(0.013)	(0.020)
Market potential (MP)	1.416***	1.183*	1.450***	1.294***	1.259***	1.331***	1.486***	1.246***
	(0.104)	(0.113)	(0.055)	(0.066)	(0.099)	(0.144)	(0.064)	(0.073)
Ln distance to the frontier lp (t-1) x MP	1.028	0.936	1.125***	1.022	1.087**	1.015	1.130***	1.009
	(0.038)	(0.042)	(0.023)	(0.027)	(0.046)	(0.061)	(0.026)	(0.030)
Observations	344,678	135,174	1,260,271	545,064	293,974	128,606	966,297	414,627

Robust s.e. eform in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Controls: all estimations include year fixed effects, 2-digit sector fixed effects, cohort fixed effects, age and age squared, employment and employment squared, an exporter/importer dummy and a dummy for foreign ownership >10%. In addition, all estimations include geography controls: latitude, longitude, altitude, terrain ruggedness index.

Table A5. Exit hazard ratios based on GDP per capita weighted market potential

Dependent variable = 1 if firm exits in year t	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	MANUFACTURING		SERVICES		KIS		LESS KIS	
Exit hazard ratios	2011-2019	2020-2022	2011-2019	2020-2022	2011-2019	2020-2022	2011-2019	2020-2022
Ln distance to the frontier lp (t-1)	0.460***	0.424***	0.572***	0.568***	0.642***	0.748***	0.553***	0.531***
	(0.020)	(0.034)	(0.014)	(0.023)	(0.035)	(0.068)	(0.015)	(0.024)
Market potential (MP)-GDP/capita weighted	1.288***	1.232*	1.319***	1.208***	1.119	1.135	1.356***	1.197***
	(0.092)	(0.146)	(0.049)	(0.071)	(0.090)	(0.150)	(0.057)	(0.078)
Ln distance to the frontier lp (t-1) x MP	0.981	0.923	1.043**	0.984	0.989	0.902	1.054**	0.994
	(0.036)	(0.057)	(0.021)	(0.031)	(0.046)	(0.067)	(0.024)	(0.034)
Observations	413,001	140,845	1,563,893	585,749	371,026	140,224	1,192,867	443,521

Robust s.e. eform in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Controls: all estimations include year fixed effects, 2-digit sector fixed effects, cohort fixed effects, age and age squared, employment and employment squared, an exporter/importer dummy and a dummy for foreign ownership >10%. In addition, all estimations include geography controls: latitude, longitude, altitude, terrain ruggedness index.

Table A6. Estimation results (exit hazard ratios) - removing firms in Madrid and Barcelona

Dependent variable = 1 if firm exits in year t	(1)	(2)	(3)	(4)
	MANUFACTURING		SERVICES	
Exit hazard ratios	2011-2019	2020-2022	2011-2019	2020-2022
Ln distance to the frontier (t-1)	0.461***	0.411***	0.558***	0.582***
	(0.020)	(0.035)	(0.014)	(0.028)
Market potential (MP)	1.380***	1.112	1.300***	1.270***
	(0.107)	(0.158)	(0.057)	(0.094)
Ln distance to the frontier (t-1) x MP	1.049	0.882	1.076***	1.036
	(0.045)	(0.071)	(0.027)	(0.046)
Observations	394,071	133,888	1,355,170	497,885

Robust s.e. eform in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Controls: all estimations include year fixed effects, 2-digit sector fixed effects, cohort fixed effects, age and age squared, employment and employment squared, an exporter/importer dummy and a dummy for foreign ownership >10%. In addition, all estimations include geography controls: latitude, longitude, altitude, terrain ruggedness index.

Table A7. Probit estimation results

Dependent variable = 1 if firm exits in year t	(1)	(2)	(3)	(4)
	MANUFACTURING		SERVICES	
	2011-2019	2020-2022	2011-2019	2020-2022
Ln distance to the frontier (t-1)	-0.27***	-0.30***	-0.19***	-0.18***
	(0.018)	(0.030)	(0.009)	(0.014)
Market potential (MP)	0.096***	0.032	0.113***	0.069***
	(0.027)	(0.045)	(0.012)	(0.019)
Ln distance to the frontier (t-1) x MP	0.01	-0.05*	0.03***	-0.00
	(0.017)	(0.027)	(0.008)	(0.011)
Observations	413,001	140,845	1,563,893	585,749

Robust s.e. in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Controls: all estimations include year fixed effects, 2-digit sector fixed effects, cohort fixed effects, age and age squared, employment and employment squared, an exporter/importer dummy and a dummy for foreign ownership >10%. In addition, all estimations include geography controls: latitude, longitude, altitude, terrain ruggedness index.