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Firm Productivity and Exit During Economic Crisis: Does Market Potential Foster Resilience?

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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. The results show that while being closer to the industry productivity frontier increases survival, this relationship is moderated by market potential, indicating heterogenous selection on productivity across space. In particular, productivity differences translate into smaller survival advantages in high-market-potential areas. However, this moderating effect of market potential was reduced during the COVID-19 pandemic, suggesting that spatial differences in productivity-based selection diminished during the crisis. This indicates that competitive dynamics were altered, most likely due to the nationwide lockdowns limiting spatial economic interactions and locally implemented support schemes.

1 | Introduction

Productivity shapes firms' ability to innovate, create jobs, and survive 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 also 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 Söderbom 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 (Fingleton et al. (2012)). 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).

Though we know that businesses in larger markets tend to be more productive (Melitz and Ottaviano 2008; Combes et al. 2012; Duranton and Puga 2020), little is known about the uneven territorial dimension of the productivity-exit relationship and

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

whether this is affected during times of crisis. Theoretical models in Behrens and Robert-Nicoud (2014) and Combes et al. (2012) predict that greater competition in larger markets tends to force out the least productive firms, facilitating a reallocation of resources toward more productive firms. Empirical evidence of this is scarce. 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.

We use data from Spain, a country characterized 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-Ávila 2014; Martín-Barroso et al. 2015). More broadly, Spain has experienced chronically weak productivity performance, with productivity levels consistently lagging behind the European Union average and the gap widening in recent decades (Pérez García et al. 2024). A persistent decline in total factor productivity (TFP) since the mid-1990s has also been documented (García-Santana et al. 2020), reflecting long-standing structural inefficiencies and resource misallocation within the economy (Díaz and Franjo 2016; García-Santana et al. 2020).

The COVID-19 pandemic further exposed these structural weaknesses. Spain experienced a sharp contraction in economic activity in 2020, accompanied by a significant decline in TFP. The government implemented an ambitious job retention program to preserve employment, the Temporary Workforce Reduction Schemes (ERTEs), that at its peak supported nearly one in four jobs and covered approximately 4.4 million workers over its duration (OECD 2024; Díaz et al. 2025). While the program helped preserve employment, emerging evidence suggests it may also have slowed the reallocation of labor from less productive to more productive firms (Hijzen and Montenegro 2024; Díaz et al. 2025).

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 show that less productive knowledge-intensive service firms were more likely to exit in core urban areas compared to other areas.

In this paper, we focus on locations with different levels of market potential to proxy effective size of accessible demand around a location, by combining local population with distance-weighted population in surrounding areas. 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 closer the productivity frontier and in areas with better market potential are more resilient. We also distinguish between manufacturing and service firms and investigate whether these industries are affected differently. As will be shown in the next section, market potential captures both demand forces as well as competition effects locally and from other markets. To shed more light on the role of local competitive pressure, we complement our analysis using a measure of local product market competition.

Our results show that higher productivity enhances a firm's chances of survival, with more productive firms exhibiting lower exit risk. This remains true during the COVID-19 period, a finding that contrasts with some of the reallocation literature that has found distortions to the “cleansing” process during economic crisis when using absolute productivity measures (Hallward-Driemeier and Rijkers 2013; Foster et al. 2016; Bloom et al. 2025).

However, the relationship between productivity and survival is moderated by local market potential, indicating that the strength of productivity-based selection varies across space. In particular, our results indicate that productivity differences translate into smaller survival advantages in high market potential areas, consistent with weaker selection on productivity in these locations. This moderating role of market potential on the relationship between productivity and firm survival, however, largely vanished during the COVID-19 pandemic, suggesting a reduction in spatial heterogeneity in the productivity–exit relationship, possibly as a result of nationwide demand shocks and supply chain disruptions, as well as local and national government intervention and extraordinary support measures. This has important implications for regional policy aimed to reduce spatial disparities.

This paper contributes 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 labor and capital to more productive firms (Hopenhayn 1992; Jovanovic 1982; Schumpeter 1942; Baldwin 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 and 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 United States was minimal. Similarly, in the United Kingdom, 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, a large literature in international trade, economic geography, and urban economics suggests that market potential may shape the relationship between firm productivity and exit. Harris (1954) shows that the potential demand faced by producers in a location depends on the distance-weighted GDP of all other locations. Using a New Economic Geography model, Redding and Venables (2004) link market access (equivalent to market potential) to a country's per capita income, showing that firms in locations with greater market access and therefore facing greater demand can afford to pay higher wages. Based on these theoretical considerations, we would therefore expect firms in locations with greater market potential to perform better.

However, the empirical evidence is mixed. On the one hand, 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; Sveikauskas 1975). On the other hand, firm exit is also influenced by the characteristics of the local economic environment (Knappe et al. 2026). Fritsch et al. (2006) and Neffke et al. (2012) provide evidence that larger, denser locations favor 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. (2021) find that firm entry and exit are both higher in larger labor markets, using US aggregate data. Renski (2008) finds significantly higher failure rates of entrants in the US 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.

In addition to demand forces, environments with greater market potential can also affect firm survival through changes in competitive pressure. The “New New Trade Theory” emphasizes how market size and integration shape firm competition and survival. In Melitz and Ottaviano (2008), greater market size increases competitive pressure, affecting both firm survival and productivity. Given that a location's market potential increases in the market size of other locations and in their connectedness, firms in locations with greater market potential have greater opportunities for growth but at the same time also face higher levels of competition, leading to more intense selection and reallocation of resources toward more productive firms. Trade openness and integration into broader markets can act as additional engines of industrial restructuring, encouraging the exit of less productive firms.

Related theoretical contributions further highlight that the relationship between market size and selection is not uniform. Behrens and Robert-Nicoud (2014) develop a monopolistic competition model of urban economics where productivity and city size are complementary in firm profits, implying heterogeneous effects of market size across firms. More productive firms benefit

the most from city size, while less productive firms suffer relatively more from the higher costs associated with larger and denser markets.

Combes et al. (2012) and Accetturo et al. (2018) similarly show that selection and agglomeration forces interact in shaping local productivity distributions, with effects depending on market access and local conditions. These frameworks therefore suggest that the relationship between market potential and selection on productivity may vary across contexts and over time, implying heterogeneous patterns of creative destruction across locations with different levels of market potential.

Importantly, the theoretical literature does not provide a clear prediction regarding the net effect of market potential and the strength of productivity-based selection. While larger and more integrated markets may intensify competitive pressures and thus strengthen selection mechanisms in some settings (Melitz and Ottaviano 2008), they may also provide environments with greater agglomeration economies, and better institutions (Rodriguez-Pose and Di Cataldo 2015), better access to finance (Lee and Luca 2019), which can support the survival of lower-productivity firms. As a result, the net effect of market potential on the extent to which productivity translates into firm exit is theoretically ambiguous. This is in line with evolutionary economic geography (EEG) that 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 favors between-industry knowledge spillovers—play a key role in survival (Basile et al. 2017; Boschma 2005; Frenken et al. 2007).

This ambiguity is consistent with recent empirical work emphasizing that aggregate reallocation dynamics depend not only on the distribution of productivity but also on the economy's responsiveness to those productivity differences. This suggests that differences across locations may arise because productivity differences translate into firm exit more or less strongly in some places than in others. Decker et al. (2020), for instance, show for the United States that declines in business dynamism over the last decades are associated with a weakening responsiveness of firm growth, exit, and entry to productivity differences.

A third strand of the literature, relevant to our Covid-19 context, relates to how the relationship between productivity and exit varies with the business cycle. According to Caballero and Hammour (1994)'s theoretical predictions, during a recession, reallocation should become stronger, though this theory does not take the spatial dimension into account. Combining this with the prediction of Melitz and Ottaviano (2008) and related literature, a possible expectation is that productivity-enhancing reallocation may become stronger in high market potential areas during recessions. 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 (Brakman

et al. 2015; Holl 2018). This could contribute to the widening of spatial disparities (Evenhuis et al. 2021).

However, distortions at play during the COVID-19 pandemic crisis may impede this. First, the policies implemented to mitigate the economic effects of COVID-19 may have affected firm exit in a geographically heterogeneous way. If COVID-19 support disproportionately kept low-productivity firms alive in high-market-potential areas, while support in low-market-potential areas was distributed more evenly across firms of different productivity levels, then the predicted tendency for high-market-potential areas to experience stronger productivity-enhancing selection through firm exit would be weakened or eliminated. Just as the implementation of government financial support varied widely across countries, it also varied across regions in Spain as a particularly decentralized country. While the central government set the overarching framework for support to firms, the Autonomous Communities and local authorities were also empowered to design and deliver firm-level support within that national framework.

A second distortion stems from the nature of the COVID-19 crisis itself. Government-mandated national lockdowns and social distancing measures disrupted normal market interactions and competitive processes, potentially reducing spatial variation in productivity-based selection.

3 | Data and Descriptives

Our panel data set is constructed from the SABI database (*Sistema de Análisis de Balances Ibéricos*). This database, collected by IN-FORMA, 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 data set 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.²

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 consists mostly of small and medium sized firms.³

Additionally, we have excluded from the analysis companies that have changed location⁴ or have been affected by mergers and acquisitions. When cleaning the data set, 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.⁵ About 80% of observations are from services (which is consistent with the GDP share of services in Spain), including 19% in knowledge-intensive services (KIS) and 61% in less knowledge-intensive services (less KIS). Figure 1 shows the evolution of exit rates in the data set. Figure 2 shows the geo-localization of our sample firms which reflects well the spatial distribution of economic activity in Spain. Figure 3 maps the spatial distribution of firm exit intensity, computed as the local density of exiting firms relative to the local density of firms. The figure highlights marked regional variation in exit intensity across Spain, suggesting that firm survival patterns are spatially uneven and potentially related to differences in productivity and market potential.

3.1 | Productivity at the Firm Level

We estimate firm-level Total Factor Productivity (TFP) using the Levinsohn-Petrin method (Levinsohn and Petrin 2003) and the Akerberg, Caves, and Frazer (ACF) correction (Akerberg et al. 2015). Our TFP measure is based on value added data as SABI does not report physical output quantities.⁶

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:

$$DFR_{i,t} = \ln TFP_{i,t} - \ln PF_{j,t}.$$

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

²The ESEE (Encuesta sobre Estrategias Empresariales) data set 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.

³This is consistent with the structure of the Spanish economy, which is characterized by a high share of small firms and a lower average firm size than many other advanced economies. On the other hand, excluding multiplant firms removes many of the most productive firms and results in our computation of the industry-level productivity frontiers being lower than if computed over the whole universe of firms. As a result, those firms considered in this paper as frontier firms may not all be treated as frontier firms if the whole universe of firms were included in the analysis. Nonetheless, as the productivity of non-frontier firms is defined relative to their industry productivity frontier, as we describe in Section 3.1, this does not affect the key results of the paper. We provide robustness checks in Section 4.5 showing that varying the industry productivity frontier does not materially change the results.

⁴Excluding relocating firms ensures that market potential remains effectively time invariant at the firm level and avoids conflating the effects of location choice with the relationship between market potential, productivity, and firm exit. In Section 4.5 relax this restriction and explicitly exploit changes in market potential stemming from relocating firms as a robustness check.

⁵Esteve-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. López-García 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.

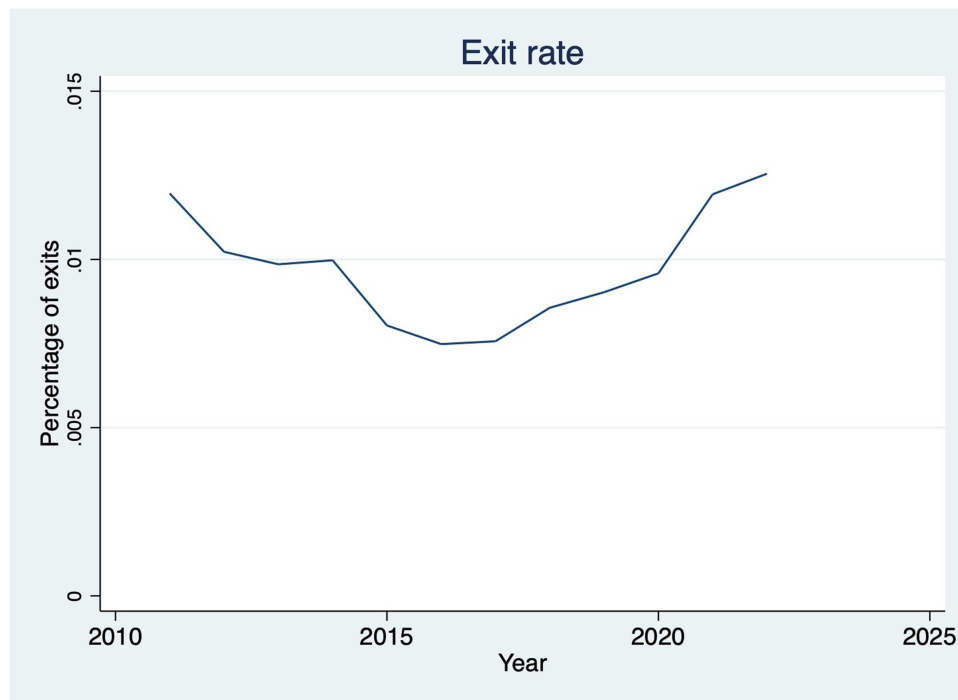
⁶Hence, one of the limitations of our approach is that there can still be unaccounted pricing heterogeneity (Van Beveren 2012).

TABLE 1 | Summary statistics.

	Mean	Stdandard deviation	Minimum	Maximum
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	26,179
Employment squared	5617.69	737444.40	1	685,340,041
Age	16.66	10.21	2	160
Age squared	381.65	520.87	4	25,600
Export	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: 2,725,879.

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.

**FIGURE 1** | Exit rates, 2011–2022. Own elaboration based on SABI data. [Color figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1111/jors.70085)]

competitiveness relative to frontier firms in the same industry. Evidence from the United States and the United Kingdom 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, while 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.⁷

⁷All 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.

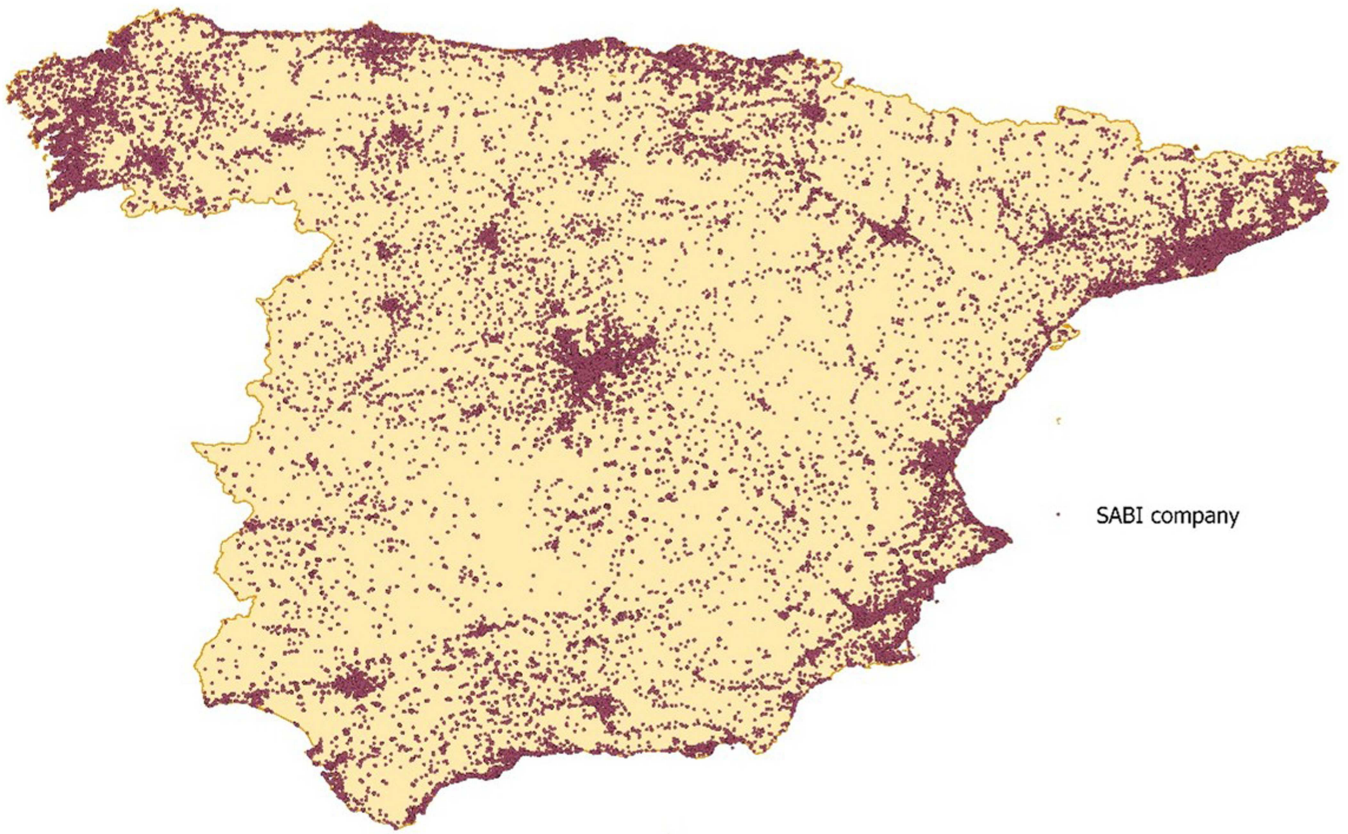


FIGURE 2 | Map of SABI firms. Own elaboration based on SABI data. [Color figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1111/jors.70085)]

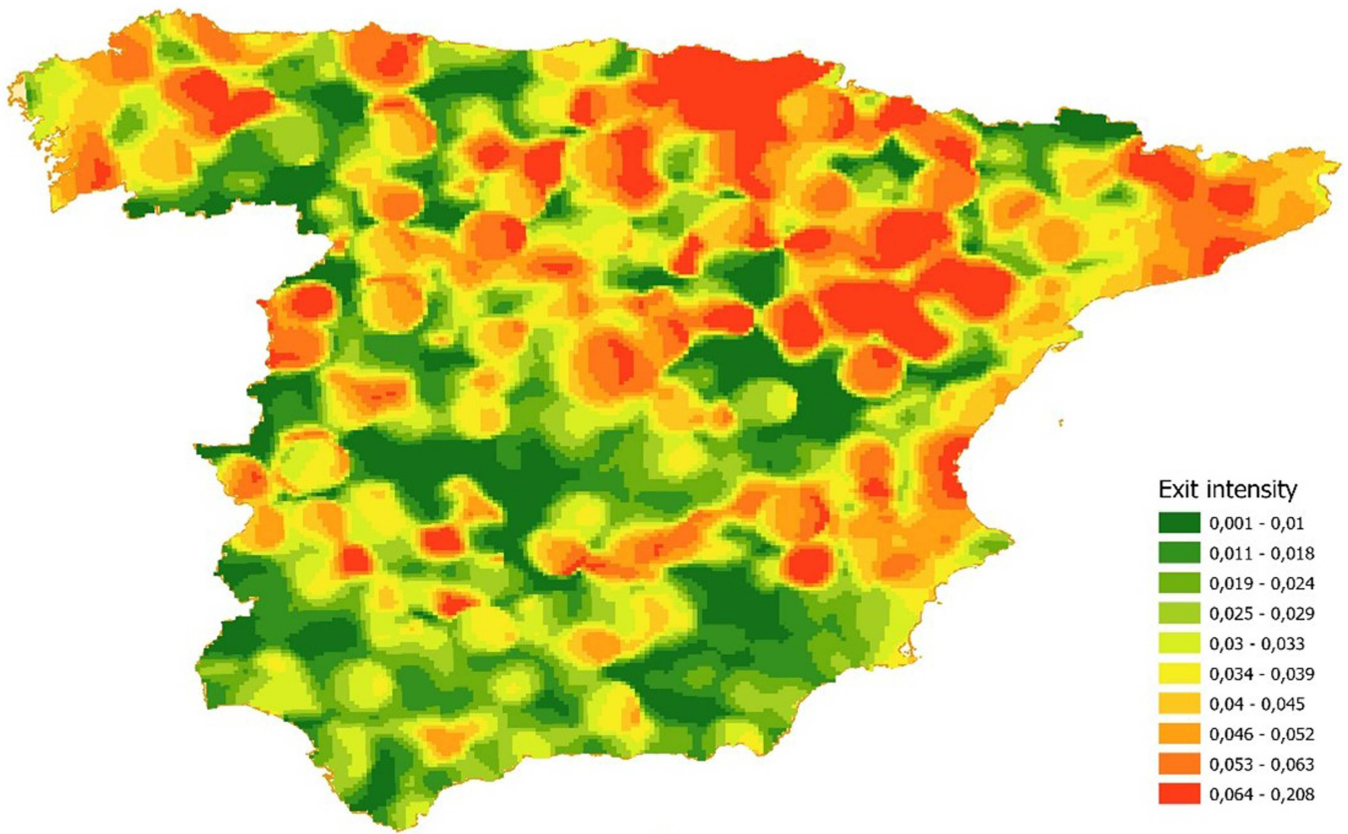


FIGURE 3 | Kernel density map of firm exit intensity. Own elaboration based on SABI data. [Color figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1111/jors.70085)]

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.

3.2 | Market Potential

Traditional 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_j , 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 L_{573} , discounted by the distance to municipality j . The destination set L_{573} 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. d_{jk} is the distance between municipalities j

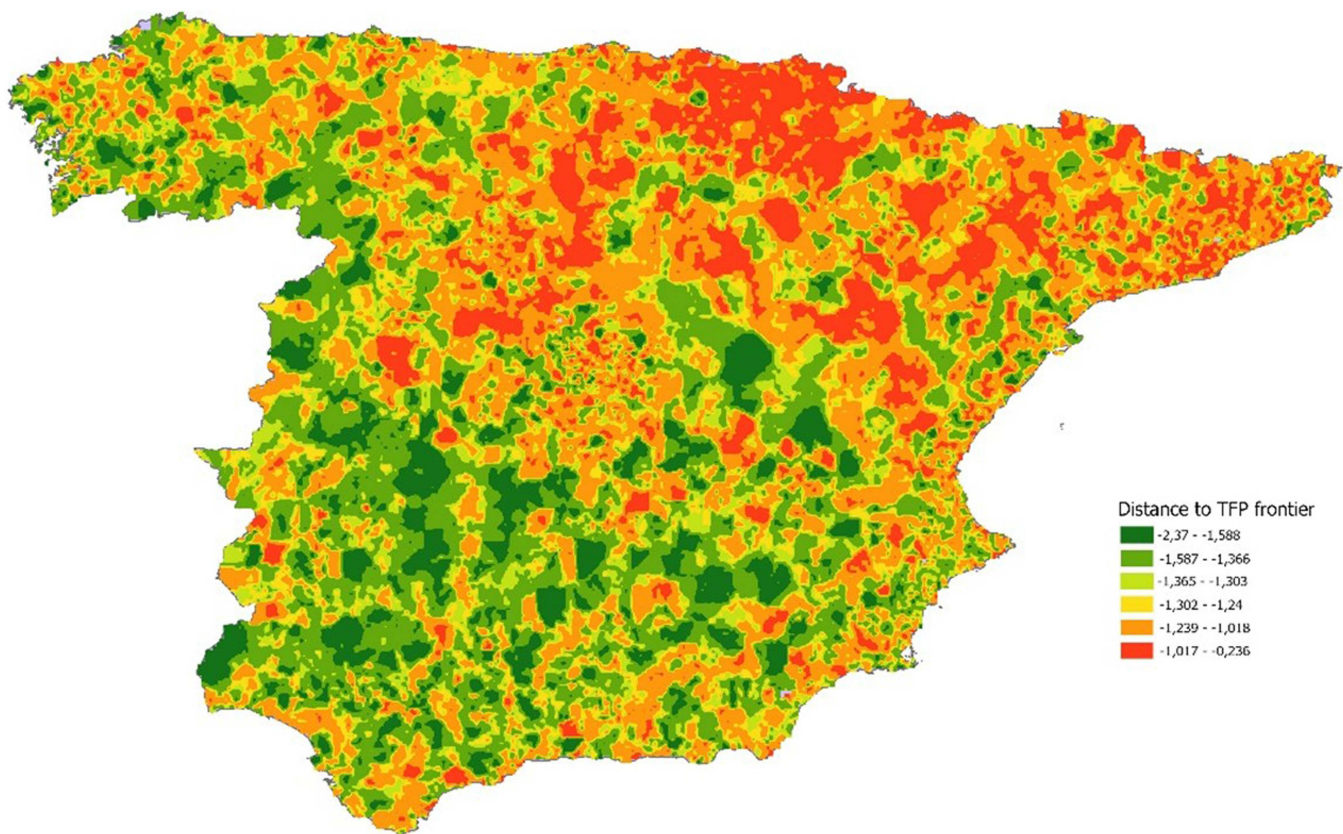


FIGURE 4 | Distance to the productivity frontier (DFR)—2022. Own elaboration based on SABI data. [Color figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1111/jors.70085)]

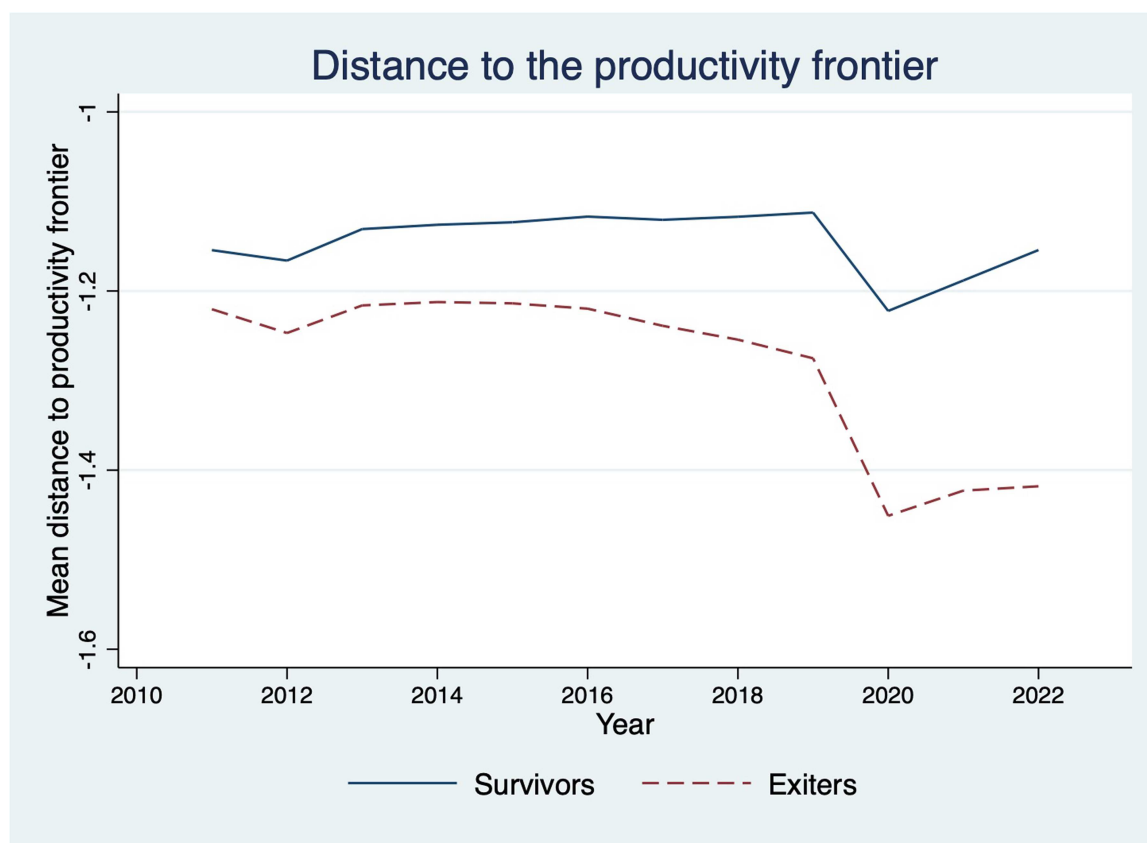


FIGURE 5 | Distance to the productivity frontier: “Survivors” versus “Exiters”. Own elaboration based on SABI data. [Color figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

and k , based on travel times along the shortest route using the Spanish road network (for more details, see Holl 2012).⁸ 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. However, as the index does not include destinations outside Spain, it should hence be regarded as a domestic market potential measure. We address this limitation in our robustness section.

As discussed in Section 2, market potential reflects both demand-side forces and competitive pressures. In Section 5.4, we examine the competition channel more explicitly.

3.3 | 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 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

⁸Travel time is calculated as the travel time along the shortest path on the 2005 road network and is expressed in 30-min units. For all destinations within a 30-min travel time, the population of the destination is not discounted by distance when calculating market potential.

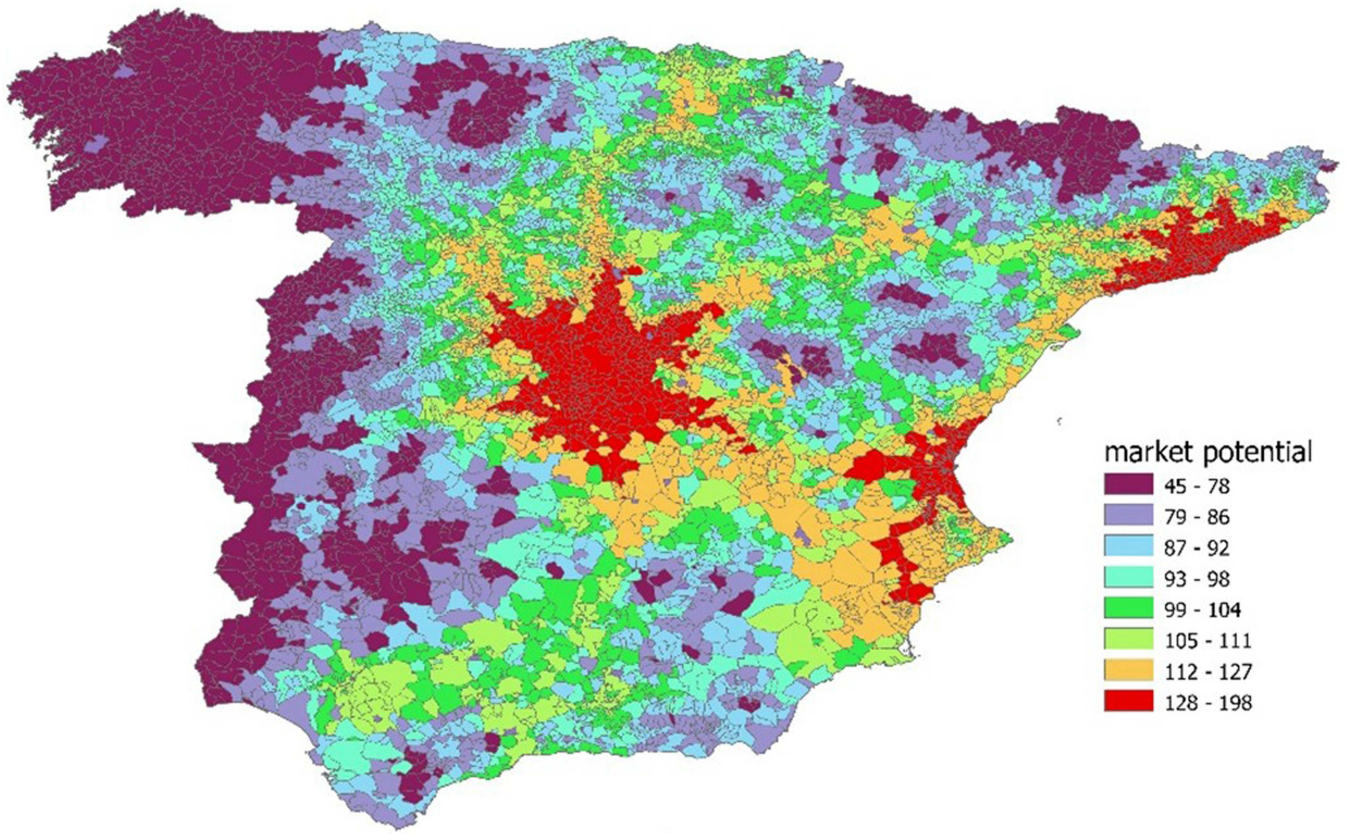


FIGURE 6 | Domestic market potential. Own elaboration (national mean = 100). [Color figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1111/jors.70085)]

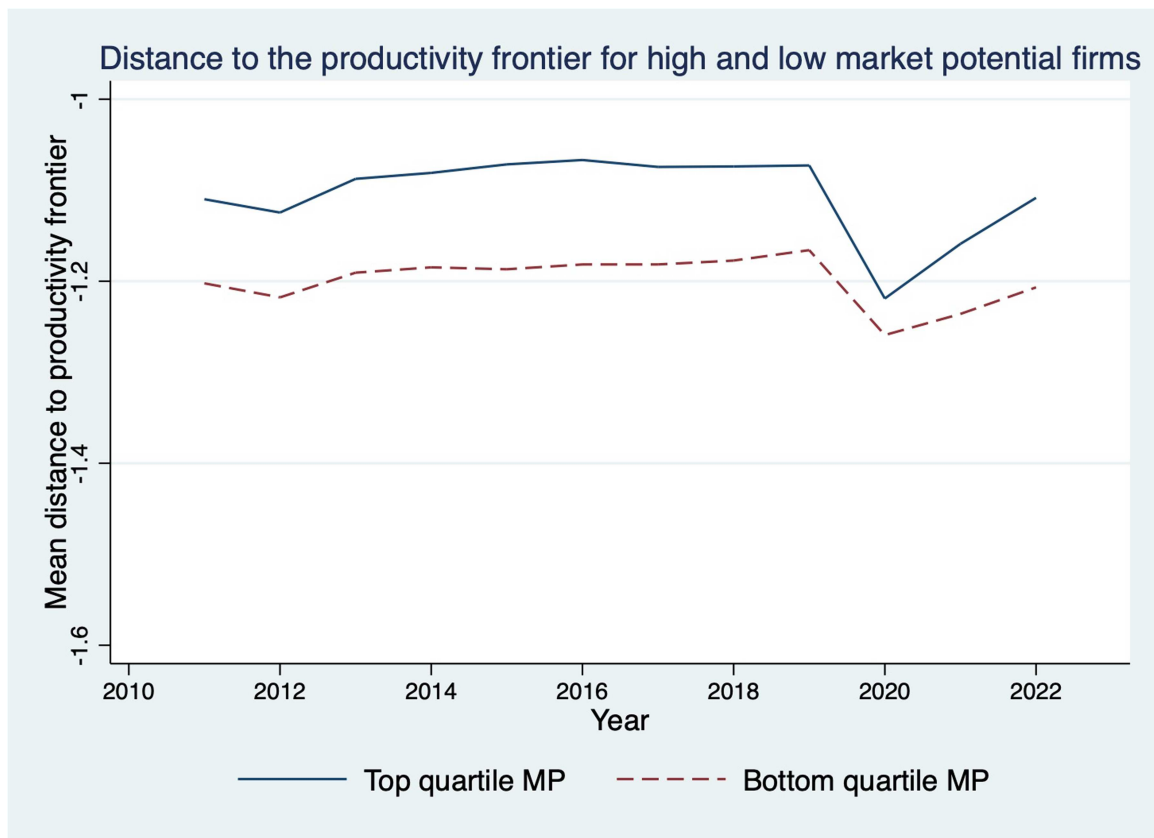


FIGURE 7 | Distance to the productivity frontier in high and low market potential locations. Own elaboration. [Color figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1111/jors.70085)]

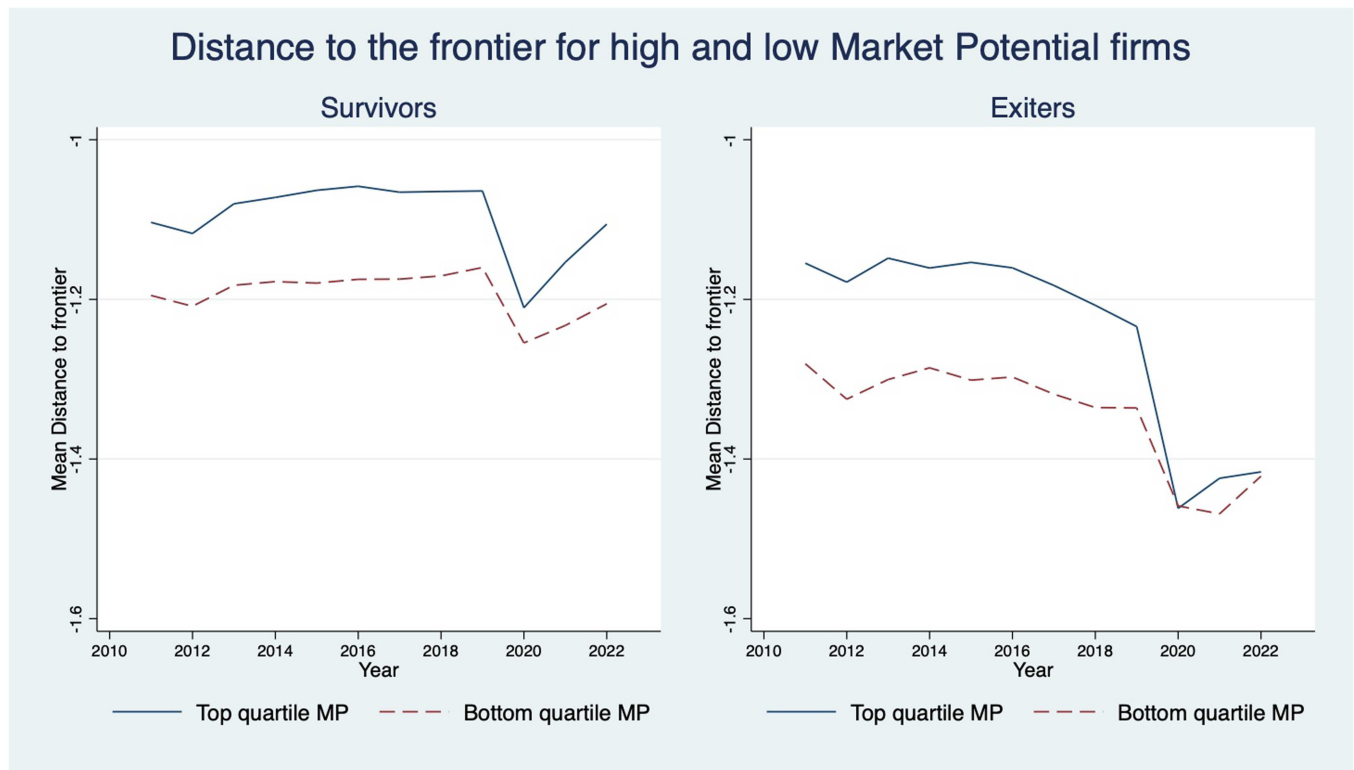


FIGURE 8 | Distance to the productivity frontier for firms in high and low market potential locations: “Survivors” versus “Exiters.” Own elaboration. [Color figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

market potential, both *Survivors* and *Exiters* tend to be closer to the productivity frontier.

4 | Empirical Strategy and Results

4.1 | Empirical Strategy

We model the determinants of firm exit using a complementary log-log (clog-log) model. This is a generalized linear model used for binary outcomes, like Logit and Probit.⁹ A key difference is that the clog-log model performs survival analysis, by fitting the discrete time model that is the analogue of an underlying Cox proportional hazards model (see Prentice and Gloeckler 1978). The exponentiated coefficients of the explanatory variables can therefore be interpreted as hazard ratios (rather than odds ratios as in Logit).

The clog-log specification is consistent with an underlying proportional hazards model in which explanatory variables shift the hazard proportionally. Moreover, the hazard ratio between any two firms is constant over time. This model is suitable for the modeling of firm exit using discrete-time event history data under a proportional hazards assumption, and previous research using this model for that purpose includes Bandick and Görg (2010) and Esteve-Pérez et al. (2018).

The proportional hazard function is formulated as:

$$h(j, X) = 1 - \exp[\exp(\beta'X + y_j)],$$

where $h(j, X)$ is the hazard in the interval between the start and end of year j after the entry date of the firm, given survival until year j . The β parameters are log hazard ratios showing the effects of the explanatory variables X on the hazard rate. A one-unit increase in a covariate X multiplies the hazard by $\exp(\beta)$. y captures the year-specific intercept.

X is a vector of explanatory variables that includes our main variables of interest: 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. The market potential variable is standardized to ease the interpretation of coefficients.

We report all coefficients in exponentiated form. An exponentiated coefficient greater than 1 indicates that the variable increases the hazard of exit, while an exponentiated coefficient less than 1 indicates the variable reduces it. We therefore expect, according to theory, the coefficient on DFR to be less than one, while the coefficient on mp is potentially ambiguous because larger markets may simultaneously intensify competition and expand demand opportunities. If firms in locations with high market potential face greater 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-

⁹A distinct property of clog-log is that it arises from a Type I extreme value distribution, whereas Logit arises from the logistic distribution and Probit from the normal.

COVID-19, to capture any changes in cleansing in high market potential areas.

Furthermore, X includes controls for the other key determinants of firm survival identified in the theoretical and empirical literature on firm dynamics: the size of the company (employment) and its square, age and its square, exporter status, foreign ownership status and indicator variables (fixed effects) for two-digit sectors and firm birth cohorts. We also include various geographical controls (latitude, longitude, a terrain ruggedness index, and the municipality's altitude). We expect larger and older firms to be less likely to exit (following seminal evidence in Dunne et al. 1989), as well as firms engaged in exports (Bernard and Jensen 2002; Görg and Spaliara 2014). Though the evidence on the role of foreign ownership in firm exit is mixed, reflecting strengths and vulnerabilities of foreign firms as well as their footloose character, Perez et al. (2004) find that among Spanish firms in the 1990s, controlling for other firm characteristics, foreign-owned firms were more likely to exit. The sectoral indicators will control for the particular vulnerability of certain industries, in general and during the Covid-19 crisis, such as industries affected by supply-chain disruptions or in which working from home was least feasible. Finally, the birth cohort indicators control for the fact that a firm's period of creation has an influence on its probability of exit, independently of how old it currently is (which is controlled for by the age variable) and of what macro-economic conditions prevail at a given time (controlled for by the year indicators). Evidence of birth cohort effects on exit includes Fukuda (2012) for Japan and Box (2008) for Sweden.¹⁰

4.2 | 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%. Our results show that firm productivity has remained a strong determinant of survival in Spain during the COVID-19 period. This finding contradicts some of the empirical reallocation literature based on other countries and using absolute productivity measures, that found either weaker or reversed selection on productivity during various economic crises (Hallward-Driemeier and Rijkers 2013; Foster et al. 2016; Bloom et al. 2025).

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

TABLE 2 | Estimation results (exit hazard ratios): Pooled across sectors.

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

Note: 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 dummy and a dummy for foreign ownership > 10%. In addition, all estimations include geography controls: Latitude, longitude, altitude, terrain ruggedness index.

competition, which reduces their chances of survival. Prepandemic, 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 prepandemic. 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.

In hazard ratio terms, this implies that, up to the onset of the pandemic, the protective effect of productivity against firm exit was weaker in areas with higher market potential. In other words, productivity differences translate into smaller survival advantages in larger and more central markets, indicating that the strength of productivity-based selection varied across location. While firms in high-market potential areas benefit from greater market access and growth opportunities, they also face greater competition. However, high market potential areas are also characterized by greater agglomeration economies, better institutions and better access to finance, which can mitigate the survival disadvantages associated with lower productivity. In this sense,

¹⁰Some other drivers of firm survival and exit have been identified in the literature, such as the innovativeness of the firm, the gender of the owner or the use of digital intangibles (Wagner 2022; Muzi et al. 2023). Unfortunately, this information is not available in our data, which could affect the estimated hazard if these factors are correlated with both firm survival and our explanatory variables. For example, digital inputs have been shown to enhance firm survival during the pandemic (D'Costa and Ioramashvili 2026), while increased time spent by women on childcare during this period may have also affected business performance and survival (Sevilla and Smith 2020). However, the direction and strength of the correlation between these factors and our key variables of interest—firm productivity and market potential—are theoretically ambiguous. As a result, while some omitted-variable bias cannot be ruled out, its direction is unclear

our results support the view that selection based on productivity is less pronounced in high market potential areas. 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 has altered competitive dynamics.

4.3 | 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 nonlocal 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-2020.¹¹

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 prepandemic 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 lessKIS 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 prepandemic 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.

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 2008.¹² Young firms are more vulnerable during economic crisis but also tend to benefit more from being in an urban local

¹¹The 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.

¹²Summary 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.

TABLE 3 | Estimation results (exit hazard ratios) by sectors.

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

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

Note: 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 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	0.401 (0.043)	0.304 (0.032)	0.523*** (0.024)	0.532 (0.030)
Market potential (MP)	1.351 (0.277)	1.505** (0.320)	1.319*** (0.091)	1.201** (0.101)
Ln distance to the frontier x MP	1.100 (0.126)	1.005 (0.097)	1.103** (0.043)	0.971 (0.043)
Observations	53,137	38,397	329,662	239,744

Note: 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 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 (0.861)	2.044* (0.806)	1.802*** (0.284)	1.043 (0.197)
Top quartile MP x Ln distance to the frontier	0.510** (0.142)	0.285*** (0.046)	0.668*** (0.063)	0.466*** (0.041)
Rest of quartiles MP x Ln distance to the frontier	0.395*** (0.043)	0.314*** (0.041)	0.481*** (0.024)	0.543*** (0.038)
Observations	53,137	38,397	329,662	239,744
Wald Test of equality of coefficients: Prob > χ^2	0.392	0.613	0.001	0.158

Note: 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 dummy and a dummy for foreign ownership > 10%. In addition, all estimations include geography controls: Latitude, longitude, altitude, terrain ruggedness index.

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.

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

TABLE 7 | Competition effects (exit hazard ratios): Pooled across sectors.

Dependent variable = 1 if firm exits in year t		
Exit hazard ratios	(1) 2011–2019	(2) 2020–2022
Ln distance to the frontier (t-1)	0.546*** (0.011)	0.533*** (0.019)
Same sector firm density	1.261*** (0.036)	1.208*** (0.059)
Ln distance to the frontier (t-1) x same sector firm density	1.078*** (0.021)	1.054* (0.032)
Observations	1.998.968	726.504

Note: 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 dummy and a dummy for foreign ownership $> 10\%$. In addition, all estimations include geography controls: Latitude, longitude, altitude, terrain ruggedness index.

effect of being closer to the productivity frontier was significantly lower in the top market potential locations.

4.4 | Competition Effects

Because the traditional market potential measure primarily captures potential demand for locally produced goods and services rather than potential competition per se, we construct an alternative measure to directly proxy competitive pressures. Exploiting the richness of the SABI data set, we use firm-level latitude and longitude to compute the number of firms within a 10 km radius that belong to the same 3-digit sector, as a proxy for local competition.

Tables 7 and 8 show our estimations where the baseline market potential measure has been replaced with the firm-level local competition proxy.¹³ Pooled across sectors, replacing market potential with local same-sector firm density yields qualitatively very similar results, confirming the main patterns regarding competition and the productivity–survival relationship (Table 7).

Examining results by sector (Table 8), higher same-sector density is generally associated with increased exit probabilities, consistent with competition reducing firm survival—except for manufacturing during the COVID-19 period. For the knowledge-intensive services (KIS) sector, the post-2020 coefficients for same-sector density are now statistically significant. While the moderating effect of market potential largely disappeared during the COVID-19 period, the interaction term between distance to the productivity frontier and same-sector firm density in manufacturing is slightly significant and less than one, indicating that the protective effect of productivity was stronger in areas with higher local competition. Overall, the results using same-sector density confirm that the pandemic altered competitive dynamics: in services, the moderating role of local competition largely disappeared, whereas in manufacturing,

productivity appears to have become more protective in denser, competitive areas during the COVID-19 period. The slightly stronger protective effect of productivity in dense manufacturing clusters during the COVID-19 period, while only significant at the 10% level, can reflect a combination of factors. As this measure of competition captures the local density of same-industry firms, it has more relevance for nontradable goods. For tradeable industries, such as some manufacturing and KIS, it captures only the local component of competition, which can explain the small discrepancies with the baseline measure of market potential. Moreover, manufacturing firms may have benefited disproportionately from government support programs such as ERTes, and their higher fixed costs could have meant that only the most productive ones could sustain these costs under high local competition during the pandemic. In contrast, service firms tend to have lower fixed costs, more flexible operations, and were often affected more uniformly by lockdowns, which may explain why the moderating effect of the local environment weakened but did not enhance the effect of productivity on firm survival.

Overall, these results suggest that our findings are largely robust to the choice of spatial economic measure. While we observe some weak differences for manufacturing when focusing specifically on local competition, the main patterns appear to reflect the broader competitive and economic intensity of the local environment, captured both by access to nearby markets and by the concentration of rival firms.

4.5 | 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, by the particular method used to measure productivity, or by the way we constructed our market potential measure.

The inclusion of firms that relocate during the sample period provides an additional opportunity to assess the robustness of the baseline results. However, while relocation may, in principle, provide useful information, relocation decisions are themselves likely endogenous to firm performance and other unobserved characteristics. In particular, more productive firms are more likely to bear the fixed costs associated with moving to high-market-potential locations and face the higher wages, land and rental costs.

Since SABI reports only the most recent location of firms, historical locations are not directly observable. To reconstruct location histories, we combine archived SABI downloads from 2010, 2015, 2019, and 2024. Firm location is assigned using the temporally closest available downloaded location information, under the assumption that relocations are gradually reflected in administrative records taking some time to get reflected. Specifically, the 2010 snapshot is used for 2011–2013, the 2015 snapshot for 2014–2017, the 2019 snapshot for 2018–2020, and the 2024 snapshot for 2021–2022.¹⁴

¹³The number of observations is slightly smaller than in the baseline Tables 2–6, as a very small share of firms (approximately 0.01%) are missing exact latitude and longitude coordinates.

¹⁴As a robustness check, we also employ a more conservative assignment strategy using the 2010 snapshot for 2011–2013, the 2015 snapshot for 2014–2017, and the 2019 snapshot for 2018–2022. Under this approach, relocations occurring after 2019 are not incorporated into the panel, implying that firms relocating between 2019 and 2022 are not identified as movers in the post-COVID-19 subsample. Nevertheless, the results for the pre-COVID-19 period remain qualitatively unchanged and are available upon request.

Using this extended panel, we first re-estimate the baseline complementary log-log models both including relocating firms as well as on the subsample of relocating firms only. The qualitative pattern of results remains unchanged across specifications, suggesting that the main findings are robust to the inclusion of relocating firms.¹⁵

Second, we estimate correlated random effects (CRE) complementary log-log models following the Mundlak approach, including firm-specific means of all time-varying covariates. This specification allows unobserved time-invariant firm heterogeneity to be correlated with location characteristics while retaining the nonlinear hazard structure. Importantly, it partially addresses concerns about endogenous sorting into high-market-potential areas by separating within- and between-firm variation.

The results from the CRE specification closely mirror the baseline estimates. Tables A3 and A4 show that both the coefficient estimates and the patterns across market potential quartiles are highly consistent with those reported in Tables 3 and 4.

A further 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 3 years preceding the pandemic (2017–2019), making it more comparable in length to the post-pandemic window. The results, reported in Table A5 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 another 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 A6, we replicate the analysis using labor 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.

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.¹⁶ Our main results remain robust when using GDP per capita weighted market potential, with the magnitude of the coefficients largely unchanged (Table A7). The only exception is the KIS sector, where market potential and its interaction with distance to the productivity frontier lose statistical significance.

A further limitation of our market potential measure is that it captures only domestic demand within mainland Spain, and

therefore does not directly account for firms' access to foreign markets. This is particularly relevant in the context of exporting firms, for which international demand may constitute a significant share of sales and may partially substitute or complement local market conditions. As a result, our baseline measure may understate the effective market access of firms that are strongly integrated into international trade networks or operating in export-oriented industries. To address this concern, we conduct a robustness check using an alternative specification of market potential that incorporates foreign destination markets, thereby extending the potential demand set beyond national boundaries. Specifically, we re-estimate the index including the NUTS 2 populations of Bordeaux, Toulouse and Montpellier for France and Porto and Lisbon for Portugal. The results in Table A8 are qualitatively similar, suggesting that the main findings are not driven by the exclusion of international markets. Nevertheless, the baseline measure should be interpreted as capturing domestic spatial market access, which remains a key determinant of firm performance and location advantages within Spain.

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 A9 are almost identical to the main results using the full sample.

As an alternative to our preferred complementary log-log estimation, we provide the results from Probit estimations of the probability of exit in Table A10. The Probit results are qualitatively similar though somewhat smaller in magnitude compared to the main results.

Finally, we conduct our main analyses with alternative definitions of the industry productivity frontier. As an alternative to defining frontier firms as those with TFP greater than the 90th centile within their 2-digit industry-year group, we have also defined the frontier as the top 5% and then the top 15%. The results are shown in Table A11. In Table A12, we also show statistics of the overall distribution of $\ln$ TFP. There are measurable differences in TFP across the top centiles of the TFP distribution of the pooled sample. However, as expected, the results are robust to the use of the alternative frontiers.

5 | 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. By implementing a firm-level analysis to investigate the issue of local resilience, we provide new empirical evidence on how productivity-based selection varies across areas with different levels of market potential and how these spatial differences evolved during the pandemic. Our analysis also contributes to the literature on reallocation during

¹⁵ Estimation results are available upon request.

¹⁶ 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.

TABLE 8 | Competition effects (exit hazard ratios) by sectors.

Exit hazard ratios	MANUFACTURING		SERVICES		KIS		LESS KIS	
	(1) 2011–2019	(2) 2020–2022	(3) 2011–2019	(4) 2020–2022	(5) 2011–2019	(6) 2020–2022	(7) 2011–2019	(8) 2020–2022
Ln distance to the frontier (t-1)	0.461*** (0.022)	0.369*** (0.036)	0.568*** (0.014)	0.561*** (0.023)	0.625*** (0.032)	0.699*** (0.061)	0.550*** (0.015)	0.528*** (0.024)
Same sector firm density	1.387** (0.202)	0.631 (0.266)	1.238*** (0.037)	1.175*** (0.060)	1.188*** (0.071)	1.260*** (0.109)	1.239*** (0.044)	1.129* (0.070)
Ln distance to the frontier (t-1) x same sector firm density	1.009	0.694*	1.067***	1.039	1.072*	1.100	1.064***	1.015
Observations	412,804	140,793	1,563,744	585,711	370,980	140,210	1,192,794	443,497

Note: 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 dummy and a dummy for foreign ownership > 10%. In addition, all estimations include geography controls: Latitude, longitude, altitude, terrain ruggedness index.

COVID-19 (Meriküll and Paulus 2024; Konings et al. 2023), with a spatial lens.

Our findings confirm that productivity—specifically being close to the productivity frontier—is a strong determinant of firm survival, even during the COVID-19 period. This finding is in contrast with some of the reallocation literature that has found distortions to the “cleansing” process during economic crisis when using absolute productivity measures (Hallward-Driemeier and Rijkers 2013; Foster et al. 2016; Bloom et al. 2025).

Our results further show that, prior to the COVID-19 period, market potential systematically shaped the relationship between productivity and firm survival. In particular, the relationship between productivity and exit was less pronounced in high market potential areas, indicating that productivity differences translated into smaller survival advantages in high market potential areas. This suggests that the strength of productivity-based selection varied across space, with weaker productivity-based selection in high market potential areas.

However, this moderating role of market potential diminished during the COVID-19 period, and we no longer observe systematic spatial differences in the productivity-survival relationship during this crisis period. In other words, the extent to which firm survival depends on productivity became more homogeneous across space. This may have been due to the nation-wide demand shocks and supply chain distributions, as well as the spatially heterogeneous implementation of government support measures and lower levels of spatial interaction in general during the lockdowns. 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.

By providing evidence on spatial differences in productivity-based selection, our research has significant policy implications. The findings suggest that younger firms, especially in manufacturing, may require more targeted support during periods of economic disruption. While support mechanisms like ERTE were effective for many firms in preventing closure during the COVID-19 pandemic, their impact appears to have been 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, then this may ultimately contribute to growing disparities in regional productivity growth and widen spatial disparities. Our results show that though the intensity of productivity reallocation does vary according to local market potential, this spatial variation disappeared during the COVID-19 years. This should therefore have led to a reduction in spatial productivity disparities between high and low market potential areas during the 2020–2022 period compared to previously.

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 data set 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 labor 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 for a wide number of firm-level and location specific factors, our estimations could still be affected by some unobserved factors which we are not able to control for (such as managerial capacities or take-up of government support) and that could be correlated with the explanatory variables. While an emerging literature exploits variation in timing and the coverage of Covid-19 policies to understand their role in firm survival, performance or productivity reallocation during the pandemic crisis (see Andrews et al. 2025; Bighelli et al. 2021 and D'Costa and Ioramashvili 2026), data for Spain on the timing, geographical coverage and uptake of various Covid-19 policy instruments is unavailable. Finally, further research could account for the potential sorting of firms into more dynamic areas.

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Ethics Statement

The project has been approved by the College Research Ethics Committee at Westminster Business School.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from INFORMA. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from <https://www.informa.es/en/business-risk/sabi> with the permission of INFORMA.

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Appendix

Figure A1, Figure A2.

TABLE A1 | Summary statistics, firms in the top quartile of market potential vs. others.

	Top quartile of market potential				Other quartiles of market potential			
	Mean	Standard deviation	Minimum	Maximum	Mean	Standard deviation	Minimum	Maximum
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	26,179	9.91	46.628	1	10,064
Employment squared	15824.64	1,433,208	1	685,000,000	2272.40	220901.200	1	101,000,000
Age	16.78	10.758	2	160	16.62	10.019	2	151
Age squared	397.18	588.639	4	25,600	376.50	496.290	4	22,801
Export	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	698,511				2,006,374			

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	Standard deviation	Minimum	Maximum
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	14,946
Employment squared	1249.198	278984.4000	1	223000000
Age	6.177	2.8445	2	14
Age squared	46.252	41.1691	4	196
Export	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 | Estimation results (exit hazard ratios) by sectors based on the correlated random effects cloglog model.

Dependent variable = 1 if firm exits in year t	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	MANUFACTURING				SERVICES				KIS				LESS KIS			
	2011–2019		2020–2022		2011–2019		2020–2022		2011–2019		2020–2022		2011–2019		2020–2022	
Ln distance to the frontier (t-1)	0.617***		0.366		0.630***		0.470***		0.605***		0.632***		0.636***		0.435***	
	(0.051)		(0.037)		(0.026)		(0.026)		(0.049)		(0.069)		(0.031)		(0.027)	
Market potential (MP)	1.289		0.548*		1.723**		3.595***		1.937		3.993***		1.584*		2.357***	
	(0.744)		(0.178)		(0.426)		(0.576)		(0.795)		(0.782)		(0.415)		(0.700)	
Ln distance to the frontier (t-1) x MP	1.016		0.947		1.069***		1.008		1.030		0.909*		1.085***		1.032	
	(0.047)		(0.065)		(0.022)		(0.029)		(0.040)		(0.051)		(0.026)		(0.036)	
Observations	434,653		149,972		1,654,530		628,833		396,081		151,670		1,258,449		474,767	

Note: 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 dummy and a dummy for foreign ownership > 10%. In addition, all estimations include geography controls: Latitude, longitude, altitude, terrain ruggedness index.

TABLE A4 | Results by market potential quartile and sectors based on the correlated random effects cloglog model.

Dependent variable = 1 if firm exits in year t	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	MANUFACTURING				SERVICES				KIS				LESS KIS			
	2011–2019		2020–2022		2011–2019		2020–2022		2011–2019		2020–2022		2011–2019		2020–2022	
Top quartile of market potential (MP)	0.798		0.894		1.175		1.057		1.393*		1.073		1.117		1.005	
	(0.167)		(0.253)		(0.121)		(0.155)		(0.276)		(0.282)		(0.136)		(0.181)	
Top quartile MP x ln distance to the frontier	0.629***		0.324***		0.761***		0.475***		0.684***		0.523***		0.788***		0.463***	
	(0.081)		(0.047)		(0.046)		(0.032)		(0.071)		(0.059)		(0.058)		(0.040)	
Rest of quartiles MP x ln distance to the frontier	0.613***		0.376***		0.606***		0.470***		0.583***		0.662***		0.611***		0.429***	
	(0.052)		(0.041)		(0.025)		(0.028)		(0.048)		(0.081)		(0.030)		(0.028)	
Observations	434,653		149,972		1,654,530		628,833		396,081		151,670		1,258,449		474,767	
Wald Test of equality of coefficients: Prob > χ^2	0.818		0.317		0.000		0.881		0.087		0.066		0.000		0.388	

Note: 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 dummy and a dummy for foreign ownership > 10%. In addition, all estimations include geography controls: Latitude, longitude, altitude, terrain ruggedness index.

TABLE A5 | 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	
	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	

Note: 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 dummy and a dummy for foreign ownership > 10%. In addition, all estimations include geography controls: Latitude, longitude, altitude, terrain ruggedness index.

TABLE A6 | Exit hazard ratios based on labor productivity instead of TFP for the distance to the productivity frontier.

Dependent variable = 1 if firm exits in year t	(1) MANUFACTURING		(2) SERVICES		(3) KIS		(4) LESS KIS	
	2011–2019		2020–2022		2011–2019		2020–2022	
	Exit hazard ratios		Exit hazard ratios		Exit hazard ratios		Exit hazard ratios	
Ln distance to the frontier lp (t-1)	0.432***	(0.017)	0.457***	(0.026)	0.534***	(0.012)	0.572***	(0.020)
Market potential (MP)	1.416***	(0.104)	1.183*	(0.113)	1.450***	(0.055)	1.294***	(0.066)
Ln distance to the frontier lp (t-1) x MP	1.028	(0.038)	0.936	(0.042)	1.125***	(0.023)	1.022	(0.027)
Observations	344,678		135,174		1,260,271		545,064	

Note: 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 dummy and a dummy for foreign ownership > 10%. In addition, all estimations include geography controls: Latitude, longitude, altitude, terrain ruggedness index.

TABLE A7 | Exit hazard ratios based on GDP per capita weighted market potential.

Dependent variable = 1 if firm exits in year t	(1) MANUFACTURING		(2) SERVICES		(3) KIS		(4) LESS KIS	
	2011–2019		2020–2022		2011–2019		2020–2022	
	Exit hazard ratios		Exit hazard ratios		Exit hazard ratios		Exit hazard ratios	
Ln distance to the frontier (t-1)	0.460***	(0.020)	0.424***	(0.034)	0.572***	(0.014)	0.568***	(0.023)
Market potential (MP)-GDP/ capita weighted	1.288***	(0.092)	1.232*	(0.146)	1.319***	(0.049)	1.208***	(0.071)
Ln distance to the frontier (t-1) x MP	0.981	(0.036)	0.923	(0.057)	1.043**	(0.021)	0.984	(0.031)
Observations	413,001		140,845		1,563,893		585,749	

Note: 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 dummy and a dummy for foreign ownership > 10%. In addition, all estimations include geography controls: Latitude, longitude, altitude, terrain ruggedness index.

TABLE A8 | Exit hazard ratios based on market potential with foreign destinations.

Dependent variable = 1 if firm exits in year t	(1) MANUFACTURING		(2) SERVICES		(3) KIS		(4) LESS KIS	
	2011–2019		2020–2022		2011–2019		2020–2022	
	Exit hazard ratios		Exit hazard ratios		Exit hazard ratios		Exit hazard ratios	
Ln distance to the frontier (t-1)	0.458***	(0.019)	0.424***	(0.034)	0.567***	(0.013)	0.567***	(0.023)
Market potential (MP) with foreign destinations	1.349***	(0.098)	1.175	(0.146)	1.415***	(0.051)	1.253	(0.071)
Ln distance to the frontier (t-1) x MP with foreign destinations	1.034	(0.041)	0.908	(0.062)	1.107***	(0.023)	1.001	(0.032)
Observations	413,001		140,845		1,563,893		585,749	

Note: 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 dummy and a dummy for foreign ownership > 10%. In addition, all estimations include geography controls: Latitude, longitude, altitude, terrain ruggedness index.

TABLE A9 | 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*** (0.020)	0.411*** (0.035)	0.558*** (0.014)	0.582 (0.028)
Market potential (MP)	1.380*** (0.107)	1.112 (0.158)	1.300*** (0.057)	1.270*** (0.094)
Ln distance to the frontier (t-1) x MP	1.049 (0.045)	0.882 (0.071)	1.076*** (0.027)	1.036 (0.046)
Observations	394,071	133,888	1,355,170	497,885

Note: 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 dummy and a dummy for foreign ownership > 10%. In addition, all estimations include geography controls: Latitude, longitude, altitude, terrain ruggedness index.

TABLE A10 | 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*** (0.018)	−0.30*** (0.030)	−0.19*** (0.009)	−0.18*** (0.014)
Market potential (MP)	0.096*** (0.027)	0.032 (0.045)	0.113*** (0.012)	0.069*** (0.019)
Ln distance to the frontier (t-1) x MP	0.01 (0.017)	−0.05* (0.027)	0.03*** (0.008)	−0.00 (0.011)
Observations	413,001	140,845	1,563,893	585,749

Note: 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 dummy and a dummy for foreign ownership > 10%. In addition, all estimations include geography controls: Latitude, longitude, altitude, terrain ruggedness index.

TABLE A11 | Alternative TFP frontiers.

Dependent variable = 1 if firm exits in year t		MANUFACTURING		SERVICES		KIS		LESS KIS	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		2011–2019	2020–2022	2011–2019	2020–2022	2011–2019	2020–2022	2011–2019	2020–2022
Frontier firms = top 5% of industry x year group in TFP	Exit hazard ratios								
	Ln distance to the frontier (t-1)	0.459*** (0.019)	0.424*** (0.034)	0.568*** (0.013)	0.568*** (0.023)	0.622*** (0.032)	0.751*** (0.071)	0.552*** (0.015)	0.531*** (0.024)
	Market potential (MP)	1.348*** (0.108)	1.139 (0.158)	1.438*** (0.058)	1.243*** (0.078)	1.275*** (0.104)	1.124 (0.149)	1.462*** (0.068)	1.237*** (0.090)
Frontier firms = top 15% of industry x year group in TFP	Ln distance to the frontier (t-1) x MP	1.031 (0.041)	0.908 (0.062)	1.103*** (0.023)	0.999 (0.032)	1.073* (0.044)	0.921 (0.063)	1.107*** (0.027)	1.006 (0.037)
	Ln distance to the frontier (t-1)	0.458*** (0.019)	0.423*** (0.034)	0.567*** (0.013)	0.567*** (0.023)	0.616*** (0.032)	0.750*** (0.071)	0.552*** (0.015)	0.531*** (0.024)
	Market potential (MP)	1.337*** (0.091)	1.177 (0.136)	1.390*** (0.047)	1.249*** (0.066)	1.253*** (0.085)	1.171 (0.129)	1.409*** (0.055)	1.236*** (0.075)
Ln distance to the frontier (t-1) x MP		1.034 (0.041)	0.905 (0.062)	1.107*** (0.023)	1.002 (0.033)	1.084* (0.046)	0.926 (0.065)	1.109*** (0.027)	1.008 (0.037)
		–0.041	–0.062	–0.023	–0.033	–0.046	–0.065	–0.027	–0.037
	Observations	413,001	140,845	1,563,893	585,749	371,026	140,224	1,192,867	443,521

Note: 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 dummy and a dummy for foreign ownership > 10%. In addition, all estimations include geography controls: Latitude, longitude, altitude, terrain ruggedness index.

TABLE A12 | Distribution of TFP in the pooled sample.

	Mean	Standard deviation	Minimum	Maximum	p1	p5	p10	p50	p90	p95	p99
Ln TFP	3.186	0.807	−3.320	8.773	1.001	1.895	2.259	3.161	4.201	4.547	5.215

Note: Number of observations: 2725879.

Source: Authors' own calculation based on SABI data.

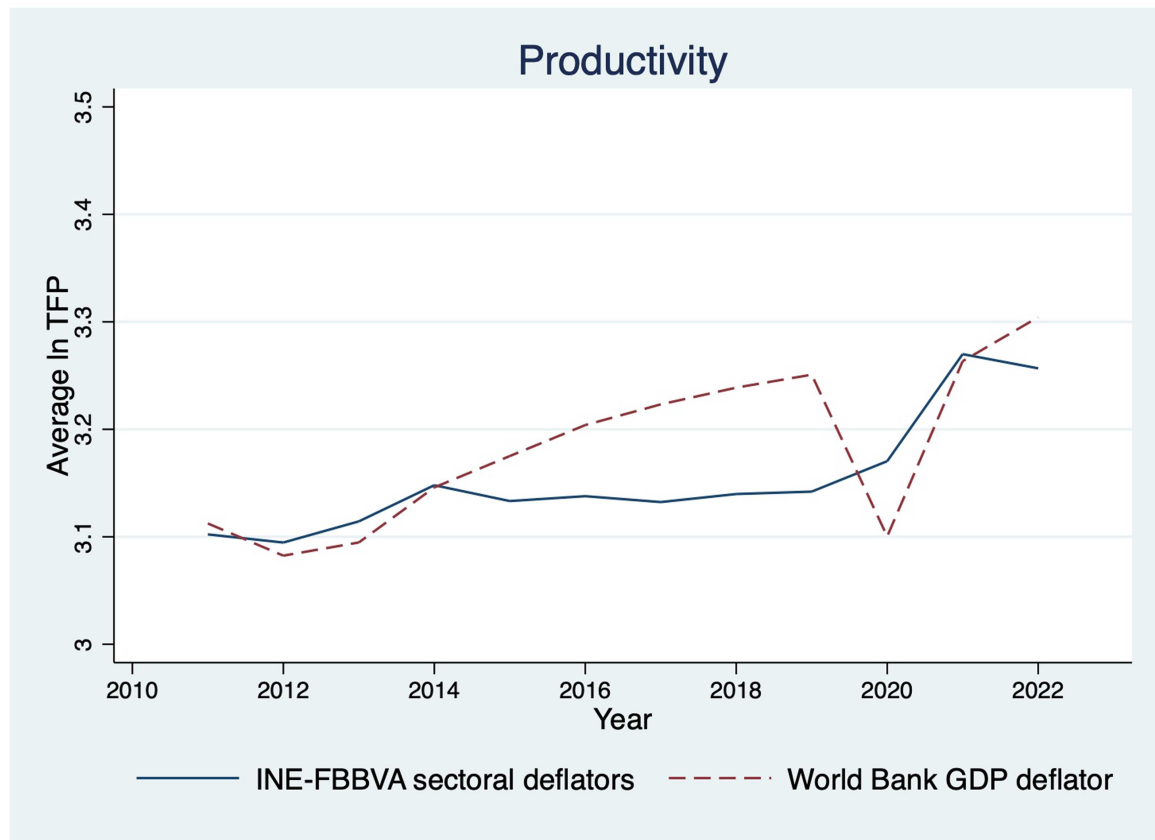


FIGURE A1 | TFP based on INE and FBBVA-IVIE sectoral deflators versus World Bank GDP deflators. [Color figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

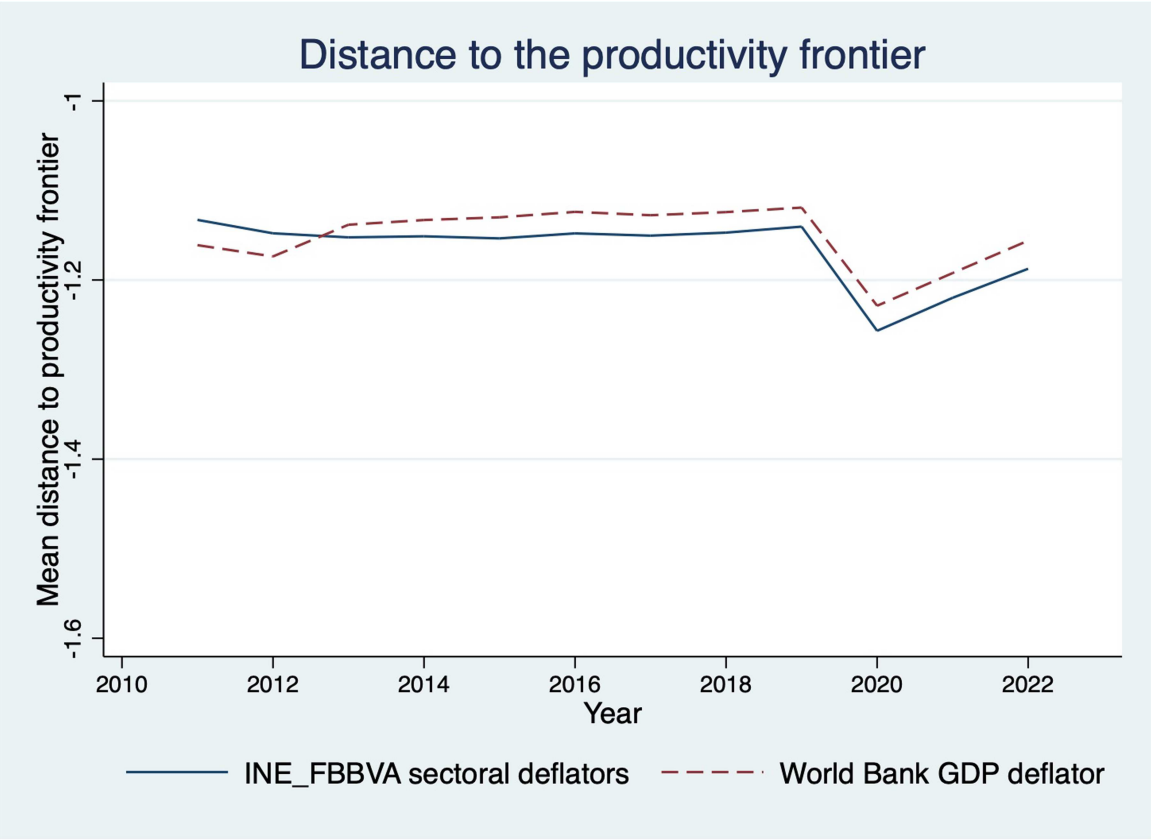


FIGURE A2 | Distance to the productivity frontier based on INE and FBBVA-IVIE sectoral deflators versus World Bank GDP deflators. [Color figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]